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Candice Destouet

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**ÉCOLE DOCTORALE SCIENCES DES MÉTIERS DE L'INGÉNIEUR
CESI LINEACT**

THÈSE

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**Application of Artificial Intelligence Techniques for
Dynamic Flexible Job Shop Scheduling Problems in the
Industry 5.0 context**

THÈSE dirigée par :
M. Bélahcène MAZARI

et co-encadrée par :
Mme Houda TLAHIG et M. Belgacem BETTAYEB

Jury

Mme Maria DIMASCOLO	Directrice de Recherche CNRS, G-SCOP, Grenoble-INP, Grenoble	Présidente
Mme Yasmina HANI	Maître de conférence HDR, QUARTZ, Université Paris 8	Rapporteur
M. David LEMOINE	Professeur, LS2N, IMT Atlantique, Nantes	Rapporteur
M. Imed KACEM	Professeur, LCMOS, Université de Lorraine, Metz	Examineur

Ubuntu,
“Je suis parce que nous sommes.”

“Être heureux [...] c’est remercier Dieu chaque matin pour le miracle de la vie.”
Pape François

“Les yeux sont aveugles. Il faut chercher avec le cœur.”
Antoine de Saint-Exupéry

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Résumé en français

1 Introduction

L'histoire industrielle a traversé cinq révolutions majeures, chacune ayant profondément transformé l'économie et la société. La première révolution industrielle (Industry 1.0) a marqué l'avènement de la mécanisation à vapeur, favorisant la production de masse et une urbanisation rapide. Cependant, elle s'est accompagnée de conditions de travail difficiles et d'une pollution croissante. La deuxième révolution (Industry 2.0), fondée sur l'électricité, l'assemblage en chaîne et l'automobile, a décuplé la production à l'échelle mondiale. Toutefois, ce progrès a également intensifié les inégalités sociales et les défis environnementaux. La troisième révolution (Industry 3.0) a introduit l'automatisation et l'informatique, transformant ainsi les industries grâce à la robotique et aux systèmes numériques, tout en soulevant des questions sur la durabilité et les inégalités. Avec la quatrième révolution industrielle (Industry 4.0), les systèmes cyber-physiques (CPS), l'Internet des objets (IoT) et l'intelligence artificielle (IA) ont émergé. Ces technologies ont permis de créer des usines intelligentes, mais elles ont soulevé des préoccupations concernant la cybersécurité, les coûts et l'adaptation des compétences. Enfin, la cinquième révolution industrielle (Industry 5.0) se distingue par sa vision centrée sur la collaboration humain-machine. Elle met l'accent sur la durabilité et la résilience face aux crises mondiales, cherchant à allier bien-être humain, avancées technologiques et préservation de l'environnement. Ces révolutions successives ont accru la complexité des systèmes de production, plaçant la gestion des ressources et l'ordonnancement au cœur des enjeux dans un monde globalisé et toujours plus concurrentiel.

Les industries modernes sont donc confrontées à des défis complexes, tels que la transformation numérique, la personnalisation des produits, la durabilité, les perturbations des chaînes d'approvisionnement, et la santé/sécurité des travailleurs. Les entreprises doivent répondre à une demande croissante de flexibilité tout en optimisant les coûts et les ressources, dans un environnement de concurrence mondiale. La durabilité devient essentielle, nécessitant des pratiques plus écologiques, la réduction des émissions nuisibles et la transition vers une économie circulaire. Parallèlement, les perturbations des chaînes d'approvisionnement, accentuées par des crises comme le COVID-19, soulignent la nécessité de chaînes plus résilientes et plus courtes. Les questions de santé et de sécurité des travailleurs, au cœur des principes d'Industrie 5.0, exigent des environnements de travail adaptés et des politiques centrées sur le bien-être. Cependant, les PME rencontrent des difficultés d'accès aux technologies avancées, creusant un écart avec les grandes entreprises. Pour relever ces défis, les industries doivent adopter des stratégies intégrant innovation technologique, durabilité et conception centrée sur l'humain, tout en améliorant la planification et l'ordonnancement pour une performance globale optimale.

Concernant la production, la révolution industrielle a représenté une avancée majeure en termes d'efficacité, notamment grâce à des innovations comme la machine à vapeur. Ces progrès ont permis de réduire considérablement les coûts de fabrication, tout en rendant les produits plus ac-

cessibles au grand public. L'apparition de la production de masse au XXe siècle, notamment grâce aux lignes d'assemblage introduites par Ford, a nécessité une organisation plus efficace des tâches et des ressources. Cette dynamique a favorisé l'émergence de la recherche sur les problèmes d'ordonnancement, désormais essentiels pour optimiser la productivité et répondre aux exigences croissantes des entreprises. En effet, ces problèmes visent à optimiser l'allocation des ressources tout en respectant un ensemble de contraintes variées, rendant leurs solutions indispensables pour une production efficiente.

Les environnements ou ateliers de production, conçus pour être adaptés aux besoins spécifiques des processus en termes de flux physiques, présentent diverses configurations et des niveaux de complexité variés concernant les problématiques d'ordonnancement de tâches de production. L'environnement à machine unique, bien que simple, peut présenter des défis d'optimisation complexes concernant l'ordonnancement. L'atelier à machines parallèles, avec plusieurs machines disponibles simultanément pour exécuter les tâches, accroît la complexité liée à l'attribution des tâches selon le type de machines (identiques, uniformes ou non reliées). Le processus d'un environnement de type "flow-shop" impose une séquence fixe d'opérations, tandis que sa variante flexible permet des routages alternatifs, augmentant la souplesse mais aussi la difficulté. L'atelier à cheminement multiple ou "job-shop" est parmi les plus complexes, se caractérisant par des séquences d'opérations spécifiques à chaque tâche (produit ou "job") et des ressources variées. Sa version flexible intègre une plus grande adaptabilité avec la possibilité de choix entre plusieurs machines pour chaque opération. Enfin, l'atelier de type "open-shop" permet aux opérations de chaque produit d'être réalisées dans n'importe quel ordre, offrant une flexibilité maximale mais multipliant les options de séquençement des opérations pour chaque produit, ainsi que celles affectées sur chaque machine.

Les problèmes d'ordonnancement industriel intègrent diverses contraintes essentielles, comme les précédences entre les opérations et entre les tâches, les dates de disponibilité et d'échéance, le traitement par lots, et les temps de préparation et de maintenance des machines. Les temps de transport/transfert intra-atelier, souvent négligés et/ou simplifiés, et les limitations de stockage influent également sur les performances. La préemption, permettant d'interrompre et de reprendre les opérations, est utile pour gérer les urgences. De plus, les principes de coproduction et de production en tant que service favorisent l'émergence des usines distribuées qui posent des défis et des contraintes supplémentaires en raison des distances géographiques et des besoins de coordination. D'autre part, les enjeux environnementaux, comme la réduction de la consommation énergétique et des émissions, deviennent primordiaux pour un développement durable et peuvent représenter des contraintes opérationnelles significatives dans les problèmes d'ordonnancement. Enfin, les contraintes humaines, telles que la disponibilité ou les préférences des opérateurs, sont de plus en plus intégrées dans les solutions modernes pour améliorer l'efficacité et l'harmonie au travail. L'intégration de ces contraintes rend les problèmes d'ordonnancement plus complexes, nécessitant des méthodes sophistiquées pour concilier fidélité au modèle et complexité computationnelle.

Les objectifs des problèmes d'ordonnancement varient en fonction des priorités du processus de production. Les objectifs temporels visent à minimiser des indicateurs comme le temps total d'exécution ou "makespan", les retards, et les temps de préparation ou de transport. Les objectifs économiques cherchent à réduire les coûts liés à la production, à la main-d'œuvre, à l'énergie, à la maintenance ou au stockage. Les objectifs axés sur les tâches se basent sur des métriques individuelles, telles que la réduction des délais ou des tâches en retard. L'optimisation des ressources privilégie une meilleure utilisation des machines. Les objectifs qualité se focalisent sur la réduction des défauts et le respect des

normes techniques. Les préoccupations environnementales incluent la réduction de la consommation énergétique et des émissions. Enfin, les objectifs liés à l'humain intègrent le bien-être, la sécurité et les préférences des opérateurs. Dans les cas complexes, l'optimisation multi-objective permet de concilier des objectifs souvent conflictuels.

En pratique, les environnements industriels sont confrontés à des perturbations imprévues, nécessitant l'adoption des stratégies d'ordonnancement dynamiques pour maintenir l'efficacité et minimiser les interruptions. Ces perturbations peuvent rendre obsolètes des solutions d'ordonnancement initiales. Pour y faire face, différentes approches sont utilisées : l'ordonnancement proactif, réactif, prédictif-réactif, et proactif-réactif, chacune visant à anticiper ou réagir aux perturbations dans le but de maintenir la stabilité et l'optimisation. L'ordonnancement dynamique repose donc sur un compromis entre anticipation et réactivité, avec un choix de stratégie dépendant de la fréquence et de l'ampleur des perturbations et des priorités du système.

Les problèmes d'ordonnancement industriel sont des défis d'optimisation combinatoire, classés en trois catégories selon leur complexité : les problèmes résolubles en temps polynomial, les problèmes NP-difficiles et les problèmes fortement NP-difficiles. Pour les résoudre, on utilise des méthodes exactes, telles que la programmation linéaire et la programmation par contraintes, ou des méthodes approximatives, comme les heuristiques et les métaheuristiques. L'intelligence artificielle, notamment l'apprentissage automatique et l'apprentissage par renforcement, s'adapte aux conditions changeantes des environnements d'ordonnancement dynamiques, souvent en combinaison avec d'autres méthodes. Elle joue un rôle central de plus en plus important dans l'optimisation des systèmes industriels modernes. Grâce à ces technologies, un ordonnanceur basé sur l'IA permet d'analyser de grandes quantités de données et de réagir en temps réel à des perturbations. Des entreprises comme General Electric, Siemens et Toyota ont intégré ces technologies pour ajuster leurs plannings de manière proactive, améliorant ainsi leur compétitivité tout en réduisant les coûts et en augmentant leur réactivité.

La transition vers l'Industrie 5.0 marque un changement de paradigme dans l'ordonnancement de la production, axé sur des systèmes centrés sur l'humain, durables et résilients. Ce travail de thèse vise à : (1) concevoir un modèle d'optimisation aligné avec ce nouveau paradigme, intégrant non seulement les objectifs économiques largement explorés dans la littérature, mais également des objectifs environnementaux et humains, et (2) développer une approche de résolution basée sur l'IA pour l'ordonnancement dynamique des ateliers de production flexibles de type "job-shop". L'objectif est de démontrer la faisabilité de ces approches et d'en souligner l'intérêt pour améliorer l'ordonnancement industriel en prenant en compte les enjeux humains, économiques et environnementaux dans le contexte de l'Industrie 5.0. Cette thèse est rédigée sous un format "par articles". Un résumé de chaque article est présenté dans les sections suivantes.

2 Problème d'ordonnancement d'atelier "job-shop" flexible dans le contexte de l'Industrie 5.0 : étude sur la réintégration de l'Humain, la prise en compte de l'environnement et l'amélioration de la résilience

Dans le contexte de l'industrie 5.0, le problème d'ordonnancement d'atelier de type "job-shop" ou "Flexible Job Shop Scheduling Problem" (FJSSP) est redéfini. Ce modèle d'ordonnancement flexible se distingue par sa capacité à prendre en compte non seulement les contraintes liées aux machines et aux tâches, mais aussi les opérateurs humains et les facteurs écologiques. La réintégration humaine

dans le processus de production met en avant des critères tels que les compétences des travailleurs, leur fatigue, leur apprentissage au fil du temps et leur exposition aux risques ergonomiques. En parallèle, la nécessité de réduire la consommation énergétique et les émissions de gaz à effet de serre impose de nouveaux défis d'optimisation dans l'ordonnancement des tâches. Le FJSSP évolue donc vers une approche où l'optimisation des performances industrielles doit concilier ces objectifs complexes et souvent contradictoires.

Les résultats montrent que la prise en compte simultanée des facteurs humains et environnementaux dans le FJSSP, bien que récente, est encore peu explorée dans la littérature. La majorité des études se concentre sur des environnements statiques, tandis que l'intégration dynamique de ces facteurs, qui reflète mieux la réalité des ateliers modernes, reste marginale. En effet, seuls 9,6 % des études intègrent à la fois les aspects humains et environnementaux, et encore moins dans des contextes d'ordonnancement dynamique. Les solutions proposées dans la littérature sont souvent basées sur des méthodes hybrides combinant des métaheuristiques et des approches d'intelligence artificielle pour gérer les incertitudes et les aléas en temps réel, augmentant ainsi la résilience du système.

La conclusion principale de cette analyse est que l'industrie 5.0 impose une redéfinition des priorités en production, où la performance ne se mesure plus uniquement en termes de coût ou de temps de production, mais également en termes de bien-être des opérateurs et d'impact environnemental. L'article propose un modèle mathématique pour résoudre le FJSSP en minimisant la consommation énergétique tout en respectant les contraintes ergonomiques des travailleurs, notamment via l'indice OCRA qui évalue les risques liés aux mouvements répétitifs des membres supérieurs. Ce modèle vise à fournir des solutions d'ordonnancement flexibles qui respectent à la fois les exigences de durabilité environnementale et les contraintes humaines, dans le cadre d'une production résiliente et réactive face aux perturbations. Les futures recherches devront explorer plus en profondeur l'intégration dynamique de ces facteurs et développer des approches capables de faire face aux exigences croissantes de personnalisation et de durabilité dans les systèmes de production modernes.

3 Problème multi-objectif d'ordonnancement durable d'un "job-shop" flexible : équilibrage des critères économiques, écologiques et sociaux

Dans le contexte de l'industrie 5.0, une approche d'ordonnancement d'atelier "job-shop" flexible est proposée, prenant en compte trois critères majeurs : économique, écologique, et social. Plus précisément, l'objectif est de trouver un équilibre entre la performance industrielle, la réduction de la consommation énergétique, et l'amélioration du bien-être des travailleurs. Pour cela, deux modèles multi-objectifs sont développés. Le premier modèle cherche à minimiser le makespan (temps total de production), la consommation d'énergie, et les risques ergonomiques pour les opérateurs, évalués à l'aide de l'indice OCRA (Occupational Repetitive Action). Le deuxième modèle remplace les risques ergonomiques par la satisfaction des travailleurs, en tenant compte de leurs préférences en matière de machines, de tâches à effectuer et de quart de travail.

Ces modèles se distinguent par l'intégration de contraintes liées aux déplacements internes, à la fois pour les produits et pour les opérateurs entre les machines, ainsi que par la prise en compte des temps de setup et des périodes de repos pour les travailleurs. Ces éléments, sont modélisés pour mieux refléter les réalités des ateliers modernes. La consommation énergétique globale est également modélisée non seulement pour les opérations de production mais aussi pour les déplacements et l'utilisation des

installations auxiliaires (comme l'éclairage ou le chauffage).

Pour résoudre ces problèmes d'ordonnancement, qui sont NP-difficiles, des algorithmes NSGA-II et NSGA-III sont utilisés, avec une amélioration par une stratégie de Q-learning, qui permet d'ajuster dynamiquement les paramètres au fil des itérations pour optimiser la recherche de solutions. Les résultats des simulations montrent que cette approche parvient à un bon compromis entre les différents objectifs de durabilité et de productivité. Différents profils de travailleurs sont testés, permettant d'analyser l'influence des préférences des opérateurs sur les performances globales du système.

En conclusion, cette étude démontre qu'il est possible d'intégrer simultanément des critères économiques, écologiques et sociaux dans les problèmes d'ordonnancement d'ateliers "job-shop" flexibles. Ces critères garantissent la sécurité et le bien-être des opérateurs, tout en réduisant significativement la pollution due à la consommation d'énergie et en préservant de bonnes performances économiques. Elle parvient à maintenir des bonnes solutions dans des délais raisonnables, ce qui est essentiel pour les systèmes industriels. L'analyse met également en évidence la nécessité de poursuivre les recherches pour affiner davantage l'intégration des facteurs humains et environnementaux. Cela permettra de mieux répondre aux exigences croissantes de l'Industrie 5.0, qui vise non seulement une production plus durable, mais aussi plus personnalisée, tout en renforçant la résilience des systèmes face aux aléas.

4 Revue de la littérature et orientations futures du problème d'ordonnancement dynamique d'un "job-shop" flexible : une décennie de recherche

Cette revue systématique, couvrant la période 2013-2024, se concentre sur les recherches autour du problème d'ordonnancement dynamique d'atelier "job-shop" flexible (DFJSSP), un enjeu clé pour les systèmes de production modernes. Au total, 303 études publiées dans la littérature sont analysées, mettant en avant les différentes stratégies d'ordonnancement, les types de perturbations et les méthodes de résolution employées pour améliorer la gestion des processus de production dans un tel environnement. Trois grandes stratégies sont identifiées : i) l'ordonnancement réactif, où les décisions sont prises en temps réel face aux perturbations ; ii) l'ordonnancement prédictif-réactif, qui ajuste un plan initial en réponse aux événements inattendus ; et iii) l'ordonnancement proactif, qui anticipe les disruptions en intégrant des marges de sécurité dans les plannings.

Les perturbations les plus fréquemment étudiées incluent l'arrivée imprévue de nouvelles tâches et les pannes de machines, deux événements critiques dans les environnements de production flexibles. Pour gérer ces imprévus, plusieurs méthodes sont utilisées, notamment les métaheuristiques, les heuristiques, et des approches basées sur l'intelligence artificielle. Ces techniques permettent de réagir efficacement tout en minimisant l'impact sur les objectifs de production.

Les objectifs abordés dans ces études sont principalement la minimisation du makespan (le temps total de production), la réduction de la charge des machines et de la consommation énergétique. Ces objectifs économiques sont de plus en plus complétés par des critères sociaux et environnementaux, comme la réduction de la fatigue des travailleurs et des risques ergonomiques, ou encore la limitation des émissions de carbone. Cela reflète une tendance vers une production plus durable, en lien avec les principes de l'Industrie 5.0, qui cherche à équilibrer les performances économiques avec des préoccupations écologiques et humaines.

En termes de méthodes de résolution, les métaheuristiques dominent largement (utilisées dans 85 % des études), en raison de leur capacité à explorer efficacement de vastes espaces de solutions.

Elles sont souvent combinées à des algorithmes d'intelligence artificielle ou à des simulations pour mieux appréhender et gérer la complexité des environnements dynamiques. Parmi ces méthodes, les algorithmes génétiques, l'optimisation par essais particuliers (Particle Swarm Optimization) et les algorithmes basés sur l'apprentissage par renforcement (comme le Q-learning) se distinguent par leur efficacité.

La revue conclut en soulignant l'importance d'intégrer davantage les critères humains et environnementaux dans les futurs travaux sur le problème DFJSSP. Cette intégration permettra de répondre aux défis croissants liés à la personnalisation et à la durabilité, ainsi qu'à la résilience en améliorant la réactivité des systèmes de production face aux perturbations, qui sont la vocation même de l'Industrie 5.0.

5 Solutions basées sur l'apprentissage automatique pour un ordonnancement dynamique durable d'ateliers "job-shop" flexibles en cas d'absence des travailleurs et de perturbations sur la production d'énergie

Ce chapitre aborde le problème d'ordonnancement dynamique durable d'atelier "job-shop" flexible (DSFJSSP), un enjeu clé pour l'industrie moderne, en intégrant simultanément des facteurs humains et environnementaux. Il se concentre sur les perturbations causées par l'absence d'opérateurs et les fluctuations dans la production d'énergie renouvelable, deux défis souvent rencontrés dans les environnements de production actuels. Le modèle développé vise à optimiser trois objectifs : la minimisation du makespan (le temps total de production), la réduction des émissions de carbone, et la gestion des risques ergonomiques pour les travailleurs à l'aide de l'indice OCRA (Occupational Repetitive Action). Le modèle proposé prend en compte plusieurs facteurs pratiques, tels que les compétences des travailleurs, la consommation énergétique des machines et des installations auxiliaires (comme l'éclairage et le chauffage), ainsi que les temps de transport et de préparation des machines. En plus de ces éléments, le système intègre une double source d'énergie (renouvelable et classique) et optimise l'utilisation de l'énergie renouvelable (solaire) en fonction des périodes de production et de stockage disponibles.

Trois méthodes basées sur l'apprentissage automatique ont été testées pour répondre aux perturbations : l'apprentissage par renforcement (Q-Learning), l'apprentissage profond (Deep Learning) et une approche hybride appelée Deep Q-Learning. Ces techniques permettent au modèle de s'adapter en temps réel aux interruptions dues à des absences d'opérateurs ou à des variations imprévues dans l'approvisionnement en énergie. Le Q-Learning a été utilisé pour gérer des situations spécifiques en fonction du moment et de l'ampleur des perturbations. Quant au Deep Learning, la méthode utilise des réseaux de neurones pour prédire les meilleures actions à entreprendre en fonction des données d'entrée. Enfin, le Deep Q-Learning combine les deux précédentes approches, en exploitant la puissance des réseaux neuronaux pour améliorer la prise de décision dans des environnements complexes et dynamiques.

Les résultats des simulations montrent que l'intégration simultanée des facteurs humains et environnementaux permet de renforcer la résilience et la durabilité des systèmes d'ordonnancement. Le Deep Q-Learning s'est révélé être la méthode la plus performante, capable d'identifier des bonnes stratégies de réordonnancement tout en minimisant les impacts sur les performances globales du système. En particulier, cette approche s'est montrée efficace pour équilibrer les objectifs de durabilité

tout en maintenant un faible niveau de perturbation dans le processus de production.

En conclusion, cette étude met en lumière la nécessité et la difficulté de prendre en compte différents types de perturbations inévitables dans les systèmes de production réels. Elle propose un modèle intégrant, à titre d'exemples, les perturbations liées aux travailleurs et à l'approvisionnement en énergie renouvelable dans les systèmes de production flexibles. Elle souligne également l'importance de l'utilisation de méthodes d'apprentissage automatique pour adapter les systèmes d'ordonnancement en temps réel, en garantissant non seulement la continuité opérationnelle, mais aussi le respect des objectifs économiques, environnementaux et sociaux. Enfin, les futures recherches pourraient explorer davantage l'intégration de sources d'énergie renouvelable multiples et d'autres types de perturbations, comme l'arrivée imprévue de nouvelles tâches ou les pannes de machines.

6 Conclusion

Cette thèse se concentre sur le développement de solutions d'ordonnancement pour les ateliers flexibles et dynamiques, en visant un équilibre entre les objectifs économiques (makespan), environnementaux (consommation d'énergie, empreinte carbone) et sociaux ($OCRA^{max}$, préférences). Les approches développées cherchent à optimiser simultanément ces trois dimensions afin de favoriser un compromis durable et efficace, en réponse aux besoins variés des systèmes de production modernes. Les modèles proposés intègrent des contraintes pratiques et réalistes, telles que la précédence, le transport, la préparation des machines, et le déplacement des opérateurs. Les perturbations dynamiques, comme l'absence de travailleurs ou les variations énergétiques, ont été traitées via des stratégies adaptatives et des approches basées sur l'IA, notamment le Deep Q-Learning, qui s'est montré particulièrement performant.

Les résultats démontrent l'efficacité des modèles pour réduire les risques ergonomiques, minimiser l'empreinte carbone et améliorer la résilience des systèmes face aux perturbations. Les perspectives incluent l'application des modèles à des données industrielles réelles, l'intégration d'énergies renouvelables variées, une meilleure gestion des événements dynamiques imprévus et une extension à des scénarios plus complexes comme la maintenance des machines ou la logistique inter-sites. Ce travail contribue à des systèmes de production plus durables, adaptatifs et centrés sur l'humain, alignés sur les objectifs de l'Industrie 5.0.

Abstract

This thesis focuses on the development of scheduling solutions for dynamic and flexible job shops, balancing economic (makespan), environmental (energy consumption, carbon footprint), and social objectives (OCRAmax, worker preferences). The approaches developed aim to optimize these three dimensions simultaneously, providing sustainable and efficient solutions for modern production systems. The proposed models incorporate practical and realistic constraints, such as task precedence, intra-workshop transport times, machine setups, and worker movements. Dynamic disruptions, like worker absences and renewable energy source fluctuations, are handled through adaptive strategies and AI-based approaches, particularly Deep Q-Learning, which has proven to be highly effective.

The results demonstrate the models' ability to reduce ergonomic risks, minimize carbon emissions, and enhance system adaptability in the face of disruptions. Future research includes applying the models to real industrial data, integrating diverse renewable energy sources, improving the management of unforeseen dynamic events, and extending to more complex scenarios such as machine maintenance and inter-site logistics. This work contributes to more sustainable, adaptive, and human-centered production systems, aligned with Industry 5.0 objectives.

Keywords : Flexible Job Shop Scheduling Problem, Dynamic Scheduling, Sustainability, Industry 5.0, Human-centric Manufacturing, Resilience, Machine learning, Multi-objective optimization, NSGA-III.

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Chapter 1

Introduction

1.1 Industrial revolutions: foundations of modern industry

The history of industry is marked by a series of transformative revolutions, each profoundly reshaping production systems and society. Figure 1.1 illustrates these revolutions, highlighting their progressively shorter durations, which reflect the accelerating pace of technological advancements. These developments will be explored in detail in the following paragraphs.

The **First Industrial Revolution (Industry 1.0)** emerged in the late 18th century, driven by mechanization powered by water and steam. Small-scale domestic production and artisan workshops transitioned to large-scale industrial systems, where machines played a central role. This marked the advent of mass production, with the textile industry being one of the first to benefit from innovations such as the spinning jenny and the mechanical loom. Mining and metallurgy also saw significant advancements, particularly with the use of steam-powered machinery for raw material extraction and processing. This revolution not only transformed production methods but also triggered profound social changes. Workers who had previously been employed in agriculture or crafts migrated to urban factories in search of better wages. Meanwhile, rural areas experienced labor shortages as populations moved to industrial hubs, accelerating urbanization. This migration fundamentally altered lifestyles, working conditions, and social structures, laying the groundwork for the modern economy. Industry 1.0 also introduced the first forms of industrial capitalism, characterized by the emergence of large corporations and a new class of factory owners. Moreover, this revolution also sparked numerous technological advancements, some of which formed the foundation for subsequent industrial transformations [3].

However, these changes came with some challenges. From a public health perspective, workers often endured dangerous and grueling conditions, while the massive use of coal marked the beginning of large-scale industrial pollution. At an organizational level, the complexity of coordinating machines and labor gave rise to the earliest forms of scheduling problems. Although rudimentary, these challenges focused on minimizing machine downtime and improving production line efficiency, setting the stage for future innovations in operational management [4].

The **Second Industrial Revolution (Industry 2.0)**, also known as the Technological Revolution, emerged in the late 19th century and continued into the early 20th century. This period saw major advancements in manufacturing, communication, and transportation. The transition from steam power to electricity, offering greater efficiency and flexibility, was a key feature. Innovations like the electric motor and electrical grids revolutionized factory operations, enabling faster and more reliable production.

1.1. INDUSTRIAL REVOLUTIONS: FOUNDATIONS OF MODERN INDUSTRY

The assembly line, popularized by Henry Ford, was another landmark development. It reduced costs, increased output, and made goods more accessible. This era also saw the rise of industries like steel, with innovations such as the Bessemer process, and chemical production of synthetic dyes, fertilizers, and explosives. Transportation technologies advanced with railways, steamships, automobiles, and air travel, drastically reducing travel times and fostering global connectivity. Urbanization surged as industries concentrated in cities, and communication technologies like the telegraph and telephone enabled faster business operations, contributing to the integration of global markets.

However, these innovations came with challenges. Mass production gave rise to a consumer economy, making products like automobiles and household appliances widely available, but it also led to deskilling as assembly line tasks became increasingly repetitive. The growing industrial workforce faced difficult working conditions, prompting the rise of labor unions. Urbanization led to overcrowded cities with poor sanitation and disease outbreaks. Economically, the gap between the wealthy and the poor widened, and environmentally, pollution increased due to heavy industry and coal reliance. From an organizational perspective, the scale and complexity of operations introduced new challenges in scheduling, logistics, and resource management, prompting early efforts to address these issues.

Although the Second Industrial Revolution was interrupted by the Second World War, its legacy continues. The innovations of this era not only transformed the way people lived, worked, and communicated but also laid the foundations for Industry 3.0, which would focus on automation and digitalization. By establishing principles of electrification, mass production, and efficiency, this period fundamentally shaped the modern industrialized world and set the stage for the globalization of the economy [5, 6].

The **Third Industrial Revolution (Industry 3.0)**, from the mid-20th century to the early 21st century, marked a shift to digital technologies, automation, and information systems, transforming industrial processes. Automation became central, with robots replacing repetitive and hazardous tasks, improving efficiency. Companies like FANUC¹ and KUKA² pioneered the development of industrial robots, while traditional assembly lines evolved into computerized production systems. Technologies such as computer-aided design (CAD), computer-aided manufacturing (CAM), and numerical control (NC) enabled more accurate, efficient production with reduced waste and greater customization.

Industry 3.0 was fueled by breakthroughs in information technology, including programmable logic controllers (PLCs) and microprocessors, which enhanced manufacturing flexibility. Telecommunications, such as satellite transmission and telematics, revolutionized global communication and laid the groundwork for the internet, which transformed data sharing and supply chain management. In parallel, biotechnology and energy engineering also advanced, with renewable energy sources like solar, wind, and biomass emerging as alternatives to coal and nuclear power.

These innovations had profound socio-economic and environmental effects. Automation reduced manual labor while creating new skilled jobs in IT, programming, and maintenance. Globalized production systems allowed multinational companies to lower costs through outsourcing, though this worsened inequality in developing countries. Biotechnology reduced reliance on tropical regions for food production, impacting small-scale farmers. Simultaneously, growing awareness of industrial pollution and resource depletion sparked the first significant efforts toward sustainable practices, laying the foundation for lean production practices and cleaner energy technologies.

¹<https://www.fanuc.com>

²<https://www.kuka.com>

1.1. INDUSTRIAL REVOLUTIONS: FOUNDATIONS OF MODERN INDUSTRY

Despite its benefits, Industry 3.0 raised challenges. Economic disparities widened, and automation displaced many traditional jobs, raising ethical concerns. Dependence on digital systems increased vulnerabilities in cybersecurity and data protection. Nevertheless, technological breakthroughs in computing, robotics, and connectivity laid the foundation for Industry 4.0, which integrates cyber-physical systems, the Internet of Things (IoT), and big data to create smarter, more adaptive industries [7].

More recently, the **Fourth Industrial Revolution (Industry 4.0)** represents a paradigm shift in industrial production, characterized by the integration of advanced digital technologies into manufacturing and logistics processes. Building on the automation of Industry 3.0, Industry 4.0 introduces interconnected cyber-physical systems (CPS), where physical machines and digital systems collaborate through seamless communication networks. Key enablers of this revolution include the Internet of Things (IoT), artificial intelligence (AI), big data analytics, and cloud computing, all of which enable real-time data collection, processing, and decision-making. IoT sensors and connected devices facilitate constant monitoring of production lines, while AI and machine learning algorithms analyze vast amounts of data to predict machine failures, optimize workflows, and improve quality control.

Innovations such as additive manufacturing (3D printing), augmented reality (AR), and autonomous robotics further transform the production landscape. Additive manufacturing enables the creation of complex, customized designs on demand, while AR enhances maintenance and training processes by overlaying virtual information onto physical environments. Autonomous robots collaborate with human workers on shop floors, adapting to new tasks and enhancing overall productivity. The advent of digital twins, virtual replicas of physical systems, allows manufacturers not only to monitor and control the physical system via its digital twin, but also to simulate and optimize processes before implementation, reducing downtime and costs.

Industry 4.0 also revolutionized supply chains, leveraging smart logistics and blockchain technology to improve transparency, traceability, and efficiency. Cloud computing and edge computing ensure that data can be accessed and processed instantly, even in decentralized environments. These innovations enable the concept of smart factories, where production systems are self-organizing, adaptive, and capable of responding to market fluctuations in real time.

While Industry 4.0 offers unprecedented opportunities for increased efficiency, customization, and sustainability, it also presents significant challenges. First, high implementation costs, cybersecurity risks, and the need for extensive workforce reskilling pose barriers to widespread adoption, particularly for small and medium-sized enterprises (SMEs) and industries in developing regions. In addition, ethical concerns, such as data privacy and the displacement of human workers due to automation, also need to be addressed. Moreover, the increased reliance on digital infrastructure heightens vulnerability to cyberattacks and system failures.

Despite these challenges, Industry 4.0 has laid the foundation for the emerging Industry 5.0, which focuses on human-centric innovation by emphasizing collaboration between humans and machines, environmental sustainability, and social well-being. By integrating advanced technologies with a focus on inclusivity and resilience, Industry 4.0 continues to reshape industries, fostering a more interconnected and adaptive global economy [8, 9].

In recent years, the emergence of the **Fifth Industrial Revolution (Industry 5.0)** marks a new era in industrial evolution, characterized by its human-centric, sustainable, and resilient approach to manufacturing and the entire value chain for goods and services. Unlike its predecessor, Industry 4.0, which focused primarily on automation and digitalization, Industry 5.0 emphasizes the collaboration

1.1. INDUSTRIAL REVOLUTIONS: FOUNDATIONS OF MODERN INDUSTRY

between humans and advanced technologies such as AI, the IoT, and collaborative robots (Cobots). The latter are designed to enhance human creativity and productivity by working alongside workers rather than replacing them. This shift aims to reintroduce the human touch into industrial processes, prioritizing creativity and problem-solving over monotonous and repetitive tasks. A core pillar of Industry 5.0 is sustainability, which advocates industries to adopt eco-friendly practices, optimize resource use, and promote the circular economy. Therefore, the integration of renewable energy sources, combined with waste reduction initiatives, are essential to balance economic productivity with ecological responsibility, and thus addressing the pressing challenges posed by climate change.

Furthermore, Industry 5.0 focuses on creating resilient and adaptive systems capable of withstanding disruptions such as supply chain crises, natural disasters, or global pandemics. Leveraging real-time data and AI-driven insights, industries can anticipate and respond swiftly to challenges, ensuring continuity and stability. Another transformative aspect is the push for hyper-personalization in production, where advanced technologies enable the customization of products and services to meet individual needs. This approach is particularly evident in fields such as healthcare, where tailored prosthetics and personalized medicine are becoming feasible. Similarly, in the fashion sector, consumers can freely co-create designs suited to their preferences, offering an unprecedented level of customer engagement and satisfaction.

While Industry 5.0 holds immense promise, it also faces significant challenges. One of the primary hurdles is addressing the skills gap: the demand for a highly skilled workforce capable of working alongside advanced technologies far exceeds current educational and training systems. Reskilling and upskilling efforts, especially at the technical and technological levels, must be prioritized to ensure an inclusive transition for all workers. Additionally, as with Industry 4.0, the high implementation costs pose a barrier, particularly for SMEs that lack the resources to invest in cutting-edge technologies. Ethical concerns, such as data privacy, cybersecurity, and the potential displacement of jobs, also demand careful attention to ensure that technological advancements do not exacerbate inequality or exploitation. Moreover, achieving true sustainability and resilience requires overcoming entrenched industrial practices and aligning global supply chains, as well as global policies and legislation, with ecological objectives, which can be both complex and resource-intensive. Finally, fostering trust in frugal, responsible and fair AI and automation is crucial, as societal apprehensions about machine decision-making and ethical governance must be addressed transparently.

Ultimately, Industry 5.0 envisions a future where industries prioritize human well-being, environmental sustainability, and technological progress in harmony. By fostering collaboration between humans and machines and promoting innovation that aligns with societal values, Industry 5.0 aims to shape a smarter, more inclusive, and sustainable global economy [10, 11].

As industries have evolved through these transformative revolutions, the complexity of managing production systems has grown exponentially. Each new era has not only brought technological advancements, but also increased demands for efficiency, adaptability, and optimization in manufacturing processes. Among the many challenges facing the operations management of advanced industrial systems, scheduling problems emerged as a critical area of focus. Ensuring the efficient allocation of resources—machines, workers, and time—became essential to maintaining productivity and meeting the increasingly uncertain and ephemeral demands of global markets in a context of fierce global competition.

1.2. MODERN INDUSTRY CHALLENGES: FROM DIGITAL TRANSFORMATION TO SUSTAINABILITY

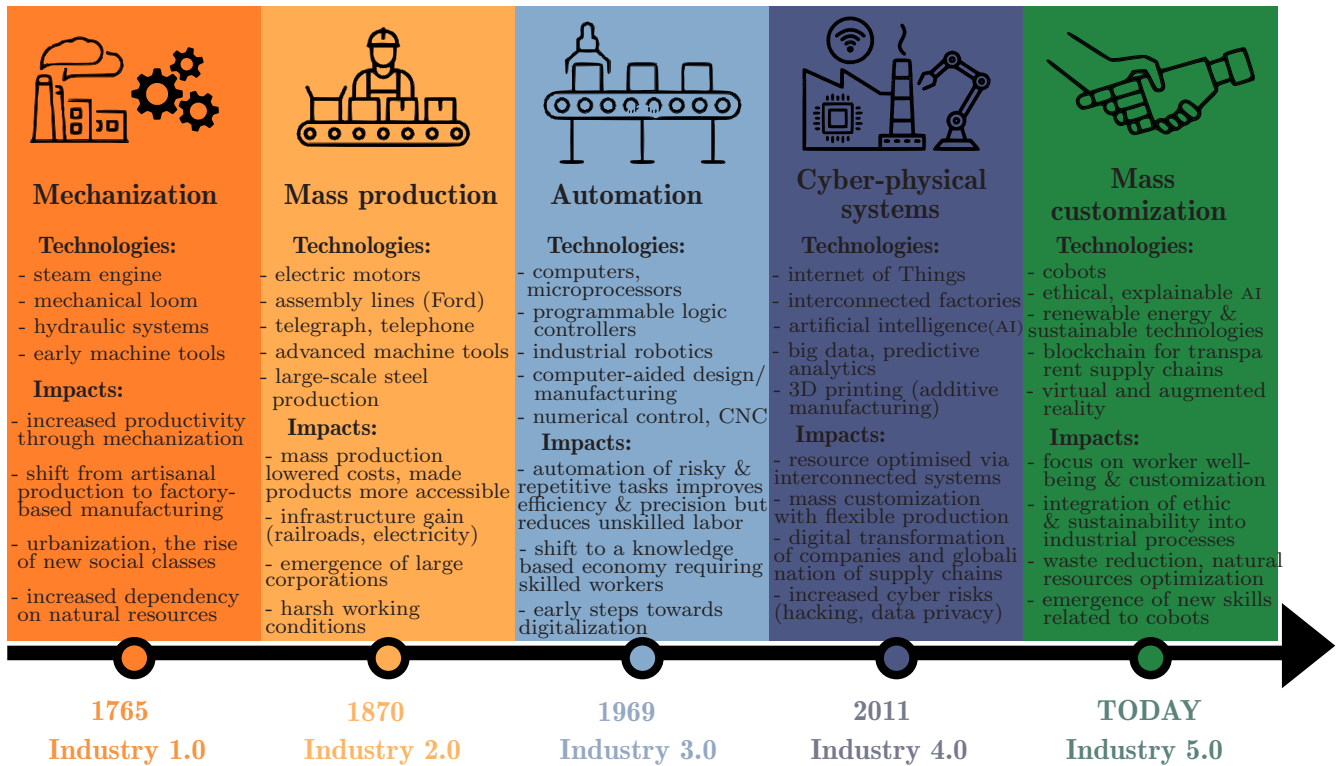


Figure 1.1: The industrial revolutions

1.2 Modern industry challenges: from digital transformation to sustainability

The current challenges faced by industries are multifaceted and arise from various technological, economic, social, and environmental factors. Some of the most pressing issues include:

- Digital transformation:** The integration of digital technologies such as automation, IoT, AI, and big data analytics has fundamentally transformed industrial operations. However, many industries face significant barriers in adopting these innovations, including high initial investment costs and the complexities of integration. Furthermore, as industries become more interconnected through digital platforms, they are increasingly vulnerable to cyberattacks and data breaches. Safeguarding sensitive industrial data, intellectual property, and operational systems against such threats is a critical challenge. Additionally, the rapid evolution of these technologies has outpaced the development of the necessary skill sets in the workforce. The rise of automation and AI has altered the nature of many jobs, leading to skill mismatches. There is an urgent need for workers equipped to handle complex, technology-driven tasks, but many industries continue to struggle with a shortage of skilled talent and insufficient training opportunities [12].
- Flexibility and Customization:** In the face of global competition, industries are under constant pressure to reduce costs while maintaining or improving quality of products and related services provided. As consumer demand for personalized products rises, industries must offer more

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flexible and customizable solutions. Achieving higher efficiency through automation, resource optimization, and smarter production techniques is crucial, but implementing these changes often involves substantial upfront investments. Balancing these investments with cost-effectiveness and efficient production, especially in traditional manufacturing models, remains a challenge that necessarily involves the optimization of production operations and its related processes. Companies must also, and above all, adapt to global competition, particularly from low-cost manufacturing regions, prompting a focus on innovation, product differentiation, and high-value-added production to stay competitive [13].

- **Sustainability and Environmental Impact:** As sustainability becomes increasingly important, industries face mounting pressure to reduce their carbon footprint, minimize waste, optimize resource use, and comply with stricter environmental regulations. Transitioning to green technologies, reducing emissions, and adopting circular economy practices are no longer optional and present significant challenges. Consumers are increasingly demanding sustainable, ethical, and transparent practices. Meeting these expectations while remaining competitive and innovative is an ongoing struggle for many industries [14].
- **Supply Chain Disruptions:** Global supply chains are vulnerable to disruptions caused by political instability, natural disasters, and pandemics (e.g., COVID-19). In response, industries are working to create more resilient supply chains by diversifying suppliers, increasing local sourcing, and investing in advanced forecasting and risk management tools [9].
- **Health and Safety:** Despite the rise of automation and advanced technologies, human operators remain crucial for tasks that require creativity, problem-solving, and decision-making. Ensuring the health, safety, and well-being of workers is now a priority, in line with Industry 5.0 principles that emphasize human-machine collaboration. Ergonomic designs, adaptive work environments, and policies that support both the physical and mental health of workers are essential to fostering sustainable and productive workplaces [9].

In summary, modern manufacturing faces growing challenges driven by the increasing demand for flexibility, customization, and sustainability in production systems. Companies must adapt to dynamic market conditions, shifting customer preferences, and stricter environmental regulations. Balancing human-centered approaches with environmental stewardship is essential for long-term sustainability and meeting societal expectations in today’s industrial landscape. Thus, production systems must not only be efficient but also agile enough to handle variability and personalized orders while minimizing environmental impact.

Beyond these challenges, industries also face significant organizational resistance to change, particularly in traditional manufacturing settings. Both management and workers may be reluctant to adopt new digital technologies, and overcoming this resistance is crucial for successful digital transformation. Furthermore, as industries increasingly rely on digital platforms, issues related to data governance—such as ownership, privacy, and ethical use—have gained importance. Ensuring effective data management is key to maximizing its value while safeguarding against misuse [10].

Another major challenge is the ongoing need for system maintenance and updates. As technological advancements continue at a rapid pace, industrial systems must evolve to stay competitive, requiring regular upgrades, monitoring, and skilled personnel. Additionally, while large corporations may have the resources to implement cutting-edge technologies, SMEs often struggle with financial and technical

barriers to digital adoption. This disparity in resources can hinder SMEs' competitiveness in the global market [10].

These interconnected challenges call for adaptive strategies that combine technological innovation, sustainability, human-centered design, and continuous improvement. Effective planning and scheduling systems play a critical role in optimizing resource allocation, managing workflows, and ensuring timely product delivery. Poor scheduling can lead to inefficiencies and delays, directly impacting performance and competitiveness. Therefore, advanced scheduling solutions, incorporating modern technologies, are increasingly vital to achieving operational excellence in today's manufacturing landscape.

1.3 Scheduling problems

Production efficiency saw a significant boost during the Industrial Revolution, driven by groundbreaking inventions like the steam engine, which dramatically reduced the time and effort required to manufacture goods. This newfound efficiency led to lower labor costs, reducing product prices and making goods accessible to a broader range of customers. However, these advancements also introduced new challenges, such as resource optimization, which sparked the first considerations of scheduling problems.

The concept of scheduling gained further prominence in the early 20th century with the rise of industrial production and the standardization of manufacturing processes. The advent of large-scale production systems, exemplified by Henry Ford's assembly lines, underscored the need to efficiently organize tasks and resources. Manufacturers recognized that operational efficiency was critical for success, as it allowed them to optimize the use of machines, workforces, and materials while minimizing production costs, shortening lead times, and enhancing overall productivity [1].

Initially, research on scheduling problems focused on fundamental challenges such as determining the optimal sequence of tasks on machines to avoid idle times and coordinating production flows, especially in complex, multi-product workshop environments. Over time, scheduling problems have become ubiquitous across most economic domains, from computer engineering to manufacturing and beyond. They are inherently complex combinatorial optimization problems, often characterized by the need to balance competing objectives and constraints. In particular, production scheduling is regarded as one of the most critical and challenging issues in manufacturing systems, and it has been extensively studied in the literature due to its significant impact on productivity and profitability [15].

As industrial systems evolved, scheduling problems grew increasingly intricate, integrating more flexible systems, multiple constraints, and diverse objectives. The dynamic nature of today's industrial landscape has further intensified these challenges, necessitating the use of advanced algorithmic and computational approaches—such as constraint programming, meta-heuristics and artificial intelligence, among many others—to develop efficient, adaptive, and robust solutions [16].

Production scheduling focuses on the efficient allocation of available resources to achieve predefined objectives, as it is essentially the process of optimizing work and time. A scheduling problem can be defined as an environment involving one or more machines with specific characteristics and a set of jobs (tasks or products consisting of one or more operations to be performed by the machines). The aim is to optimize a single objective or a set of objectives by assigning each job to a specific machine at a specific time, while avoiding conflicts between operations and adhering to machine capacity, capability, and/or availability constraints. The following sections explore the various

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scheduling problems encountered in industrial applications and academic research. This includes an analysis of different machine environments, commonly faced constraints, objective functions, dynamic events, and the resolution methods employed to address these challenges [17].

A common tool used in visualizing and managing scheduling problems is the Gantt chart, which provides a clear graphical representation of job schedules. It helps in understanding how tasks are assigned to different machines and how resources are utilized over time. By displaying tasks as horizontal bars over a timeline, Gantt charts make it easier to spot bottlenecks, overlaps, and idle times, thereby aiding in the optimization of production schedules. Gantt charts are often used to illustrate the solution of scheduling problems, offering a practical and intuitive way to visualize the impact of scheduling decisions.

1.3.1 Machine environment

The **single-machine environment** is the simplest and most fundamental configuration in scheduling problems. It serves as the foundation for understanding more complex scheduling models and provides valuable insights into optimization techniques. A single-machine environment consists of a single resource available to process all tasks. The tasks must be ordered to minimize/maximize one or more specified criteria. Although they seem simple and unable to fully capture the complexity of real-world multi-machine environments, some single-machine scheduling problems belong to NP-hard class. Moreover, the methods developed to solve these problems can be very useful, as they can often be adapted to more complex problems or used as components in decomposition approaches. Figure 1.2 illustrates an example of single-machine environment, where four products need to be processed on a machine.

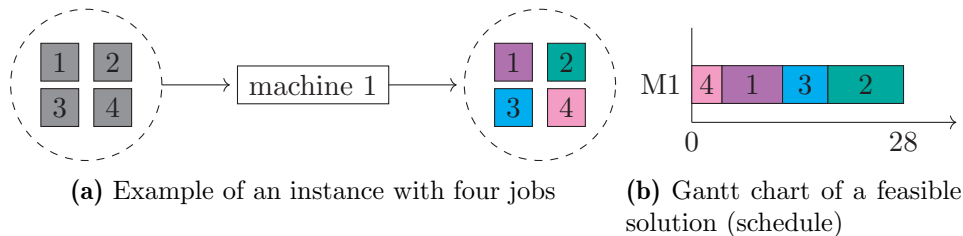


Figure 1.2: Single-machine environment

The **parallel-machine environment** extends the single-machine environment by introducing multiple machines that can operate simultaneously to process tasks. This environment is more complex than single-machine scheduling and is widely used to model real-world scenarios in industries where tasks can be distributed across several resources. In a parallel-machine environment, there are multiple machines available, all capable of processing tasks. Each task must be assigned to exactly one machine. There are different variants of parallel machines, which may be identical, uniform, or unrelated, depending on their processing capabilities and performance characteristics. Identical machines have the same processing capabilities, uniform machines differ in processing speeds but maintain proportional processing times, and unrelated machines have different capabilities, and task processing times vary arbitrarily across machines. Figure 1.3 illustrates the parallel-machine environment with an example with nine products and three machines. Here the three machines are identical and the products can be processed on each of them.

1.3. SCHEDULING PROBLEMS

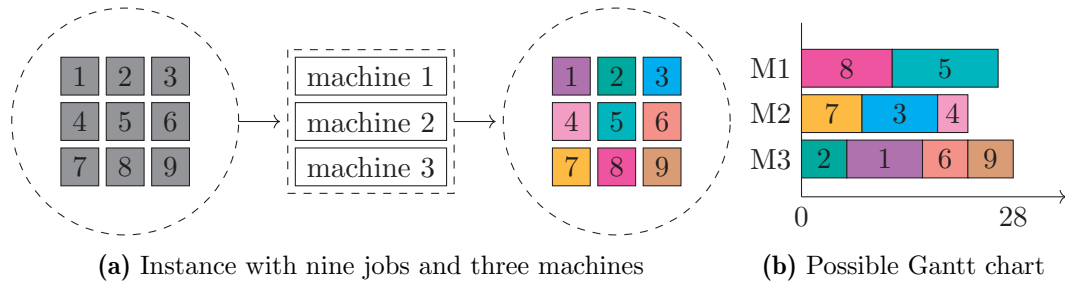


Figure 1.3: Parallel-machine environment

The **flow-shop environment** represents a well-studied and important class of scheduling problems, often abbreviated as FSSP, commonly found in manufacturing systems where jobs must undergo a fixed sequence of operations. In this system, multiple machines are arranged in series, with each machine performing a specific operation in a predetermined order. Each job consists of a set of operations that are processed on the machines in the same sequence, ensuring consistency across all jobs in the system. Figure 1.4 illustrates a flow-shop environment, where three products are processed sequentially on three different machines. Each machine performs a specific operation on each product. We denote the j^{th} operation of product i as O_{ij} .

An extension of the traditional flow shop scheduling environment is the flexible flow shop, designed to accommodate greater flexibility in the production process. Unlike the standard flow shop, the flexible flow shop allows for alternative routing options. There are typically multiple stages of operations, each consisting of several machines that can perform the same or similar tasks. A job can be routed to any available machine in a stage, depending on machine availability, processing time, or other constraints. This added flexibility allows for better resource utilization, the ability to handle variations in job requirements, and the accommodation of machine breakdowns or maintenance. However, it also introduces additional complexity in scheduling and requires more sophisticated optimization techniques to ensure efficiency in production.

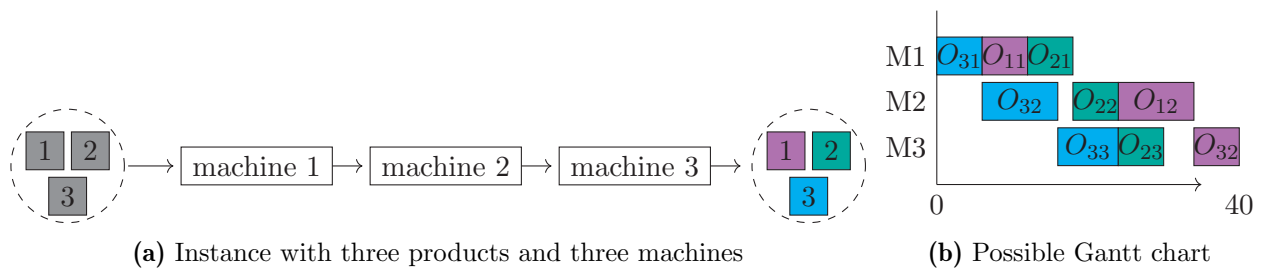


Figure 1.4: Flow-shop environment

The **job-shop environment** is the origin of one of the most prominent and challenging classes of scheduling problems, often regarded as one of the most difficult combinatorial optimization problems. In a job shop scheduling problem (JSSP), multiple machines are available, each capable of performing a variety of operations. Jobs are processed according to their specific production requirements, and each job may need to visit different machines. The sequence of operations can vary for each job, adding complexity to the scheduling process. One of the primary challenges in the job-shop environment lies in the diverse and complex routing requirements for jobs. Additionally, machine capacities and

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resource availability can fluctuate, further complicating the scheduling and sequencing tasks. Job-shop scheduling is commonly encountered in industries that manage a wide range of products, with different production specifications, ensured with custom manufacturing, such as in aerospace, and automotive parts production. These sectors require scheduling systems capable of handling a variety of operations, meeting tight delivery deadlines, minimizing production costs, and optimizing resource management. Figure 1.5 illustrates a job-shop environment where three products must be processed on three machines, each following a different sequence. For instance, the first product starts on machine 1, then proceeds to machine 3, and finishes on machine 2, while the second product begins on machine 2, moves to machine 1, and completes on machine 3. The accompanying Gantt chart shows an example of a feasible solution, i.e. a possible schedule. As the number of machines and products increases, the number of solutions grows exponentially.

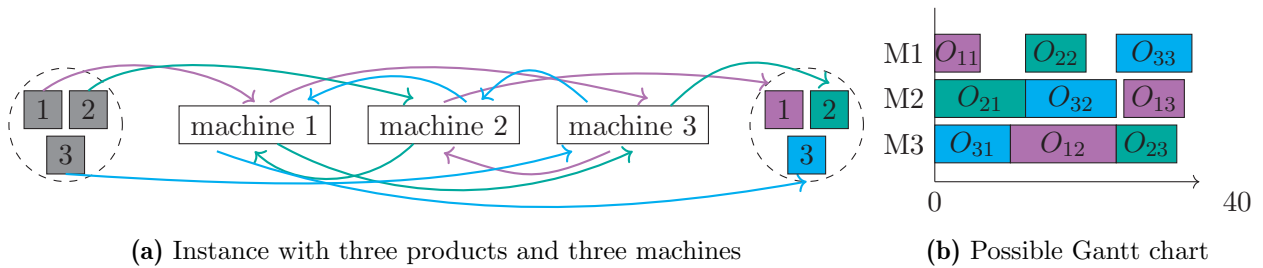


Figure 1.5: Job-shop environment

In the early 1990s, researchers introduced a significant extension of the classical job-shop scheduling problem (JSSP), known as the flexible job-shop scheduling problem (FJSSP). Unlike the JSSP, where each operation is assigned to a specific machine, the FJSSP allows operations to be processed on any machine within a given subset, providing greater flexibility. This increased flexibility adds complexity to the problem, as it requires not only the sequencing of operations but also their assignment to the most suitable machines. The FJSSP has become highly relevant in real-world manufacturing systems, where flexibility and adaptability are essential for meeting customer demands and addressing unexpected disruptions. Its complexity, coupled with its practical importance, has spurred extensive research into developing effective modeling techniques and resolution methods. These range from traditional optimization algorithms, utilizing exact and approximate methods, to cutting-edge AI-based approaches, significantly advancing the ability to tackle the evolving challenges of modern manufacturing environments. Figure 1.6 illustrates an example of a flexible job-shop environment. In this setup, operation O_{11} can be processed either on machine 1 or machine 2. This introduces two sub-problems: selecting a machine for each operation and determining the sequence of operations on each machine. The added flexibility increases the complexity of the scheduling problem.

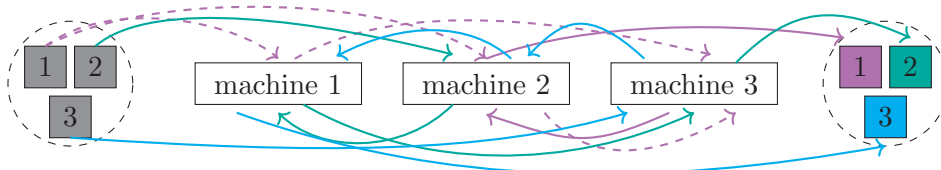


Figure 1.6: Flexible job-shop environment

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The **open-shop environment** is a less restrictive variant than the more structured job-shop and flow-shop environments. In an open-shop system, there are multiple machines available, each capable of performing a variety of operations. However, unlike job-shop systems, where each job has a predefined sequence of operations that must be followed, the order in which the operations are performed in an open-shop environment is not fixed. Instead, jobs can be processed on any machine in any order, providing a high degree of flexibility. This flexibility allows for more dynamic scheduling and operation assignments based on availability, machine capabilities, and other factors. In an open-shop scheduling problem (OSSP), the key task is to determine the best machine to assign each operation at any given point in time while ensuring that each job is processed and completed within the required timeframe. Figure 1.7 illustrates an example of an open-shop environment, where products must be processed on three machines in any order. This flexibility results in a significantly high number of possible routing options.

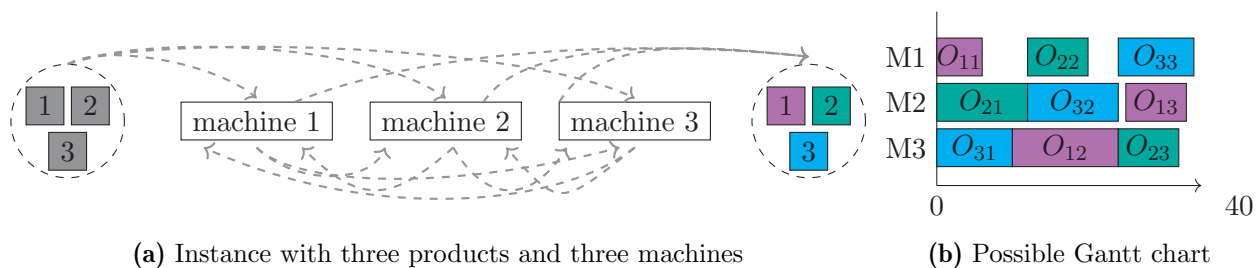


Figure 1.7: Open-shop environment

1.3.2 Constraints

Depending on the machine environment, as well as the specific characteristics of each factory or product, numerous constraints and requirements must be taken into account when developing a production scheduling solution [18]. While these requirements may vary across different cases, some are applicable to a wide range of real-world manufacturing scenarios. It is often impossible to address every possible constraint, but the following are some of the most relevant and commonly encountered in practice:

- **Precedence:** Although precedence constraints have been studied for several decades, they remain a widely researched topic within the academic community because they can be challenging to integrate in some complex cases. There are two main types of precedence constraints:
 - Between operations within the same job: In flow-shop, job-shop, or open-shop environments, a product typically passes through multiple machines. Before moving from one task to the next, the previous task must be completed.
 - Between different jobs: While it is often assumed that jobs are processed independently, this is not always the case. Some jobs may serve as intermediates for others, meaning the first task of a dependent job cannot begin until all tasks of its predecessor jobs are completed. Therefore, these constraints must be considered and integrated into the model in advance to optimize the scheduling process.

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- **Release and Due Dates:** Release dates indicate when a job becomes available for processing, while due dates represent the deadlines by which the job must be completed. These dates can also be considered part of the scheduling objectives. It is crucial to adhere to due dates, as products must be ready for delivery on time, and missing these deadlines can have serious consequences. However, finishing jobs too early can also be problematic, potentially causing wear on parts or incurring storage costs. Therefore, both early and late completion may require the application of penalties to maintain balance and optimize the scheduling process.
- **Setup time:** Setup times refer to operations on machines that are not directly part of production, such as adding or removing parts, calibration, cleaning, and testing. These can occur before or after a task is processed and may be required every time a new product is handled. To minimize setup costs, tasks requiring similar machine configurations can be scheduled consecutively, a method known as sequence-dependent setups. While setup times are often overlooked or included in processing times, they can significantly impact production and should be carefully managed to avoid misleading information that affects the overall process.
- **Maintenance time:** Although often overlooked in scheduling studies, maintenance is crucial in manufacturing systems to prevent and remedy production equipments failures. In today's competitive market, manufacturers may prioritize delivery reliability at the expense of effective production and maintenance strategies. However, incorporating maintenance into scheduling can improve system performance and robustness. Strategically planned maintenance also supports long-term competitiveness and sustainability by enhancing resource conditions and extending the functional life of equipment.
- **Transportation time:** During the production process, parts and products may need to be moved between machines and storage areas, often using some transporters such as conveyors, robotic arms, or automated vehicles. This introduces delays as products are not immediately available for the next machine, and transportation resources are limited. To optimize scheduling, transporters must be synchronized with the production process, or jobs may need to be assigned to specific vehicles and transport tasks sequenced. Despite its impact on scheduling performance, transportation time was long overlooked in scheduling studies, but it has emerged as a major concern in recent decades.
- **Storage:** Storage buffers are limited spaces where products are stored during or after production. Overfilled or poorly managed storage can cause production delays and/or quality or logistics issues. Thus, considering storage constraints in scheduling approaches leads to more realistic solutions and helps prevent and/or absorb some production flow disruptions.
- **Pre-emption:** Pre-emption allows operations to be paused and resumed later, which may be necessary when more urgent jobs arrive or due to unforeseen events like client cancellations or machine breakdowns. In contrast, when jobs cannot be interrupted, pre-emption is not allowed. Pre-emption can be crucial in certain scenarios to maintain production flexibility and responsiveness.
- **Distributed factories:** While scheduling is typically focused on individual factories, the scheduling of supply chains has evolved, increasing complexity. Products may be assigned to different, geographically distant factories, and transportation between these facilities must also be considered.

- **Environmental aspects:** Addressing the environmental impact of manufacturing requires incorporating several energy-related constraints into models. One key constraint is the total energy consumption cap, which limits the overall energy used during a specified period to ensure operations remain within a predefined energy budget. Each machine is assigned an energy consumption rate based on its power rating and operating time, with the total energy usage required to stay under this limit. Another important constraint is peak energy consumption, which restricts the maximum power usage at any given moment to avoid overloading the system, especially during periods of high energy demand. This helps prevent surpassing capacity limits and ensures energy resources are distributed efficiently across the production process. Additionally, industries may be constrained by time-based energy pricing, where consumption must be optimized around peak and off-peak hours. This requires scheduling energy-intensive tasks during times when energy costs are lower, without exceeding allowable limits during more expensive peak periods. If renewable energy sources are integrated, there may be constraints on the proportion of total energy that must come from renewables, requiring careful coordination between renewable supply and production demand. Companies are also constrained by carbon emission limits, which tie energy consumption to environmental regulations, demanding that production processes adhere to specified emission thresholds.
- **Human aspects:** Human-related constraints in models aim to account for the physical, mental, and professional well-being of operators. These constraints include managing operator availability, ensuring that tasks are only assigned within the operators' working hours and considering breaks and rest periods to avoid fatigue. Additionally, operators can only perform tasks for which they are qualified, which implies the need for constraints regarding skills and training. Ergonomics also play a role, requiring the scheduling system to avoid task assignments that could lead to physical strain, as well as managing task rotation to minimize health risks. Furthermore, operators' preferences for specific types of tasks or work shifts must be considered to improve job satisfaction and maintain productivity. By incorporating these constraints, the model not only optimizes production processes but also ensures a healthy, skilled, and satisfied workforce.

The constraints mentioned above are crucial to make scheduling problems as realistic as possible in industrial settings. Each constraint reflects an important aspect of production process management, whether it involves meeting due dates, minimizing setup times, or considering human resource availability. Integrating these constraints allows for more realistic system optimization and better alignment with the practical requirements of manufacturing environments. However, expanding the number of constraints can significantly increase the complexity of the model, necessitating the use of more advanced methods and algorithms to identify efficient solutions. This highlights the trade-off between model fidelity and the computational complexity of scheduling solutions [18]. If the constraints are there to delimit the space of admissible solutions, the choice of the best solution remains to be made according to one or more objective functions to be optimized. In the following section, we will explore the objective functions used to evaluate and guide the optimization of these complex scheduling problems.

1.3.3 Objectives

In scheduling problems, the objective function is crucial in determining how solutions are evaluated and optimized. The choice of objective function reflects the specific goals of the production process,

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which can vary greatly depending on the industry, available resources, and constraints. Common objectives include:

- **Time-related objectives:** These aim to minimize key time metrics, such as makespan (time required to complete all jobs), tardiness, earliness, setup times, and transportation times. Addressing objectives based on these metrics helps ensuring timely production and delivery.
- **Cost-related objectives:** Minimizing production costs is a largely common priority, often tied to factors like processing times, labor costs, energy consumption, machine maintenance, and storage expenses, aiming for cost-efficiency across the entire production operation.
- **Job-based objectives:** These focus on individual job metrics rather than minimizing overall processing time, such as reducing job completion times, minimizing the number of tardy jobs, or managing the number of jobs in stock or in process.
- **Resource-based objectives:** These target optimizing resource utilization, such as balancing workloads across machines by minimizing total, average, or maximum workloads, leading to more efficient and sustainable resource management.
- **Quality-related objectives:** These emphasize maintaining product standards by minimizing defects, rework, or scrap rates. Objectives may include ensuring or improving the average outgoing quality level, reducing process variability, and ensuring compliance with technical specifications and industry standards.
- **Pro-environmental objectives:** These mainly aim to minimize negative environmental impact of production processes, by reducing energy consumption, carbon emissions, noise pollution, and promoting sustainability through recycling and eco-friendly practices.
- **Human-based objectives:** These prioritize factors that affect workers, such as reducing fatigue, enhancing well-being and safety, maximizing worker preferences or skill levels and learning rates to create a more harmonious and efficient working environment. In fact, human-oriented objectives are not necessarily in conflict with productivity objectives and can instead indirectly serve as a lever to improve the productivity and resilience of the production system.

In more advanced and more realistic cases of the economic domain, where decision problems are rarely mono-objective, multi-objective optimization is required to balance multiple conflicting goals, such as maximizing production throughput while minimizing environmental impact. These objective functions guide the optimization algorithms used in scheduling, ensuring that the solution not only meets operational constraints but also delivers the best performance according to the defined criteria.

1.3.4 Dynamic scheduling

In most real-world manufacturing environments, disturbances may occur over time, creating dynamic environments. These disruptions can force production to halt until the problem is resolved, making it essential to be prepared to handle them efficiently. This may lead to changes in the initial optimal solution for the scheduling problem. Disturbances may include the arrival of urgent new jobs, job cancellations, changes in processing times, machine availability (due to maintenance or breakdowns), and even worker absences [19].

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To address this dynamic environment, we distinguish four different scheduling approaches:

- **Pro-active scheduling:** this approach anticipates and mitigates the impact of potential disruptions before they occur. Instead of waiting for a disruption to react to, the system incorporates uncertainty and possible disturbances into the scheduling process from the outset. The goal is to create a more robust schedule, minimizing the need for frequent and costly real-time adjustments, and improving overall system performance under uncertainty. Key principles of pro-active scheduling include:
 - Buffering: incorporating time or resource buffers into the schedule to absorb the effect of unexpected delays or disruptions;
 - Stochastic models: using probabilistic models to estimate the likelihood of certain disruptions and adjust the schedule accordingly. These models often leverage predictive analytics to use historical data to predict when and where disruptions are likely to occur.
- **Completely-reactive scheduling:** no pre-planned schedule is created in advance. All scheduling decisions are made in real-time, based entirely on current system conditions and available resources. This approach considers disruptions as the norm, making flexibility and adaptability the foundation of the scheduling process. Key characteristics include:
 - No initial schedule: no predefined or optimized schedule exists before jobs arrive in the system. Job operations assignments and resource allocation are determined in real-time as jobs progress and conditions evolve;
 - Full dependency on real-time data: scheduling decisions rely solely on real-time information about the system. As new information comes in, the system continuously adjusts without reference to a fixed plan;
 - Immediate response to disruptions: because there is no static schedule to follow, the system can immediately respond to any disruption. Jobs are assigned based on current resource availability, making the system highly adaptable and reactive in nature.

Completely-reactive scheduling maximizes flexibility, but often at the expense of stability. The absence of a predefined plan demands highly efficient decision-making to handle each new job or disruption promptly, prioritizing immediate problem resolution over long-term optimization.

- **Predictive-reactive scheduling:** this method combines predictive and reactive strategies to handle disruptions. A schedule is first created based on predicted conditions, but when unexpected events occur, it is adjusted in real-time. To avoid widespread disruptions, changes are often localized to the affected area, maintaining stability in the overall production flow. Predefined conditions on some criteria help determine when to trigger rescheduling, ensuring reactive interventions remain manageable. The goal is to balance proactive planning with the flexibility to respond to unforeseen events, thereby reducing inefficiencies caused by overreacting or underpreparing. Key features include:
 - Initial predictive schedule;
 - Rescheduling: when disruptions deviate from predicted conditions, the system dynamically updates the schedule to minimize the impact of these disruptions and maintain optimal performance.

- **Proactive-reactive scheduling:** a hybrid approach that combines proactive and reactive strategies to manage disruptions effectively. The idea is to create an initial, robust schedule that anticipates potential disruptions while maintaining the flexibility to adapt when unforeseen events occur. Key characteristics include:

- Initial robust schedule: designed with an anticipation of uncertainty assessed using historical data or probabilistic models, preparing for disruptions without sacrificing efficiency;
- Rescheduling: when unanticipated disruptions occur;

The key challenge of proactive-reactive scheduling is balancing the stability of the proactive schedule with the flexibility of reactive adjustments. It aims to avoid too many frequent rescheduling actions while maintaining operational efficiency under uncertainty.

Dynamic scheduling in manufacturing environments requires a careful balance between anticipating and reacting to disruptions in real-time. The choice of strategy—whether proactive, reactive, predictive-reactive, or proactive-reactive—depends on the nature of the system, the frequency and magnitude of disruptions, and the need for stability versus flexibility. Each approach has its strengths and weaknesses, but combining proactive preparation with reactive adaptability offers the most robust solution to maintaining efficient production under dynamic conditions.

1.3.5 Complexity and resolution method

Scheduling problems are widely recognized as complex combinatorial optimization challenges. Their difficulty is influenced by various factors, including the machine environment, the number of resources, jobs, and tasks, the constraints imposed, and the nature and number of objective functions. Based on their computational complexity, scheduling problems can be classified into three main categories: polynomial-time solvable problems, NP-hard problems, and strongly NP-hard problems [17].

- **The polynomial time solvable problems:** These are problems that can be solved in polynomial time, meaning the time required to find a solution grows at a manageable rate (polynomially) with the size of the input. They are considered "easy" or "tractable," as their solutions can be efficiently computed using deterministic algorithms.
Example: In scheduling, a single-machine problem with the objective of minimizing the sum of job completion times falls into this category and is solvable in polynomial time.
- **NP-hard problems:** These problems have no known polynomial-time algorithms for finding solutions. They are deemed "intractable" for large instances because solving them requires exponential time in the worst case. However, verifying a given solution can still be performed in polynomial time.
Example: The job-shop scheduling problem, where the goal is to determine the optimal schedule for a set of jobs on a set of machines, is a classic NP-hard problem. As the number of jobs and machines increases, the problem becomes computationally prohibitive.
- **Strongly NP-hard problems:** A subclass of NP-hard problems, strongly NP-hard problems remain computationally difficult even when the numerical values of the input are bounded by a polynomial function of the problem size. These problems are particularly challenging because

their complexity arises from both the combinatorial structure and the input data size.

Example: The flow-shop scheduling problem with multiple machines, where the objective is to minimize the makespan, is strongly NP-hard. Even small problem instances with just a few jobs and machines are computationally difficult to solve optimally.

As noted by Pinedo in [17], many scheduling problems can be classified into one of these three categories, although some problems have not been proven to belong to a specific class. Introducing additional constraints, objectives, uncertainties, or dynamic events further increases the complexity of the problem. Understanding this complexity is crucial for choosing appropriate resolution methods.

Scheduling problems are typically addressed using two broad categories of methods: exact methods and approximate methods [20]. Exact methods aim to find the optimal solution to scheduling problems by either exploring the entire solution space systematically or by finding optimality through techniques such as branch and cut, which iteratively eliminate infeasible regions of the search space. While they guarantee optimality, their computational time often increases exponentially for larger or more complex problems, especially those classified as NP-hard or strongly NP-hard. Among these methods, we find the Simplex algorithm, Branch and Bound, Branch and Cut, Dynamic Programming, and others. Solvers such as Gurobi, CPLEX, and Julia implement these techniques to find optimal or near-optimal solutions. In some cases, these solvers return solutions with a gap, indicating the difference between the best found solution and the theoretical optimal solution.

Approximate methods are widely employed to provide high-quality solutions to scheduling problems within reasonable computational times. While these methods do not guarantee optimality, they are effective in generating near-optimal solutions, which are often sufficient for practical applications. These methods can be categorized into several types, each with distinct characteristics:

- **Heuristic methods:** These problem-specific approaches are designed to quickly generate feasible solutions. They are typically simple, fast, and can serve as either initial steps or standalone solutions. Common heuristic methods include dispatching rules, priority rules, and greedy algorithms, which are all efficient in terms of computation time, but may not always lead to the best possible solution.
- **Metaheuristic methods:** These general-purpose optimization algorithms are specifically designed to explore large solution spaces while avoiding local optima. Metaheuristics balance exploration (searching for new areas) and exploitation (refining known good solutions). Popular metaheuristics used in scheduling problems include Genetic Algorithms, Tabu Search, Simulated Annealing, Ant Colony Optimization, and Particle Swarm Optimization, among others. They are highly versatile and capable of tackling complex problems but may require significant computational effort.
- **Simulation:** A powerful tool for analyzing and solving scheduling problems by modeling real-world systems and their behaviors. It allows the evaluation of different scheduling strategies within a controlled, virtual environment. Common simulation techniques include Discrete Event Simulation, Monte Carlo Simulation, and Agent-Based Simulation. These techniques are valuable for understanding system dynamics and testing, validating, and selecting the most suitable among different scheduling policies under various conditions.
- **Artificial Intelligence techniques:** AI methods leverage computational intelligence to solve scheduling problems, often focusing on learning, adaptation, and optimization. These techniques are par-

ticularly well-suited for complex, dynamic, and large-scale problems. AI techniques in scheduling include Machine Learning (supervised learning, reinforcement learning, and deep learning), as well as Expert Systems. These methods can adapt to changing conditions and learn from data, making them effective for dynamic environments.

In addition to these individual methods, hybrid approaches that combine two or more techniques are increasingly popular in the literature. For example, combining metaheuristic and AI techniques can capitalize on the strengths of both, enhancing solution quality and computational efficiency. Furthermore, the integration of optimization and simulation has gained significant attention. In such models, optimization techniques are used to explore the solution space and find optimal or near-optimal solutions, while simulation is employed to model uncertainty, variability, and dynamic changes in the system. This combination allows for more accurate predictions and better decision-making, particularly in systems where traditional optimization methods may struggle to account for the complexity or stochastic nature of the problem. By coupling optimization with simulation, practitioners can not only find high-quality solutions but also gain deeper insights into system behavior, improving overall system performance under realistic conditions. The next section will focus specifically on the use of artificial intelligence in scheduling problems, which is a rapidly growing area of research and the subject of this thesis.

1.4 Scheduling and artificial intelligence

Artificial Intelligence (AI) has become a cornerstone of computerized decision-making systems in modern industrial systems, driving innovation and enabling solutions to complex problems that were previously difficult or impossible to solve. In the context of manufacturing and production, AI plays a key role in developing operations management tools to enhance performance and adaptability. As industries strive to improve efficiency, reduce costs, and adapt to changing market demands, AI provides the advanced tools necessary to solve intricate problems related to resource allocation, process optimization, and real-time decision-making [21].

AI is integrated into industrial systems through various technologies, such as machine learning algorithms, deep learning models, and expert systems. These advanced techniques enable industries to process vast amounts of data, identify patterns, and make decisions that would be impractical or too time-consuming for human operators. For instance, AI can help dynamically adjust production schedules, predict equipment failures, and optimize operations, all of which contribute to greater efficiency and responsiveness [22].

The adaptability of AI systems is crucial, especially in the face of unforeseen disruptions such as job insertion, order cancellation, machine breakdowns or workforce absences. AI systems can continuously monitor system performance, learn from past experiences, and adjust operations accordingly, ensuring that the production processes remain efficient and resilient. By optimizing tasks in real-time, AI enables industries to stay competitive and responsive to market conditions.

Machine learning, especially reinforcement learning, has become a widely used approach for solving scheduling problems [23]. By learning from past decisions and outcomes, these algorithms predict the most effective scheduling actions, continuously improving over time. For example, reinforcement learning agents can prioritize tasks based on the current system state, adapting schedules in real-time to account for disruptions such as equipment failures or operator absences.

Several leading companies have successfully implemented AI in their operations³. For example, General Electric, IBM, and Siemens, have applied machine learning algorithms in predictive maintenance and scheduling to foresee equipment failures before they happen. This proactive approach allows for better maintenance planning and minimizes production downtime, significantly boosting efficiency. Airbus has leveraged AI for task scheduling within their assembly lines, using AI to dynamically adjust schedules and ensure that resources are allocated efficiently while meeting production deadlines [24]. Similarly, Toyota has integrated reinforcement learning into its production scheduling systems to optimize job-shop scheduling [25]. The intelligent AI-based system continuously learns from real-time data and adjusts production schedules based on factors like worker availability and machine malfunctions, improving throughput and reducing delays.

In conclusion, the integration of AI techniques and tools into industrial systems has revolutionized scheduling processes, making decision-making faster, more accurate, and adaptive. Through techniques such as machine learning, optimization algorithms, and simulation-based methods, industries can now solve complex scheduling challenges, enhance operational efficiency, and maintain resilience in the face of disruptions.

1.5 Synthesis and research gaps

The shift toward Industry 5.0 introduces a new paradigm in manufacturing scheduling, emphasizing human-centric, sustainable, and resilient systems [11]. This evolution demands advanced solutions that balance economic, environmental, and social objectives. Key challenges and emerging priorities include:

- **Human integration:** Scheduling must account for worker health, safety and preferences while optimizing production. Adaptive models are required to accommodate human variability and ensure ergonomic working conditions;
- **Environmental consideration:** Modern manufacturing systems need to minimize energy consumption, reduce waste, and comply with environmental regulations, all while maintaining productivity;
- **Resilience to disruptions:** To handle increasingly dynamic environments, scheduling methods must incorporate real-time adaptability, predictive capabilities, and robust solutions for disruptions.

Most existing methods focus on single or limited goals, such as minimizing makespan or energy consumption, often overlooking broader multidimensional trade-offs. For instance, human-centric factors like worker ergonomics and well-being, or environmental aspects, such as energy sustainability and carbon emissions, are frequently underrepresented. These gaps highlight the need to bridge the disconnect between theoretical models and their practical applicability.

Additionally, as noted in the literature, a significant research gap lies in the inability of current methods to simultaneously incorporate the diverse, interdependent constraints found in real manufacturing systems [18]. Most studies rely on oversimplified assumptions, rendering them impractical for industrial application. Some of the main challenges in current research include:

³<https://aimagazine.com/top10/the-top-10-predictive-maintenance-companies-using-ai>

- **Comprehensive modeling:** Existing approaches often fail to integrate multiple constraints, such as machine capabilities, worker availability, environmental factors, and job priorities, into a unified framework;
- **Scalability and efficiency:** Despite advancements in scheduling research, many methods are computationally intensive and do not scale well for large, complex problems, limiting their usability in dynamic, high-volume environments;
- **Insufficient real-world validation:** A gap persists in validating theoretical models against real-world data, making it challenging to assess their robustness and adaptability.

Addressing these gaps requires innovative approaches that combine the strengths of traditional optimization and AI techniques. Hybrid models that integrate real-time data, leverage human expertise, and optimize for multi-criteria objectives represent a promising direction for future research. Furthermore, fostering collaboration between academia and industry is essential to ensure that emerging solutions are both innovative and practically applicable.

1.6 Thesis objectives and research questions

The primary objective of this thesis is to develop AI-based models to address flexible and dynamic job shop scheduling problems, while integrating human and environmental considerations into the proposed solutions. This work aims to contribute to overcoming the limitations of current methods and to propose some innovative robust, adaptive, and sustainable scheduling frameworks that align with the principles of Industry 5.0.

As mentioned in the previous section, existing methods for job shop scheduling often rely on static assumptions and fail to fully capture the complexities of real-world manufacturing systems. These gaps include a lack of comprehensive models, limited scalability, and insufficient integration of multidimensional objectives, such as worker well-being and environmental sustainability. To address these challenges, this thesis aims to achieve the following main objectives:

- **Integrating human and environmental criteria:** Incorporate ergonomic factors, worker safety, and energy efficiency into scheduling models to achieve human-centric and environmentally sustainable solutions;
- **Proposing innovative multi-criteria optimization frameworks:** Design models that balance economic, environmental, and social dimensions to reflect the complex trade-offs increasingly sought in the management of in modern manufacturing systems;
- **Developing adaptive AI models:** Propose and validate AI-driven approaches, such as reinforcement learning, deep learning, and hybrid AI techniques, capable of managing dynamic scheduling scenarios involving uncertainties like workforce absences or machine breakdowns;
- **Validating models through realistic scenarios:** Apply the proposed approaches to real-world or simulated industrial settings to demonstrate their robustness, scalability, and practical applicability.

Based on the identified research gaps and the outlined objectives, this thesis seeks to explore and address the following research questions:

- **Q1-Realism in modeling:** How can scheduling models be designed to faithfully and accurately capture the complexities and constraints of real-world manufacturing systems?

- **Q2-Integration of new criteria:** How can human and environmental factors be simultaneously integrated into flexible job shop scheduling problems to enhance sustainability?
- **Q3-Balancing objectives:** What methodologies can effectively balance economic, environmental, and human-centric criteria in flexible job shop scheduling decisions?
- **Q4-Incorporating dynamic events:** What strategies and techniques can be employed to develop dynamic scheduling models that adapt to disruptions and changes in the production environment, such as those linked to workers and energies disruptions?
- **Q5- AI-based resolution methods:** Which optimization methods and frameworks are best suited to solve flexible and dynamic scheduling problems while meeting multiple objectives?

By addressing these objectives, the thesis aims to contribute to advancing the state of the art in flexible job shop scheduling research, aligning it with the vision of Industry 5.0 and promoting sustainable, resilient, and human-centric manufacturing systems.

1.7 Thesis structure

This thesis report is mainly structured into six chapters, including the current general introduction, 4 chapters in the form of scientific articles (2 already published and 2 under evaluation), representing the main contributions of the thesis, and a last chapter for the conclusion and perspectives. Supplementary materials, including appendices and a comprehensive bibliography, are provided at the end of the document. At the very start, a French abstract offers an overview of all the chapters, followed by an English abstract. A list of tables and figures is included to facilitate navigation and improve readability. The following section provides a concise summary of the upcoming chapters.

Chapter 2 - Flexible Job Shop Scheduling Problem under Industry 5.0: A survey on Human Reintegration, Environmental Consideration and Resilience Improvement

This paper introduces the Sustainable Flexible Job Shop Scheduling Problem (SFJSSP) as a novel approach to scheduling that prioritizes human well-being and energy efficiency in line with the principles of Industry 5.0. The study begins with a comprehensive review of the past decade's literature on Flexible Job Shop Scheduling Problems (FJSSP), focusing on contributions that incorporate human and/or environmental considerations. Through this review, we identify significant development trends in manufacturing scheduling and highlight the evolution of research priorities.

The paper then proposes a mathematical model for the SFJSSP that extends the Classical Flexible Job Shop Scheduling Problem (CFJSSP) by integrating human-centered criteria, such as ergonomic risks and worker safety, along with environmental factors like energy consumption and carbon emissions. This dual-focus approach addresses a notable gap in the current literature, where studies rarely consider both human and environmental dimensions simultaneously, particularly in dynamic and complex manufacturing environments. Furthermore, the review reveals a scarcity of dynamic FJSSP studies capable of responding to real-time disruptions such as workforce absences or machine breakdowns. To address these gaps, this paper offers a framework for future research that emphasizes the integration of dynamic adaptability and multidimensional optimization, paving the way for Scheduling 5.0. By aligning with the principles of Industry 5.0, this work aims to contribute to the development of smarter, more sustainable, and human-centric manufacturing systems.

This chapter has been published in the *Journal of Manufacturing Systems*, edited by Elsevier [26].

Appendix A complements this article by providing an update of the state-of-the-art review with more recent publications, as the main study was published in early 2023.

Chapter 3 - Multi-Objective Sustainable Flexible Job Shop Scheduling Problem: Balancing Economic, Ecological, and Social Criteria

In this paper, we addressed the Sustainable Flexible Job Shop Scheduling Problem (SFJSSP), focusing on energy consumption and worker safety and preferences as key factors. To model this problem, we proposed two multi-objective Mixed Integer Non-Linear Programming (MINLP) formulations aimed at balancing economic, environmental, and social objectives. The two models differ in their treatment of the social criterion: the first model minimizes the $OCRA^{max}$ index, which assesses ergonomic risks associated with task execution and mitigates the risk of musculoskeletal disorders, while the second model maximizes Sat^{min} , representing the minimum satisfaction level among all workers. This incorporates their preferences for working shifts, machine assignments, and task variety. Both models were solved using Non-dominated Sorting Genetic Algorithms, specifically NSGA-II and NSGA-III, which were enhanced with a Q-learning-based parameter tuning mechanism for genetic operators and a reinforcement learning-based local search method. We validated the models using datasets inspired by the literature and conducted sensitivity analyses to examine the impact of variations in worker numbers and preferences.

The results highlight the interconnected influence of economic, environmental, and social criteria across diverse instances. Our findings emphasize that integrating worker safety and preferences, while creating trade-offs with other objectives, strengthens system resilience by reducing risks such as absenteeism, injuries, and fatigue. To address these trade-offs, we proposed a method for selecting an optimal schedule tailored to specific contextual requirements, achieving balanced outcomes across all criteria. Ultimately, this work underscores the importance of incorporating environmental and social considerations into scheduling processes, offering a foundation for decision-makers to navigate challenges posed by evolving social priorities and advancements in manufacturing and service systems.

This research work has been published in *Computers & Industrial Engineering*, edited by Elsevier [27]. A preliminary version of this work was presented at *the 2023 IFIP international conference on Advances in Production Management Systems (APMS 2023)* [28].

Chapter 4 - Systematic Review and Future Directions in Dynamic Flexible Job Shop Scheduling: A Decade of Research

This chapter provides a comprehensive review of the state-of-the-art in Dynamic Flexible Job Shop Scheduling Problems (DFJSSP). It examines a diverse range of studies addressing various scheduling strategies, disruptive events, and multi-objective optimization approaches. Key solution methods proposed in the literature are analyzed, with attention to their performance on established benchmarks. Spanning studies from 2013 to the present, this work offers a critical synthesis of advancements in DFJSSP and identifies emerging challenges and opportunities in dynamic scheduling for manufacturing systems.

By highlighting recent progress and persisting research gaps, this chapter serves as a valuable reference for scholars and practitioners aiming to develop more robust, adaptive, and efficient scheduling methods. It also emphasizes the importance of aligning dynamic scheduling approaches with the evolving needs of modern manufacturing environments.

This chapter is currently under revision for publication in the *Journal of Intelligent Manufacturing*, edited by *Springer Nature*.

Chapter 5 - Machine Learning-Driven Solutions for Sustainable and Dynamic Flexible Job Shop Scheduling under Worker Absences and Energy Disruptions

In this chapter, we addressed a dynamic flexible job shop scheduling problem that integrates critical human and environmental considerations. Specifically, we incorporated worker safety using the $OCRA^{max}$ metric to minimize ergonomic risks, alongside environmental factors such as variability in renewable energy production. This problem was formulated as a multi-objective nonlinear integer programming model and evaluated using three machine learning-based approaches to determine its ability to adapt to disruptions.

Through a detailed analysis of disruptions, including operator absences and fluctuations in green energy availability, we evaluated three rescheduling strategies: total rescheduling, partial rescheduling, and the right-shift strategy. Our findings revealed that total rescheduling, while comprehensive, often results in significant deviations from the original schedule, making it less practical in dynamic environments. Partial rescheduling emerged as a balanced approach, effectively managing disruptions while maintaining adherence to the initial plan. The right-shift strategy proved efficient for managing small-scale disruptions, demonstrating its utility in specific scenarios. These results underscore the need for adaptive scheduling methods to address the challenges of modern manufacturing systems, where human and environmental factors are pivotal to achieving operational efficiency and sustainability.

Furthermore, we compared three machine learning techniques, namely Q-learning (QL), deep learning (DL), and deep Q-learning (DQL), to determine the optimal rescheduling strategy for different disruption states following various perturbations. Our analysis highlighted DQL as the most effective approach, outperforming QL and DL in terms of adaptability and solution quality, particularly in complex and dynamic scenarios.

This chapter is currently under review for publication in the *Computers & Operations Research* journal, edited by Elsevier. A preliminary version of this work was presented at *the 2024 IEEE 20th International Conference on Automation Science and Engineering (CASE 2024)* [29].

Chapter 6: Conclusion

This chapter provides a comprehensive conclusion to the thesis by summarizing the key findings and contributions. It also outlines several promising perspectives for future research, including potential extensions of the proposed models, their practical applications in real-world industrial settings, and opportunities for further exploration of dynamic and sustainable scheduling solutions in alignment with Industry 5.0 principles.

1.8 Positioning within the existing literature

In this section, we position our work within the broader context of the existing literature by reviewing and comparing studies that address the SFJSSP. We focus on key aspects such as model characteristics, constraints, objective functions, and the management of dynamic disruptions. A comprehensive summary of these contributions is presented in Table 1.1, which highlights the strengths,

1.8. POSITIONING WITHIN THE EXISTING LITERATURE

limitations, and innovative approaches of each study. The final two rows of the table summarize our own work (Chapters 3 and 5), providing a clear indication of our positioning within the literature. In terms of objective functions, models that integrate all three criteria—economic, environmental, and social—into a multi-objective optimization framework are rarely explored in the existing literature. Additionally, key constraints such as transport times, worker movement, and machine setup times are often overlooked in most studies. Research on the dynamic SFJSSP is still in its early stages, with only two other studies addressing dynamic events within the scheduling process. Furthermore, ergonomic risks and worker rest times are significantly under-researched. Our first study addresses these gaps by incorporating human factors such as ergonomic risks, rest times, and worker skills, alongside energy consumption to account for the environmental dimension. All three criteria are reflected in both the objective functions and the constraints related to transport, movement, and setup times. Building on this foundation, our second study further expands the model by integrating renewable energy sources, carbon emissions, and dynamic disruptions related to worker availability and energy production. This creates a more comprehensive model of the DSFJSSP.

References	Human Factors					Env. factors					Objective(s)			Constraint(s)				Disruption(s)				
	Lc	Er	Lr	Re	Sk	Ce	Ec	Ne	Rc	Re	Ep	Eco.	Env.	Hum.	T	Tr	Su	Ma	Mb	Ja	Wa	Ve
[30]	×				×						×	×					×					
[31]					×							×										
[32]					×							×					×					
[33]				×	×							×				×	×					
[34]			×		×				×	×		×	×		×							
[35]					×	×	×					×	×									
[36]			×		×	×	×					×	×									
[37]	×	×	×	×	×	×	×					×	×					×				
[38]	×				×							×	×			×	×					
[39]		×			×			×				×	×									
[40]			×		×	×	×					×	×								×	
[41]	×				×							×	×									
[42]					×							×	×									
[43, 44]	×				×			×	×	×		×	×	×								
[45]		×				×	×	×				×	×	×								
[46]		×			×			×				×	×	×								
[47]	×				×			×	×	×		×	×	×								
[48]	×		×	×	×			×				×	×	×							×	
Chapter 3 [27]	×	×	×			×						×	×	×	×	×	×					
Chapter 5	×	×	×	×		×	×			×		×	×	×	×	×	×				×	×

Lc: labor cost; Er: Ergonomic risks; Lr: Learning rate; Re: Rest; Sk: Skill; Ce: Carbon emission; Ec: Energy consumption; Ne: Noise emission; Rc: Recycling; Re: Renewable energies; Ep: Electricity price; Eco: Economic; Env: Environment; Hum: Human; T: Transport; Tr: Travel; Su: Setup; Ma: Maintenance; Mb: Machine breakdown; Ja: Job arrival; Wa: Worker absence; Ve: Variation in energy production.

Table 1.1: Articles on FJSSP integrating both human and environmental factors from 2013 to 2024

Flexible Job Shop Scheduling Problem under Industry 5.0: A survey on Human Reintegration, Environmental Consideration and Resilience Improvement

Abstract

The Job Shop Scheduling Problem (JSSP) has been widely studied in recent decades. Various approaches have been proposed to support scheduling decisions according to the evolving production environment. The emergence of technological advancements in the context of Industry 4.0 has brought many changes and made production scheduling more and more efficient. Today's Industry 5.0 environment pays much attention to human considerations, sustainability, and resilience. These modern production environments can be accurately represented by the flexible shop floor scheduling problem in which various coordinating machines (with many alternative routing possibilities) and different operators are challenging. Recent literature on JSSP, which considers the human in the loop, has shown that the well-being and skills of workers significantly affect scheduling performance. In addition, knowing that industries are responsible for a significant part of the world's energy consumption and greenhouse gas (GHG) emissions, new studies in scheduling focus on environmental factors. This paper introduces the Sustainable Flexible Scheduling Problem (SFJSSP) as a human and energy-efficiency-centered scheduling problem. First, we review the last decade's literature on Flexible Job Shop Scheduling Problems (FJSSP) with human and/or environmental considerations. Next, we analyze the development trends in manufacturing scheduling problems. Finally, we discuss future research challenges to move towards scheduling 5.0 and suggest a mathematical model that considers human and environmental factors (in addition to the factors considered by the Classical Flexible Job Shop Scheduling Problem (CFJSSP)).

Keywords: Industry 5.0, Flexible job-shops scheduling problem, Literature review, Dynamic scheduling, Human-centric manufacturing, Environmental consideration, Sustainability, Resilience

2.1 Introduction

In recent years, manufacturing systems have undergone many changes thanks to new technologies, especially with the emergence of Industry 4.0 (I4.0). I4.0 combines revolutionary new information

and communication technologies (ICT) with real-time production and virtual simulation approaches to make operations management increasingly efficient. Cyber-Physical (Production) System CP(P)S, Internet of Things & Services (IoT&S), Horizontal and Vertical Integration, Adaptive Manufacturing, Big Data and Cloud are the major I4.0's concepts and technologies. They have been introduced into factories to increase automation and, thus, the production systems' efficiency. These concepts and technologies impact scheduling the most [15]. To complement and expand the I4.0 industrial revolution, a new paradigm called Industry 5.0 (I5.0) is emerging. I5.0 focuses on decisive factors, not only from an economic and technological point of view but also concerning environmental and social dimensions. This relatively rapid transition from I4.0 to I5.0 is driven by the ever-changing customers' needs and aspirations and the new economic, societal, and environmental pressing challenges worldwide. Indeed, I5.0 aims to develop and reinforce mainly three characteristics: human-centricity, sustainability, and resilience. These characteristics are defined as the literature's three interconnected core values for I5.0 [9].

Production systems of the I5.0 era should, first of all, be centered on humans. The latter are considered as a central element of a Human-Cyber-Physical Production System (HCPPS), which is part of a global ecosystem value chain. This systemic approach is essential to meet the ever-increasing aspirations for sustainability and to increase the resilience of HCPPS in the face of increasingly frequent and diverse disturbances. Thus, Operator 5.0 is introduced as “*a smart and skilled operator who uses human creativity, ingenuity, and innovation, aided by information and technology, to overcome obstacles on the way to developing new, cost-effective solutions for ensuring manufacturing operations' long-term sustainability and workforce well-being in the face of difficult and/or unexpected conditions (...)*” [49]. These new needs and objectives of human-centricity, sustainability, and resilience are the concern of all functions of any company (HR, Design, Production, Marketing, Logistics, Finance, *etc.*) and at the different decision-making levels, *i.e.* operational, tactical, and strategic. Production scheduling is at the forefront of achieving these objectives at the operational level. However, these new concerns of I5.0 will induce additional variables, constraints, and criteria to be considered in scheduling problems, which are already generally very difficult to solve.

Scheduling problems have been widely studied in the literature of all industrial sectors, especially the manufacturing industry, with various production workshops. In this paper, we focus only on Flexible Job-Shop Scheduling Problems (FJSSP) incorporating human factors, environmental factor, or both in connection with I5.0. This is in line with the flexible durable scheduling problem (SFJSSP) paradigm as recently defined in the literature, *e.g.* [46]. We review recent publications to analyze new trends in scheduling problems and solutions considered in the context of I5.0. We highlight current issues and future research challenges in FJSSP. The remainder of the paper is organized as follows. Section 2.2 describes scheduling problems and their trends through the different industries' evolution. Section 2.3 explains our literature search methodology. Section 2.4 presents and analyzes articles integrating human and/or environmental factors. Then, future research directions and challenges are discussed in Section 2.5.

2.2 Problem description

2.2.1 Scheduling problems introduction

Scheduling problems emerged in the 1950s as a decision-making process to accompany the advent of mass production. Because of the direct impact of scheduling on production efficiency, much research has focused on this problem since 1956 [50]. In the scheduling problems, tasks are assigned to resources, and their execution is sequenced under different constraints to optimize one or more objectives (that will be detailed later in this section). Scheduling problems occur in various domains, such as manufacturing, transportation, services, or finance.

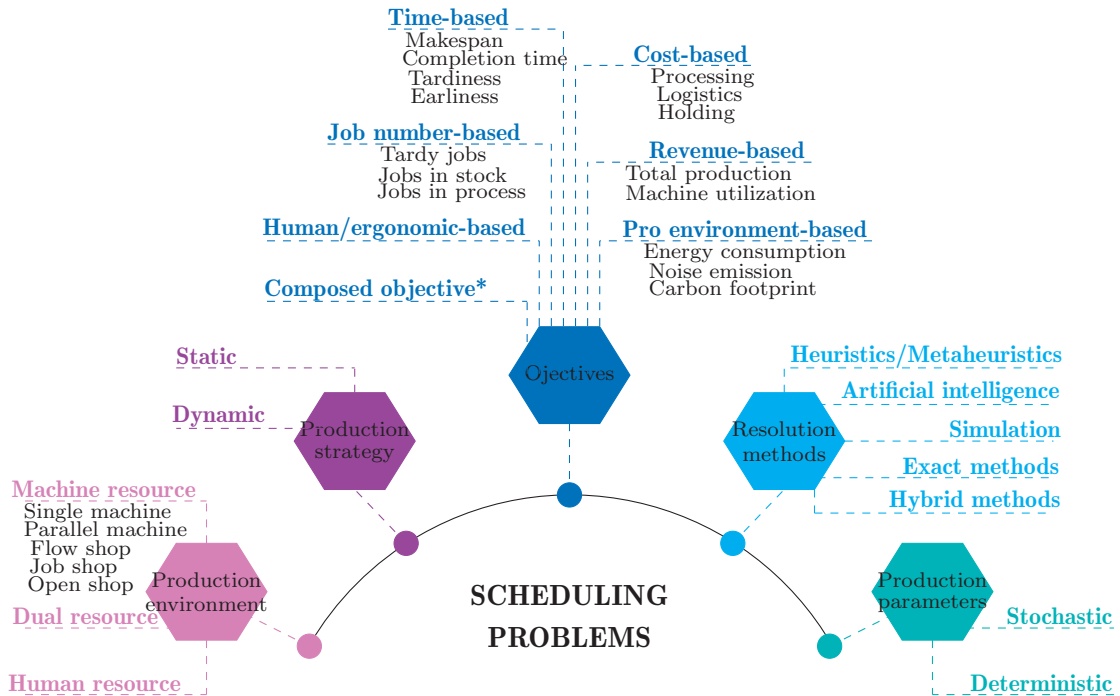
Several criteria, illustrated in Figure 2.1, characterize scheduling problems. The first criterion is the objective function, which can be time-related (*e.g.* minimizing the makespan or the tardiness), cost-related (*e.g.* minimizing resources operating costs), jobs number-related (*e.g.* minimizing the number of late jobs). It can also be robustness-related (*e.g.* maximizing the robustness of the scheduling), or quality-related (*e.g.* maximizing the number of tasks successfully realized). The time-related objective function minimization is the most studied in literature due to customers' demand. Recently, new objectives have emerged: pro-environment-based (*e.g.* minimizing energy consumption or carbon emission) and human-based (*e.g.* minimizing workers' risks or maximum workload). These objectives can be considered separately (single optimization objective) or in conjunction with each other (multi-objective optimization). The second criterion is the scheduling environment/strategy, which can be static or dynamic. Dynamic scheduling considers hazards, such as machine breakdowns or new job insertions, which makes the problem formulation closer to reality but more challenging to solve. The third criterion is related to the nature of the scheduling problems' parameters which can be stochastic or deterministic. Deterministic production ensures that parameters are known, unlike stochastic production, where one or more parameters, such as processing time or machine availability, are random variables revealed as production proceeds. Another criterion for classifying scheduling problems is the production environment, specifically characterized by the numbers and types of resources used and the way they are arranged to perform the different steps of the production process. In the case of a single-step process, there is either the single-machine environment, where a single machine processes all tasks, or the parallel machine environment, where several similar machines can do the step. When the process is multi-step, *i.e.* tasks are divided into operations that have to be processed on different machines, we talk about the workshop environment. Depending on the routing constraints of the process steps of different products, a workshop can be configured as a flow shop, a job shop, or an open shop. In a flow shop, the sequence of operations to execute is fixed and is similar for all tasks. In a job shop, the sequence is fixed but can differ from task to task. In an open-shop environment, the sequence is not set. [1] reported that the most studied production environments in literature are the flow shop and the job shop, due to their many applications in real-life manufacturing systems. Beyond these classical environments, the literature contains studies of specific industrial scheduling problems that have been formalized and solved, and whose solutions are effectively applied. The specificities of these problems can be related to: i) production process (reentrant/reverse flow, batch manufacturing, continuous/discrete flow, *etc.*), ii) resources (setup time, availability, degradation, learning, *etc.*), iii) products (perishability, handling, quality, *etc.*), or iv) decision approach (single/multi-objective, distributed/centralized, single/hybrid, *etc.*)

Scheduling problems can be solved in different ways using exact and approximate methods. How-

2.2. PROBLEM DESCRIPTION

ever, most of the scheduling problems are NP-Hard and exact methods are not efficient in terms of computation time and memory consumed. In this sense, simple and hybrid approximate approaches based on heuristic, metaheuristic, simulation, and artificial intelligence methods allow finding suitable solutions close to the optimum in a reasonable time.

To summarize, scheduling problems can take many forms depending on the resources, the available data, and the requested objective. Moreover, they continue to evolve with the development of new technologies and the appearance of new challenges changing the production environment and/or the objectives. These new scheduling problems, which we focus on the most in this article, will be detailed in the following sections. We are particularly interested in two key aspects of I5.0: the human and the environment.



*composed objective: multi-objective composed with those mentioned above.

Figure 2.1: Scheduling problems characterization

2.2.2 Scheduling challenges in the I5.0 era

Towards more flexibility

Classical Job Shop Scheduling Problem (CJSSP) is the most basic JSSP. In the CJSSP, we are given a set of n jobs $J = \{J_1, J_2, \dots, J_n\}$ and a set of m machines $M = \{M_1, M_2, \dots, M_m\}$. Each job j consists of n_j operations $O_j = \{O_{1j}, O_{2j}, \dots, O_{n_jj}\}$, which have to be processed in a predefined unique sequence, where each operation must be processed on a predefined machine. All machines are different, and their processing times are constant. The total number of machines of each type is equal

2.2. PROBLEM DESCRIPTION

to one. The objective of CJSSP is to decide the start time of each job on each machine it must visit, while optimizing a targeted performance requirement. This problem is characterized by two classical constraints related to the precedence between the operations of the same job and the impossibility of simultaneously executing several operations on the same machine. Even though the CJSSP model could be considered a typical “academic” case, it is often used to approximate real-world problems and is very useful to understand and develop solutions/approaches to scheduling problems. Therefore, this model has always attracted significant attention from academic researchers.

A production workshop is said to be “flexible” when it allows some or all operations to be processed by a set of machines, instead of only one in the case of a classical “non-flexible” environment. FJSSP can be defined (as the CJSSP) by a set of jobs divided into operations to be processed on a set of machines in a given sequence. Unlike the CJSSP, some operations in the FJSSP can be processed on a set of machines. The goal is to find the optimal machine assignment for each operation and an optimal operations sequence on each machine to minimize or maximize one or several desired performance criteria. The targeted criteria can be: (1) time-based (makespan, completion time, tardiness, earliness, *etc.*), (2) Job-Number-based (number of tardy jobs, number of jobs in stock, number of jobs in the process, *etc.*), (3) cost-based (processing cost, logistics cost, holding cost, *etc.*), (4) revenue-based (machine utilization, total production revenue, *etc.*) or (5) energy- and/or pro-environment-based (noise emission, carbon footprint, *etc.*). FJSSP should consider different constraints, the main ones related to the precedence between operations, the availability of resources, and the release and/or due dates of the jobs considered.

Figure 2.2 gives an example illustrating the difference between CJSSP and FJSSP. In this figure, solid arrows mean that the machine for the next operation is fixed, while dashed arrows mean that the next operation can be assigned to one of several possible machines. FJSSP does not contain the restriction of one production resource per operation, which extends the size of the feasible solutions space, making the FJSSP a stronger NP-hard problem than the CJSSP. Moreover, many FJSSP studies assumed that scheduling is carried out in a static production environment. However, today’s production workshops are dynamic and subject to multiple random events (random arrival of jobs, machine breakdowns, insertion of urgent orders, *etc.*). In this case, scheduling must be dynamically updated in real-time. For this purpose, the dynamic version of the FJSSP (DFJSSP) can respond effectively to fluctuations in demand and possible unexpected disruptive events. Currently, dynamic scheduling problems, which better represent real manufacturing systems (subject to randomness), are receiving more and more attention from scientists and industrialists in terms of models and solution approaches suitable for fast, real-time decision-making.

Several exact and approximate approaches can be used to solve the FJSSP. Exact methods such as mixed integer programming, branch and bound, or constraint programming are used to guarantee solution optimality. However, due to the NP-Hardness of the problem, this kind of method is only efficient with small instances. As shown in [51], most research has focused on solving this problem by applying heuristics or metaheuristics (genetic algorithm, simulated annealing, *etc.*) to find near-optimal solutions. Artificial intelligence methods represent another approach to deal with FJSSP, especially in a dynamic environment [52, 53]. In particular, machine learning techniques can handle NP-complete optimization problems with an extensive data set and improve the resolution of NP-hard manufacturing problems [54]. These techniques can learn from dynamic events and react automatically, thus helping to solve dynamic scheduling problems in a production system equipped with “smart” connected components and commonly referred to as an intelligent manufacturing system.

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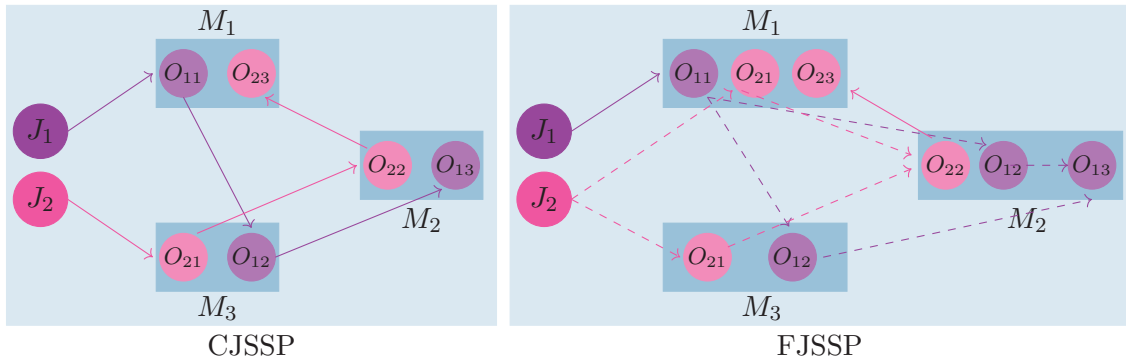


Figure 2.2: CJSSP vs. FJSSP

Towards more responsiveness

Throughout the transition from Industry 3.0 (I3.0) to I4.0 (from the 90's onwards) and thanks to several technological advances, scheduling techniques have undergone many changes to improve responsiveness in the face of not only internal technical and organizational hazards (machine breakdowns, workers absence, process drifts, *etc.*), but also external hazards and constraints (fluctuations in demand, supplier disruptions, logistical incidents, *etc.*). Intelligent scheduling, also known as smart scheduling, arises to support the evolution of the industrial environment using smart manufacturing tools. The traditional job shop scheduling of the I3.0 era is based on centralized or semi-distributed control architecture. With the I4.0 revolution, decentralized scheduling is enabled by new and emerging industrial ICT-based manufacturing technologies, thus allowing the development of innovative approaches of intelligent distributed and parallel scheduling.

As shown in Figure 2.3 adapted from [1], production scheduling before the 3rd industrial revolution was mainly concerned with mass production lines, making high volumes of standardized products. Following the market trends with the increasing demand for customized products, mass production evolved into mass customization, giving customers a wider choice of products [18].

Indeed, if in mass production the product market is segmented and usually only one product is offered in each market segment, mass customization classifies customers into different segments and groups customers' needs into the same market segment. Then, based on these grouped needs, customers are offered different product configurations within a predefined product family [55]. [56] gives a comprehensive review and discusses the enabling technologies development allowing the evolution of manufacturing paradigms from mass production to personalization. Mass customization focuses on products made only for individuals, at scale, to meet the requirements of those individuals without compromising environmental, economic and social impacts [57]. In a recent study, [58] point out that in mass customization, customers have a wide choice of products but are not fully involved in the design phase because the designer predetermines the choice of combinations. Today the demand for personalized products (color, size, fit, *etc.*) has never been higher and personalization is the main challenge for companies to meet customers' needs. Mass customization then evolved into the paradigm of mass personalization by combining the new technologies of I4.0 and the human creativity brought back with I5.0 to production. To go beyond mass customization, mass personalization paradigm represents "a personalized experience based on cocreation" [13]. In mass personalisation, customer's needs are satisfied at the personal level. The basic product design and features can change to provide unique

2.2. PROBLEM DESCRIPTION

products tailored to each individual [59]. Mass personalization differs from mass customization by expanding the design space, improving the customer experience and enhancing the creativity and innovation by customers [60]. While mass customization offers a choice from a range of available products, mass personalization allows customers to create their own unique products. Moreover, as mentioned by [57], mass personalization is primordial to meet the main challenges of I5.0.

From a manufacturing systems perspective, the traditional manufacturing of the I3.0 era turned into smart manufacturing, becoming increasingly flexible and dynamic to face new production challenges. This evolution has been possible thanks to new technologies and paradigms developed during the late 20th - early 21st centuries, such as IoT, CPS, Cloud Computing, Digital Twin, Agent-based systems, Artificial Intelligence, and Big Data. These technologies and techniques indicate the birth of I4.0 era. With I4.0, centralized scheduling has become a decentralized one, where autonomous agents are connected to each other and to the decision center, as presented in [61]. In this system, each agent can make its own decision and interact with the other agents continuously, which allows for real-time production monitoring and control. In addition, big data tools make it possible to collect and store a large amount of data throughout the production process, giving the possibility to analyze and understand the system and continuously improve its performance [8, 50]. With cloud computing, cyber-physical-system, and the internet of things, manufacturing systems can be seen as the fusion of the physical process and the virtual world, which led to the birth of the cloud manufacturing (CMfg) paradigm, including a scheduling service [62, 63]. In the virtual world, the process is simulated and adapted continuously with real-time data collected in the physical process, which simulation improves in case of disturbance. These technologies bring to the scheduling function the possibility to be more and more dynamic and flexible, being able to react and adapt the production process in real-time. Adopting these new technologies is inevitable to make scheduling solutions as efficient and robust as possible. Although CMfg has been around for several decades already, scheduling problems in CMfg have only gained significant interest in the last decade. The majority of published research in this area deals with dynamic scheduling problems using the multi-agent systems paradigm combined with artificial intelligence tools [64, 65, 66, 67, 68, 69]. Two recent articles by [64] and [65] give a more complete review of this subject.

Towards more sustainability

The rising concern for sustainability in the I5.0 context has led to a renewed focus on energy efficiency and re-humanization of production systems [70]. Nowadays, the impact of environmental and social aspects on scheduling in manufacturing plants should be studied with the same importance, if not more, than economic and technological aspects, given the rapidity of catastrophic climate and demographic changes worldwide. This paper focuses on the FJSSP which considers the human and/or environmental factors. In our survey, we refer to this problem as the Sustainable Flexible Job Shop Scheduling Problem (SFSSP). In fact, even though I4.0 brought new approaches and tools to improve, among other things, the efficiency and robustness of scheduling solutions, new types of challenges emerged in production systems and value chains in general, in line with the economic, societal, and environmental changes worldwide. A new type of scheduling appears with I5.0: sustainable scheduling, described in the following subsections.

Nowadays, the environmental aspects and the preservation of the planet's health facing to the population increase and the depletion of natural resources represent one of the most interesting chal-

2.2. PROBLEM DESCRIPTION

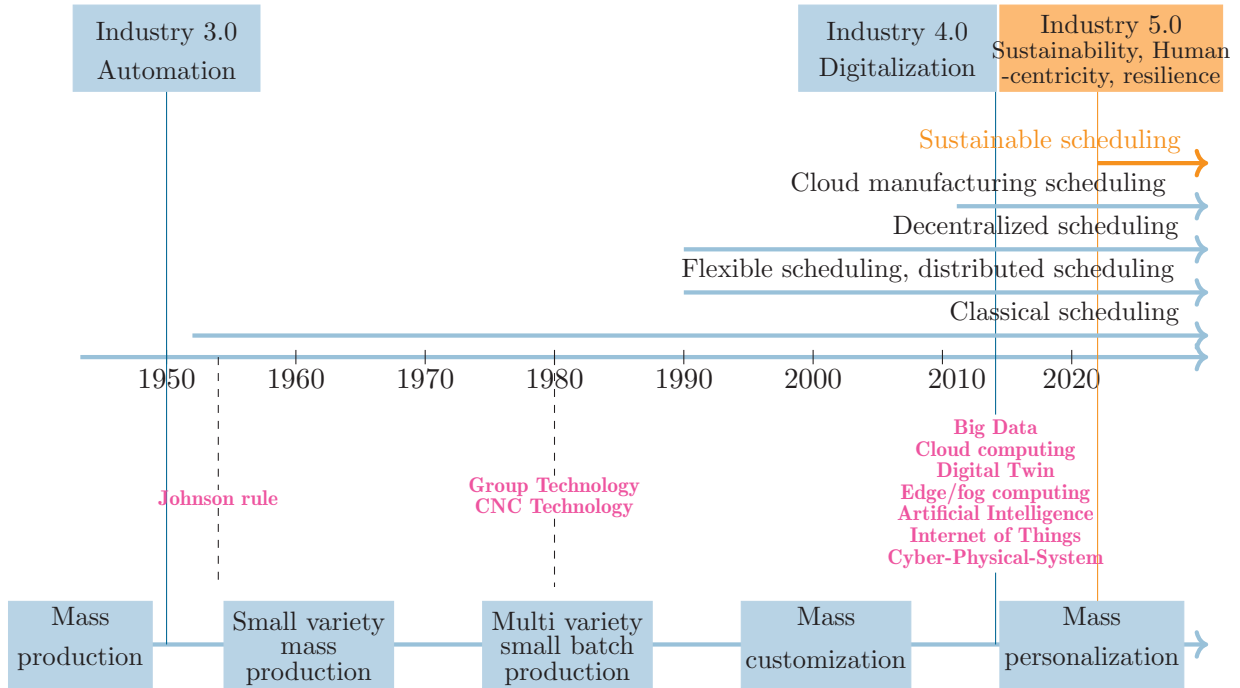


Figure 2.3: History of production scheduling, based on the one in [1] completed with Industry 5.0

lenges for the I5.0. The main reason for this interest is the impact of industrial processes, energy consumption, and carbon emission on the planet [71]. For many years, industries have been focused almost exclusively on the economic aspects, but this no longer viable perspective must change. [2] reported that the industrial sector is responsible for 31.7% of the world’s energy consumption (see Figure 2.4). Moreover, industries use resources that are not always renewable, and whose price becomes increasingly higher as they become scarcer.

Reducing energy consumption and carbon emissions is a significant challenge to preserve the planet and achieve considerable savings for industries. [72] provides examples of fields such as agriculture, food, medicine, or surgery that need to shift into green industries.

Considering environmental factors in scheduling problems has gained interest in the last years with the emergence of the I5.0 era. Scheduling problems in job shops are related to energy consumption. In order to improve the energy efficiency of industrial plants, it is now necessary to take environmental factors into account when developing scheduling strategies. In scheduling problems, environmental factors have been studied in the last few years, as proved in [73]. In this article, the authors review 297 articles from 2016 to 2021. 54 of them consider environmental parameters, minimizing energy consumption, carbon, or noise emission. The studied papers represent only 18 % of the literature, but this objective of green production is increasingly studied, combined with efficiency objectives. The increasing number of articles published, in the last few years, on energy-efficient scheduling problems makes our review a relevant topic.

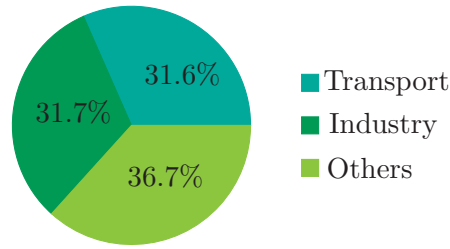


Figure 2.4: Total world energy consumption [2]

Towards more human-centricity

One of the most significant challenges raised by scheduling problems in the context of I5.0 is the human reintegration into the manufacturing environment, which has been greatly transformed by the increased automation and the use of some advanced, sometimes intriguing technologies such as VR/AR, AI, Blockchains, *etc.* In fact, for many decades, most research on production scheduling has focused only on machine resources while ignoring or simplifying the presence of operators in the process model. However, in most real-life cases, the machines are operated by one or several workers and/or share with them the same workspace.

First, the complexity of adding human factors to a system model may partly explain this oversight. A machine can be modeled as a resource, characterized by quantitative and qualitative attributes such as availability, skills, speeds, *etc.* A worker is more difficult to analyze and model [74]: he (or she) may have different costs, skills, learning rates, *etc.*, but above all, each worker has his (or her) own behavioral patterns related to his private life, personality, age, morphology, or any other type of factor that may directly or indirectly affect the performance of the production system. He (she) also presents various constraints of unavailability associated with breaks, days off, training, sick leaves, *etc.* It has often been reported in the literature that human operators impact the performance of production systems, primarily through their skills and abilities [75]. Thus, despite the difficulty of modeling, human behavior patterns must be considered to have the most realistic scheduling possible while optimizing resource utilization and reducing the gap between theoretical and effective performance.

Secondly, with the advent of I4.0 new technologies, industrialists and researchers have focused on the automation process, placing the objective of making machines more connected and more “intelligent” at the center of research while almost ignoring the human aspect and the environmental aspect as well. Consequently, industrial workers showed dissatisfaction and distrust of I4.0 and I5.0, seeing their jobs replaced by machines and impacting their social prosperity [76]. As [77] mentioned, “Humans should never be subservient to machines and automation, but machines and automation should be subservient to humans”. As a result, operators and machines should work together, and a new generation of operators appeared to meet the changing needs in the industry. An operator 4.0 can not only use and co-work with new technologies but can also work helped, even augmented, by them [78]. The objective is to give repetitive and tedious tasks to machines and robots and transform them into “ideal companions”, while workers operate more complex and high-value-added tasks that require thought and creativity [76]. This is possible with cobots, designed to work with humans and enable proper human-machine interaction. This collaboration combines human creativity and machine efficiency, making mass personalization more feasible. This is why cobots are considered as a fundamental

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element for a resilient I5.0 taking better advantage of the relationship between machines, technology and human mind [58].

Human centricity and environmental efficiency-related new challenges have led to the birth of the I5.0 era, which will bring back the human touch [21] and will be conscious of the future generation by integrating sustainability as a primary decision criterion during the design and operation of production systems. As mentioned by [11], I5.0 recognizes “the power of industry to achieve societal goals beyond jobs and growth, to become a resilient provider of prosperity, by making production respect the boundaries of our planet and placing the worker well-being at the center of the production process”. The industry needs to focus on integrating human values and environmental factors to take care of current and future generations. Note that human, social and societal aspects are usually confused, which is why the term “sustainable scheduling” is often used to refer to scheduling problems that consider the environmental factor associated with human and/or social and/or societal factors.

Towards more resilience

The third value when discussing I5.0 is resilience [9]. The resilience of a system is its ability to overcome alterations caused by one or more disruptive elements and return to its initial state with normal functioning or even by improving it. [11] define resilience as “the ability to cope flexibility with change”.

Resilience is an essential property of systems, closely related to reliability, robustness and recoverability. In the scheduling domain, reliability refers to the probability that a schedule will be executed correctly (as planned) under given conditions for a specific period. Robustness defines the ability to perform well under external disruptions and to sustain good scheduling performance. Therefore, scheduling resilience can be defined as the ability to recover and maintain the scheduling performance after the occurrence of a disruptive event. It is a post-disruption property that focuses on re-optimizing and maintaining production scheduling performance.

Despite various existing methods to solve the JSSP, it is still challenging to implement these methods in the real-time manufacturing system due to complex dynamic occurring events. The proactive, predictive and reactive approaches were widely used in the production shops to deal with complexity. Proactive scheduling considers the current predictable changes in advance when generating the original schedule. Reactive scheduling emphasizes adjustments to current scheduling when uncertain events occur. Predictive scheduling considers uncertainties in generating the original schedule. In real systems, dynamic scheduling can be completely-reactive, predictive reactive, or robust proactive [19]. The differences between the static and the different dynamic scheduling types are illustrated in Figure 2.5.

In the illustrative example of Figure 2.5, the objective is to schedule three jobs represented with three different colors (pink, violet, and brown). Each of these jobs is composed of three operations, subject to precedence constraints, *i.e.* an operation cannot start before the previous operation of the same job is finished. We compare the efficiency of four different types of schedules when a disruption occurs. In this example, the disruptive event is a breakdown of the first machine between t_1 and t_2 , making the machine unavailable until it is repaired. The impact of this machine failure is illustrated in Gantt charts showing the difference between the pre-planning and what actually happens during the processing time. In a static case, the pre-scheduling is applied no matter what. Thus, the process must wait for the machine to be repaired before restarting. The difference between the pre-scheduling

2.2. PROBLEM DESCRIPTION

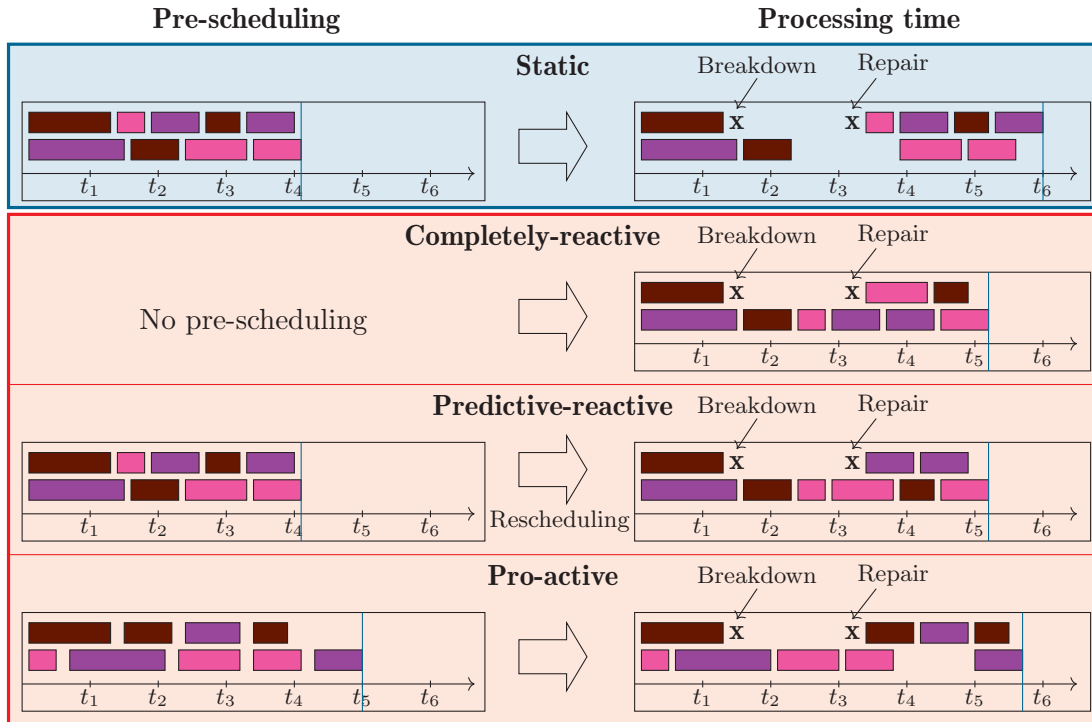


Figure 2.5: Static and dynamic scheduling

and the reality is significant. In a dynamic completely-reactive case, there is no pre-scheduling, and the scheduling is done as tasks come into the system. The breakdown of the machine has less impact on the process, which avoids that machine until its repair. In predictive-reactive scheduling, when the machine breaks down, a rescheduling adapts to the hazard. Finally, robust pro-active scheduling considers in the pre-scheduling the disruptions that may occur during the process. Operations are sequenced one after the other with a short time interval between each one to allow more time in case of trouble. In addition, robust proactive scheduling calculates the probability of a hazard occurring so that scheduling is done accordingly. Thus, the gap between the two end dates is reduced. As shown in the Figure, static scheduling is strongly impacted by disturbances, while dynamic scheduling can return quickly to its initial state.

Proactive and reactive scheduling paradigms aim to reduce the impact of the disturbances but some disruptive events' impact may exceed, sometimes, the ability of the rescheduling to restore the system performance. In this case, scheduling resilience should retain attention when solving the dynamic scheduling problem. To the best of our knowledge, resilience is less considered in the literature than the proactive and reactive scheduling approach and still needs more consideration. Recently, some papers deal with this new paradigm. For example, [79] examine the concept of resilient scheduling for manufacturing systems and propose a three-layer resilient scheduling paradigm to divide the control policy into three modes: processing sequence regulation, system parameter adjustment, and structure change. The authors designed a big data-driven framework to protect manufacturing systems from these changes.

Thanks to new technologies arising in the I4.0 era, production is digitized and synchronized, and

the system becomes intelligent and capable of reconfiguring itself. More precisely, data processing enables the prediction of hazards that can occur, such as machine breakdown, new job insertion, missing operator, *etc.* Also, artificial intelligence methods help the system learn from past events and permit real-time scheduling. It allows the system variability adaptation while maintaining its quality and customer satisfaction objective.

Most studies in the literature deal with static scheduling because dynamic scheduling is more complex. Moreover, solving the scheduling problem dynamically with new technologies will help the system to improve its resilience and should be investigated more in the future. We can further enhance resilience by considering the workers and environmental aspects. Restoring the human factor will lead to smart manufacturing integrating human brains and the ability to think and react in an unexpected cases. Humans can manage disaster recovery strategies while machines cannot [21]. [72] adds “Good resiliency can only exist once people are incorporated in areas where the human touch is essential”. Regarding environmental aspects, minimizing pollution and energy consumption in scheduling will lead to cleaner production to preserve our planet and environment. Since most resources are non-renewable, encouraging recycling and slowing consumption will lead to a more stable system.

I5.0 presents new challenges, and a trade-off must be made between ecology and society ([9]; [58]). The objective is to achieve sustainable, human-centric, and resilient manufacturing. The following sections will describe and analyze these aspects in more detail.

2.3 Research method

This paper focuses only on FJSSP due to their various real-world applications [80]. We limit our review to articles published from 2013 onward, which marked the beginning of the I4.0 [1]. I4.0 rhymes with digitalization, new technologies, smart manufacturing, and thus production efficiency. We choose to examine the articles from the beginning of the fourth revolution to determine approximately when human and environmental consciousness began to appear in the literature. We conducted our research on two search engines, namely “Google Scholar” and “Scinapse” completed with papers found through “Connected Papers”. The keywords used were Flexible Job Shop Scheduling Problem (FJSSP) combined each time with a word related to the human factor (human, workers, dual resources, ergonomic) or the environmental factor (green, energy, carbon, sustainable), as shown in Figure 2.6.

After applying these keywords, another sorting was done. In the first stage, we retained only the papers concerning FJSSP and eliminated the others. In the second step, we kept either the papers integrating workers as a resource, the papers considering environmental concerns, or the papers combining both. After a final screening to identify precise and reliable articles, 135 papers were selected for this survey. We also chose to keep only the articles redacted in English. With this selection, we obtained articles that consider one or more aspects of FJSSP in I5.0, namely the human factor or the environmental factor, thus towards more sustainable and human values-based production scheduling. The studied articles are presented and analyzed in the next section.

2.4 Results and Analysis

In this section, we consider the 135 earlier selected articles. The selected papers are classified according to three criteria: the environmental factor (Table 2.2), the human factor (Table 2.1) and

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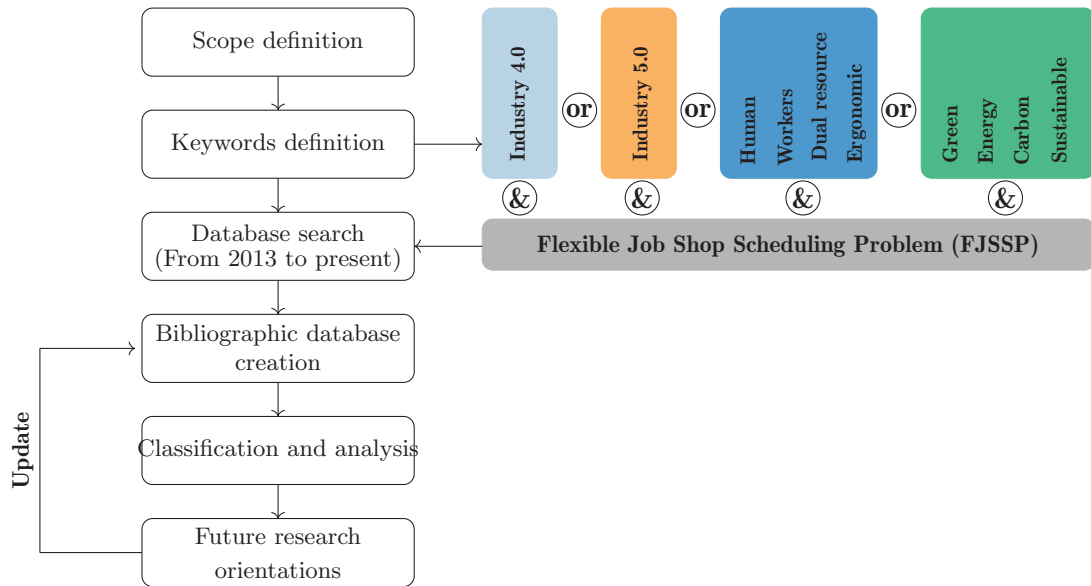


Figure 2.6: Research Method

the two factors simultaneously (Table 2.3).

The papers considering the human factor are mentioned by the following metrics: Skills (Sk), Cost (Co), Learning rate (Lr), Ergonomic risks (Er), Rest (Re) and Age (Ag).

Papers taking into account the environmental factor are specified in the "Environmental factor" column by the following parameters: Energy consumption (Ec), Carbon emission (Ce), Noise emission (Ne), or Recycling (Re).

In most reviewed articles, the time or economic objective is associated with the energy objective. Only few papers consider simultaneously the economic, environmental, and human factors. Once again, regarding the growing importance of the human factor in the current manufacturing systems, this emphasizes the importance of taking the human factor into account in future research.

References	Human Factors						Objective(s)		
	Ag	Lc	Er	Lr	Re	Sk	Eco.	Env.	Hum.
[81]	×					×	×		Cmax
[82]		×					×		Cmax, C, mW
[83]		×					×		Cmax, mW, Lc
[84]		×					×		Js, C
[85] ; [86]		×					×		Cmax, C
[87]				×			×		Cmax
[88]					×	×			Cmax F
[89]					×				Cmax, mW
[90]						×			Cmax, R
[91]; [92]; [93]; [94]; [95]; [74]; [96]; [97]; [98]; [99]; [100]						×			Cmax
[101]						×			E/T
[102]* [103]; [104]						×			Cmax, E/T
[105]*						×			Rd

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[106]		×	Cmax, Rd	
[107]		×	Cmax, mW, E/T	
[108]; [109]		×	Cmax, mW	
[110]		×	Cmax, mW	wW
[111]**			Cmax, C	
[112]**			Cmax	
[113]**			T, Wip	wW

Ag: Age; Lc: labor cost; Er: Ergonomic risks; Lr: Learning rate; Re: Rest; Sk: Skill; Cmax: makespan; mW: Machine workload; C: Cost; R: Reliability; E/T: Earliness/Tardiness; wW: Workers workload; Rd: Rescheduling disruptions; Js: Job satisfaction; Wip: Work in process; *: dynamic scheduling; **: Human is considered as a dual resource and no specific factor is indicated.

Table 2.1: Articles on FJSSP integrating the human factor from 2013 to 2022

References	Env. factors				Objective(s)		
	Ce	Ec	Ne	Rc	Eco.	Env.	Hum.
[114]	×	×	×		Cmax	Ec; Ne	
[115]	×	×			C; E/T;		
[116]	×	×			Cmax; C; Q;	Ce	
[117]	×	×			Cmax; C; E/T	Ce	
[118]	×	×			Cmax	Ce	
[119]	×	×			Cmax	Ec	
[120]*	×	×			Cmax; mW;		
[121] ; [122]; [123]; [124]; [125]	×	×			Cmax; mW	Ce	
[126]	×	×			Cmax; mW	Ec	
[127]*	×	×			Cmax; R	Ec	
[128] ; [129]	×	×			Cmax; E/T	Ce	
[130]	×	×			Cmax; Wip; mW	Ce	
[131]	×	×			EC; E/T		
[132]	×	×			E/T	Ce	
[133]		×	×		Cmax	Ec; Ne	
[134]		×			C	Ec	
[135]		×			C; EC	Ec	
[136]		×			Cmax; C	Ec	
[137]*		×			Cmax; C; mW; Q	Ec	
[138]		×			Cmax; C; Q	Ec	
[139]		×			Cmax; C; R		
[140];[141]		×			Cmax	Ec; IO	
[142]; [143]; [144]; [145]; [146]; [147]; [148]; [149]; [150]; [71]; [151]; [152]; [153]; [154]; [155]; [156]; [157]; [158]; [159]; [160] ; [161]* ; [162]* ; [163]* ; [164]*; [165]*; [166]*		×			Cmax	Ec	
[167]; [168] ; [169] ; [170]		×			Cmax; EC		
[171]		×			Cmax; Ft; IT		
[172] ; [173]*; [174]		×			Cmax; mW	Ec	
[175]*		×			Cmax; mW; E/T		
[176] ; [177]		×			Cmax; mW; E/T; Q	Ec	
[178]*; [179]*		×			Cmax; Rd	Ec	
[180]*		×			Cmax; R	Ec	
[181]		×			Cmax; E/T		
[182]		×			Cmax; E/T; C	Ec	

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[183]* ; [184]*; [185]*	×	Cmax; E/T	Ec
[186]	×	Cmax; E/T; mW	Ec
[187]; [188]; [189] ; [190] ; [191] ; [192] ; [193]; [194] ; [195]*	×	E	
[196]	×	EC; E/T	
[197]	×	mW	Ec
[198] ; [199]*	×	T	Ec
[200]*	×	T; IT	

Ce: Carbon emission; Ec: Energy consumption; Ne: Noise emission; Rc: Recycling; C: Cost; EC: Energy cost; Cmax: makespan; Q: Quality; R: Reliability; Wip: Work in process; mW: Machine workload; E/T: Earliness/Tardiness; Ec: Energy consumption; Ce: Carbon emission/footprint; Ne: Noise emission; Rd: Rescheduling disruptions; IO: Turn On/Off; Js: Job satisfaction; *: dynamic scheduling

Table 2.2: Articles on FJSSP integrating the environmental factor from 2013 to 2022

References	Human Factors						Env. factors				Objective(s)		
	Ag	Lc	Er	Lr	Re	Sk	Ce	Ec	Ne	Rc	Eco.	Env.	Hum.
[35]						×	×				Cmax	Ce	
[43]		×				×	×	×	×		Cmax; Lc	Ec; Ne; Rc	S
[45]			×				×	×	×		Cmax	Ce	Lr
[30]		×				×					Cmax; EC; Lc; mW		
[31]						×						Ec	
[32]						×						Ec	
[37]		×	×			×	×				Cmax; Lc	Ce	
[44]		×				×	×	×	×		Cmax; Lc	Ec; Ne; Rc	S
[46]			×			×					Cmax	Ec	Er
[38]		×				×					Cmax; E/T; Lc; IT	Ec	
[34]				×		×	×				Cmax	Ec; Ne	
[39]			×			×		×			Cmax	Ne	
[47]		×				×	×	×			Cmax; Lc	Ec; Ne; Rc	S

Ag: Age; Lc: labor cost; Er: Ergonomic risks; Lr: Learning rate; Re: Rest; Sk: Skill; Ce: Carbon emission; Ec: Energy consumption; Ne: Noise emission; Rc: Recycling; EC: Energy cost; IT: Idle time ; Cmax: makespan; mW: Machine workload; C: Cost; E/T: Earliness/Tardiness; Ce: Carbon emission/footprint; Ec: Energy consumption; Ne: Noise emission; Rc: Recycling; S: Safety.

Table 2.3: Articles on FJSSP integrating both human and environmental factors from 2013 to 2022

The 135 referenced articles have been published in 67 different journals or books. However, about 50 % of these publications have been found in only 10 journals, as shown in Figure 2.7.

Figure 2.8 presents a chronological sorting of the reviewed articles. The Figure highlights the growth of interest for green production. The articles that first considered the environmental factor in the FJSSP date back to 2014. Over the last six years, at least eight papers per year consider energy consumption in their study. The consideration of the human factor in FJSSP varies over the years. In 2013, only a few articles were already considering the workers. Based on this graph, one can notice the lack of articles considering both environmental and human factors. Therefore, moving towards the I5.0 and more resilient production systems requires that research works focus more on integrating environmental and human factors.

Figure 2.9 details the proportion of articles incorporating the environmental and human factors separately or simultaneously in the two cases of static and dynamic FJSSP. As previously mentioned,

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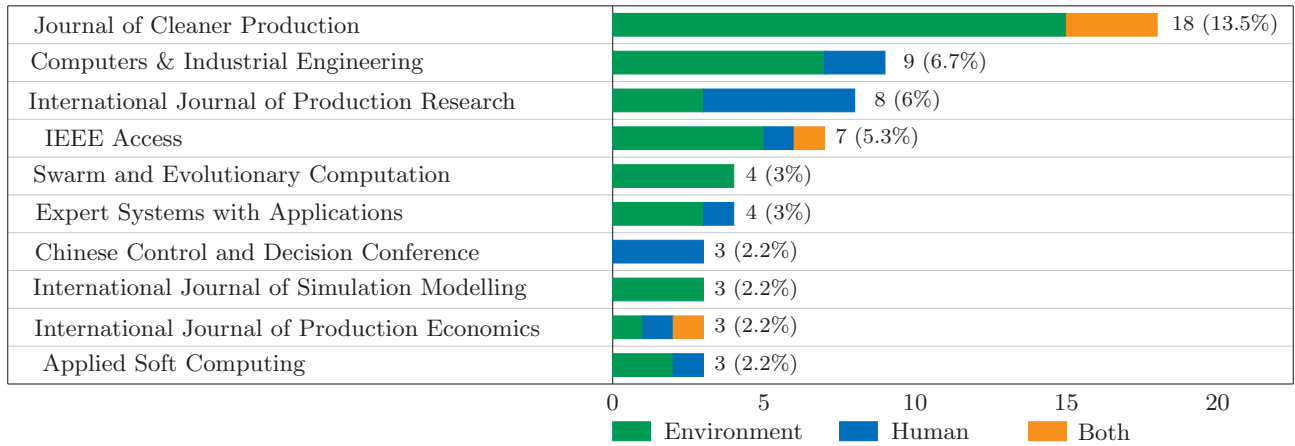


Figure 2.7: Top 10 journals publishing about FJSSP with human and/or environmental factors

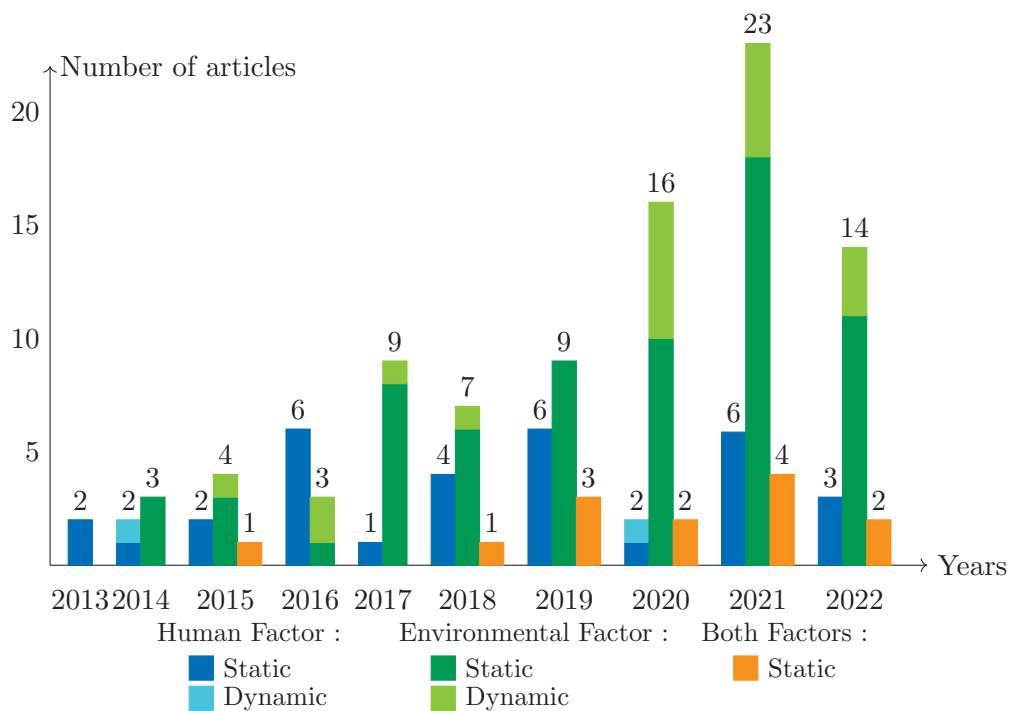


Figure 2.8: Enumeration of the surveyed literature integrating human and/or environmental factors

there is a correlation between these two dimensions and resilience. The Figure shows that most papers integrating at least one of the two factors solve the problem in a static production environment. Specifically, 69% of the reviewed papers consider the environmental factor, while 31% consider the workers. Only 9.6% integrate both factors, and only 15.6% deal with a dynamic environment. Furthermore, papers including both factors always solve static scheduling. Once again, the graph proves the lack of studies integrating workers and the environment simultaneously and any such study solving the problem dynamically. The lack of research studies integrating environmental and human factors in

the case of dynamic FJSSP, demonstrates a real need to integrate these aspects while improving the performance of today’s industrial systems. To achieve an increasingly sustainable, human-value-based, and resilient industry, we must study the FJSSP in these directions. The following two subsections provide more details on integrating human and environmental factors in the FJSSP.

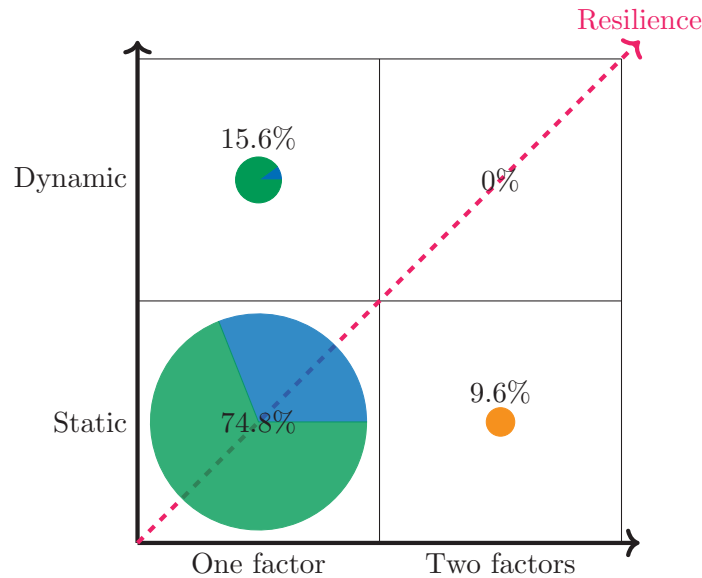


Figure 2.9: Proportion of articles integrating one or two factors (Human and Environment), considering static or dynamic scheduling

2.4.1 Human Factor

In most cases, an FJSSP that considers the human factor is called a Dual Resource Constrained FJSSP (DRCFJSSP). It means that we consider both machines and workers as resources. One or more workers can operate the same machine, and a worker can operate one or more machines simultaneously. Figure 2.10 illustrates a DRCFJSSP, highlighting the difference between an FJSSP with only machine consideration, as seen in Figure 2.2, and a DRCFJSSP. For each operation, a worker has to be assigned to the corresponding machine to process it. Workers are also flexible, meaning that they can operate different machines. Workers’ consideration adds complexity to the model, as we have even more possibilities to make decisions. The three sub-problems in a DRCFJSSP are: (1) allocating each operation on the optimal machine, (2) assigning an optimal worker to process it, and (3) finding the optimal operation sequence on each machine. We can apply the dual resource-constrained problem to automobile manufacturing, equipment manufacturing and electronic products manufacturing, *etc.*, see for example [87].

Generally, workers are difficult to represent in a mathematical model. The complexity of providing an accurate decision or action that a worker would make is very high, and operator errors are responsible for about 60-90 % of failures in a system [201]. In the literature, we notice various criteria for modelling a worker. First, some articles identify a worker by his skills [104, 93, 88]. With this characterization, a worker can have different skills, meaning that he can be more or less efficient de-

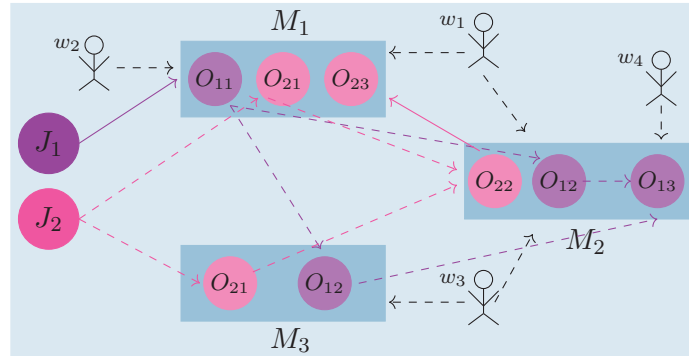


Figure 2.10: Dual Resource Constrained Flexible job-shop Scheduling Problem

pending on the machine. These skills vary from one worker to another and change the processing time of a task, thus impacting the scheduling. Directly linked to the worker’s qualifications, some papers take into account the worker’s learning rate [87, 37, 34]. In these models, workers’ skills evolve as they spend more time on a machine. Therefore, a worker who spends a lot of time on a machine will quickly increase his competence and thus reduce the processing time of the tasks he performs on this one. On the other hand, if he varies and spends time on several machines, he will be more versatile, which improves the production system’s flexibility. During his/her working time, a worker is exposed to different kinds of health risks, often called ergonomic risks [45, 46, 39]. In a production process, ergonomic risks can be exposure to temperature and noise, vibrations affecting tendons, muscles, bones, or the nervous system, physical and mental effort, or bad postures that can cause musculoskeletal disorders. Different methods such as OCRA, RULA, REBA or EAWS were proposed in the literature to measure the human-related work risks. These methods, among others, are summarized in Table 2.4 (adapted from [202]). The upper limbs correspond to the neck, trunk, waist, wrist, arms, and forearms, and the lower limbs correspond to the knees and legs [203].

Method	Body part	Parameters considered
RULA	Upper limb	Posture, muscle use, weight, task duration, frequency
OCRA	Upper limb	Rest, frequency, strength, posture, temperature, vibration
REBA	Upper and lower limb	Posture, muscle use, weight, task duration, frequency, hand coupling
OWAS	Full body	posture, lifted weight
EAWS	Full body	posture, strength, manual material handling

Table 2.4: Ergonomic methods description

The ergonomic methods presented in Table 2.4 are used in particular in assembly line problems due to the repetitiveness of worker’s movement [204] or workforce assignment problems [75], but also in some FJSSP [46]. For example, the OCRA index provides results such as “no risk”, “low risk” or “high risk” on the worker regarding the achieved task. We often model the ergonomic risk as a not-to-exceed limit in the constraints. Workers must therefore be assigned tasks that do not expose them to too many risks. For instance, if a machine requires an awkward posture, the same worker will

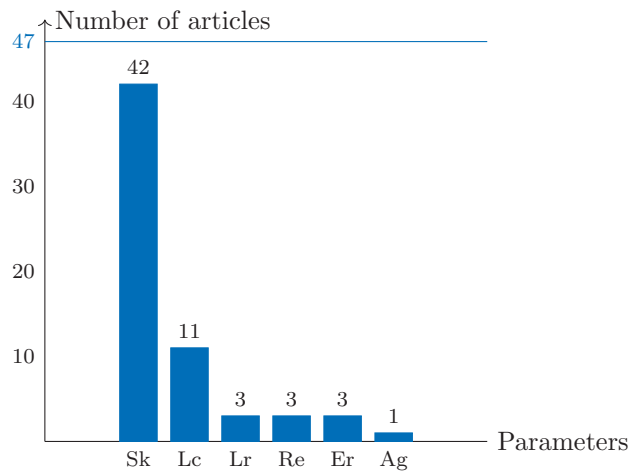
not be assigned to this one for too long during the day. Also, we can consider the fatigue and rest time of the workers [89, 81, 88]. Fatigue can be calculated as in [81] with energy expenditure during the work process and the workers' rest time. [88] implements a worker-dependent recovery parameter to model workers' fatigue reduced during rest time. Workers' fatigue influences the scheduling as the more an operator is tired, the less efficient he will be [203], affecting processing times. Including rest time during a schedule can change tasks order or tasks beginning. For example, if no pre-emption is allowed, a worker cannot start to process an operation if the latter cannot be over before the worker's rest time. [81] also considers workers' age, influencing workers' fatigue and physical condition. Finally, the cost of workers can be considered, as in [85, 43, 47]. The cost to employ a worker depends on his skills and experiences. It can be calculated as an hourly wage or a sum for each task processed, depending on the task. Thus, we can model workers with many parameters that greatly influence the schedule.

Figure 2.11 summarizes the most taken-into-account parameters based on the 47 selected articles and considering the human factor. Almost all found papers distinguish workers' skills, whereas about a quarter consider labor cost, and only a few of them take into account learning rate, rest time, ergonomic risk, or age. What emerges from this figure is that most of the models treat workers almost as if they were machine resources. A machine has a capacity and a processing cost, and so do the workers. However, human operators are much more complex, and workers' differences (age, gender, anthropometry, etc.) and well-being should be considered more. A worker feeling safe, healthy, well surrounded (machines, teams, managers), valued, and involved is more motivated at work. Thanks to that, the production process is improved, and the system becomes more resilient, employing operators feeling good in their work environment and therefore more likely to perform better. [205] proposes an Industrial Human Needs Pyramid which links everyday human needs with the manufacturing system. This pyramid highlights the parameters needed to model the operators. Five levels are presented: safety, health, belonging, esteem, and self-actualization. The authors conclude that manufacturing should consider workers personally, considering their differences on all levels, from physical to psychological. The goal is to create a system where "individual well-being and sustained manufacturing growth are mutually reinforcing" [205]. In addition, nowadays and for years to come, the active population is ageing, which should increase the need to reduce ergonomic risks at work [206].

To go further, we can divide the articles integrating human factors into two families: the ones considering the human factor in the objective function and those considering the human in the constraints. Only 28% of these articles measure the human factor in the objective function. In the other types of objectives, the most repeated are minimizing the makespan, the production cost, or the total tardiness. As detailed in Figure 2.12a, papers adding human factors to the objective function optimize the workers' cost most of the time. On the same time, some papers minimize ergonomic risks [46, 45], worker's fatigue [88] or worker's workload [110, 113].

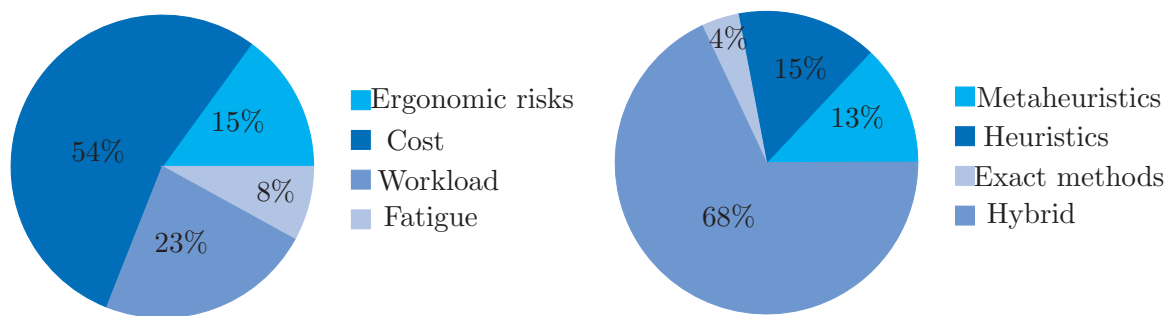
Regarding resolution methods, different exact, heuristic, meta-heuristic and hybrid methods are widely explored in the literature. In our analysis, we focus only on the papers considering the Human or/and environmental factors and try to analyze the trends in the FJSSP regarding the resolution methods. Most papers use a hybrid method, composed of meta-heuristics combined with local search, as shown in Figure 2.12b. Most often, the genetic algorithm or an improvement of it is used.

As previously mentioned, 28% of the papers integrating human parameters also consider environmental parameters, such as energy consumption, carbon emission, or noise emission. [31] has proven



Sk: skill, Lc: Labor cost, Lr: learning rate, Re: rest, Er: Ergonomic risks, Ag: age.

Figure 2.11: Distribution of the reviewed papers regarding human's parameters



(a) Human parameters considered in the objective function **(b)** Resolution method used based on the 47 articles integrating human factor

Figure 2.12

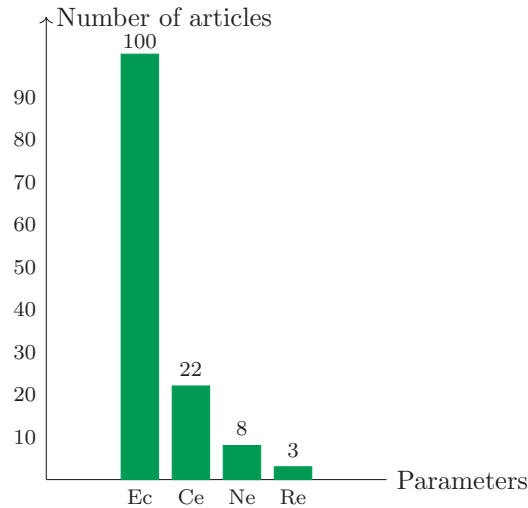
that workers' skills can impact energy consumption in production. A worker with high skills will be more efficient, decreasing processing time and thus energy consumption. As seen in this Section, bringing back the human touch in manufacturing leads to many changes in the scheduling problems, especially in the FJSSP, creating challenges for future research. Future studies must focus more on ergonomic risks and differences between workers to ensure human well-being.

2.4.2 Environmental Factor

According to [207], green production has started to attract attention since 2013. From this date, this topic's research has increased, especially during the last three years. FJSSP follows this trend as shown in Figure 2.8. The industry is responsible for a third of energy consumption in the world [2], so being aware of energy saving in manufacturing could help reduce pollution emissions and improve resource utilization. Green production can pay attention to energy consumption, carbon emission,

noise emission, or even recycling. The challenge here is to provide “environment-friendly” scheduling, while trying to optimize economic aspects and satisfy customers. For instance, if a machine is very efficient but needs lots of power to work, there is a trade-off between speeding up the production process and reducing pollution. Generally, the age of machines is heterogeneous in factories. New ones use less energy than older ones, which use more energy and emit more pollutants [208]. As a result, the choice of machines for production must be adapted.

Concerning FJSSP, we collected 101 papers integrating environmental parameters in their models since 2013, detailed in Table 2.2. Figure 2.13 shows which factors are the most used. Undeniably, energy consumption is the one that has received the most attention, present in 100 articles on 101. Besides, carbon emission has attracted attention in 22 articles directly linked to energy consumption. Most of the time, the models measure environmental parameters in the objective function. 98% of these 101 articles try to maximize green production, and 89% of them are multi-objective, meaning that there is a trade-off between several objectives.



Ec: energy consumption, Ce: carbon emission, Ne: noise emission, Re: recycling

Figure 2.13: Environmental parameters considered in the literature

Among all these articles, we notice different ways of modeling energy consumption. First, as described in Figure 2.14, the machines go through various stages during the process. These stages don’t use the same quantity of energy. For instance, [140] proposed an approach to simultaneously reduce the makespan, the energy consumption and the number of turning-on/off machines. Other works consider the idle state of a machine, *e.g.* [189]. A set-up or a maintenance intervention can be carried out on a machine before or after the execution of an operation, consuming another amount of power, as considered in [185] and [139]. Finally, when a machine processes a task, it can have different energy consumption, linked with the operation’s type and duration [43]. In addition, a machine can have different speeds during the process, leading to a variation in energy consumption or even noise emission [164]. Some articles schedule the shutdown of a machine if idle times are too long to reduce consumption [188].

At the same time, other activities in the factory also need power, such as transport, loading and unloading [71, 188]. In fact, when a product goes from one machine to another, it has to be transported,

loaded on the machine, and therefore unloaded, which is energy-consuming. In this way, transport can have an impact on the schedule. For instance, the machine chosen for an operation can depend on the previous machine selected for the same job while trying to limit transport time and thus the power consumed. Finally, the lighting, the heating, the air conditioning, *etc.* are auxiliary energies used during a production process, which are also considered in FJSSP literature, *e.g.* [193]. These energies are related to the makespan because the longer it takes to produce, the more power is required. Figure 2.14 summarizes all the activities that consume energy within a production workshop. We can model different parameters associated to these activities to optimize the overall energy consumption, without deteriorating other performance indicators related to customers' satisfaction. However, this is still a significant challenge for future research in the scheduling domain, especially the dynamic FJSSP.

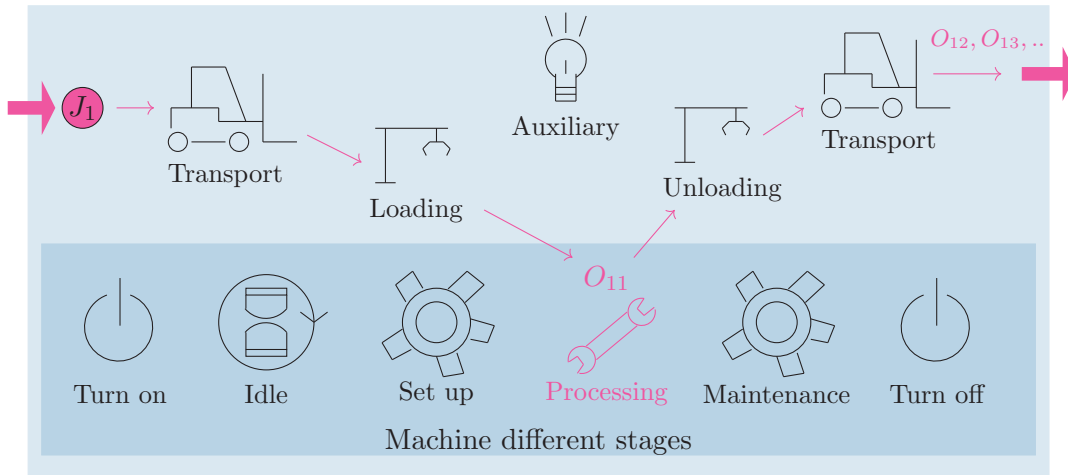


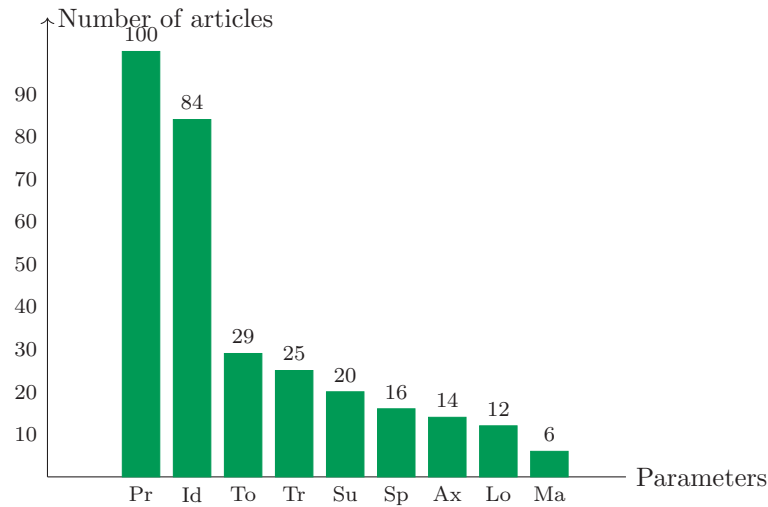
Figure 2.14: Energy consumption in a workshop

The parameters described previously are not always considered in mathematical models. Figure 2.15 details how much articles integrate them in their studies, based on those optimizing energy consumption. The power consumed during the processing time is always considered. Most of them take into account the idle times of the machines but apart from these two, the other parameters are less studied in the literature.

Regarding resolution methods, most papers use hybrid methods to solve the green scheduling as shown in Figure 2.16. These hybrid methods are composed of meta-heuristics combined with local search or artificial intelligence methods. The latter can improve the solution by learning the system the right or wrong solutions. Moreover, artificial intelligence methods can deal with a dynamic environment. The rest of the studies use meta-heuristics (*e.g.* genetic algorithm), heuristics, artificial intelligence methods (*e.g.* agent-based methods, Q-learning) or exact methods.

To summarize, energy consumption during the production process is increasingly studied in the literature, often including the consumption of processing time and idle time. However, few studies have worked on energy consumption during transport, set-up, loading, unloading, and maintenance times. Similarly, auxiliary energy needs, such as lighting or air conditioning, need to be further considered. This environmental awareness helps factories to become more sustainable and to take the first step towards Industry 5.0. Then, the human factor should be increasingly considered as same as

2.5. FUTURE RESEARCH



Pr: processing time, Id: idle time, To: turn on and off, Tr: transport, Ax: auxiliary, Su: set-up, Sp: machine speeds, Lo: loading and unloading, Ma: maintenance

Figure 2.15: Energy parameters considered in flexible job-shops

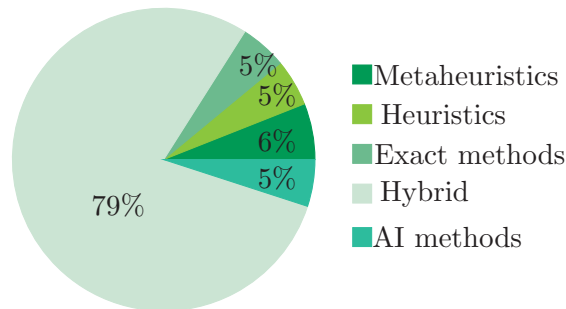


Figure 2.16: Resolution method used based on the 101 articles considering environmental factor

the economic and environmental factors. In fact, based on the 101 articles trying to maximize green production in FJSSP, only 13 of them integrate the human factor in their models. Nevertheless, the majority of reviewed papers emphasize the necessity for research to be conscious of both human and environmental values to improve the manufacturing systems' performance and the well-being of the present generation as well as future generations.

2.5 Future research

This paper reviewed and analyzed how human and environmental factors are considered in the literature of FJSSP. The scheduling models and methods were transformed by the arising of Industry 4.0 concepts and technologies and are nowadays challenged by the new concerns related to the human-centricity and environment efficiency of the current Industry 5.0 context. Looking at our analysis, only few papers consider the sustainable (economic-human-environment) scheduling problem, and efforts

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still need to be directed towards this problem exploration. In this section, we suggest a mathematical model to solve a Sustainable Flexible Job Shop Scheduling Problem (SFJSSP) with Dual Resource Constraint, aiming to minimize the total energy consumption. Our model should limit the worker's exposure to repetitive upper limb movements based on the standard OCRA index. The following subsections briefly described our model and provide the general mathematical model. Future extensions of the model are also discussed.

2.5.1 Problem statement

In our model, we consider both human and machine resources. For this purpose, we divide the tasks into four categories: the ones managed by both workers and machines (human-robot collaboration), the ones handled by either workers or machines, the ones operated only by workers (*e.g.* customized item), and the ones processed only by machines (*e.g.* difficult tasks). In addition, multiple workers can handle one operation, and a resource cannot perform several tasks simultaneously. Thus, we must specify the number of workers needed for each task. Obviously, both resources are not always available. Each operation allocated to a resource must wait until the previous task on that resource is completed. In addition, set-up times must be executed on machines when two consecutive jobs require different settings. Added to this is the maintenance time, whether it is predictive maintenance to anticipate breakdowns or repair. These procedures cause the unavailability of the machines that should be considered in the model.

For workers' availability, we must take into account more parameters. As mentioned earlier in this paper, recovery times and maximum workload must be included in the model to prevent and reduce workers' fatigue. In parallel, the ergonomic risks for each worker must be limited, affecting their health and efficiency. It can be calculated by an index such as OCRA, EAWS, RULA, *etc.* Several uses of these indexes in the same model can help to consider the problem entirely. These ergonomic constraints will impact the distribution of workers' tasks. Directly linked, the sequence of tasks that the worker performs can influence his efficiency [75], affecting resource allocation. In addition, when a worker moves from one machine to another, there is an additional time involved, namely travel time. Moreover, the workers have different skills that can evolve along the production process according to their learning rate. The model must consider these aspects. Finally, the operators have different costs (wages) depending on their skills and experience. These costs must be integrated into the model, affecting the total production cost.

All these parameters will make the model more complex but more conscious of resource availability and efficiency. So, first, we integrate them as constraints. Then, we can easily adapt the model to maximize workers' well-being in the objective function, placing humans at the center of the problem.

Our choice is to minimize the total energy consumption. The first reason for this choice is that the environment is one of the two topics we want to focus on to move towards an I5.0. Second, defining energy as a constraint is complex because we don't have a clear idea of the limit not to be exceeded during the process. If we set the energy in the objective, the model will provide the most energy-efficient scheduling, regardless of the energy consumption limit.

2.5.2 Mathematical modelling

Assumptions

The following assumptions are made to model the considered SFJSSP:

- Each operation is processed by one operator on one machine;
- An operator can execute only one operation at a time;
- An operator rests 12.5% of his worked time when he wants during the day. It can be adapted according to factory rules;
- A period is equal to 7h or 8h, and a worker is assigned to one period to two (A worker is assigned every morning, afternoon, or night. These constraints can be adapted according to factory rules).

Objective function

We suggest a mono-objective formulation of the SFJSSP to minimize the total energy consumption as follows:

$$\min ET + EM + EC$$

ET corresponds to the energy linked to transport. EM denotes the machines' related energy and EC refers to the auxiliary energy. The latter is directly related to the makespan: the longer the production process, the more energy is consumed for lighting, heating, *etc.* Thus, by minimizing energy consumption, the makespan should also be minimized. Through this objective, the environmental factor is considered. Human factors, on its side, will be considered in the constraints.

Constraints

We consider three family constraints: workers-related, precedence-related, and tasks-related. First, the workers' constraints are defined as follows:

- $OCRA \leq 2.2$ → OCRA index respected for all workers;
- Rest time $\geq 12.5\% \times$ work time → Rest time respected for all workers;
- Period + next period = 1 → A worker can't be assigned on two consecutive periods.

Besides, we have three types of precedence constraints. The first type is related to tasks of the same job, as a task can't start before the completion time of the previous task added to transport time and waiting time. Waiting time can be for example cooling or drying. The second type of precedence constraint concerns the precedence of tasks assigned to the same worker, as a task can't start before the completion time of the previous task added to travel time and rest time for the chosen worker. Finally, the third type is related to tasks executed on the same machine and states that a task can't start before the completion time of the previous task added to the set-up time. The precedence-related constraints are defined as follows:

- Completion time + Transport + Waiting \leq Starting time of the next task;
- Completion time + Transport + Rest \leq Starting time of the next task;

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- Completion time + Set-up \leq Starting time of the next task.

Finally, the task-related constraints ensure respecting due dates, starting time and completion time in the period the task is assigned on. We define these constraints as follows:

- Completion time \leq End time of the period;
- Starting time \geq Starting time of the period;
- Completion time \leq Due date.

2.5.3 Perspectives

In this study, we propose a mono-objective model to minimize energy consumption. Our model considers the human factor in the constraints by limiting workers' repetitive movements. However, the human factor can be modeled as an objective function making our model multi-objective, for example, one considers to:

- Maximize the workers' flexibility: the purpose is to reinforce the worker's multi skills. In this sense, the system would be more flexible, allowing the operators to use more machines.
- Maximize the worker's well-being, thanks to ergonomic indexes as mentioned previously. For example, we can minimize the maximum ergonomic index, thus reducing the ergonomic index of each worker.

By combining these objectives, we should be able to measure how much the workers and the environmental factors can impact the performance of the shop floor. We can imagine a multi-objective human-environment-economic model.

The SFJSSP we suggest in this paper is static. For small instances, our model can be solved with an exact method. Besides, the objective will be to provide a dynamic SFJSSP able to deal with uncertainties that can occur during the production process. The resilience will also be enhanced by improving the system's ability to react to disruptive events. We may use, among others, the triangular fuzzy number to represent uncertainties in manufacturing systems as presented by [209]. In the last few decades, several methods have been used to solve the dynamic FJSSP. The two most used are metaheuristics and dispatching rules; however, these later are ineffective in finding an optimal solution [52]. Metaheuristics deal with the dynamic scheduling problem by decomposing it into several static sub-problems, which leads to a time-consuming solution [52]. On the contrary, artificial intelligence methods have proved their efficiency in dealing with real-time scheduling problems. To confirm this point, regarding the 135 articles selected in our studies, we notice differences between the resolution methods used in static and dynamic cases. Figure 2.17a shows that exact methods can solve static FJSSP, and on the contrary, Figure 2.17b demonstrates that no study has used these methods to solve dynamic scheduling. Moreover, artificial intelligence methods are used in dynamic cases while no static scheduling is solved with them. Hybrid methods used in dynamic cases most of the time combine meta-heuristics and artificial intelligence methods.

We plan to solve our model using machine learning methods. In particular, we are interested in the deep reinforcement learning technique. [210] assures that "deep reinforcement learning can give immediate action for the problem if the model is well trained" and can handle combinatorial optimization problems. Further, [211] states that the fuzzy logic method can optimize multiple goals.

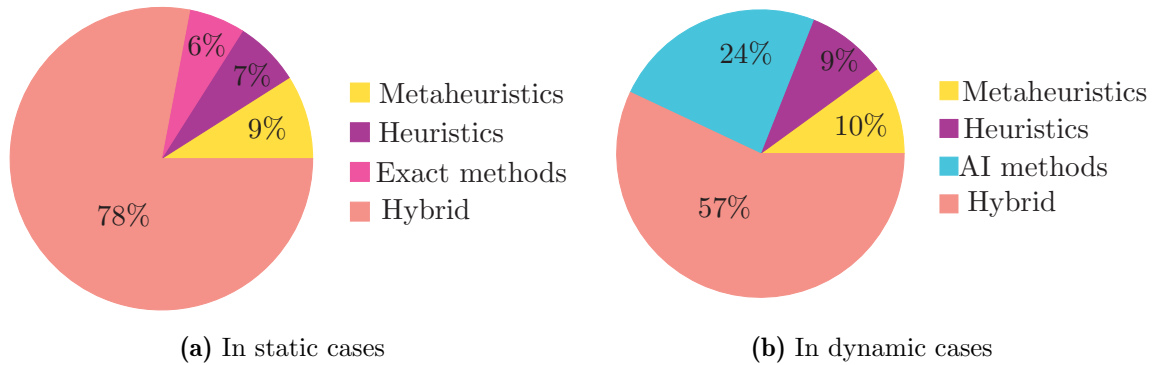


Figure 2.17: Resolution method used in case of static or dynamic FJSSP, based on the 135 articles selected

In that sense, we will study the fuzzy logic to solve our multi-objective model. To go further in our approach, we plan to test our model on a real industrial case to improve it.

2.6 Conclusion

This paper presents a survey of FJSSP considering the environmental and human factors. We start by introducing the evolution of scheduling problems, particularly in the last decade from the emergence of Industry 4.0 to now. Scheduling problems have been widely studied in the literature under different production types, characteristics, environments, and objective functions. This interest is due to the high impact that scheduling has on the production process. FJSSP is the most encountered in the real-world case. For decades, research focused on economic aspects, minimizing the makespan or the production cost as an evaluation criterion. Recently, I4.0 has brought new technologies that increase production efficiency, driving the research on solving the scheduling problem in this new context. Today new challenges are emerging, namely human’s well-being, sustainability, and resilience. They tend to move towards an I5.0, filling in the gaps of I4.0. The objective is to use technologies in an intelligent way, placing humans at the head of the system and being conscious of our planet.

Most of the articles reviewed primarily consider economic and energy consumption objectives. Few papers consider, at the same time, the economic, environmental, and social dimensions. Growing importance is increasingly accorded to the sustainable FJSSP. Also, most previous studies consider the makespan as the main and single objective. Considering multi-objective models which take into account the three pillars of sustainability, is becoming trend research. Regarding resolution methods, most papers use hybrid methods to solve the scheduling problem considering human or environmental factors. These hybrid methods are composed of meta-heuristics combined with local search or Artificial Intelligence (AI) methods.

This survey proved a lack of studies integrating both factors linked to I5.0, namely human and environmental consideration, and a lack of dynamic FJSSP studies. These gaps provide a direction for future work to keep up with the manufacturing trend towards Industry 5.0.

Multi-Objective Sustainable Flexible Job Shop Scheduling Problem: Balancing Economic, Ecological, and Social Criteria

Abstract

Industry 5.0 makes it imperative to reevaluate the manner of using resources in manufacturing systems to ensure sustainability. In this context, scheduling problems are encountering new environmental and human-related challenges, and the concept of sustainable scheduling has gained importance, aiming to balance economic, environmental, and human factors. In this paper, we propose two multi-objective mathematical models to simultaneously address these three factors as objective functions. In the first model, we consider the operator safety while using the Occupational Repetitive Action (OCRA) index to assess ergonomic risks related to task execution. The second model includes workers' preferences in terms of machines, shifts and task variety. The objective is to improve the general well-being of workers by proposing a schedule that respects as much as possible their preferences. Both models integrate the travel time of workers and products between machines. To solve these NP-hard scheduling problems, we use the Non-dominated Sorting Genetic Algorithms II and III (NSGA-II and NSGA-III), enhanced with a Q-learning strategy for parameter selection and a variable neighborhood search based on reinforcement learning. The obtained results provide a comprehensive analysis of the interactions between these criteria, demonstrating the capability of such approach to achieve a favorable balance between multiple objectives while addressing the new challenges of production scheduling in Industry 5.0 context.

Keywords: Industry 5.0, Sustainable Flexible Job-shops Scheduling Problem, Multi-objective optimization, Human Centric Manufacturing, Environmental consideration, NSGA-II, NSGA-III

3.1 Introduction

Today's Industry 5.0 context is human-centered, and integrates societal and environmental concerns alongside advanced technologies. In this context, manufacturing systems have undergone significant changes, encompassing both organizational and functional transformations. After Industry 4.0 has amplified the digitization of data, facilitated transparent data exchange, and automated production processes, thereby improving the performance of manufacturing systems, Industry 5.0 aims to further enhance these systems' resilience by integrating environmental and social considerations [9]. In the industrial context, resilience refers to the capacity of a system to endure disruptions and promptly

and autonomously return to its standard operation, with original performance. In [212], the authors propose a methodology for assessing resilience based on technical, organizational, social, and economic dimensions in the era of Industrial 4.0. At the organizational level, proactive recovery planning mechanisms across various decision-making levels are deemed essential, particularly concerning operational level for dynamic scheduling.

To address the impact of significant dynamic events on system performance, new scheduling techniques from the so-called “resilient scheduling” paradigm have emerged [79]. Production scheduling must therefore adapt to incorporate new constraints related to human and environmental factors, employ new decision strategies (dynamic/real-time approaches), and align with the relevant objectives of the “5.0 production line”, including minimizing energy consumption and maximizing operator well-being [15]. The “classical” production scheduling problems have been widely discussed in the scientific literature, and researchers have been confronted with the complexity of solving them, as they are generally NP-hard. Different mathematical single- and multi-objective optimization models have been suggested and different exact and approximate resolving methods have been proposed to solve them (e.g. Branch-and-Bound, Constraint Programming, Genetic Algorithm, Tabu Search, Ant Colony Optimization, etc.).

In this paper, we consider the scheduling problem of a flexible job shop and we propose a model that takes into account human and environmental factors alongside the traditional economic considerations. For the remainder of the paper, this problem is referred to as Sustainable Flexible Job Shop Scheduling Problem (SFJSSP) [28]. We present two multi-objective optimization models designed to simultaneously optimize various criteria associated with economic, environmental, and societal factors. Thus, we are looking for a solution that concurrently achieves favorable outcomes for all three criteria. In the first model, the makespan (maximum completion time), the total energy consumption and the exposure to musculoskeletal risks of the operators are jointly minimized. This last criterion is represented by the OCRA index, which is a standardized measure used to evaluate operators’ exposure to tasks involving various upper limb musculoskeletal risk factors [213]. In the second model, the human criterion is substituted by the minimum level of satisfaction among all workers. This criterion, which is to be maximized, is computed on the basis of workers’ preferences regarding machines, variety of tasks, and working shifts. To the best of our knowledge, only a few scheduling research works have considered the three sustainability indicators simultaneously in the same multi-objective optimization model [43, 46, 45]. In this paper, we also take into account product transport time as well as worker travel time between processing machines, making our study original and challenging. These transportation constraints are frequently overlooked or oversimplified in the literature, despite their potential to significantly impact the production system performance indicators, such as the makespan [214] and the energy consumption [194]. Neglecting these constraints can introduce time delays to task initiation when workers or products are not available at the designated machines, and increase the overall energy consumption. Additionally, we take into account setup constraints between two jobs on the same machine, along with defining working hours and rest time for each worker.

To solve our multi-objective model, we propose using two non-dominated sorting-based evolutionary algorithms, namely NSGA-II and NSGA-III (Non-dominated Sorting Genetic Algorithm II and III) enhanced with a Q-learning strategy for parameter selection during the offspring creation, and a variable neighborhood search based on reinforcement learning to improve the quality of the solutions. We test our model on different simple and extended instances from literature, which have been tailored to our problem by generating certain parameters associated to the human aspect, travel distances and

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speeds, and setup times. We evaluate our model’s performance by defining and testing some typical worker preference profiles, analyzing how variations in these profiles impact the results. Furthermore, we explore the influence of the number of workers on the OCRA index. This comprehensive analysis provides insights into the robustness and applicability of our proposed model across different scenarios.

The rest of this article will be structured as follows. Section 3.2 provides a comprehensive review of the current state of the art by exploring transportation constraints and discussing various methodologies used to solve the multi-objective SFJSSP problems. In Sections 3.3 and 3.4, we introduce the proposed optimization models and describe the algorithms used to solve them. Section 3.5 presents the instances and metrics used to test the proposed algorithms and to analyze the obtained results. Section 3.6 studies the performance of the algorithms used, and section 3.7 reports our results and sensitivity analysis regarding the number of workers and their different profiles. Section 3.8 concludes our paper and outlines some research perspectives.

3.2 Related works

3.2.1 Sustainable scheduling problems

The growing emphasis on sustainability within the Industry 5.0 context has redirected attention towards energy efficiency and operator well-being considerations [70]. Today, the impact of environmental and social factors on scheduling in manufacturing requires equal analyze alongside economic considerations. As a result, sustainable scheduling has emerged in production systems, necessitating a balance among the economic, the human and the environmental aspects. In [26], the authors provide a comprehensive analysis of the flexible job shop scheduling problem considering both human and environmental factors. Sections 3.2.1 and 3.2.1 summarize the literature on scheduling problems aimed at reducing the energy consumption and improving the human factor, respectively.

Energy consumption considerations

Today, preserving the planet in the face of a growing population and depleting natural resources is a major challenge. Knowing that industrial activities represent a substantial part of global energy consumption and the environmental impact it induces [71], taking into account energy consumption as an objective function to be minimized in scheduling problems can significantly contribute to reduce pollution. For instance, using one machine instead of another may increase processing time but reduce energy consumption and gas emissions, which can be decisive for achieving frugal and environmentally friendly scheduling. For many years, industries have predominantly prioritized economic imperatives. However, as societal aspirations and regulatory frameworks evolve, a significant paradigm shift is ongoing. Thus, ensuring a judicious trade-off between economic prosperity and environmental preservation is becoming an imperative for long-term sustainability.

Over the past decade, with a notable emphasis in the last three years, many research articles have focused on the concept of green production. In a comprehensive review by [73], 297 articles on scheduling problems published between 2016 and 2021 were analyzed. Notably, 54 of these articles specifically addressed environmental factors, encompassing considerations such as energy consumption and carbon emissions. The most prevalent environmental concern in the literature is the reduction of energy consumption [26, 207], specifically during operational processing [43]. However, it is important

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to note that energy consumption can arise from various stages of the production process, including set-up and maintenance operations [136, 215], loading and unloading products, transportation between machines [144], turning on and off machines [144], operating auxiliary facilities and equipment [165], and even during machine idle periods [149].

Beyond energy consumption, a limited number of studies incorporate carbon emissions into their models [114, 116], a metric directly linked to energy consumption. In other approaches, [39] endeavored to mitigate noise pollution by minimizing machine speed increments, while [43] introduced a recycling tool ship, both relatively rare in the literature. Typically, environmental models are multi-objective, aiming to minimize energy consumption alongside economic factors such as total cost or makespan. In some studies [45, 46], a third criterion focusing on societal considerations is also minimized, thus achieving a sustainable schedule.

Human factors considerations

While Industry 4.0 introduced automation and intelligent systems, Industry 5.0 aims to shift towards a human-centered approach, fostering a synergy between machines and workers to enhance social prosperity [76]. Many studies on production scheduling have traditionally focused on machine resources, overlooking the pivotal role of operators within the model. However, these machines are typically operated by one or more workers, each possessing distinct skills that influence their speed, work quality, and capability to perform specific operations. Unlike machines, workers require structured work schedules, adequate rest periods, and a safe working environment, rendering them more challenging to model and manage properly. Given their significant impact on system efficiency and resilience, it is imperative to incorporate their considerations, as underscored in recent research [72].

The integration of the human factor in the SFJSSP has been relatively underexplored [43]. However, some studies have addressed worker considerations in scheduling in various ways. Firstly, economic aspects, such as worker costs and skills, have been incorporated. For instance, [43] propose a model aimed at minimizing labor costs, where the processing cost for each worker is dependent on their skills. [93] and [104] present models where workers' varying skill levels influence machine operation and consequently affect processing times. [87] examine the learning effect on workers, suggesting that increased time spent on a machine leads to improved skills.

Furthermore, worker safety and well-being are critical considerations. Acknowledging the positive impact of worker happiness on reducing turnover, minimizing absenteeism, and enhancing overall system efficiency [216], several studies have focused on these aspects. [81], [88], and [89] address worker fatigue by incorporating rest periods to ensure safety and efficiency. Specifically, [217] demonstrate that short breaks after each task improve system performance.

For ergonomic risks, various indices are suggested in the literature for different static and dynamic scheduling problems, extensively detailed by [218]. The most well-known indices include RULA (Rapid Upper Limb Assessment), REBA (Rapid Entire Body Assessment), OCRA (OCcupational Repetitive Action), OWAS (Ovako Working Posture Analysis System), NIOSH (National Institute for Occupational Safety and Health), and EAWS (European Assembly Worksheet). RULA and OCRA focus on upper limbs, while REBA also includes lower limbs. OWAS and EAWS consider the full body. These indices differ in the parameters they assess, such as posture, frequency, or lifted weight. A more detailed comparison of their features can be found in [26]. [75] utilize three of these indices—OCRA, OWAS, and NIOSH—in a single model to comprehensively address ergonomic risks.

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In our study, we use the OCRA index, which is considered the most comprehensive for assessing upper limb risks. According to the European standard EN 1005 and the international standard ISO 11228-3, OCRA index can be used to analyze and predict the onset of musculoskeletal disorders. Introduced by [213], the OCRA index compiles a range of risk factors associated with technical actions, including posture, frequency, strength, lack of rest, total duration, and additional risks like vibration or temperature. Technical actions refer to basic manual tasks performed during the work cycle, such as holding, turning, and pushing [219]. During one shift, a worker's OCRA index is calculated as the ratio between the Actual number of performed Technical Actions (ATA) and the Recommended number of Technical Actions (RTA): $OCRA = ATA/RTA$.

The recommended number of technical actions is formulated as $RTA = CF \times PM \times FM \times RM \times ARF \times (RcM \times DuM)$. This calculation incorporates several multipliers, each ranging between 0 and 1 based on the specifics of each task: PM (posture multiplier), FM (force multiplier), RM (repetitiveness multiplier), and ARF (additional risks multiplier). Additionally, it includes multipliers independent of specific tasks but dependent on the work environment: RcM (lack of recovery multiplier) and DuM (overall duration multiplier). The constant of frequency of technical actions per minute, CF , is set at 30.

Then, the OCRA index for each worker is a real, positive and unitless numerical value, providing a measure of his ergonomic risk exposure. [220] and [218] define six levels of risks depending on OCRA index, presented in Figure 3.1.



Figure 3.1: Risks of musculoskeletal disorders depending on OCRA Index

From another perspective, some studies incorporate workers' preferences into their models. [221] maximize the on-time delivery jointly to worker satisfaction, which is represented by job preferences. In a subsequent publication, [222] strike a trade-off between makespan and worker satisfaction, demonstrating the feasibility of finding schedules that effectively address both objectives. In this study, workers select a preference level, indicating their liking or disliking for each machine along with a desired level of variety in an identical parallel machine scheduling problem. [223] maximize employee satisfaction by taking into account their seniority and shift preferences. [224] maximize workers' satisfaction considering workers' availability, productivity, priority preference, seniority level and required number. In the study of [225], the decision-maker preferences are integrated when addressing a multi-objective flexible job shop scheduling problem. The outcomes reveal a discernible improvement in the quality of solutions achieved through this integration. All these studies highlight the significance of workers' well-being at work, underlining that it should be taken into account beforehand when establishing production schedules, as "happy workers are also productive workers" [216].

3.2.2 Scheduling problems with internal transport constraints

While investigating scheduling problems, many research papers neglect the internal transportation times and their induced constraints [150, 110]. However, it is important to recognize that these product movements are time-consuming and that neglecting them can lead to delays and altered overall process times [214]. [194] analyze the impact of transportation on completion time and energy con-

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sumption, establishing a strong connection between these variables. [226] underscored the significance of considering internal transportation times as equally crucial as task scheduling within a workshop. They focused on scheduling transportation tasks carried out by Autonomous Guided Vehicles (AGVs), aiming primarily to prevent collisions and deadlocks. [196] prove that considering transportation time can reduce the energy consumption and tardiness penalty by 24% and may avoid idle times of machines. [147], [149] and [150] addressed the flexible job shop scheduling problem while accounting for transportation time constraints. They aimed to minimize completion time and reduce energy consumption in a flexible workshop. In their model, the authors considered energy consumption during task execution as well as during transport within the workshop. [165] study the same problem with insufficient transportation resources in a dynamic context, allowing new job insertions and machine breakdowns.

On the other hand, incorporating multi-skilled operators into the workshop cannot be effective without introducing additional constraints related to travel times. Given their flexibility, operators may be assigned to different machines, which means that the schedule has to take into account the time needed for a worker to move from one machine to another. These constraints can be viewed as workforce routing problems. Workforce scheduling and routing problems are discussed in the review by [227]. Operators' travel time is often overlooked in the design and operation of manufacturing processes. However, [88] study the fatigue levels of workers during the manufacturing process, assuming that travel time does not count as working time or rest time and that it has a neutral effect on the level of fatigue.

3.2.3 Multi-objective scheduling problems

Multi-objective problems (MOPs) are thoroughly documented in the literature, and various methods have been proposed to address them. [228] explain four approaches: the global criterion method, the linear combination with weights, the ϵ -constrained method, and the multi-objective genetic algorithms.

- The global criterion method: This approach has the advantage of being simple and efficient [229]. Its principle is based on minimizing the distance of the solutions from an ideal solution. Nevertheless, it is computationally expensive and does not always obtain non-dominated solutions in the Pareto sense.
- The linear weight combination method: In this approach, the objective function is written as a weighted sum of all the considered objectives. We thus pass from a multi-objective model to a single-objective one. The difficulty with this method is to find the weights for each objective and it only allows to obtain a small number of solutions [230].
- The ϵ -constraint method: This approach also keeps only one objective and transforms the others into constraints. It is easy to implement and enables a rich representation of the efficient set [231]. The main disadvantages of this approach is its computational time and the difficulty in certain cases to encode the objectives.
- The multi-objective evolutionary algorithms: This approach is widely used in the literature. In these algorithms, the procedure starts from an initial population of solutions, and thanks to certain operators, generally bio-inspired, the population evolves over the iterations. The

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expected ultimate goal is that the population converges to the Pareto-front representing the set of non-dominated solutions [232].

Among the evolutionary algorithms, two variants of the Non-dominated Sorting Genetic Algorithm (NSGA) caught our attention to solve the SFJSSP problem: (1) NSGA-II [233] which is used many times and is often improved when combined with other methods (local search, meta-heuristics, *etc.*) (2) NSGA-III which was proposed by [234], and differs from NSGA-II in its selection mechanisms. As mentioned by [235], these two algorithms have shown good results and seem to be efficient for problems like ours. In this study, the authors tested both algorithms on different instance sizes and demonstrated that NSGA-III consistently outperforms NSGA-II in terms of the hypervolume metric for each instance size. [45] compared the performances of NSGA-II and NSGA-III using a case study with three different metrics: the number of non-dominated solutions, the uniform distribution of the non-dominated solutions, and the level of non-dominated solutions. The authors found that NSGA-III outperforms NSGA-II across all three metrics. Both this study and the one by [46] include in their objective functions the three aspects considered in this paper, namely: the economic aspect (makespan), the environmental aspect (energy consumption or carbon emissions), and the societal aspect (ergonomic risks). [46] employed an improved NSGA-III, noting that while NSGA-III inherits the framework and advantages of NSGA-II, it also integrates a selection strategy based on reference points, ensuring the convergence and diversity of the next generation of individuals. [43] and [37] use other evolutionary algorithms, namely a new hybrid genetic algorithm and the memetic algorithm, to find a solution ensuring the best trade-off between human, environmental and economic aspects.

With the advent of machine learning and artificial intelligence, new methodologies have emerged that greatly enhance traditional computational techniques. Evolutionary algorithms can be enhanced with reinforcement learning, a field of machine learning that allows for adaptive parameter adjustment. While [236] demonstrate that reinforcement learning has been more intensively studied in single-objective evolutionary algorithms, recent research has increasingly focused on integrating these methods into multi-objective evolutionary algorithms. For instance, [237] introduce a multi-objective evolutionary algorithm based on decomposition, which incorporates a Q-Learning-based parameter adaptation strategy to improve diversity. Similarly, [238] employ a multi-objective immune algorithm guided by Q-Learning to optimize neighborhood selection. Both studies emphasize that integrating Q-Learning enhances both exploitation and exploration capabilities, leading to superior results across all evaluated metrics.

More recently, reinforcement learning models have been also developed to select decision rules for multi-objective problems [239]. These kinds of Artificial-Intelligence-based algorithms can be particularly efficient for dynamic scheduling problems.

3.3 Problem description

3.3.1 Assumptions

In this study, we propose two non-linear integer programs for solving the SFJSSP which will be referred to as ‘First model’ (or MOP1) and ‘Second model’ (or MOP2) throughout the remainder of this paper. MOP1 aims to minimize, simultaneously, the makespan (f_1), the energy consumption (f_2) and the maximum OCRA index among all workers (f_3). MOP2 seeks to minimize the makespan

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(f_1) and the energy consumption (f_2), while maximizing the minimal satisfaction of all workers (f_4). In our study, sustainability encompasses both environmental and human considerations. For the environmental aspect, this involves accounting for energy consumption. For the human aspect, it includes knowledge, safety, and workers' preferences.

We consider three types of energy-consuming activities: i) execution of operations on machines, ii) internal transportation of products, and iii) operation of auxiliary installations (lighting, heating, *etc.*). We presume that, for a given schedule, the energies consumed by auxiliary installations are directly correlated with the makespan, because longer processing time require more energy for lighting, heating, and other related purposes. The energy consumption during processing operations depends on the specific operation types and on the machines and workers involved in each operation. Additionally, we assume that energy consumption during transportation is solely determined by the distance between machines and remains consistent across all products.

Regarding the human consideration, we focus not only on workers' skills, but also on their safety and well-being through: i) their rest time and OCRA index in the first model (MOP1) and ii) their satisfaction in the second model (MOP2). For each worker and each time period, the OCRA index is computed based on the number of technical actions and multiplying factors related to posture, force, repetitiveness, additional risks (such as vibration or temperature), lack of rest, and overall process duration. According to the European standard EN 1005 [240] and the international standard ISO 11228-3 [241], the OCRA method is recommended to analyze, predict and prevent the onset of musculoskeletal disorders.

In the formulation of MOP1, we aim to minimize the OCRA index for each worker among other objectives. In the MOP2 formulation, we impose the OCRA index to be less than 2.2, as recommended by ISO 11228-3, to ensure an acceptable level of risk exposure for workers. The MOP2 aims to maximize workers' satisfaction by accounting for three dimensions of preferences regarding: i) machines, which is a positive real ranging from 0 to 1, reflecting the degree of liking to work on a given machine, ii) tasks variety, which is also a positive real between 0 and 1 representing the proportion of different machines to which a worker likes to be assigned, and iii) working shift, which varies in the same range as previous dimensions, with values close to 0 indicating a preference for morning periods, values close to 1 indicating a preference for afternoon periods, and a number near 0.5 indicating a neutral preference.

The FJSSP is basically defined by a set of jobs $\mathcal{J} = \{j_1, j_2, \dots, j_J\}$, each one divided in a set of operations $\mathcal{O}_j = \{O_{j1}, O_{j2}, \dots, O_{jK_j}\}$ to be executed on a set of machines $\mathcal{M} = \{m_1, m_2, \dots, m_M\}$ in a given sequence. In the FJSSP we considered in this paper, operations must also be assigned to a worker. We assume that every worker is capable of performing any task. However, the time required to complete a task is contingent on the individual worker assigned to it. Indeed, a more skilled worker will be faster. Then, we have to handle three sub-problems: optimizing the assignment of both machine and worker for each operation, and the optimal sequence for each machine and each worker.

To develop our mathematical model, we made the following assumptions. We note that these assumptions can be customized to align with the specific rules and regulations of the factory or company.

- each operation requires exactly one operator and one machine to be processed;
- machines and operators can perform one operation at a time;
- an operator rests 8 % of his working time after each operation;

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- the time horizon is composed of two shifts of 7 hours per day.

3.3.2 Mathematical model

Notations

The notations used to formalizing our mathematical models are detailed below.

Sets, indices and parameters

W	set of workers, $w = 1..W$.
\mathcal{M}	set of machines, $m = 1..M$.
\mathcal{J}	set of jobs, $j = 1..J$.
\mathcal{K}_j	set of operations of j noted O_{kj} , with $k = 1..K_j \forall j \in \mathcal{J}$.
\mathcal{T}	set of periods, $t = 1..T$.
$start_t, end_t$	starting and ending time of period t .
p_{kjwm}	processing time of operation O_{kj} on machine m with worker w .
$s_{kjm'j'}$	setup time of machine m between operations o_{kj} and $o_{k'j'}$.
$tp_{mm'}$	transport time of a product between machines m and m' .
$t_{mm'}$	travel time for a worker between machines m and m' .
e_{jkw}	energy consumption to execute operation O_{kj} on machine m with worker w .
$e_{mm'}^{trans}$	energy consumption to transport a product from machine m to machine m' .
e^{aux}	energy consumption for auxiliary installations by time unit.
ata_{kjm}	number of technical actions to execute operation O_{kj} on machine m .
pm_{kjm}	posture multiplier when executing O_{kj} on machine m .
rm_{kjm}	repetitiveness multiplier for executing O_{kj} on machine m .
fm_{kjm}	strength multiplier for executing O_{kj} on machine m .
arf_{kji}	additional risks multiplier for executing O_{kj} on machine m .
rcm	recovery period multiplier.
dum	duration of repetitive task multiplier.
cf	constant frequency of technical actions per minute.
p_{wm}^{mac}	preference level of worker w for machine m .
p_w^{var}	preference level of variety for worker w .
p_w^{shift}	shift preference for worker w .

Decision variables

S_{kj}	starting time of operation O_{kj} ;
C_{kj}	ending time of operation O_{kj} ;
$Cmax$	total processing time, makespan.
R_{kjw}	rest time of worker w after operation O_{kj} .
V_{tw}	binary variable equal to 1 if worker w is assigned to period t .
X_{kjwmt}	binary variable equal to 1 if O_{kj} is executed on machine m by worker w in period t .
$Y_{k'j'w}$	binary variable equal to 1 if O_{kj} is executed by worker w before $O_{k'j'}$.
$Z_{k'j'm}$	binary variable equal to 1 if O_{kj} is executed on machine m before $O_{k'j'}$.

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$N_{kjm k' j' m'}$	binary variable equal to 1 if O_{kj} is executed on machine m and $O_{k'j'}$ on machine m' .
ET	total energy consumption for transport.
EM	total energy consumption for operations.
EC	total energy consumption for auxiliaries installation.
ATA_{wt}	real number of technical actions for worker w in period t .
RTA_{wt}	recommended number of technical actions for worker w on period t .
$OCRA^{max}$	OCRA maximum for all workers and all periods.
A_{wm}	number of times worker w is assigned on machine m .
B_{wm}	binary variable equals to 1 if worker w is at least once on machine m .
Sat_w^{mac}	level of satisfaction of worker w for machine assignment.
Sat_w^{var}	level of satisfaction of worker w for variety.
Sat_w^{shift}	level of satisfaction of worker w for shift assignment.
Sat_w^{total}	level of satisfaction total of worker w .
Sat^{min}	minimum level of satisfaction of all workers.

Objective functions

As previously mentioned, we are focusing on four objectives and have developed two models to address them. By minimizing these objectives simultaneously, we aim to achieve an optimal solution that balances production efficiency, energy efficiency, and operator safety and well-being. The specific objective functions considered are as follows:

$$f_1 : Cmax \quad (3.1)$$

$$f_2 : ET + EM + EC \quad (3.2)$$

$$f_3 : OCRA^{max} \quad (3.3)$$

$$f_4 : -Sat^{min} \quad (3.4)$$

In the first model (3.5), we minimize f_1 , f_2 and f_3 simultaneously. In the second model (3.6), we replace f_3 by f_4 , while always considering f_1 and f_2 .

$$MOP1 : \min \{f_1, f_2, f_3\} \quad (3.5)$$

$$MOP2 : \min \{f_1, f_2, f_4\} \quad (3.6)$$

Constraints

The constraint (3.7) defines the makespan, as the completion time of the last operation in the schedule. Constraints (3.8), (3.9) and (3.10) compute energy consumption linked, respectively to

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internal transport operations, processing operations, and the functioning of auxiliary installations.

$$Cmax \geq C_{kj} \quad \forall j \in \mathcal{J}, k \in \mathcal{K}_j \quad (3.7)$$

$$ET = \sum_j \sum_k \sum_m \sum_{m'} N_{kjm(k+1)jm'} \times e_{mm'}^{trans} \quad (3.8)$$

$$EM = \sum_j \sum_k \sum_m \sum_w \sum_t X_{kjwmt} \times e_{kjwm} \quad (3.9)$$

$$EC = Cmax \times e^{aux} \quad (3.10)$$

Equations (3.11) to (3.15) represent the constraints applicable to workers, shared across both models. Equation (3.11) guarantees that each worker is allocated once in two successive time periods, i.e. the same working shift, Equation (3.12) ensures their rest time after each operation performed. Equations (3.13) and (3.14) compute the real and recommended number of technical actions for each worker at each period, with the ratio between these counts representing the OCRA index, and Equation (3.15) defines the $OCRA^{max}$ as the maximum OCRA index reached among all workers during all time periods.

$$V_{tw} + V_{(t+1)w} = 1 \quad \forall t \in \mathcal{T}, w \in \mathcal{W} \quad (3.11)$$

$$R_{kjw} = 0.08 \times \sum_m X_{kjwmt} \times p_{kjwm} \quad \forall t \in \mathcal{T}, w \in \mathcal{W}, j \in \mathcal{J}, k \in \mathcal{K}_j \quad (3.12)$$

$$ATA_{wt} = \sum_j \sum_k \sum_m ata_{kjm} X_{kjwmt} \quad \forall w \in \mathcal{W}, t \in \mathcal{T} \quad (3.13)$$

$$RTA_{wt} = rcm \times dum \times \sum_j \sum_k \sum_m cf \times pm_{kjm} r m_{kjm} f m_{kjm} ar f_{kjm} \times X_{kjwmt} p_{kjwm} \quad \forall t \in \mathcal{T}, w \in \mathcal{W} \quad (3.14)$$

$$OCRA^{max} \geq \frac{ATA_{wt}}{RTA_{wt}} \quad \forall t \in \mathcal{T}, w \in \mathcal{W} \quad (3.15)$$

Equations (3.16), (3.17) and (3.18) are precedence-related constraints linked to, respectively, two operations of the same job, two operations assigned to the same machine, and two operations assigned to the same worker.

$$S_{(k+1)j} \geq C_{kj} + \sum_m \sum_{m'} N_{kjm(k+1)jm'} \times tp_{mm'} \quad \forall j \in \mathcal{J}, k \in \mathcal{K}_j \quad (3.16)$$

$$S_{k'j'} + (1 - \sum_m Z_{kjm k'j'}) M \geq C_{kj} + s_{kjm k'j'} \quad \forall j, j' \in \mathcal{J}, k, k' \in \mathcal{K}_j, \mathcal{K}_{j'} \quad (3.17)$$

$$S_{k'j'} + (1 - \sum_w Y_{kjw k'j'}) M \geq C_{kj} + \sum_w \sum_t R_{kjw} + \sum_m \sum_{m'} N_{kjm(k+1)jm'} \times t_{mm'} \quad \forall j, j' \in \mathcal{J}, k, k' \in \mathcal{K}_j, \mathcal{K}_{j'} \quad (3.18)$$

Finally, constraint (3.19) states that an operation is executed exactly by one worker and one machine, and constraints (3.20) and (3.21) ensure that an operation starts and ends at the same period.

$$\sum_w \sum_m \sum_t X_{kjwmt} = 1 \quad \forall j \in \mathcal{J}, k \in \mathcal{K}_j \quad (3.19)$$

$$C_{kj} - (1 - \sum_w \sum_m X_{kjwmt})M \leq end_t \quad \forall j \in \mathcal{J}, k \in \mathcal{K}_j, t \in \mathcal{T} \quad (3.20)$$

$$S_{kj} + (1 - \sum_w \sum_m X_{kjwmt})M \geq start_t \quad \forall j \in \mathcal{J}, k \in \mathcal{K}_j, t \in \mathcal{T} \quad (3.21)$$

In the second model, we add the constraints (3.22) to (3.27). First, we ensure that *OCRA* index does not exceed 2.2 for each worker and period with constraint (3.22). The constraints (3.23), (3.24) and (3.25) compute for each worker the level of satisfaction regarding, respectively, machine affectation, variety and shift assignment, while the constraints (3.26) compute the total level of satisfaction for each worker and constraints (3.27) define the minimum level of satisfaction among all workers.

$$OCRA^{max} \leq 2.2 \quad (3.22)$$

$$Sat_w^{mac} = \frac{\sum_m p_{wm}^{mac} \times A_{wm}}{\sum_m A_{wm}} \quad \forall w \in \mathcal{W} \quad (3.23)$$

$$Sat_w^{var} = 1 - \frac{|\sum_m B_{wm} - p_w^{var} \times |M||}{|M|} \quad \forall w \in \mathcal{W} \quad (3.24)$$

$$Sat_w^{shift} = (1 - p_w^{shift}) \times V_{0w} + p_w^{shift} \times V_{1w} \quad \forall w \in \mathcal{W} \quad (3.25)$$

$$Sat_w^{total} = \frac{Sat_w^{mac} + Sat_w^{var} + Sat_w^{shift}}{3} \quad \forall w \in \mathcal{W} \quad (3.26)$$

$$Sat^{min} \leq Sat_w^{total} \quad \forall w \in \mathcal{W} \quad (3.27)$$

Table 3.3 summarizes the two multi-objective optimization models we consider.

	First model (MOP1)	Second model (MOP2)
Objective functions	f_1, f_2, f_3	f_1, f_2, f_4
Constraints	(3.7) to (3.21)	(3.7) to (3.27)

Table 3.3: Summary of the two models

Regarding the problem's complexity, it has been demonstrated that FJSSP is NP-hard, and thus, it can be deduced that SFJSSP shares this NP-hardness [46]. Solving such a complex problem with an exact method is feasible only for small-scale instances. To obtain a high-quality solution close to the optimal one in a reasonable time, we have implemented two types of non-dominated sorting-based evolutionary algorithms: NSGA-II and NSGA-III. These algorithms are described in the next section.

3.4 Algorithms description

The non-dominated sorting genetic algorithms have been widely used to solve multi-objective problems, in particular for scheduling problems [242, 146, 136]. These algorithms are based on the

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Pareto-dominance principle, explained in section 3.4.5.

The basic framework of these algorithms is as follows: we start with a population P_0 composed of N solutions (see section 3.4.2). At each iteration, we create an offspring population Q_t of size N thanks to crossover and mutation operators (see section 3.4.3). We gather P_t and Q_t and obtain a population R_t that contain $2N$ solutions. Then, we keep the N best solutions to composed the next population P_{t+1} of size N . These solutions are chosen thanks to their dominance level (see section 3.4.5) to ensure elitism, added to other methods presented in sections 3.4.5 and 3.4.5 to ensure diversity. The next sub-sections describe in details how the algorithms work.

3.4.1 Chromosome coding

A solution is described by a three-layer chromosome, representing our three sub-problems, as shown in Figure 3.2. The first one represents the operations sequence (OS), which is a repetition of job indices. The k^{th} occurrence of a job index j in the sequence means o_{kj} . The second and third layers represent the solutions of machine allocation and operator allocation problems, respectively (MA and WA). The code of MA comprises numbers ranging from 1 to M (indices of machines), designating the specific machine assigned to execute the operation. Similarly, WA encompasses numbers between 1 and W (indices of workers), indicating the worker assigned to carry out the operation. For the solution coding of MOP2, an additional information is introduced in WA, specifically regarding shift assignments. For instance, the notation 20 indicates that worker 2 is assigned to the respective operation during the morning shift 0, whereas 21 designates worker 2 during the afternoon shift 1. This additional information is necessary, as all tasks that are assigned to the same worker has to be assigned to the same shift. In Figure 3.2, O_{11} is executed on machine 2 by worker 2 on an afternoon shift, O_{12} on machine 1 by worker 1 on a morning shift, etc. Note that all operations assigned to the same workers are assigned to the same shift.

	o_{11}	o_{12}	o_{21}	o_{31}	o_{32}	o_{13}	o_{22}	o_{23}
	↑	↑	↑	↑	↑	↑	↑	↑
OS	1	1	2	3	3	1	2	2
MA	2	1	3	3	3	1	2	2
WA	21	10	10	21	10	10	21	21

Figure 3.2: Genes representing our solutions (the sequence of operations OS, the machines allocation MA, and the workers allocation WA)

3.4.2 Initialization

At the beginning of our algorithm, we initialize the initial population using heuristics adapted to each mathematical model, as shown in table 3.4. In both models, the population is divided into quarters: one quarter is initialized randomly, another quarter uses a processing time heuristic, another quarter uses an energy consumption heuristic, and the final quarter relies on a human factors heuristic. This diversified initialization strategy aims to produce high-quality solutions through heuristics while

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introducing variability through random generation. In addition, we implement a multi-start approach, in which several initial solutions are generated throughout the execution of the algorithm, guaranteeing resistance to local optima and allowing new solution paths to be explored.

		N individuals			
		25%	50%	75%	100%
First model	OS	randomly generated			
	MA	randomly generated	for each task, select the pair machine/worker that minimize processing time	for each task, select the pair machine/worker that minimize energy consumption	for each task, select the machine that minimize OCRA and assign it to the operator with the lowest OCRA
	WA				
Second model	OS	randomly generated			
	MA	randomly generated	for each task, select the pair machine/worker that minimize processing time	for each task, select the pair machine/worker that minimize energy consumption	for each task, select the worker with the lowest preference level and the machine he prefers
	WA				
	SA		Assign workers that make the first operations to the morning periods	Assign workers that make the first operations to the morning periods	Assign workers to the shift they prefer

Table 3.4: Population initialization method

3.4.3 Offspring generation

At the commencement of each iteration, we create an offspring population, denoted as Q_t , consisting of N individuals derived from the existing parent population P_t . The generation of this offspring population is accomplished through the application of crossover and mutation operators, which are detailed in sub-sections 3.4.3 and 3.4.3. The offspring generation aims to explore new solutions, trying to improve the parent population through two distinct approaches. Firstly, by merging promising solutions within the parent population, thereby drawing on the strengths of several alternatives. Secondly, by moving away from the parent population, where genes are randomly exchanged to encourage exploration and discovery of new solutions. In the next iteration, we will retain the best solutions from the population of parents and offspring.

Crossover operators

Crossover operators are used to explore the neighborhood of good solutions by exchanging genes from two different solutions. To choose which solutions to crossover, we use a tournament selection. It randomly selects k solutions, compares them with the crowded comparison operator (3.4.5), and keeps the two best chromosomes to cross them. In our algorithm, we first sequentially apply a crossover on OS, then a crossover on MA, and finally on WA, not necessarily on the same operation for each

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of them. For the operation sequence, we apply the crossover operators as described in Figure 3.3a. We randomly select operations, here o_{12} , o_{32} and o_{22} , and we keep their positions on the parent 1 for the child 1, and their positions on the parent 2 for the child 2. We complete the child 1 with the missing operations sequenced as on the parent 2 and the opposite for the child 1. For the crossover on the machines allocation, we randomly select operations and exchange their machine allocation on the parent 1 with their machine allocation on the parent 2 (see Figure 3.3b). When conducting crossover on the chromosome layer WA, we first apply a crossover similar to MA, exchanging worker allocation for different operations. Then, we add another crossover for shift assignment. We randomly designate operators and interchange their shifts between two chromosomes, thereby automatically altering the shift assignment for their respective tasks. For a visual presentation, Figure 3.3c demonstrates the shift exchange involving worker 3.

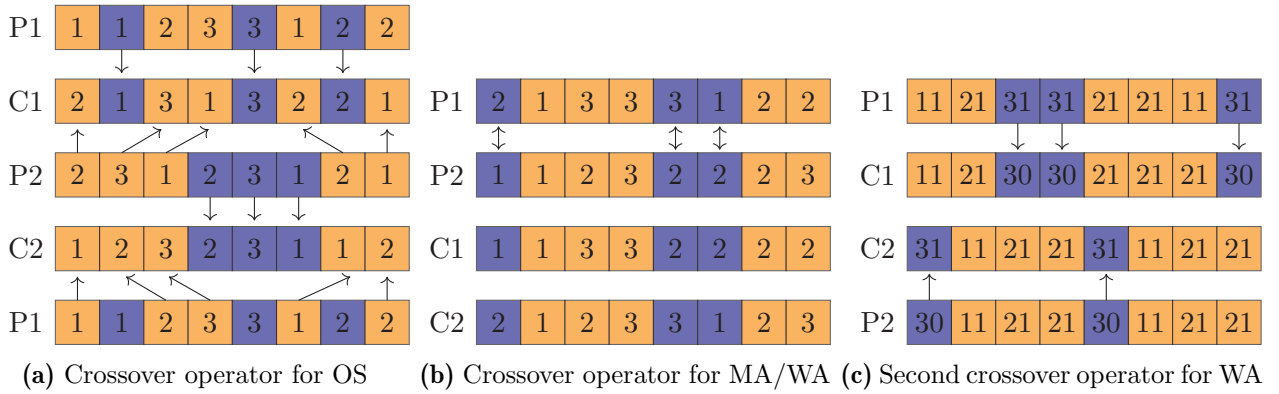


Figure 3.3: Crossover operators

Mutation operators

Mutation is a technique used to diversify solutions and avoid local optimum. The mutation operations are applied after the crossover operations with a probability p . For OS, we randomly select an operation, and move it to a random other place, as shown in Figure 3.4a. For MA, we randomly select an operation and replace its machine by another randomly selected one (Figure 3.4b). For WA, we proceed a first mutation similar to MA for worker mutation, and a second one for shift mutation. For this last one, we randomly select workers and change their shift, and so the shift assignment for their respective task (3.4c).

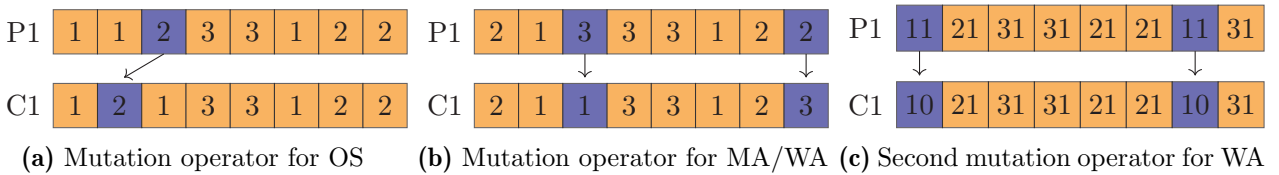


Figure 3.4: Mutation operators

Q-learning method for parameters setting

In the sections 3.4.3 and 3.4.3, we described the crossover and mutation operators to create the offspring solution R_t . These operators depend on different parameters:

- First, in the process of selecting solutions for crossover, we employ a tournament selection method, introducing a parameter denoted as k that specifies the number of solutions to be compared. A larger k entails running the tournament on a larger pool of solutions, which tends to favor the selection of high-quality solutions. Conversely, a smaller k results in a comparison among a randomly chosen subset of solutions from the parent population P_t , potentially allowing for the selection of solutions that are less efficient but contributing to diversity. In the former scenario, we emphasize elitism, while in the latter our focus is on promoting diversity and exploring uncharted solution spaces.
- Secondly, the mutation process is applied to a chromosome with a specified probability denoted as p . When p is set close to 0, the probability of retaining our already favorable solution is heightened. Conversely, when p approaches 1 the probability of inducing a mutation in the chromosome increases, thereby facilitating the exploration of novel solution domains. As before, the p parameter plays a pivotal role in either reinforcing elitism or encouraging diversity within the population.

To efficiently set the parameters k and p , we implement a Q-learning method, which possesses the capability to dynamically adjust these parameters in response to the specific state or context at hand. The Q-learning method operates as follows: within a given state, an agent selects a particular action. Following the outcome of this action, a corresponding reward is assigned to the state/action pair, and the agent continuously updates its knowledge throughout the course of the process, as described in [243]. The states, actions, and rewards employed in our algorithms are detailed in the rest of this section.

Actions: the various potential actions are distinct settings for our parameters. Specifically, we establish four possible values for each parameter: k can assume values from the set $\{0.125, 0.17, 0.25, 0.5\}$ (this parameter will be multiplied to the population size), and p can be chosen from the set $\{0.2, 0.4, 0.6, 0.8\}$. During each iteration, the algorithm selects a single value for each parameter.

States: We define four distinct states based on the notions of convergence and diversity. In each iteration t , the convergence metric CV_t is computed using the function $SetCoverage(P_1, P_2)$ which quantifies the percentage of solutions in population P_1 that are dominated by at least one solution in population P_2 (see section 3.5.1). Simultaneously, the diversity metric DV_t is calculated in accordance with the methods outlined in section 3.5.1, relying on the inter-solution distances within a population. Then, $\Delta CV = \frac{SetCoverage(P_t, P_{t-1})}{SetCoverage(P_{t-1}, P_t)}$ and $\Delta DV = \frac{DV_t}{DV_{t-1}}$. Then, we define our four states in a manner similar to the approach described by [237]:

- S_1 : Diversity and convergence are improved, $\Delta CV < 1$ and $\Delta DV > 1$.
- S_2 : Convergence is improved but not diversity, $\Delta CV < 1$ and $\Delta DV \leq 1$.
- S_3 : Diversity is improved but not convergence, $\Delta CV \geq 1$ and $\Delta DV > 1$.
- S_4 : Convergence and diversity are not improved, $\Delta CV \geq 1$ and $\Delta DV \leq 1$.

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Rewards: The reward function prioritizes the enhancement of solution diversity. When improvements in both diversity and convergence occur, the reward is maximized. If only diversity shows improvement, the reward is slightly lower, and a similar reduction applies when only convergence improves. Ultimately, the lowest reward is assigned when neither diversity nor convergence witness improvement. The reward function is defined as follows:

$$Reward = \begin{cases} 10 & \text{if } \Delta CV < 1 \text{ and } \Delta DV > 1 \\ 5 & \text{if } \Delta CV \geq 1 \text{ and } \Delta DV > 1 \\ 0 & \text{if } \Delta CV < 1 \text{ and } \Delta DV \leq 1 \\ -5 & \text{if } \Delta CV \geq 1 \text{ and } \Delta DV \leq 1 \end{cases} \quad (3.28)$$

During each iteration, we are situated in a state denoted as s_t . We make a decision by taking an action labeled as a_t , and as a result, we receive a reward, indicated as r_t . Subsequently, the Q-value is updated according to the following formula:

$$Q(s_t, a_t) = (1 - \alpha) \times Q(s_t, a_t) + \alpha(r_t + \lambda \times \max_a Q(s_{t+1}, a)), \quad (3.29)$$

where α represents the learning rate and λ represents the discount factor. The learning rate α typically ranges between 0 and 1. A value of α close to 1 can render the Q-value highly volatile, making it extremely responsive to fluctuations. Conversely, a value of α approaching 0 tends to favor historical information, resulting in a conservative Q-value. To strike a balance between adaptability and stability, we introduce a dynamic α coefficient that changes with each iteration. This coefficient is defined as $\alpha(t) = 1 - 0.9 \left(\frac{t}{T}\right)$, where T signifies the total number of iterations. Consequently, in the early iterations, the Q-value is heavily influenced, while as the process progresses, the Q-value becomes increasingly stable.

The discount factor λ plays a critical role in temporal reward considerations. A value of λ near 0 primarily emphasizes immediate rewards, whereas a value closer to 1 places greater significance on rewards in the distant future. In this context, we opt to establish λ at a value of 0.8.

The Q-learning algorithm is represented by the flowchart in Figure 3.5. The algorithm initiates with all Q-values set to zero. In each iteration, a crucial decision arises between exploration and exploitation. During exploration, the algorithm randomly selects an action and observes the associated outcome, thereby enhancing its learning process. In contrast, exploitation entails evaluating the current system state and opting for the action that maximizes the reward function. In the early stages of the algorithm, exploration takes precedence to facilitate learning, while as the iterations progress, the system tends more towards exploiting its acquired knowledge. To facilitate this transition, we employ the following epsilon-greedy exploration strategy: i) Set ϵ to 1, ii) At each iteration, choose a random number between 0 and 1, iii) If the generated number is less than ϵ , then choose a random action (exploration), otherwise take the best action Q-value (exploitation), and iv) Update epsilon: $\epsilon \leftarrow \epsilon \times 0.99$. Under this strategy, the value of ϵ decreases gradually as the process is running. Consequently, in the early stages, exploration takes precedence, while as the algorithm progresses, it focuses more and more on exploiting the acquired knowledge. It's important to note that these steps are integral components of the overall algorithm framework.

3.4.4 Fitness calculation

Each solution within the population is evaluated through a fitness function comprising three components, aligned with the three distinct objective functions: the makespan, the total energy consumption,

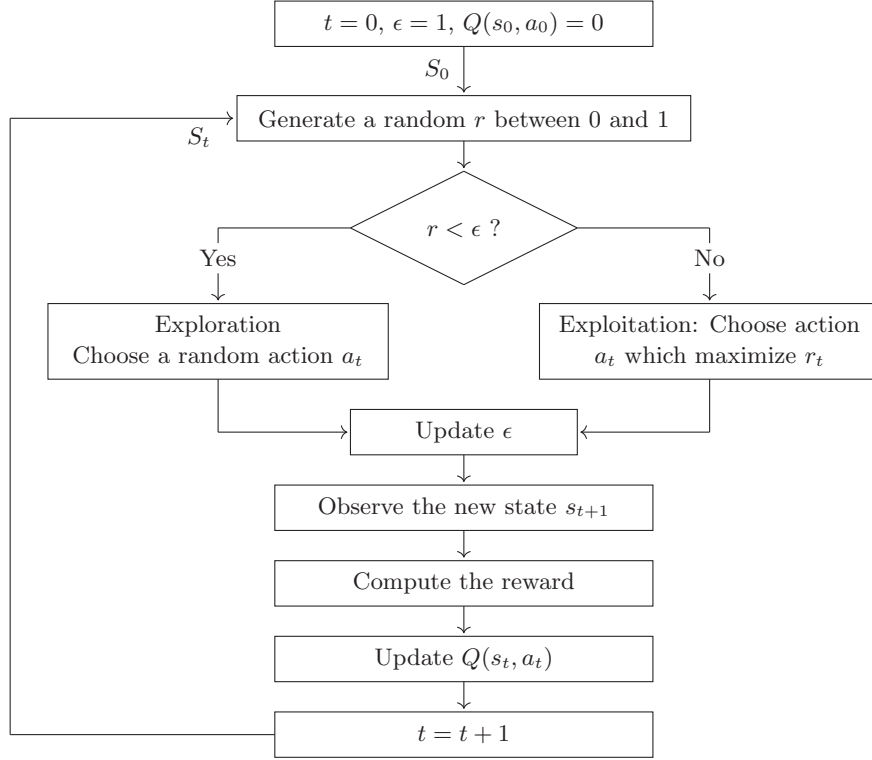


Figure 3.5: Q-learning framework

and either the maximum OCRA index (in the first model MOP1) or the minimum preference level (in the second model MOP2).

To calculate these components in MOP1, we employ a decoding process for the three genes associated with each solution. Initially, we consider the first operation from the OS layer of the chromosome. Utilizing information from the MA and WA layers, we can determine the machine and worker to which the considered operation is assigned, allowing us to deduce its start and end dates. We then proceed to the next operation on the OS layer, where the assigned machine and worker are known. To establish the start date for this operation, we consider the maximum date among the following cases: i) The end date of the preceding task of the same job, taking into account the transport time between the respective machines; ii) The end date of the preceding task assigned to the machine, incorporating the setup time between the two operations; and iii) The end date of the previous task assigned to the worker, accounting for the time required to transition from the prior machine to the current one, along with the worker's rest time. This approach ensures that all precedence constraints are meticulously respected. In the case where the end time of the operation exceeds the end time of the period (t), we shift the operation to the beginning of period $t + 2$ to accommodate the selected operator's availability. This process is repeated until all operations in the OS layer are scheduled, enabling us to calculate the makespan, the total energy consumption (inclusive of transport, auxiliary, and task execution), and the maximum OCRA index among all operators across all periods.

For MOP2, the procedure is analogous, but with the inclusion of an additional information that specifies the shift in which workers and tasks are scheduled. This introduces an extra set of constraints impacting the start and end times of the task.

3.4.5 Solutions selection

Dominance

In the context of a multi-objective optimization problem aimed at minimization, Pareto dominance is defined as follows [244, 228]:

Definition 1: We define $\mathcal{O} = \{1, 2, \dots, O\}$ the set of objective functions (in our case, $\mathcal{O} = \{1, 2, 3\}$). A solution \mathbf{x} is said to dominate a solution \mathbf{y} , denoted as $\mathbf{x} \prec \mathbf{y}$, if and only if:

$$\begin{cases} \forall o \in \{1, 2, \dots, O\} : f_o(\mathbf{x}) \leq f_o(\mathbf{y}) \\ \exists o' \in \{1, 2, \dots, O\} : f_{o'}(\mathbf{x}) < f_{o'}(\mathbf{y}) \end{cases}$$

Definition 2: The Pareto-Front is the set of solutions whose objectives cannot all be improved simultaneously. It means that we cannot improve one of the objectives without damaging another one. These solutions are non-dominated by any other solution.

At the end of each iteration t , we need to select N solutions from the set R_t to form the forthcoming population P_{t+1} . Our primary objectives are to maintain elitism and retain solutions that closely approximate the Pareto Front. To achieve this, we assess the level of dominance for each solution within R_t . Solutions that are not dominated by any other are grouped into a first front denoted by \mathcal{F}_0 and assigned the rank 0. Solutions dominated by only one other solution are categorized into a second front denoted by \mathcal{F}_1 and assigned the rank 1, and so forth. Subsequently, we traverse the fronts in order, starting from front \mathcal{F}_0 , and select solutions from these fronts until the size of P_{t+1} reaches the specified limit of N . In most cases, we reach a front, denoted as front l , where it is not possible to retain all of its solutions, as this would cause P_{t+1} to exceed the size constraint of N . In such situations, we must decide which solutions from this front to select in order to reach the desired size of N for P_{t+1} . The specific method employed for this selection varies depending on the algorithm used. For instance, NSGA-II utilizes the crowded-comparison operator, as detailed in section 3.4.5. In NSGA-III, a three-step procedure is employed, encompassing normalization, association, and niche preservation, as outlined in section 3.4.5. These techniques help to promote the exploration of new areas of research, thus guaranteeing the diversity of the solutions obtained and mitigating the risk of falling into local optima.

Crowded-comparison operator

The crowded-comparison operator plays a crucial role in NSGA-II, particularly in the selection of solutions that will make up the subsequent population, denoted as P_{t+1} . As described in section 3.4.5, we systematically explore the initial fronts, commencing from the front \mathcal{F}_0 , retaining solutions from these fronts as long as the cumulative count does not surpass N . However, if the inclusion of solutions from the front \mathcal{F}_l would lead to a population size exceeding N , we employ the crowded distance criterion to select only a specific number of solutions from the front \mathcal{F}_l in order to complete P_{t+1} to its designated size of N .

To maximize the coverage of solutions and steer clear of local optima, we prioritize diversity within the set of explored solutions by leveraging the concept of crowded distance. This entails calculating,

for each solution, its distance to all other solutions as a summation across the three objective functions. Smaller crowded distances indicate that a solution is closely surrounded by other solutions, signifying its proximity within the solution space. In contrast, solutions with larger crowded distances are more isolated from their counterparts. Priority is afforded to solutions with larger crowded distances, as they offer the potential to explore novel solution neighborhoods and expand the scope of our research area.

In summary, we employ the crowded comparison operator to compare two solutions. Initially, we examine their ranks: if they differ, we favor the solution with the lower rank (i.e. closer to the Pareto front) to uphold elitism, otherwise we opt for the solution with the largest crowded distance, thereby promoting diversity.

Normalization, association, and niche-preservation

NSGA-III shares a similar framework with NSGA-II, with the key distinction lying in the method of solution selection. While NSGA-II relies on the crowded-comparison operator, NSGA-III employs an alternative technique as elaborated in [234]. Briefly, this method comprises three distinct steps. The initial step involves the determination of reference points. Following the approach outlined in [234], these reference points are strategically positioned on a normalized hyperplane that is evenly oriented across all objective axes and intersects each axis at a value of 1. The number of reference points (H) corresponds to the binomial coefficient computed by $H = C_p^{M+p-1}$, with p the number of divisions along each objective and M the number of objectives. In our scenario, we are dealing with three objective functions, and we opt to partition each of them into four segments, resulting in a total of 15 reference points. The placement of these reference points is illustrated in Figure 3.6. In Figure 3.6b, we provide an example of our normalized solutions, with the majority positioned below the hyperplane, as we are addressing a minimization problem. The ideal point, emphasized in Figure 3.6a, is defined as $(0, 0, 0)$. Subsequently, we connect this ideal point to each of the reference points using vectors, which we will refer to as the ‘reference lines.’ A subset of these lines is depicted in green in Figure 3.6a.

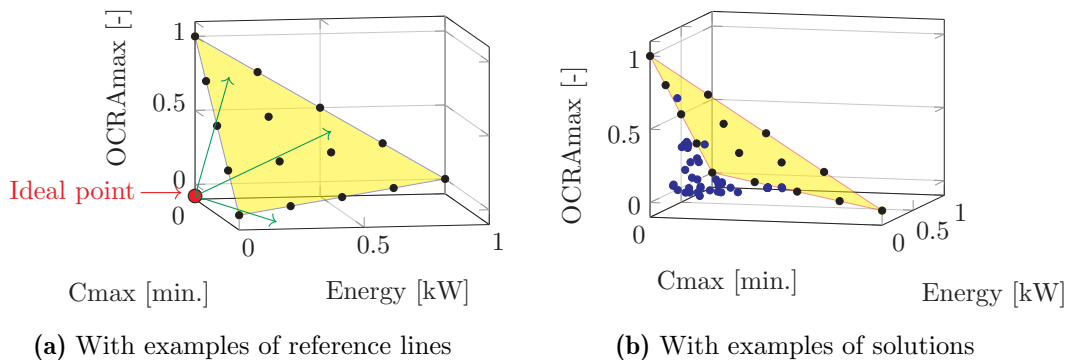


Figure 3.6: Reference points and normalized hyperplane

The second step involves the assignment of each solution to a reference line and, consequently, to a specific reference point. To achieve this, we calculate the perpendicular distance of each solution from every reference line. A solution is then paired with the reference point corresponding to the reference line with the shortest distance to that solution.

The third step involves niche preservation. In this phase, we compute the number of solutions n_p associated with each reference point p within P_{t+1} . Until the size of P_{t+1} reaches N , we execute the following procedure. First, we identify the reference point with the minimum n_p . Then, if there are multiple reference points with the same minimal value, we randomly select one. If several solutions within \mathcal{Fl} are associated with this reference point, we randomly choose one and increment n_p . However, if there are no associated solutions from \mathcal{Fl} , the reference point is excluded from the selection process.

3.4.6 Local search

At the end of each iteration, we perform a local search to enhance the exploitation capabilities of the algorithm, aiming to potentially improve the quality of solutions [237]. This local search is based on variable neighborhood search algorithm and is applied to a subset of τ randomly selected solutions from the new population. In this study, we employed 5 different local search techniques based on our problem. However, conducting all of them on each solution would be overly time-consuming, and selecting one randomly may reduce the likelihood of success. Hence, we adopt a reinforcement learning approach, inspired by the methodology outlined in [237], to strategically choose the most promising local search for each solution. The 5 employed local search techniques are as follows:

- LS_1 : Randomly select two operations and exchange their position in the chromosome OS .
- LS_2 : Randomly choose an operation and adjust its machine and worker allocation to the machine/worker pair that minimizes its processing time.
- LS_3 : Randomly choose an operation and adjust its machine and worker allocation to the machine/worker pair that minimizes its energy consumption.
- LS_4 : Randomly choose a worker and change its shift assignment.
- LS_5 for MOP1: Randomly choose an operation and assign it to the machine that minimizes the $OCRA$ index.
- LS_5 for MOP2: Randomly choose an operation and assign it to the machine preferred by the worker assigned to it.

Two memory matrices, namely Success Memory (SM) and Failure Memory (FM), are used in the algorithm as depicted in Figure 3.7. Initially, both SM and FM are empty and are updated at each iteration t . The probability associated with each local search is initially set to 0.2. Determining the maximum size of SM and FM ($smax$) and the number of solutions τ to explore per iteration are crucial parameters. We have opted to set them at 20% of the number of iterations and 20% of the population size, respectively. At each iteration t , the counters for success and failure solutions for each local search LS_i , respectively denoted as ns_i and nf_i , are reset to 0. τ solutions are randomly selected, and a roulette algorithm is executed to select the local search to be used for each solution based on their associated probabilities. Subsequently, a new solution is generated using the chosen local search LS_i . If the new solution dominates the previous one, ns_i is incremented; otherwise, nf_i is incremented. After performing the τ local searches, the counts ns and nf are appended to the end of SM and FM , respectively. If the size of SM and FM exceeds $smax$, the oldest records are removed. Then, the probability of each local search is updated using the formula $prob_i = \frac{SR_i}{SR_i + FR_i}$, where $SR_i = \sum_{j=1}^{smax} ns_{ij}$ and $FR_i = \sum_{j=1}^{smax} nf_{ij}$. Finally, each probability is normalized by dividing by the sum of all probabilities: $PR_i = \frac{prob_i}{\sum_{k=1}^5 prob_k}$.

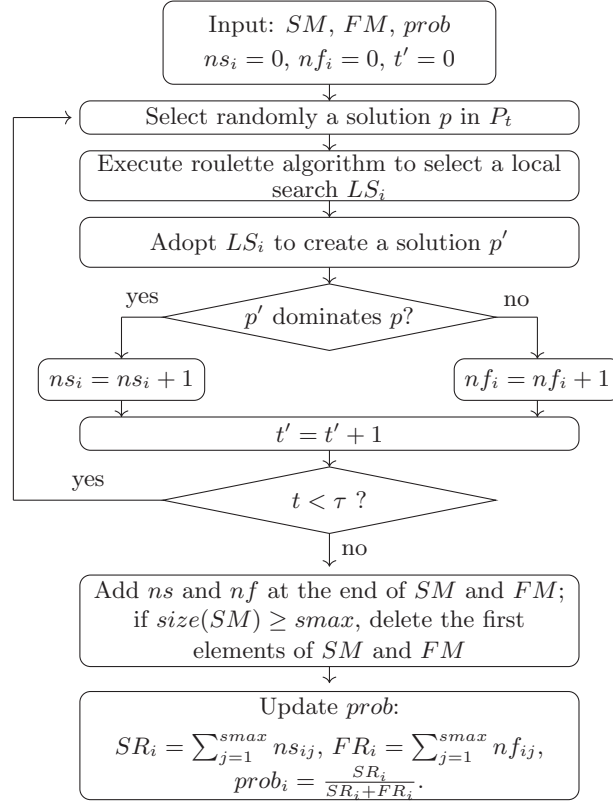


Figure 3.7: Variable neighborhood search based on reinforcement learning

3.4.7 NSGA-II and NSGA-III

In this subsection, we provide a brief overview of the fundamental framework of the NSGA-II and NSGA-III algorithms that we have implemented. The distinct steps involved in both algorithms are outlined in Figure 3.8, and the improvements made in this work are highlighted in bold. The primary divergence between these two algorithms pertains to their respective solution selection mechanisms. In each iteration, solutions are chosen from the l top-ranked fronts to form the population P_{t+1} . To fill the remaining slots and reach a total of N individuals, NSGA-II employs the crowded comparison operator, whereas NSGA-III employs a combination of normalization, association, and niche-preservation techniques.

Regarding the stopping criteria, we impose a minimum number of iterations and a condition based on the ongoing improvement of solutions (iterations continue as long as significant improvements are observed). Furthermore, we implement a multi-start strategy, starting with several multiple initial solutions to mitigate the risk of falling into local optima.

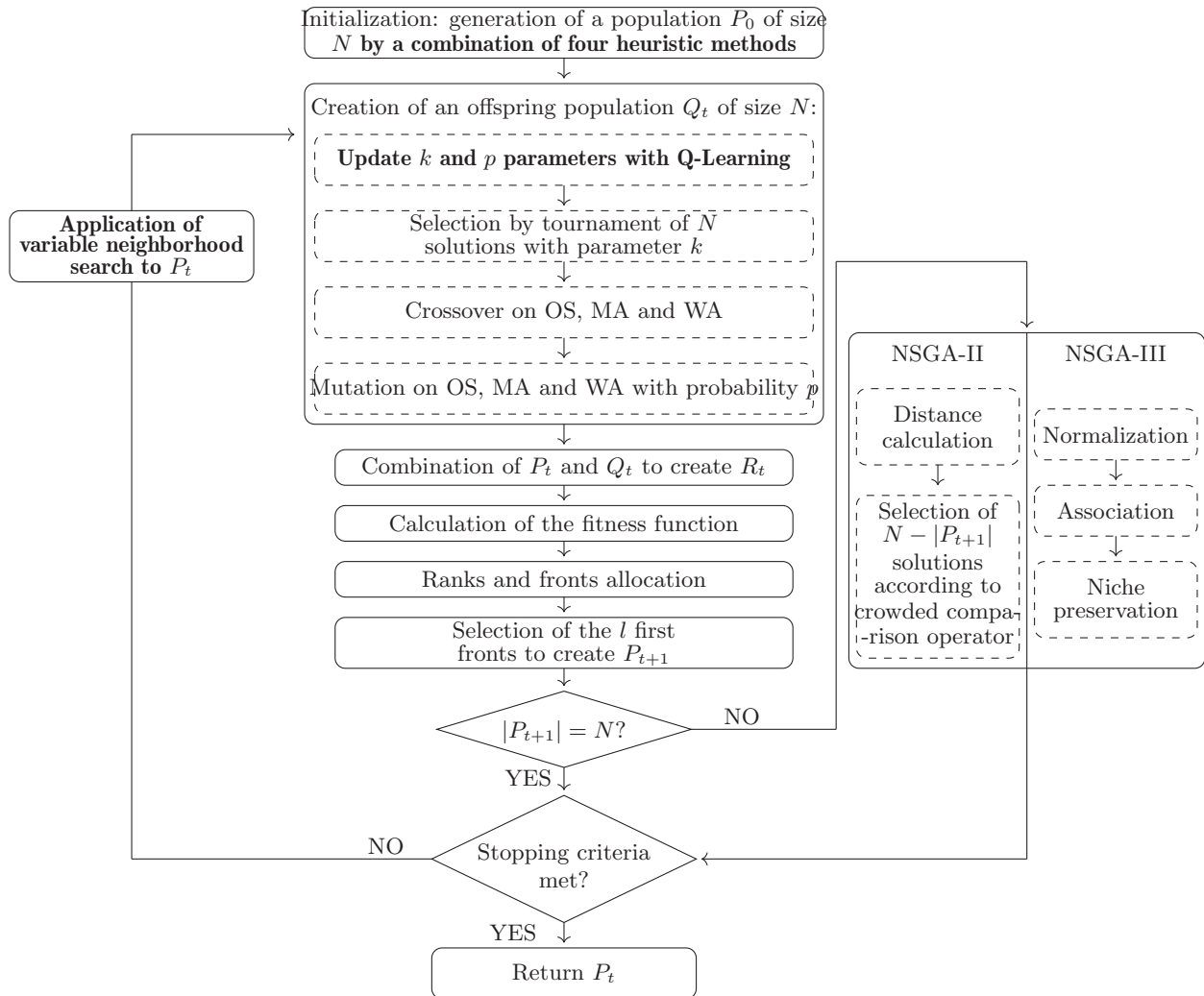


Figure 3.8: NSGA-II and NSGA-III description, with improvements highlighted in bold

3.5 Metrics and used instances

3.5.1 Metrics

Comparing two solutions in a single-objective problem is straightforward. In the case of minimization, the smallest solution is deemed superior, while for maximization, it's the largest. However, in multi-objective problems, a solution can outperform another in one objective while underperforming in another. To evaluate the performance of different algorithms in such scenarios, we rely on various metrics. In this study, we will employ four key metrics: the hypervolume (Hv), the set coverage (Sc), the diversity (Dv), and the inverted generational distance (IGD) to assess the quality and distribution of the solutions.

Hyper volume: this metric quantifies the volume enclosed by all solutions within the ensemble. It

serves as one of the most effective metrics for assessing the quality of algorithms in the context of multi-objective problems. The hyper volume takes into account both the convergence of solutions toward the Pareto front and the diversity among these solutions. To calculate the hyper volume, we utilize the ‘LebMeasure’ algorithm, as introduced by [245].

Figure 3.9 illustrates how the hyper volume operates in a 2D scenario with two objectives. The process involves calculating the area of the rectangles, as depicted in the figure. In cases with 3 objectives, calculating the hyper volume is similar to measuring the volume of cubes. A larger hyper volume value corresponds to a better set of solutions. In the figure, the red set in subfigure (a) outperforms the blue set in subfigure (b). The orange point serves as the reference point for hyper volume calculation and represents the worst value in both objectives.

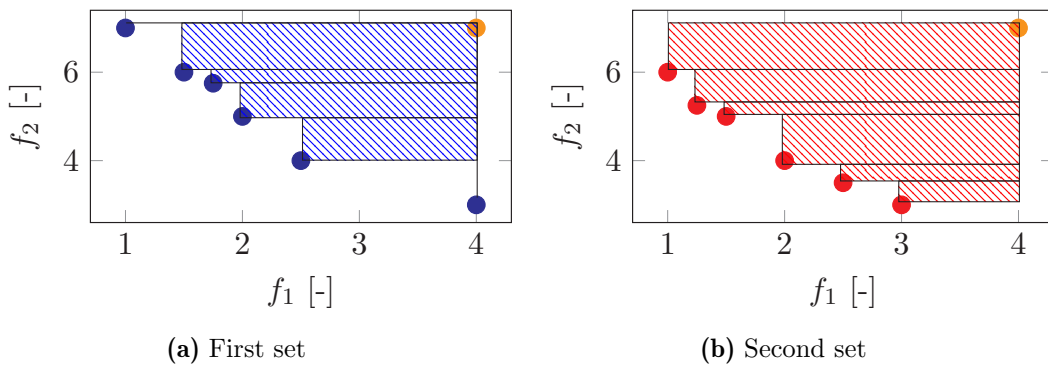


Figure 3.9: Comparison of two solution sets using the hyper volume metric for two objective functions

Set coverage: We employ the set coverage metric, as defined by [246]. Let P_1 and P_2 represent two sets of solutions. $Sc(P_1, P_2)$ quantifies the proportion of solutions in P_1 that are dominated by at least one solution in P_2 . If $Sc(P_1, P_2)$ yields a higher value than $Sc(P_2, P_1)$, it implies that set P_2 is superior to set P_1 . This metric is instrumental in ascertaining which set of solutions closely approximates the Pareto front. Moreover, we integrate this metric into our algorithm to evaluate the convergence (CV) of our solutions.

Diversity: We incorporate a diversity metric, as outlined in [237], which is denoted by $Dv(P_1) = \frac{\sum_{i=1}^{N-1} |d_i - \bar{d}|}{(N-1)\bar{d}}$. Here, $N = |P_1|$, d_i represents the Euclidean distance between two adjacent points in P_1 , and \bar{d} signifies the average value of d_i . A higher value of Dv signifies a greater diversity among the solutions. This metric serves the purpose of evaluating whether the algorithm has successfully escaped local minima and explored a diverse range of solutions.

Inverted generational distance: This metric is used to evaluate the distance of a set of solutions to the Pareto front. In most cases, the Pareto front is difficult to calculate due to the complexity of the problem. The metric is calculated as follows [247]: $IGD(P, P^*) = \frac{1}{|P|} * \sum_{i=1}^{|P|} d_i$, where P is the set of solutions evaluated, P^* the set Pareto front, and d_i is the Euclidean distance of a solution i to the closest solution in the Pareto front.

3.5.2 Instances

To evaluate and validate our algorithms, we conducted tests using diverse instance types, inspired from the works of [248] for small instances, and [180] for bigger instances. These two data sets encompass jobs, operations, machines, and associated processing times. We enriched them with supplementary data encompassing energy consumption, worker characteristics, and transport/setup times, as documented in existing literature. For instance, energy data was sourced from [114] and [180], OCRA index data from [219], and transportation/setup time data from [149]. For clarity, we denote instances influenced by [248] as kcm_i and instances influenced by [180] as FJ_i , as outlined in Table 3.5a. Table 3.5b presents additional data used for all instances. For workers' skills, we take into account a coefficient factor at the time of task execution. A smaller value of the factor indicates a higher level of worker's skills.

To provide a practical demonstration of the two models introduced in this study, we tested them using an instance described in [114], representing an engineering case study at an engine plant operated by DF Motor Corporation. The plant operates as a partially flexible job shop, specializing in the production of four distinct product types: plate brackets, fan brackets, fan hubs, and adapter flanges. The manufacturing floor is equipped with eight machines, including two millers, two drilling machines, one machining center, one manual lathe, and two computer numerical controlled lathes. In our study, we adapt the instance to our model by adding 8 workers, along with all information concerning their activities. We consider a production planning composed of ten units of each product type, resulting in instance comprising 40 jobs, 570 operations, and 8 machines. We will refer to this instance as *DFMC* throughout the remainder of the paper.

3.6 Algorithms performance

This section showcases performance study of the proposed algorithms through several comparisons. First, we compare the NSGA-II and NSGA-III performances. Then, we present the NSGA-III combined with Q-Learning (QNSGA-III) results and compare them to the NSGA-III results with fixed parameters. We also evaluate QNSGA-III versus another evolutionary algorithm, namely the Strength Pareto Evolutionary Algorithm 2 (SPEA2), improved with Q-learning (QSPEA2). Subsequently, we analyze the results of QNSGA-III with and without heuristic initialization and variable neighborhood search.

To ensure a robust comparison of the algorithms, we conducted multiple runs on each considered instance using identical parameters. We opted to base our analysis on 10 runs, under the assumption that the results maintain a consistent level of reliability. For each run, we generate populations consisting of 100 chromosomes, and we carry out 6 sets of 100 iterations, amounting to a total of 600 iterations.

3.6.1 NSGA-II vs NSGA-III performance comparison

To address our problem, we use the NSGA-II and NSGA-III. We begin by comparing the performance of these algorithms. The results for instances kcm_1 , kcm_2 , kcm_3 , kcm_4 are summarized in Table 3.6. In this table, a result written in bold signifies that NSGA-III outperforms NSGA-II. Notably, NSGA-III exhibits superior performance across all metrics. For a more detailed analysis of

3.6. ALGORITHMS PERFORMANCE

Inst. ID	# jobs	# tasks	# machines	# workers	proc. time (min)	energy (kW)
<i>kcm</i> ₁	4	12	5	3	[1 – 54]	[4 – 15]
<i>kcm</i> ₂	10	29	7	5	[1 – 56]	[4 – 15]
<i>kcm</i> ₃	10	30	10	7	[1 – 17]	[4 – 15]
<i>kcm</i> ₄	15	56	10	4	[1 – 85]	[4 – 15]
<i>FJ</i> ₀₅	18	78	6	4	[1 – 20]	[15 – 20]
<i>FJ</i> ₁₀	31	125	15	8	[1 – 20]	[15 – 20]
<i>FJ</i> ₁₅	46	182	15	8	[1 – 20]	[15 – 20]
<i>FJ</i> ₂₀	60	234	30	20	[1 – 20]	[15 – 20]
<i>DFMC</i>	40	570	8	8	[1 – 12]	[0.15 – 1.36]

(a) Instances

energy for transport (by time unit)	3.9
energy auxiliaries (by time unit)	1
transport time (min)	[1 – 3]
setup time (min)	[0 – 1]
travel time (min)	[0.5 – 2]
workers' skills	[0.9 – 1.3]
nb of technical actions	[10 – 70]
posture multiplier	1-07-0.6-0.5
fatigue multiplier	1-0.85-0.65-0.35-0.2-0.01
repetitiveness multiplier	1-0.85-0.7
additional factors multiplier	1-0.95-0.9-0.8
preferences machines, variety, shift	[0 – 1]

(b) Additional data

Table 3.5: Instances composition

numerical values across all instances and metrics, refer to Figure 3.10. Our results align with the conclusion of [235], which mention that NSGA-III is more adapted than NSGA-II for solving problems with more than two objective. Figure 3.11 compares two sets of solutions obtained for the instance *kcm*₁ using NSGA-II and NSGA-III, with the Pareto front derived from the ϵ -constraint approach using Gurobi solver (denoted as GUROBI). Specifically, the mean IGD for the solutions obtained with NSGA-II and NSGA-III are 0.163 and 0.147 respectively for MOP1, and 0.1732 and 0.1476 respectively for MOP2. This indicates that the solutions obtained with NSGA-III are closer to the Pareto front compared to those obtained with NSGA-II.

Inst. ID	<i>kcm</i> ₁	<i>kcm</i> ₂	<i>kcm</i> ₃	<i>kcm</i> ₄
Sc	50%	69%	88%	98%
Hv	0%	14%	35%	39%
Dv	-16%	5%	-32%	44%

Table 3.6: Comparison between NSGA-II and NSGA-III performance

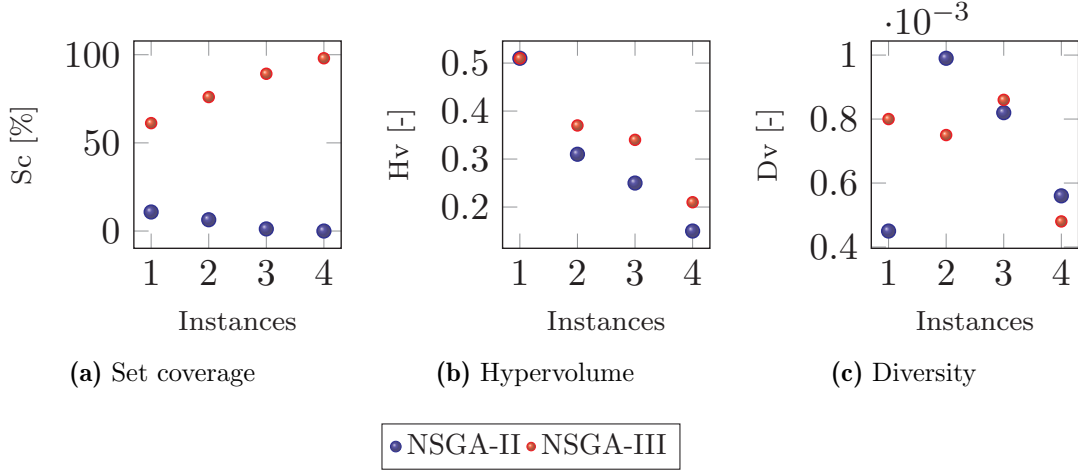


Figure 3.10: Comparison between NSGA-II and NSGA-III performance

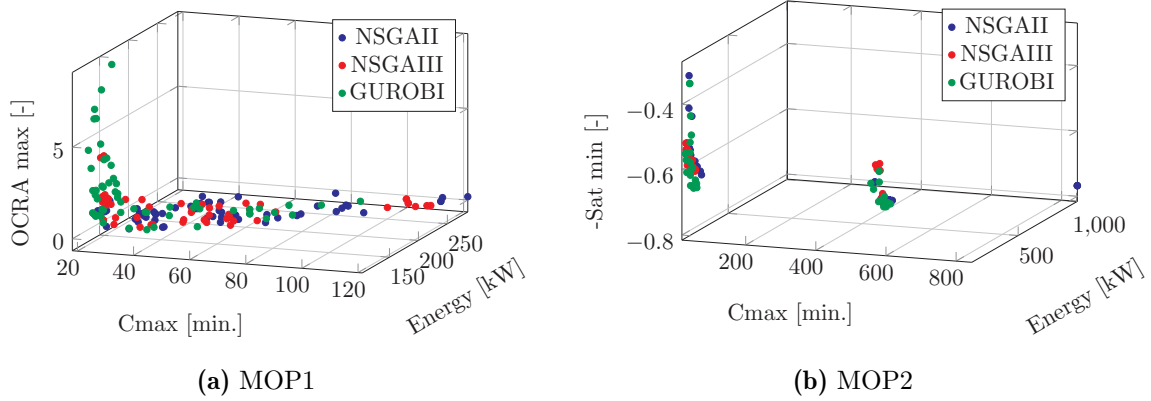


Figure 3.11: Comparison of NSGA-II, NSGA-III and GUROBI results through the kcm_1 instance for MOP1 and MOP2

3.6.2 Q-learning vs Fixed parameters based comparison

In this section, we compare NSGA-III with fixed parameters (k and p) and with Q-learning (QNSGA-III), while excluding the heuristic for initialization. To simplify, we present only the MOP1 results in this section since those obtained with MOP2 led to the same trends and conclusions. We denote the populations obtained with Q-learning as P_Q and those obtained with fixed parameters as P_f . We experimented with four parameter pairs (p, k): (0.2, 0.125), (0.2, 0.5), (0.8, 0.125), and (0.8, 0.5). The results are summarized in Table 3.7. In this table, percentages written in bold indicates that the results obtained with Q-learning are better. The set coverage gap represents the difference between the two set coverages, calculated as $Sc(P_f, P_Q) - Sc(P_Q, P_f)$. The hyper volume gap is determined using the formula $\frac{Hv(P_Q) - Hv(P_f)}{Hb(P_f)} \times 100$. Similarly, the diversity gap is computed with the formula $\frac{Dv(P_Q) - Dv(P_f)}{Dv(P_f)} \times 100$. Note that the hyper volume and diversity percentages may appear relatively high due to the use of small numerical values. We notice the fact that the Q-learning method significantly enhances the majority of the solutions. With only a few exceptions, there is a notable

3.6. ALGORITHMS PERFORMANCE

enhancement in diversity for each instance.

		0,2-0,125	0,2-0,5	0,8-0,125	0,8-0,5
kcm_1	Sc	-14%	56.8%	5.6%	65%
	Hv	-10.1%	8.29%	1.87%	8.29%
	Dv	17.28%	65.16%	46.54%	31.12%
kcm_2	Sc	-42.8%	48.4%	-0.4%	64.2%
	Hv	-5.23%	6.49%	1.46%	9.2%
	Dv	38.29%	64.91%	27.07%	25.45%
kcm_3	Sc	18%	72%	40%	90.6%
	Hv	1.54%	3.78%	1.08%	10.45%
	Dv	42.47%	-6.43%	-13.76%	74.10%
kcm_4	Sc	-5%	25.8%	31.6%	83.4%
	Hv	11.69%	13.45%	14.91%	23.68%
	Dv	23.98%	13.87%	-13.5%	31.21%

Table 3.7: Comparison between NSGA-III with Q-learning and NSGA-III with fixed parameters

Table 3.8 presents the computation times for each instance and configuration. The provided values represent the normalized time (by the best time identified for each instance). A bold '1' signifies the configuration with the shortest computational time. Other values serve as multipliers of the best time, providing a relative comparison across configurations. For all instances, when using Q-learning or a fixed parameter of $p = 0.2$, both algorithms exhibit faster performance compared to a parameter value of $p = 0.8$.

		Q	0,2-0,125	0,2-0,5	0,8-0,125	0,8-0,5
kcm_1		1.08	1.05	1	1.19	1.11
kcm_2		1.02	1.02	1	1.18	1.13
kcm_3		1.08	1.08	1	1.18	1.28
kcm_4		1.03	1.01	1	1.16	1.08

Table 3.8: Normalized calculation times across instances relative to the optimal performance

In a recent study, [249] identified NSGA-II and the Strength Pareto Evolutionary Algorithm 2 (SPEA2) as two of the most successful evolutionary algorithms. The SPEA2 is characterised by the parameters k and p , which can either be fixed or determined using the same Q-Learning approach applied in QNSGA-III. To evaluate the differences and perform a deeper analysis in the integration of Q-Learning, we implemented both SPEA2 with fixed parameters, as proposed by [250], and enhanced version incorporating Q-Learning, referred to as QSPEA2. Figure 3.12 gives a comparison of the non-dominated solutions obtained with NSGA-III, QNSGA-III, SPEA2 and QSPEA2 through the kcm_1 instance. The mean IGD values obtained for SPEA2 and QSPEA2 are 0.2 and 0.19 respectively, indicating that the solutions obtained with Q-Learning are closer to the Pareto front.

Table 3.9 shows the gap between the hypervolume of the solutions obtained with GUROBI and those obtained with SPEA2, QSPEA2, NSGA-III, and QNSGA-III. It is noted that NSGA-III outperforms SPEA2, and the Q-Learning approach yields better results than fixed parameters in both algorithms.

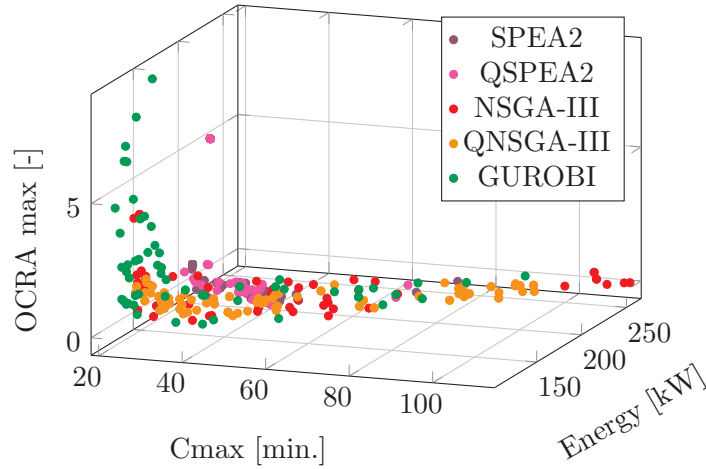


Figure 3.12: Comparison of SPEA2, QSPEA2, NSGAIII, QNSGAIII and GUROBI using the kcm_1 instance for MOP1

Algorithms	SPEA2	QSPEA2	NSGA-III	QNSGA-III
Hv gap	4.35%	4.24%	2.39%	2.18%

Table 3.9: Hypervolume gaps of SPEA2, QSPEA2, NSGA-III, QNSGA-III in comparison to GUROBI using the kcm_1 instance for MOP1

For a deeper analysis, we tested the original NSGA-III, as proposed and implemented by [251] in the Pymoo library for Python. We compared our QNSGA-III with the original NSGA-III using the DAS-CMOP7, DAS-CMOP8, and DAS-CMOP9 instances from [252], each featuring 12 different levels of difficulty. Specifically, difficulty levels 1, 5, and 9 are diversity-hard problems; levels 2, 6, and 10 are feasibility-hard problems; levels 3, 7, and 11 are convergence-hard problems; and levels 4, 8, and 12 exhibit all three types of difficulties. The comparison results are presented in Table 3.10, using the Inverse Generational Distance (IGD) and the Hypervolume as metrics. Results highlighted in bold indicate that our QNSGA-III outperformed the original NSGA-III. Notably, the QNSGA-III demonstrated better performance on diversity-hard problems and on problems that exhibit all three types of difficulties. This outcome makes sense, as the reward mechanism in Q-Learning prioritizes diversity over other metrics. For feasibility-hard and convergence-hard problems, the original NSGA-III achieved better results, suggesting areas for future improvement of our algorithm. However, it is important to note that our QNSGA-III was designed for a specific problem, and its convergence on instances of this problem may be higher than on more general problems.

3.6.3 Random vs Heuristic initialization based comparison

The preceding results were generated utilizing random initialization without the application of local search. Subsequently, we conducted a comparative analysis with results obtained through heuristic initialization coupled with variable neighborhood search, as presented in Table 3.11. To establish a baseline for comparison, we reference the results generated by QNSGA-III. Entries highlighted in bold signify instances where solutions derived from heuristic initialization and local search application

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	Diversity hardness		Feasibility hardness		Convergence hardness		The 3 difficulties					
	IGD	Hv	IGD	Hv	IGD	Hv	IGD	Hv				
DAS-CMOP7	1	66%	37%	2	-21%	-2%	3	51%	25%	4	14%	6%
	5	58%	25%	6	-24%	-2%	7	-40%	-15%	8	29%	3%
	9	69%	37%	10	-29%	-2%	11	-111%	52%	12	-458%	-29%
DAS-CMOP8	1	62%	62%	2	-15%	-5%	3	5%	11%	4	-9%	2%
	5	62%	53%	6	-14%	-3%	7	-3%	20%	8	9%	7%
	9	54%	39%	10	-21%	-5%	11	-142%	-341%	12	1%	6%
DAS-CMOP9	1	4%	-7%	2	29%	24%	3	1%	-7%	4	49%	23%
	5	8%	-5%	6	-14%	2%	7	-41%	-6%	8	42%	14%
	9	-9%	-3%	10	73%	62%	11	-20%	-95%	12	84%	81%

Table 3.10: Comparison between the original NSGA-III and the QNSGA-III

outperform those obtained from random initialization without local search. The analysis indicates that incorporating heuristic initialization and local search enhances both diversity and hypervolume across all instances. Nevertheless, it is noteworthy that in certain cases, set coverage is superior with random initialization. This phenomenon may be attributed to the potential for encountering local optima with our heuristic approach.

Inst. ID	kcm_1	kcm_2	kcm_3	kcm_4
Sc	-5%	1%	11%	1%
Hv	32%	50%	50%	9%
Dv	71%	77%	94%	75%

Table 3.11: Comparison between QNSGA-III and IQNSGA-III

Figure 3.13 illustrates the comparison between solutions obtained using NSGA-III alone and those obtained using the enhanced version of NSGA-III with Q-Learning, the heuristic method, and the local search application (IQNSGA-III). The IGD for the sets of solutions obtained by NSGA-III and IQNSGA-III are respectively 0.147 and 0.119 for MOP1, and 0.1476 and 0.0794 for MOP2, underscoring the superiority of the enhanced NSGA-III in terms of proximity to the Pareto front. The hypervolume gap between the solutions obtained with GUROBI and those obtained with IQNSGA-III is 1.31%, which outperforms the hypervolume gap of 2.18% achieved by QNSGA-III.

3.7 Results and sensitivity analysis

This section presents the obtained results of both models on kcm and FJ instances first, and then on the engineering case $DFMC$. Section 3.7.1 and 3.7.2 present the results and sensitivity analysis of MOP1 and MOP2 respectively, obtained using IQNSGA-III. As a reminder, MOP1 aims to minimize the makespan, the energy consumption and the OCRA index and MOP2 aims to minimize the makespan, the energy consumption and the workers preferences. In 3.7.1 and 3.7.2, we respectively evaluate the sensitivity of MOP1 to the workers number variation and the sensitivity of MOP2 to the workers preferences profiles variation.

3.7. RESULTS AND SENSITIVITY ANALYSIS

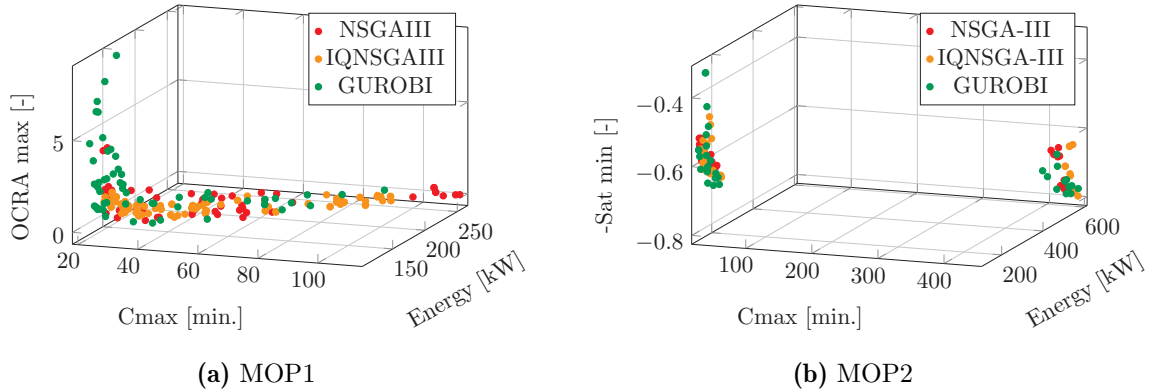


Figure 3.13: NSGA-III, IQNSGA-III, and GUROBI results comparison for kcm_1

3.7.1 First model

Results analysis

At the end of the algorithm, we obtain a final population consisting of 100 chromosomes, each representing a distinct solution. Among these solutions, certain ones are non-dominated by any others. Figure 3.14 shows the set of solutions obtained for the instance kcm_4 . The solutions depicted in red represent the non-dominated solutions that are not outperformed by any others, while the remaining solutions are shown in blue. We observe that, in this instance, there exists a positive correlation between the makespan and energy consumption, where longer processing times result in higher energy consumption. This is due to the link between the energy consumed by the auxiliary equipments and the energy consumed overall the process duration. Conversely, $OCRA^{max}$ decreases as the makespan and the energy consumption increase. This can be explained by the fact that reducing the makespan often necessitates reducing the frequency and/or duration of workers' rest periods, which systematically increase their OCRA indices.

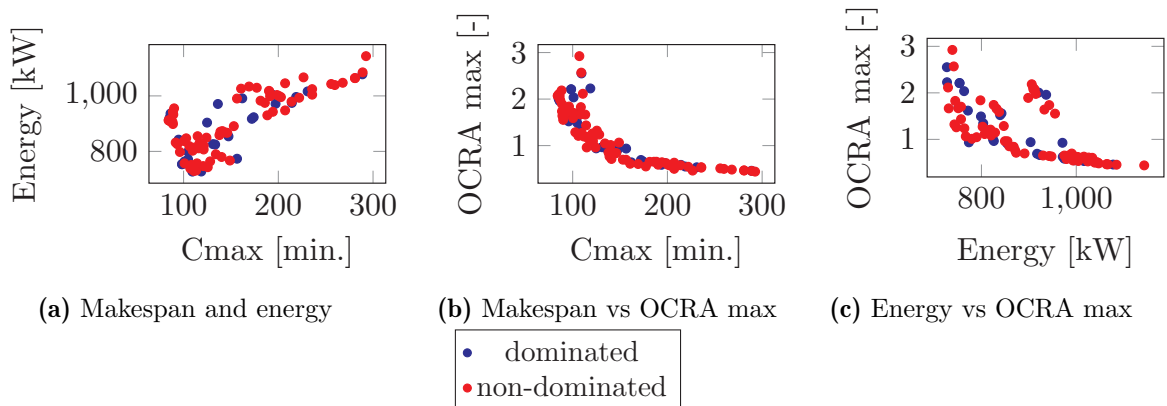


Figure 3.14: Display of the 100 solutions of kcm_4 on two-by-two axes

Divergent trends emerge when examining the curves for larger instances, e.g. FJ_{20} as showed by Figure 3.15. Notably, the makespan remains in contradiction with $OCRA^{max}$, whereby an increase

3.7. RESULTS AND SENSITIVITY ANALYSIS

in makespan results in a decrease in $OCRA^{max}$. However, the positive correlation between total energy consumption and makespan is no longer revealed due to the large number of tasks, extensive machine usage leading to energy consumption for transport, and heightened energy expenditure in task execution. Consequently, the auxiliary energy factor has a comparatively smaller impact on overall energy consumption. Conversely, the opposite tends to hold true, i.e. small makespan values are associated with higher energy consumption, while larger makespan values exhibit small energy consumption. Nevertheless, energy consumption and $OCRA^{max}$ exhibit a stronger positive correlation, with both metrics having relatively low values concurrently.

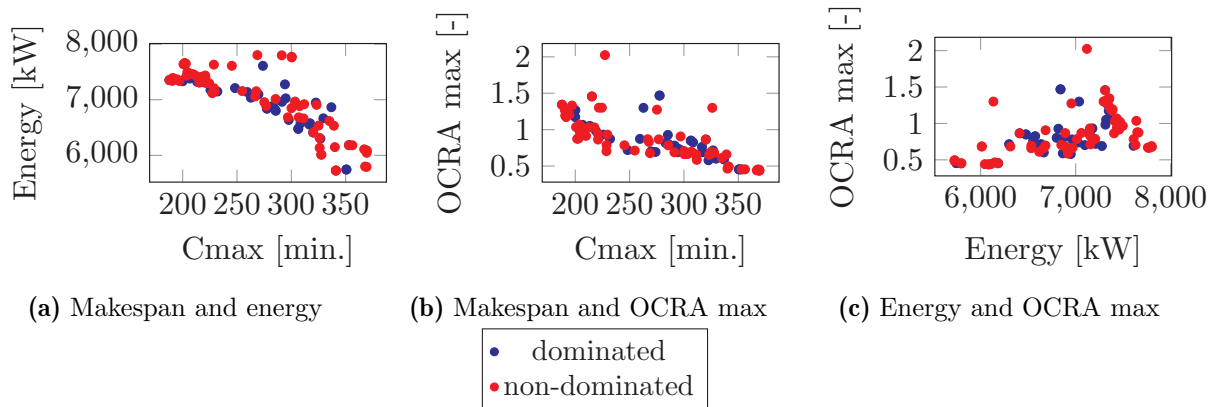


Figure 3.15: Display of the 100 solutions of FJ_{20} on two-by-two axes

Our algorithm provides a range of solutions based on various criteria. Subsequently, the final decision involves selecting a schedule for implementation. The key consideration is determining the most suitable schedule based on the specific situations we may encounter. As an example, we will take the kcm_4 instance. Figure 3.16 illustrates the set of the non-dominated solutions obtained. We normalized each objective value by dividing it by the worst value found. The blue curve represents the normalized $OCRA^{max}$ values, the green curve represents the normalized energy consumption values, and the pink curve represents the normalized makespan values. Additionally, the orange curve represents the average value of these three criteria for each solution. The minimum value for each curve is denoted by a round circle. Specifically, solutions 0, 2, 10, and 33 have the minimum values of $OCRA^{max}$, makespan, average value, and energy consumption, respectively. The corresponding schedules can be found in Figure 3.17 in the following order: solutions 2, 33, 0, and 10.

The first schedule minimizes the makespan by efficiently assigning tasks to the most efficient workers and machines to execute them. The energy consumption remains relatively low due to the correlation between the makespan and auxiliary equipments energy consumption, while the $OCRA$ values remain below 2.2 thanks to the short duration of the process. The second schedule focuses on minimizing total energy consumption by selecting machines with low energy usage for each task. Additionally, efforts are made to keep tasks of the same job on the same machine to minimize energy expenditure on internal transport. Although the makespan remains favorable due to the correlation between makespan and auxiliary energies, only one $OCRA$ value slightly exceeds 2.2 (for worker 2) while remaining close to targeted threshold. The third schedule achieves very low $OCRA$ values, but is the longest in duration and consumes the highest amount of energy. It prioritizes worker safety, allocating tasks to machines and workers that offer maximum security, regardless of the time required.

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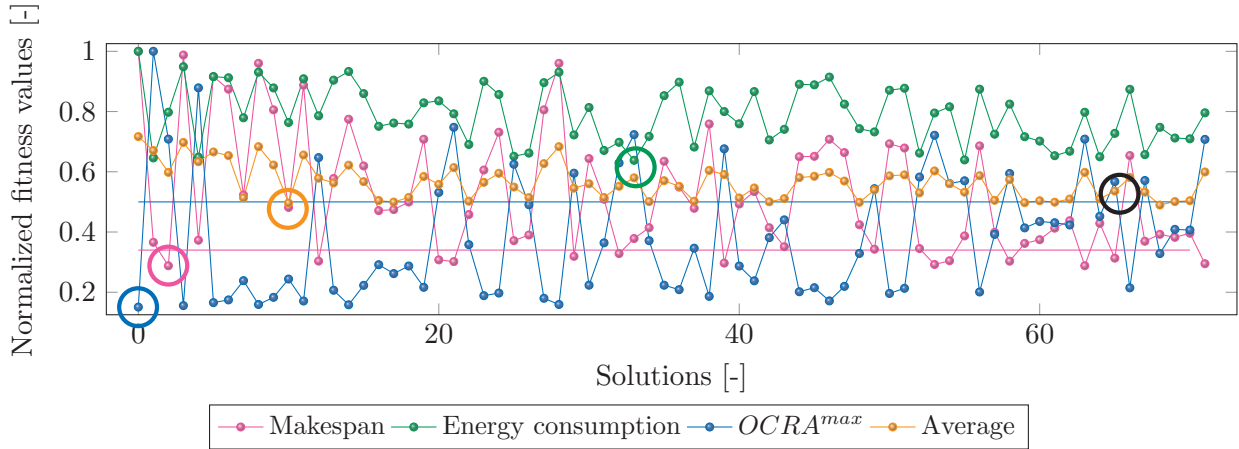


Figure 3.16: Normalized fitness values for the non-dominated solutions

However, this schedule is not practical for industrial purposes as the makespan is 3.5 times longer than the optimal duration. To strike a balance among these three schedules, we select the schedule with the minimal average normalized fitness values. This fourth schedule, depicted in the figure, does not achieve optimal values for any objective but comes close to them. It represents a good compromise between economic, environmental, and human factors.

Then, if we are in a normal situation, the fourth schedule offers a balanced approach that considers economic efficiency, environmental impact, and worker well-being. Nevertheless, when confronted with a critical aspect, there is flexibility to temporarily adjust the schedule. For instance, situations may arise where workers frequently experience stress, fatigue, or injuries such as musculoskeletal disorders, and then the schedule can be adapted to favor workers' well-being among others aspects. Additionally, circumstances such as a peak in pollution or economic challenges might prompt us to adapt the schedule, opting for a less polluted schedule or a more concise timeframe. To emphasize a particular aspect without compromising others significantly, we can establish an upper bound for that specific aspect and seek the optimal schedule that minimizes the other two criteria. For instance, if our emphasis is on human factors, we might set $OCRA^{max}$ under 1.5 (the upper level of the optimal range, as shown in Figure 3.1). This corresponds, in Figure 3.16, to solutions where the normalized $OCRA^{max}$ is under 0.5 (indicated by the straight blue line). We then examine the average solution within this range and select the one with the minimum values, while adhering to the $OCRA^{max}$ constraint; in this case, it aligns with the fourth schedule (solution 10 in the Figure 3.16). Similarly, for a focus on economic considerations with a set makespan under 100 minutes, corresponding solutions would have a normalized makespan under 0.34 (indicated by the straight pink line in Figure 3.16). Applying the same methodology, we identify the schedule that minimizes the average of all criteria while respecting the makespan constraints. This solution is marked with a black circle on Figure 3.16, corresponding to the solution 65. The same reasoning applies to environmental factors, not presented here.

We have demonstrated that our set of solutions provides a broad range of scheduling possibilities. Depending on the specific situation, we can formulate a flexible schedule that simultaneously addresses all three aspects or gives priority to a particular one, while ensuring consideration for the others. The methodology outlined below serves as a valuable aid in the scheduling problem decision-making process. To test our model in a scenario that closely mirrors real-world conditions, we use the *DFMC* instance.

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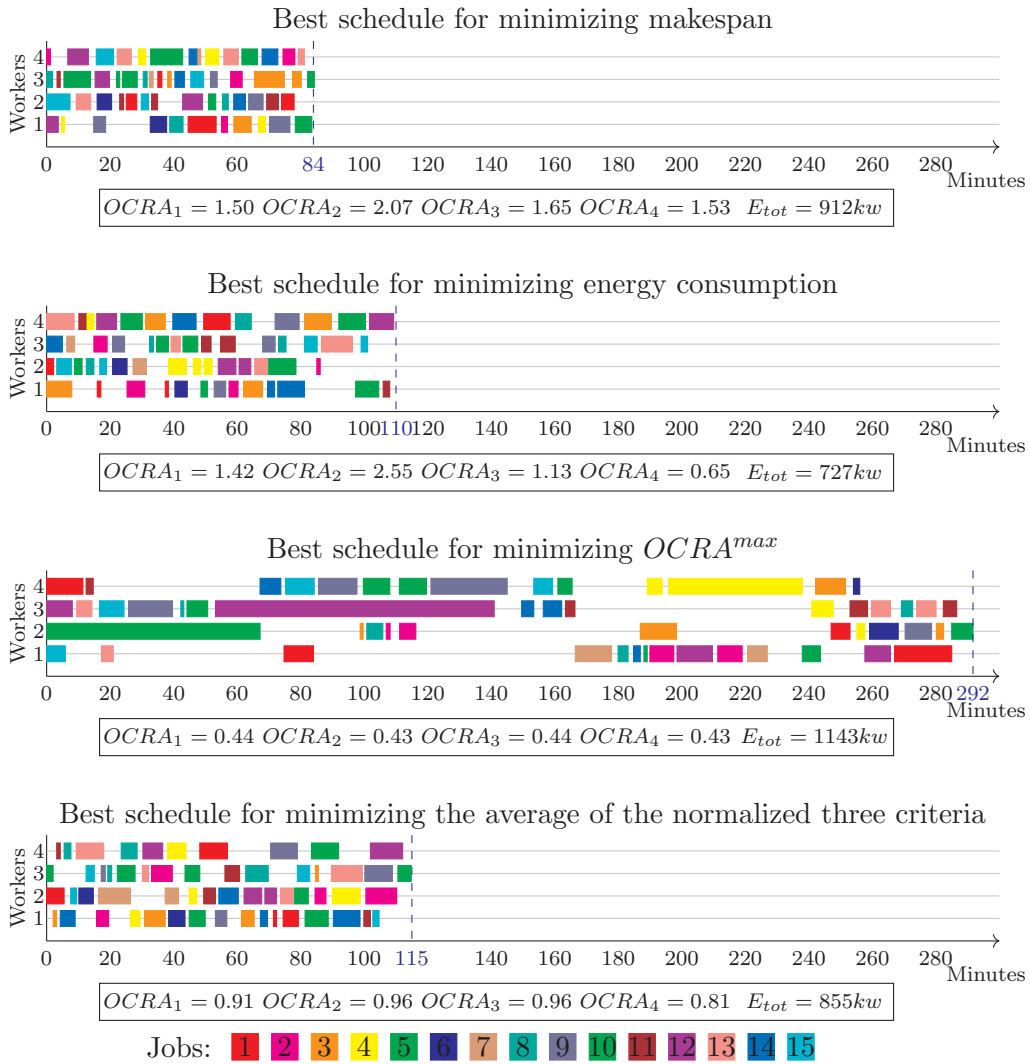


Figure 3.17: Comparison of different schedules

Results obtained are depicted in Figures 3.18 and 3.19. The makespan and energy consumption exhibit a positive correlation, with the exception of solutions featuring the smallest values of makespan and energy consumption. However, we observe a consistent increase in energy consumption alongside makespan. Conversely, the value of $OCRA^{max}$ demonstrates an inverse correlation with both energy consumption and makespan. Once again, achieving a satisfactory trade-off between the three criteria can be facilitated through the normalization of the objectives, as illustrated in Figure 3.16. The minimum makespan value found is 1165, the minimum energy consumption is recorded as 2172, and the minimum $OCRA^{max}$ index is 0.91. The solutions derived from the normalization process yield a makespan of 1201, energy consumption of 2350, and $OCRA$ index of 1.26. It's noteworthy that this solution is very closely aligned in terms of makespan and energy consumption. A good balance is achieved between the three criteria.

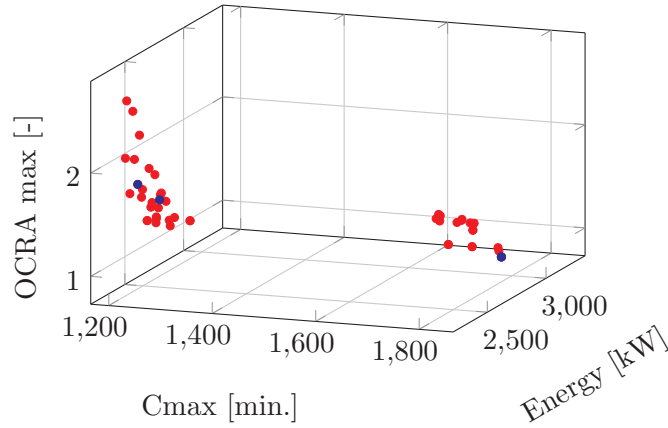


Figure 3.18: Display of the 100 solutions of *DFMC*

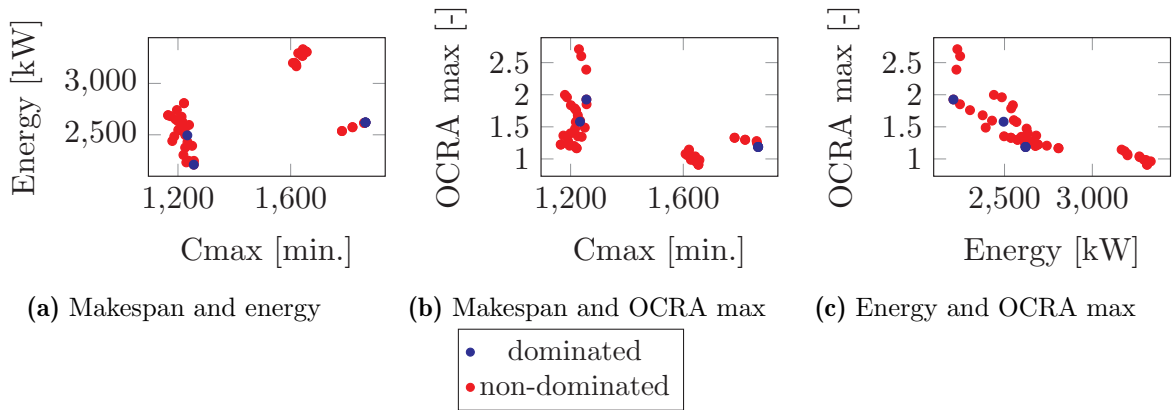


Figure 3.19: Display of the 100 solutions of *DFMC* on two by two axes

Sensitivity analysis

We examine the influence of human-related parameters on the three specified criteria. Analyses were conducted for varying numbers of workers involved in the process. This involved the generation of 10 instances for each of the following scenarios: 25% additional workers, 50% additional workers, 25% fewer workers, and 50% fewer workers. Subsequently, we conducted some statistical analysis on the results obtained from these instances. The outcomes of the various instances tests are succinctly presented in Figure 3.20 for FJ_{15} and in Figure 3.21 for *DFMC*. In both figures, the box plots represent the dispersion of the results found for the three criteria. Then, the median, the best value, the worst value, and the quartiles are highlighted. The point indicates the value of the corresponding criterion with the minimization of the average of the three normalized criteria (refer to Figure 3.16).

The findings based on the results of the FJ_{15} instance show that increasing the workforce has a notable impact on all three criteria, particularly on makespan and $OCRA^{max}$. Analysis of the results reveals that a 25% and 50% increase in the number of workers correlates with a respective reduction of median makespan values by 12.5% and 20%. Conversely, a reduction in the workforce by 25% and 50% results in an increase of 21% and 69% in the median makespan values. Regarding $OCRA^{max}$,

3.7. RESULTS AND SENSITIVITY ANALYSIS

notable fluctuations in values are observed with the reduction and addition of workers. Specifically, the worst values exhibit an increase of 14% and 35% when the workforce is reduced by 25% and 50%, respectively. Conversely, when workers are added, there is a corresponding decrease. Similarly, the median values of $OCRA^{max}$ demonstrate variations ranging from 2% to 24% when adjusting the number of workers upward or downward. The energy consumption is less sensitive to the variations of the number of workers, as the best average value vary from 1% to 6%, and the median value from 0,5% to 1,5%.

Regarding $DFMC$ instance, a notable difference is observed in the three criteria when the number of workers is adjusted. As the number of workers decreases, both the makespan and energy consumption increase across all statistical measures: median, lower bound, upper bound, lower quartile, and upper quartile. This trend is also evident in the normalized values of the three criteria. Specifically, for $OCRA^{max}$, the lowest value is found in the scenario with 12 workers, while the highest value is observed in the scenario with 4 workers.

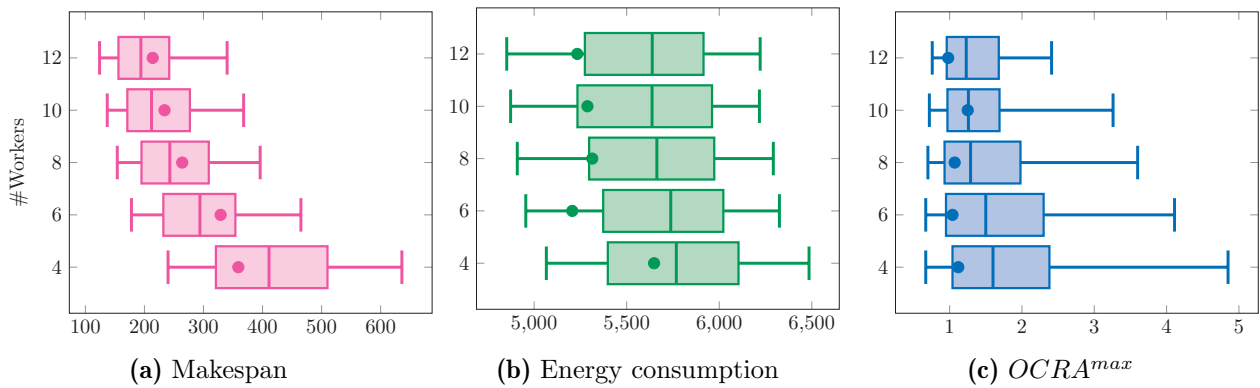


Figure 3.20: Box plot analysis: impact of workforce variations on FJ_{15}

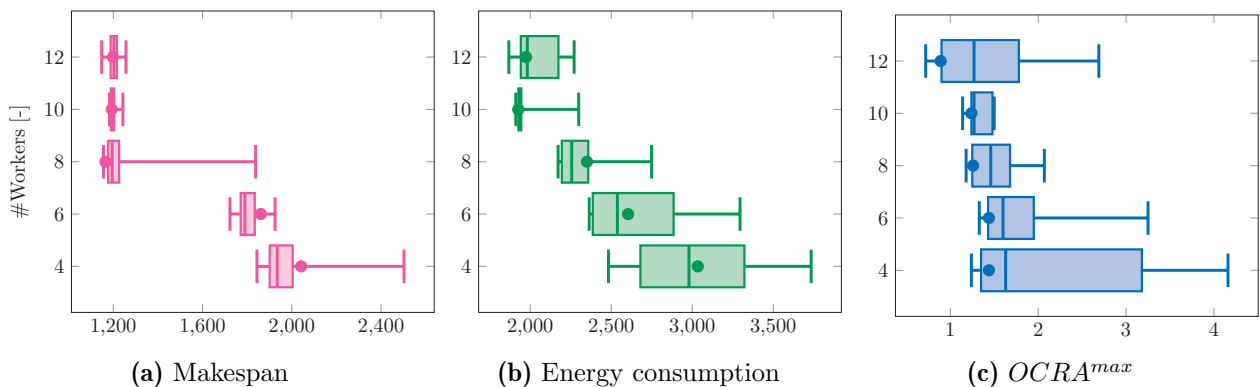


Figure 3.21: Box plot analysis: impact of workforce variations

3.7.2 Second model results

Results analysis

For the MOP2 model, we introduce the notion of worker preferences and define profiles for these workers based on their preferences. Figure 3.22 illustrates the results obtained with a short instance (kcm_4) using random generated preferences. First, we can observe notably elevated values for both makespan and energy consumption. This is attributed to the preferences among workers for different shifts. Although it is feasible to complete all operations within a single shift in our instances, the consideration of individual worker preferences necessitates the assignment of several workers to different shifts. Consequently, operations assigned to these workers must wait until their designated shift to commence. This problem should not arise with larger instances. Besides, we note a discernible positive correlation between makespan and energy consumption for kcm_4 , with both criteria conflicting with the minimum value of satisfaction, denoted as $-Sat^{min}$.

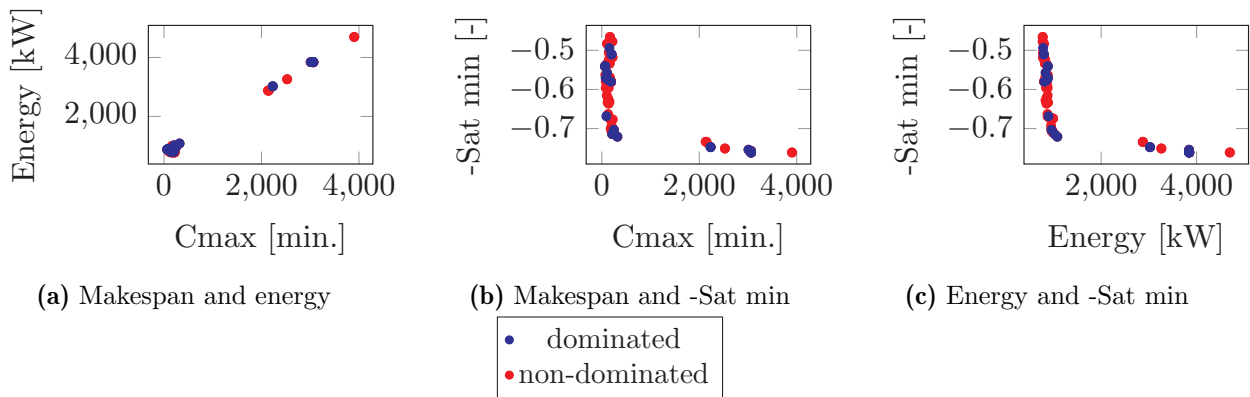


Figure 3.22: Display of the 100 solutions of kcm_4 on two-by-two axes

In the case of the FJ instances, the minimum satisfaction conflicts with both energy consumption and makespan, as shown in Figure 3.23. Regarding makespan and energy consumption, an increase in makespan values correlates with a corresponding rise in energy consumption when the makespan attains really high values. Conversely, when makespan values fall below 1000, a contrasting trend emerges. For a visual representation of this significant correlation, a zoom on the area of interest is given in Figure 3.24. We analyze similar trends to those observed in the first model. Specifically, the three criteria are found to be conflicting for the FJ instances, while for kcm_4 , there exists a positive correlation between makespan and energy consumption. This correlation can be attributed to the relatively small number of tasks, which places greater emphasis on auxiliary energy considerations.

Figures 3.25 and 3.26 showcase the outcomes of $DFMC$ instances. The makespan and energy consumption exhibit a positive correlation, while the satisfaction minimum demonstrate an inverse correlation with both criteria. The minimum makespan, energy consumption, and maximum satisfaction found are 1237, 1947 and 0.58, respectively. The solutions derived from the normalization process yield a makespan of 1253, an energy consumption of 2024, and a maximum satisfaction of 0.53. Once again, the normalization of the objectives can achieve a good trade-off between the three criteria.

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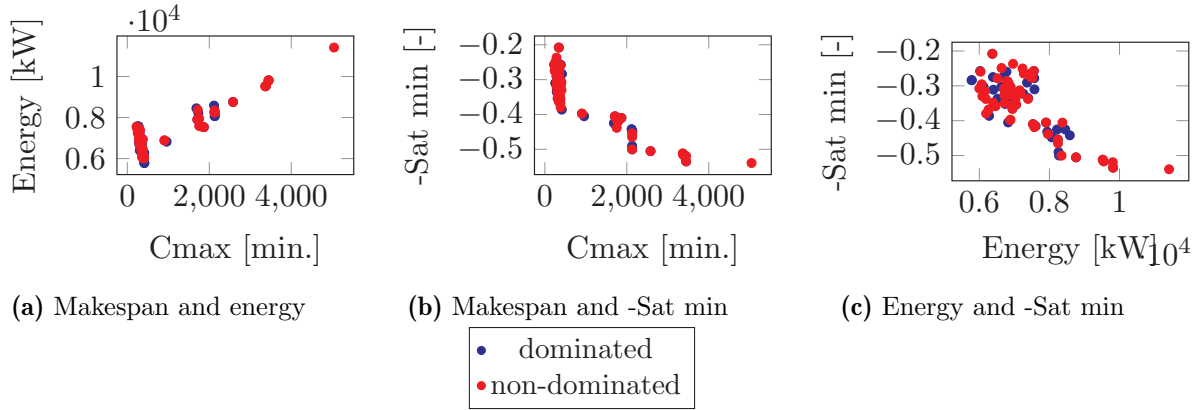


Figure 3.23: Display of the 100 solutions of FJ_{20} on two-by-two axes

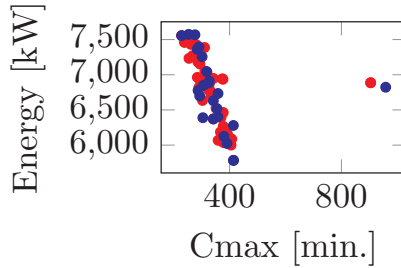


Figure 3.24: Zoom on Figure

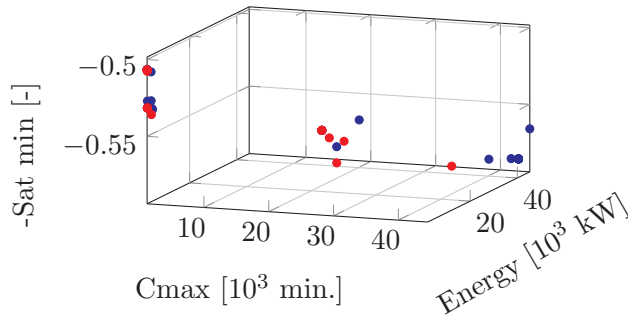


Figure 3.25: Display of the MOP2 solutions

Sensitivity analysis

Next, our objective is to examine the fluctuations in the three criteria based on different workers' profiles. We defined four distinct profiles:

- profile1: exhibits a preference for morning shifts and a diverse range of machine assignments;
- profile2: exhibits a preference for morning shifts but without variations in the types of machines used;
- profile3: exhibits a preference for afternoon shifts and a diverse range of machine assignments;

3.7. RESULTS AND SENSITIVITY ANALYSIS

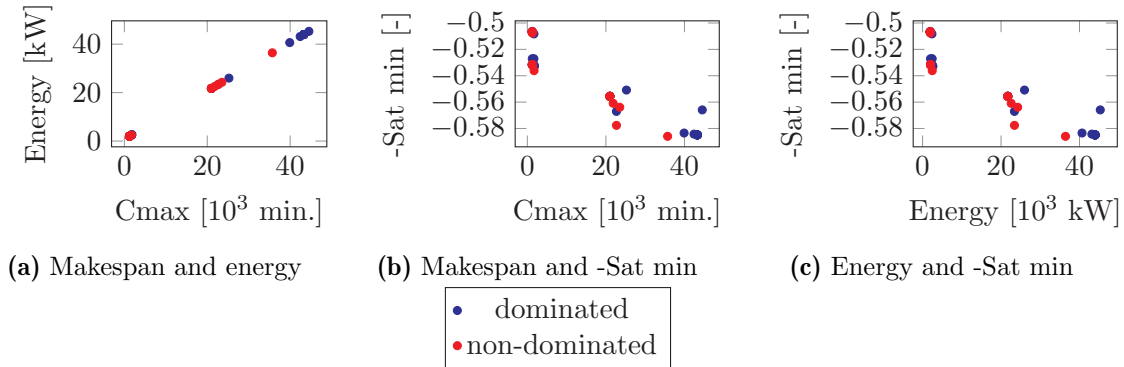


Figure 3.26: Display of MOP2 solutions on two by two axes

- profile4: exhibits a preference for afternoon shifts but without variations in the types of machines used;

Then, we have different scenarios, based on these profiles:

- scenario 1: the workforce comprises individuals exclusively aligned with profile 1;
- scenario 2: the workforce comprises individuals exclusively aligned with profile 2;
- scenario 3: the workforce comprises individuals exclusively aligned with profile 3;
- scenario 4: the workforce comprises individuals exclusively aligned with profile 4;
- scenario 5: the workforce comprises 50% of individuals aligned with profile 1 and 50% of individuals aligned with profile 3 ;
- scenario 6: the workforce comprises 50% of individuals aligned with profile 2 and 50% of individuals aligned with profile 4;
- scenario 7: the workforce comprises 50% of individuals aligned with profile 1 and 50% of individuals aligned with profile 2;
- scenario 8: the workforce comprises 50% of individuals aligned with profile 3 and 50% of individuals aligned with profile 4;
- scenario 9: the workforce comprises 25% of individuals aligned with each profile.

Given the small size of our instances and the ability to execute all tasks within a single shift, it is not meaningful to analyze results in the context of scenario 5, 6, and 9 for FJ_{15} . This is because such analyses would yield high makespan values, which, in reality, may not be reflective of practical scenarios. Then, we choose to compare results for scenario 1, 2, and 7, analyzing the impact of the preferences for variability or regularity on each metric. A series of 10 tests for each scenario have been conducted on distinct instances. The findings are visually represented in Figure 3.27. Figure 3.27a, 3.27b, and 3.27c specifically illustrate the distribution and trends associated with makespan, energy consumption, and preferences, providing a comprehensive overview of the model's performance across these key metrics. Firstly, in terms of minimum satisfaction, it is evident that a preference for variability ensures a better minimum satisfaction. This indicates that workers are more likely to change tasks, which is conducive to achieving favorable results in the other two criteria. Specifically, the median value of scenario 1 is 20% and 18% better than the median values of scenario 2 and scenario 7, respectively. Regarding makespan and energy consumption, the median values are not

3.8. CONCLUSION

significantly affected by worker preferences. However, the worst values show a substantial increase with scenario 2 (133% for makespan and 8% for energy consumption). Across all three criteria, scenario 1 consistently yields the best results, scenario 2 the worst, and scenario 7 falls in between. Therefore, it can be concluded that workers' flexibility contributes to achieving favorable makespan and energy consumption values. Consequently, having workers who favor variability over regularity is preferable.

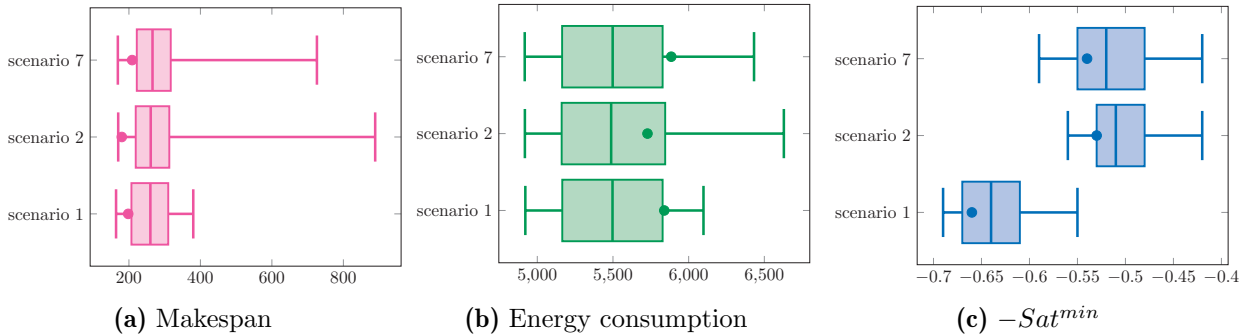


Figure 3.27: Box plot analysis: solutions variation in FJ_{15} based on different workers' profiles

For the *DFMC* instance, we utilize scenario 5 to assess preferences for diversity, scenario 6 to examine preferences for regularity, and scenario 9 to evaluate the impact of a homogeneous distribution of workers across the four distinct profiles. The results of these analyses are presented in Figure 3.28. Compared to scenario 5, the median makespan increases by 112% in scenario 6 and by 121% in scenario 9. Similarly, the median energy consumption increases by 85% in scenario 6 and by 97% in scenario 9. The fluctuations in the lower bound and the best mean of the normalized criteria are negligible. However, for the satisfaction criterion, scenario 5 shows significant improvements in the lower bound, median, and best mean of the normalized criteria compared to the other two scenarios.

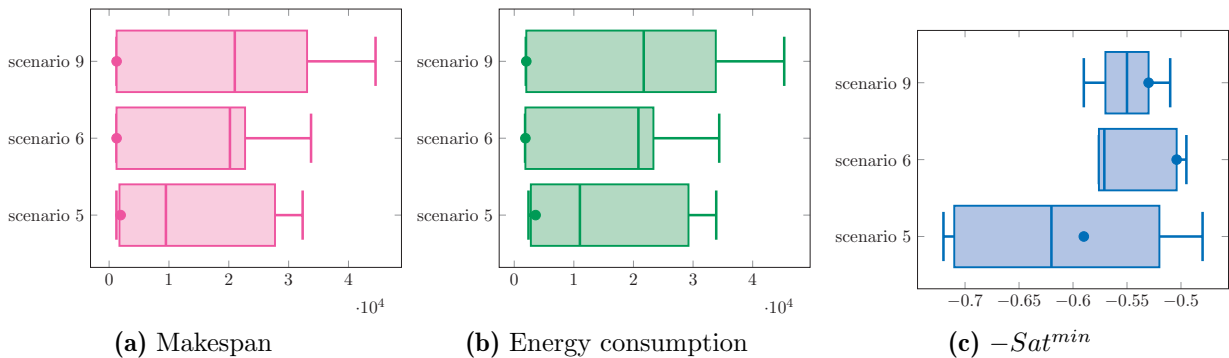


Figure 3.28: Box plot analysis: solutions variation based on different workers' profiles

3.8 Conclusion

In this paper, we addressed a sustainable flexible job shop scheduling problem considering energy consumption and worker's safety and preferences. We proposed two multi-objective Mixed Integer Non-

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Linear Programs (MINLP) to model this problem. Our ultimate goal is to achieve a balance between economic, environmental and social aspects. The social criterion was addressed differently in the two models. While the first model minimizes the $OCRA^{max}$ index which assess ergonomic risks related to task execution and subsequently addresses the risk of musculoskeletal disorders, the second model maximizes Sat^{min} , which represents the minimum satisfaction level among all workers and integrates their preferences regarding working shift, machines and tasks variety. Both models are solved using Non-dominated Sorting Genetic Algorithms, NSGA-II and NSGA-III, enhanced particularly through a Q-learning method for genetic operators' parameters tuning and a local search based on reinforcement learning. We tested our models on data sets inspired from the literature and analyze their sensitivity regarding the workers number and preferences variations.

Our findings underscore the interconnected impact of each criterion across diverse instance sets. The global conclusion is that environmental and social considerations are integral to the scheduling process and must not be overlooked. Integrating worker safety and preferences introduces a conflict with the other two criteria but enhances the system resilience, mitigating risks such as absenteeism, injuries, and fatigue. Consequently, we propose a method for selecting an optimal final schedule tailored to specific contextual requirements, demonstrating favorable outcomes across all three criteria. These models serve as a foundation for decision-makers to tackle upcoming challenges associated with the evolving social landscape and the revolutions in advanced manufacturing and service systems.

We acknowledge some limitations of this study. Firstly, the models are static and are not designed to handle disruptions. That is why, in our future work, we aim to develop a dynamic model capable of responding promptly and in real-time to process-related hazards, particularly those involving workers, such as absenteeism and diligence at work. A dynamic model would enhance the resilience of the system, allowing it to recover quickly and maintain optimal performance. Secondly, regarding the workers, this study is still in its early stages. Currently, the rest time for workers is set at 8% of their working time. Conducting a more detailed study on worker fatigue and optimizing break times could significantly enhance the model's effectiveness. Additionally, other ergonomic risk index should be studied and compared, depending on the types of manufacturing processes, and more worker profiles could be studied, with a deeper analysis of their behavior and preferences. Finally, our algorithm could be applied to other scheduling models, particularly those with different objective functions, such as minimizing tardiness or cost.

Systematic Review and Future Directions in Dynamic Flexible Job Shop Scheduling: A Decade of Research

Abstract

This paper presents a comprehensive overview of the current state-of-the-art on Dynamic Flexible Job Shop Scheduling problems (DFJSSP). It reviews a wide range of studies that address different scheduling strategies, various types of disruptive events, and multiple objectives. The numerous solution methods developed in the literature and tested on significant benchmarks are also analyzed. This paper compiles studies on DFJSSP from 2013 to the present, offering valuable guidance for future research in this area. It highlights the progress made and addresses new challenges in dynamic scheduling and its application in manufacturing systems.

Keywords: Dynamic scheduling, Flexible job-shops, Scheduling strategies, Solving methods, State-of-the-art

4.1 Introduction

Scheduling problems play a crucial role in numerous fields such as IT, healthcare, agriculture, services, transport, and production systems [17]. Their significance is particularly evident in the manufacturing industry, where resources mainly consist of machines and workers. The tasks to be scheduled typically represent specific operations that need to be performed on particular products. In the manufacturing sector, efficient scheduling ensures optimal use of resources, minimizing downtime, and enhancing productivity. Depending on the type of manufactured product and production line, scheduling can exhibit various characteristics and has continually evolved due to theoretical and technological advancements, as well as societal changes and the emerging needs of manufacturing [1]. As a result, extensive research has been performed into various production environments and scheduling types.

Generally, two scheduling strategies are used: static and dynamic. Static scheduling involves establishing a schedule before the process begins and keeping it unchanged throughout, without allowing any changes to the task sequence. However, any disruptive event will shift all the tasks following it to the right. In fact, real-world scenarios often present unpredictable events such as priorities fluctuations and resource-related issues, rendering predefined schedules infeasible for execution without modifica-

tions. Therefore, the dynamic scheduling, which extends beyond static scheduling by responding to real-time events, permits adjustments in reaction to unforeseen circumstances. The significance of studying dynamic scenarios is increasing, as it is considered more practical in managing disruptions, and enhancing the resilience of systems, which is a crucial characteristic of the current Industry 5.0 manufacturing systems [26]. In these complex manufacturing systems, job-shop scheduling is one of the most critical challenges in production scheduling.

The job-shop scheduling problem is a complex and challenging combinatorial optimization problem that has been extensively addressed in the scientific literature. Various methods have been developed to tackle this problem. While exact methods can provide optimal solutions, they often become limited for large instances due to high computational demands. Heuristic and metaheuristic methods offer more feasible solutions by balancing solution quality with computational time. However, these methods are limited in handling dynamic environments with uncertainties. This limitation necessitates the development of more adaptive approaches. Leveraging real-time data, predictive analytics, adaptive algorithms and hybrid methods can considerably improve the ability to maintain effective and efficient schedules in unpredictable and ever-changing manufacturing environments. These advanced techniques enable more responsive and robust scheduling, better suited to dynamic job-shop environments.

This paper relates to a specific family of job-shop scheduling problems, namely Flexible Job Shop Scheduling Problems (FJSSP), which is widely encountered in real-life manufacturing scenarios, particularly when studied in dynamic cases. FJSSP occur in manufacturing environments where machines and processes can be reconfigured or are versatile enough to handle different types of jobs. DFJSSP involve the complexities of flexible job shop environments with the added challenge of dynamic changes. The goal of this paper is to provide an overview of research on DFJSSP. An in-depth review of the literature, over the period 2013-2024, identified 303 articles addressing DFJSSP in various forms. These articles cover different types of disturbances, strategies, policies, and solving methods. Throughout the rest of this study, we aim to answer the following research questions:

- Q1: What are the different types of DFJSSP, and which ones are most commonly studied ?
- Q2: What are the most efficient approaches to solving DFJSSP ?
- Q3: What are the current major challenges in DFJSSP ?
- Q4: What are the emerging ideas and trends in DFJSSP research ?

Section 4.2 introduces the nomenclatures used throughout the document. Section 4.3 offers a concise description of scheduling problems, particularly focusing on FJSSP and dynamic scheduling. Section 4.4 outlines the research methodology employed to compile the 303 identified papers. In Section 4.5, we provide a comprehensive overview of these papers and their characteristics. We analyze trends in: the use of different scheduling strategies, the type of disturbances investigated the, types of objectives pursued, the solving methods employed, and the sustainable criteria considered. Finally, Section 4.6 concludes the study and outlines future research directions.

4.2 Nomenclatures

For easier reading of the article and to aid in understanding the subsequent sections, tables 1, 2 and 3 introduce the used nomenclatures. i) Table 4.1 for the objective function nomenclature, ii) Table 4.2 for the disruptions nomenclature and iii) Table 4.3 for the solving methods nomenclature.

4.2. NOMENCLATURES

Ag	Agreement	IC	Inventory cost	R	Robustness
C	Cost	Id	Idle resource	RP	Rejected parts
CE	Carbon emission	M	Maintenance cost	S	Stability
Cmax	Makespan	MBP	Machine breakdown probability	SL	Service level
CS	Customer satisfaction	MW	Machine workload	St	Stress level
EC	Energy consumption	NP	Noise pollution	SU	Space utilization
E/T	Earliness/Tardiness	Ot	Overtime	Tr	Transport
Ft	Worker fatigue	P	Profit	WiP	Work in progress
Fw	Flowtime	Q	Quality	Wt	Waiting time

Table 4.1: Nomenclature for the objective function

CEP	Change in employee proficiency	MB	Machine breakdown	TC	Transport equipment charging
CDD	Change in due dates	MD	Machine deterioration	UDD	Uncertain due dates
CPT	Change in processing times	NP	Not precised	UEC	Uncertain energy consumption
DA	Delay in arrival	OC	Order cancellation	UPT	Uncertain processing times
JA	Job arrival	OI	Operation inspection	URT	Uncertain relase time
LM	Lack in materials	OM	Order modification	UST	Uncertain setup times
Ma	Maintenance activities	RP	Reprocessing	UTT	Uncertain transport time
MA	Machine addition	TB	Transport equipment breakdown	WA	Worker absence

Table 4.2: Nomenclature for disruptions

ABC	Artificial bee colony	GNHC	Global neighbourhood hill climbing	MVO	Multi verse optimization
ACO	Ant colony optimization	GP	Genetic programming	NN	Neural network
AISA	Artificial immune system algorithm	GRAS	Greedy randomized adaptive search	NSGA	Non-dominated sorting GA
BA	Bat algorithm	GT	Game theory	OFA	Optimal foraging algorithm
BFO	Bacterial foraging optimization	HA	Hungarian algorithm	Po	Policy based
BO	Biogeography based optimization	H	Heuristic	PR	Priority rules
BSA	Backtracking search algorithm	HH	Hyper Heuristic	PSO	Particle swarm optimization
CCA	Cooperative coevolutionary algorithm	HS	Harmony search	QL	Q-Learning
CS	Cuckoo search	IA	Immune algorithm	QPSO	Quantum PSO
DEA	Differential evolution algorithm	ICA	Imperialist competition algorithm	RL	Reinforcement learning
DES	Discreet event simulation	JA	Jaya algorithm	SA	Simulated annealing
DR	Dispatching rules	LR	Lagrangian relaxation	SMO	Spider monkey optimization
DRL	Deep reinforcement learning	LSA	Lightning search algorithm	TL	Teaching learning
EA	Evolutionary algorithms	MA	Memetic algorithm	TS	Tabu search
EAD	EA based on decomposition	MAS	Multi agent system	TSO	Tuna swarm optimization
EDA	Estimation distribution algorithm	MBO	Migrating birds optimization	VDO	Vibration damping optimization
FA	Firefly algorithm	MC	Monte Carlo simlation	VNS	Variable neighbourhood search
FPA	Flower pollination algorithm	MCTS	Monte Carlo tree search	VWA	Virtual workflow algorithm
GA	Genetic algorithm	ML	Machine learning	WOA	Whale optimization algorithm
GEP	Gene expression programming	MS	Micro swarm optimization		

Table 4.3: Nomenclature for solving methods

4.3 Dynamic scheduling problem characterization

4.3.1 Problem description

Scheduling problems first emerged in the 1950s, coinciding with the rise of mass production in manufacturing. Essentially, scheduling entails a decision-making process that assigns tasks to resources and sequences them over time, aiming to optimize one or more performance measures jointly or separately [17], while respecting the associated constraints. Across the literature, various objective functions have been identified. Time-based objectives are common, with the most frequent being the minimization of the maximum completion time, known as makespan. Additionally, there are cost-based objectives (e.g. minimizing production costs), job number-based objectives (e.g. minimizing the number of tardy jobs), or revenue-based objectives (e.g. maximizing total production revenue). With the advent of Industry 5.0 and the growing emphasis on environmental and social considerations, new objective types are emerging. These include pro-environmental objectives, such as minimizing energy consumption, and human-centric objectives, like minimizing workers' risks. These objectives can be optimized individually or as part of a multi-objective approach, where several criteria are optimized simultaneously. However, it is important to note that these criteria often conflict with each other, necessitating a careful trade-off analysis to find the most balanced solution.

Various production environments exist, including single-machine, parallel-machine, flow shop, job shop, and open shop configurations. Given their widespread applicability in real-world scenarios, this paper addresses, specially, the job shop environment, with a particular emphasis on flexible job shops. This problem is denoted in the literature as FJSSP. In FJSSP, we are given a set of n jobs, denoted as $J = \{J_1, J_2, \dots, J_n\}$ and a set of m machines, represented as $M = \{M_1, M_2, \dots, M_m\}$. Each job j is composed of n_j operations, outlined as $O_j = \{O_{1j}, O_{2j}, \dots, O_{n_jj}\}$, with each operation required to follow a predefined and distinct sequence. Here, the flexibility lies in the fact that a task can be executed by multiple machines instead of just one in the classical job shops. Consequently, FJSSP is composed of two subproblems: the determination of the optimal machine for each task, and the arrangement of an optimal sequence of tasks on each machine.

Scheduling problems can be tackled through various strategies, either static or dynamic. In the static strategy, a predetermined schedule is established and followed regardless of any disruption that may occur during production. Conversely, dynamic strategies consider the ever-changing manufacturing environment, which is prone to numerous disruptions and unforeseen events. Dynamic scheduling is often more reflective of real-world scenarios, helping to bridge the gap between theoretical assumptions and practical applications. The distinction between static and dynamic scheduling was initially made by [253] and gained significant attention in the latter half of the 20-th century, particularly as industries faced increasing complexity and variability in production environments. Dynamic scheduling allows for swift responses to fluctuations in customer orders, resource availability, material shortages, and other unforeseen events. This enhances productivity, efficiency, and customer satisfaction. Dynamic scheduling can be implemented through a variety of strategies and policies tailored to different types of disruptions and resolved using diverse methods. Section 4.3.2 delves into the three primary strategies identified in the literature, while Section 4.3.3 provides a comprehensive overview of the various disruptions that may arise during the process. Finally, Section 4.3.4 examines the solving methods commonly employed in dynamic scheduling scenarios.

4.3.2 Strategies, policies and measures

In the context of dynamic scheduling, strategies refer to the types of dynamics employed. Three primary strategies are considered: completely reactive scheduling, predictive-reactive scheduling, and proactive scheduling [19].

Completely reactive scheduling: In this case no pre-schedule is established, and decisions are made in real-time as jobs enter the system. These decisions are typically local, reacting to immediate conditions without foresight into future events. They can handle a wide range of disturbances, due to the real-time and continuous decisions. Dispatching rules and heuristics are commonly employed in completely reactive approaches, offering rapid and straightforward implementation. However, their efficiency may be compromised by temporal myopia and the limited scope of information considered, often leading to suboptimal, or even unfeasible scheduling outcomes.

Predictive-reactive scheduling: In this strategy a pre-schedule is established, allowing for the rescheduling as needed throughout the process in response to disruptions and real-time events. This adaptive strategy permits deviations from the initial schedule. Uncertainty and unforeseen events can have two significant negative impacts on initial schedules. Firstly, it can degrade schedule performance, which is measured by comparing the realized schedule to the predictive one. This effect is known as robustness. A schedule is considered robust if its performance remains intact despite disruptions. Secondly, unexpected disruptions can lead to inconsistency, known as stability. A schedule is stable if the completion times of unaffected operations do not deviate from the original schedule in disrupted situations [254].

Several robustness and stability measures have been developed and compared in the literature [255, 256, 257]. For instance, the robustness measure can be computed as follows:

$$\rho = \frac{|Obj^r - Obj^p|}{Obj^p} \quad (4.1)$$

with Obj^r and Obj^p the realized and predictive objective function respectively. The stability measure can be computed as follows:

$$\sigma = \frac{\sum_{i=1}^{n'} \sum_{j=1}^{q'_i} |C_{ij}^p - C_{ij}^r|}{\sum_{i=1}^n (n_i - q'_i)} \quad (4.2)$$

where n represents the total number of operations, n' denotes the number of unfinished and being processed jobs, q'_i stands for the number of unfinished and being processed operations of job i , C_{ij}^p denotes the predicted completion time of operation j of job i in the pre-scheduling, C_{ij}^r represents the realized completion time of operation j of job i , and $(n_i - q'_i)$ indicates the number of operations to be rescheduled for job i [254]. These measures can be conflicting; while stability measures focus on the consistency of individual operation completion times, robustness measures focus on the overall performance degradation of the schedule. For instance, a stability-focused scheduling may aim to minimize deviations in completion times of unaffected operations, even if it means sacrificing overall schedule performance in the face of disruptions. On the other hand, a robustness-focused scheduling may prioritize maintaining overall schedule performance, even if this entails greater deviations in the completion times of individual operations. Consequently, in some cases, improving stability may lead

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to decreased robustness, and vice versa. Balancing these conflicting objectives is a major challenge in the design of efficient dynamic scheduling algorithms.

In predictive-reactive scheduling, various rescheduling policies can be implemented, dictating when to initiate rescheduling activities. Three primary types are identified in the literature: periodic-driven, event-driven, and hybrid policies. In the periodic-driven policy, rescheduling occurs at predetermined intervals, irrespective of disruptions or changes in the production environment. However, determining an optimal periodicity is crucial in this case because too frequent rescheduling can destabilize the schedule, while insufficiently frequent rescheduling may compromise responsiveness and efficiency [258]. Conversely, the event-driven policy triggers schedule adjustments in response to specific events or disruptions. This approach enables timely responses to disturbances, leading to rapid adjustments and the generation of new scheduling schemes. Yet, in environments with frequent disturbances, continuous rescheduling can undermine system stability. Some studies combine both policies, employing fixed rescheduling intervals while also considering sudden disturbance events [258]. This hybrid policy aims to balance the advantages of both approaches. The effectiveness of these policies depends on the types and frequencies of disruptions, with each having its own strengths and drawbacks [259].

When it comes time to reschedule, various approaches can be employed. Firstly, the schedule can be entirely regenerated, encompassing all ongoing and pending operations to create a completely new schedule. Alternatively, a schedule repair approach can be adopted. This can be executed in two ways: a partial repair or a right shift strategy. The right shift strategy involves postponing all remaining operations to ensure schedule feasibility. On the other hand, partial rescheduling targets operations directly or indirectly influenced by real-time events [260]. While the completely rescheduling strategy offers the broadest solution space, it often requires extensive search time. Local rescheduling strategies offer a more limited solution space but provide more stable rescheduling solutions. The improved right shift rescheduling strategy tends to be the simplest to implement [178].

Proactive scheduling: Proactive scheduling strategies aim to construct a predictive schedule that anticipates the effects of disturbances before they occur in the production process. Unlike the completely reactive and predictive-reactive strategies, which react to events in real-time, proactive scheduling seeks to prevent and mitigate disruptions by implementing preventive actions. One of the key challenges in proactive scheduling is determining robustness measures. To enhance the robustness of the schedule, diverse approaches can be deployed, including the integration of buffer times, fuzzy logic, stochastic or interval-based processing times [261], predictive models for unforeseen events like machine breakdowns or order changes [262], and the adoption of scheduling techniques tailored to specific manufacturing contexts. [263] delve into various types of uncertain parameters and the corresponding methodologies used to tackle them. Uncertainties can be modeled in three main ways: (i) bounded form, involving the use of intervals to estimate uncertainty. These intervals cover the full range of potential values for the uncertain parameter, and can be determined by analyzing historical data. Robust optimization is often employed for this type of uncertainty; (ii) probability description, where uncertainties are characterized by associated probabilities of events, interpreted in terms of their occurrence frequency. Stochastic programming, particularly with multiple stages, is suitable for handling this kind of uncertainty; (iii) fuzzy description involves fuzzy programming, utilizing fuzzy sets and membership functions based on possibility theory. A fuzzy set, governed by a membership function, quantifies the degree of membership to a set, with higher values indicating higher possibilities and lower values implying lower possibilities. By proactively considering potential disruptions and uncertainties, proactive scheduling enhance overall system performance, minimize delays, and improve

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productivity.

The three aforementioned strategies have been extensively explored in the literature, each offering its own set of advantages and drawbacks, which are summarized in Table 4.4.

Strategies	Advantages	Drawbacks
Completely reactive	real-time responsiveness flexibility (handle wide range of disturbances) simplicity (heuristic, dispatching rules)	local optimum, suboptimal based on immediate condition (no long term consequence or visibility)
Predictive-reactive	real-time responsiveness optimal or near-optimal solution long-term visibility	can lead to instability complexity to implement
Proactive	minimize impact of disturbances improve stability feasible solutions for every possible scenario	complexity (prediction models, scenarios) data dependency uncertainty can be unanticipated or overestimated

Table 4.4: Advantages and drawbacks of each dynamic approaches

Some studies have adopted a hybrid proactive-reactive approach, which blends elements of predictive-reactive and proactive strategies. These models seek to both preemptively address disruptions in the initial schedule, akin to proactive methods, while retaining the flexibility to reschedule in response to unforeseen events, similar to reactive approaches. These models are inherently complex to implement and solve. However, they offer distinct advantages such as minimizing the impact of disturbances on the pre-scheduled plan, thereby ensuring stability and capability to react effectively to unforeseen events that were not anticipated during the scheduling process [264].

4.3.3 Disturbances classification

In dynamic production processes, various disturbances may arise, potentially disrupting the production schedule to varying degrees. [265] recently classified disturbances into two types: gradual disturbances and abrupt disturbances. Gradual disturbances refer to fluctuations in parameters such as processing times. While they may not significantly impact operational stability or cause immediate disruptions, their cumulative effect gradually deteriorates process performance over time. On the other hand, abrupt disturbances, such as order insertions or machine breakdowns, have a significant impact on operational stability, often necessitating immediate readjustments to prevent unnecessary losses in production performance. Although both types of disturbances affect production performance, they require different handling strategies.

Disturbances can also be classified into two other types: job-related and resource-related [19]. Job-related disturbances encompass changes in market demand and customer orders, such as order cancellations, additions, modifications, alterations in due dates, or shifts in priority. Job-related disturbances can entail uncertainties in job parameters, including fluctuations in processing times, setup times, or release dates. On the other hand, resource-related disturbances are associated with disruptions affecting various resources throughout the production process. These disruptions may involve machine-related issues such as breakdowns, deterioration, maintenance activities, machine additions, breakdowns or charging of transportation equipment, uncertainties in transport times, and

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more. Furthermore, resource-related disturbances can also encompass worker-related issues such as absenteeism, fatigue, injuries, errors, or fluctuations in proficiency levels over time. While workers may enhance their skills and efficiency through learning, they may also experience forgetting and/or fatigue, leading to decreased efficiency. Lastly, disturbances may also arise due to shortages or delays in materials required for processing operations. To summarize, disturbances can be classified as presented in Table 4.5. Please refer to Table 4.2 for the nomenclature.

	Gradual	Abrupt
Job-related	CPT, UDD, UEC, UPT, URT, UST	CDD, DA, JA, OC, OI, OM, RP
Resource-related	CEP, MD, UTT	LM, Ma, MA, MB, TB, TC, WA

Table 4.5: Nomenclature and classification of disturbances

Generating disturbances in benchmarks can be challenging. For example, for simulating machine breakdowns, many studies rely on [255], where the probability of a breakdown is determined using an empirical relationship based on the workload of a machine divided by the total workload. This study distinguishes between breakdowns of long and short duration, and specifies two potential times for breakdown occurrences: early or late in the production process. In terms of job arrival, order modifications, or cancellations, their occurrence patterns often adhere to some predefined probability distributions [175], such as the Normal distribution [266] or the Poisson distribution [267]. As discussed in Section 4.3.2, uncertain parameters like processing times, due dates, setup times, or transport times are typically represented using bounded forms [268], probability distributions [269], or fuzzy numbers [270].

4.3.4 Solving approaches

The solving approaches employed in dynamic scheduling can be broadly categorized into two types: exact and approximate approaches [271]. Exact approaches like solvers, constraint programming, and backtracking search algorithms theoretically offer optimal solutions. However, their application in real-world scenarios is often impractical due to the computational complexity of the problem, as scheduling problems are generally NP-hard. Approximate approaches provide solutions that are close to optimal within a shorter time frame. The aim is to strike a balance between speed and solution quality. Among the various approximate methods, several categories stand out: heuristics, metaheuristics, rules, simulation, and artificial intelligence algorithms.

Metaheuristic methods

Metaheuristics, in particular, hold significant prominence across scheduling problems due to their efficiency. These methods excel in tackling complex problems by efficiently exploring and reducing the vast solution space. Their versatility allows them to adapt to a wide array of problems while remaining relatively simple to design and implement [272]. Metaheuristics can be categorized into three main types: evolutionary, nature-inspired and trajectory-based. The first category includes evolutionary algorithms, such as genetic algorithms, memetic algorithms and non-dominated sorting genetic algorithms, which excel in multi-objective optimization. Inspired by principles of natural selection and evolution, these algorithms manage a population of solutions at each iteration. The second category comprises nature-inspired algorithms, like particle swarm optimization, artificial bee

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colony optimization, and ant colony optimization, which mimic the collective behavior observed in nature. Lastly, trajectory-based algorithms aims to iteratively improving solutions by exploring their neighborhoods for potential enhancements.

Rules-based methods

The rule-based scheduling methods are called dispatching or priority rules. Several rules are commonly employed, including First-Come-First-Served (FCFS), Shortest Processing Time (SPT), Earliest Due Date (EDD), Critical Ratio (CR), Longest Waiting Time (LWT), Slack Time Remaining (STR), Longest Processing Time (LPT), Least Work Remaining (LWR), among others [273, 266]. However, the effectiveness of these rules can be limited by their narrow focus on available information, often resulting in suboptimal scheduling decisions. To address this limitation, some studies propose composite dispatching rules tailored to specific scheduling problems [52]. Moreover, recent advancements have seen the integration of dispatching rules with artificial intelligence methods, allowing for adaptive selection of dispatching rules based on the real-time state of the production process [266].

AI-based methods

In the realm of dynamic scheduling, artificial intelligence (AI) algorithms have emerged as a crucial component, with reinforcement learning (RL) and deep reinforcement learning (DRL) at the forefront. In fact, while traditional optimization techniques often struggle to adapt to the dynamic nature of such problems, AI-based approaches are increasingly showing their effectiveness and therefore emerge as the most prevalent. RL stands out for its adaptability to environmental uncertainty and its capacity for autonomous learning throughout the process. In RL, the state is the current environmental context, the action represents the choices available to an agent at each stage, and the reward signifies the consequence of an action taken in a particular state. This framework encourages agents to maximize rewards by reinforcing favorable choices and penalizing unfavorable ones. RL algorithms fall into three categories: model-free, model-based, and integrated approaches that combine both model-free and model-based methods. In model-free methods, we distinguish value-based methods, such as Q-Learning, and policy-based methods, like proximal policy optimization [274]. The DRL, an evolution of RL, revolutionizes the approach by substituting traditional action-state matrices with neural networks, effectively merging RL with the power of deep learning. It provides a robust framework for training agents to navigate in dynamic and complex environments. Nevertheless, DRL introduces its own set of challenges, including increased computational demands and the necessity for substantial data resources [275]. Multi-Agent Systems (MAS) play a vital role in resolving dynamic scheduling challenges by deploying intelligent agents capable of perceiving, reasoning, and acting within dynamic and uncertain environments. MAS leverages a diverse array of artificial intelligence techniques and methodologies, including game theory, machine learning, and optimization, to facilitate effective coordination and decision-making among autonomous agents [19].

Simulation-based methods

Simulation methods involve creating a computer model of a system to mimic its behavior over time. This model can represent the interactions and dynamics of different system components, enabling different scenarios to be explored and different scheduling strategies to be evaluated. Examples of

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simulation methods for dynamic scheduling include discrete-event simulation [276] and Monte Carlo simulation [106]. The most common solving methods for dynamic scheduling are regrouped and classified in Table 4.6. Please refer to Table 4.3 for the nomenclature.

Exact methods (EM)	Approximate methods (AM)						
	Metaheuristics (MH)			Rules (DR)	Artificial intelligence (AI)	Simulation (Si)	Heuristic (H)
	Evolutionary algorithms (EA)	Nature-inspired (NI)	Trajectory-based (TB)				
simplex, HA, BSA	GA, GP, NSGA, MA, EAD, GEP, EDA, CCA	PSO, JA, ABC, IA, ACO, TL, BFO, MS, ICA, MVO, WOA	TS, VNS, SA, GRAS, VDO	EDD, SPT, CR, LWR, FCFS, LPT, LWT, STR	RL, DRL, MAS, GT	DES, MC	H, HH

Table 4.6: Most used solving methods for dynamic scheduling

Figure 4.1 provides a comprehensive overview of the dynamic scheduling field, summarizing its diverse characteristics such as strategies, policies, approaches, types of disruptions, objective functions, and solving methods employed.

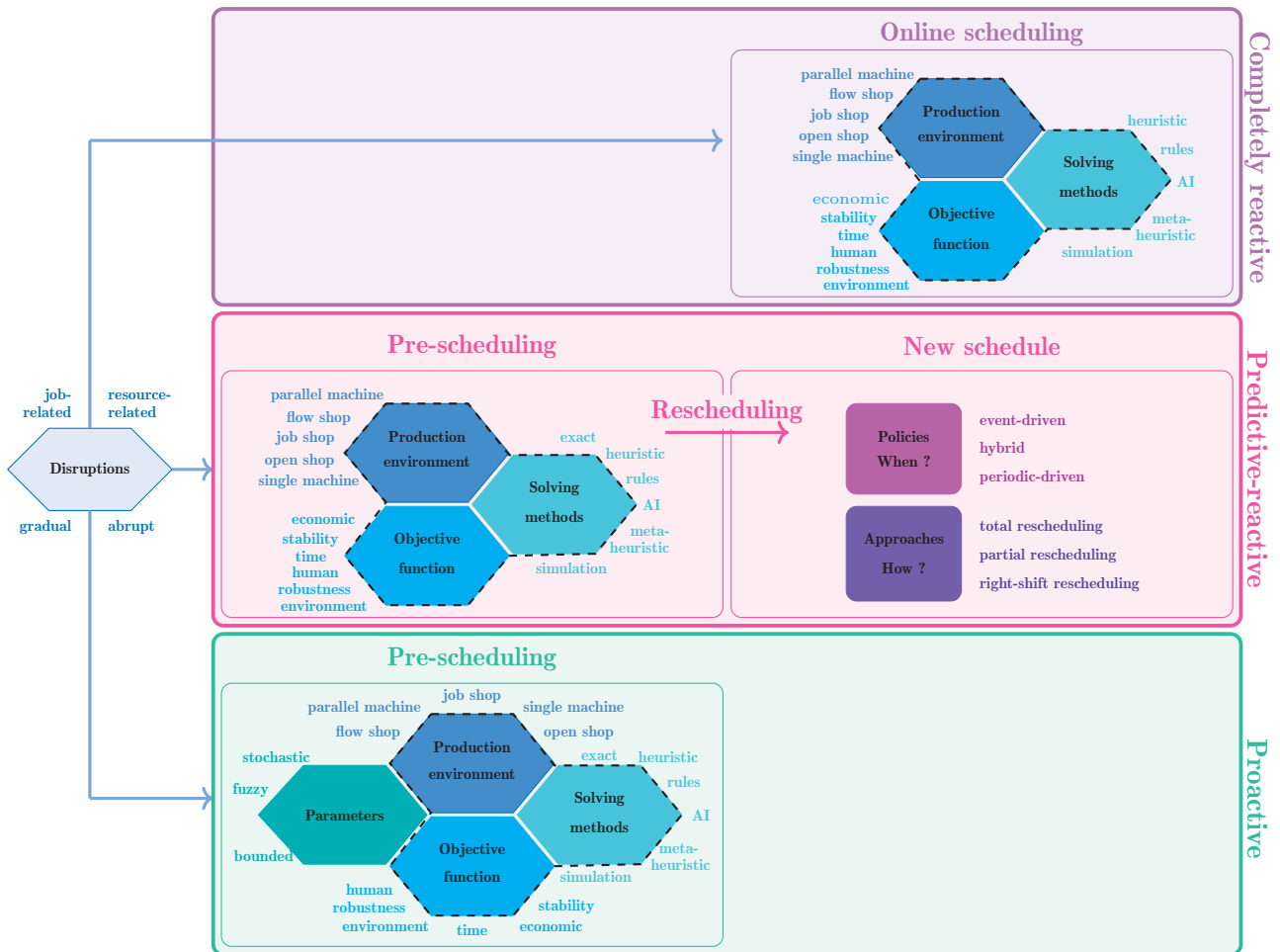


Figure 4.1: Dynamic scheduling problems characteristics

4.4 Research method

As previously mentioned, in this study, we investigate the Dynamic Flexible Job Shop Scheduling Problem (DFJSSP), given its extensive real-world applications among various scheduling problem types. Our search scope is limited to articles published since 2013 which aligns with the advent of Industry 4.0 [1]. This approach builds upon our previous research [26].

The first keyword of our exploration is “Flexible job shop scheduling”. To identify dynamic models pertaining to the FJSSP, we systematically combine this keyword with others, each capturing different dynamic aspects: “Dynamic”, “rescheduling”, “disturbance”, “disruption”, “robust”, “fuzzy”, “stochastic”, “real time”, “uncertain”, “predictive”, “reactive”, or “proactive”. By employing these twelve keywords, we aim to access articles addressing dynamic FJSSP across the completely reactive strategy, the proactive strategy, and the predictive-reactive strategy. Figure 4.2 outlines the framework of our research methodology. The research was conducted using Scopus database, where initially 465 papers were identified. Following a selection process tailored to our study’s objectives, we retained 247 papers. Further investigation into these papers, including their citations and references, led to the inclusion of an additional 37 papers. Additionally, search alerts identified 19 more relevant papers, bringing the total number of papers for our study to 303.

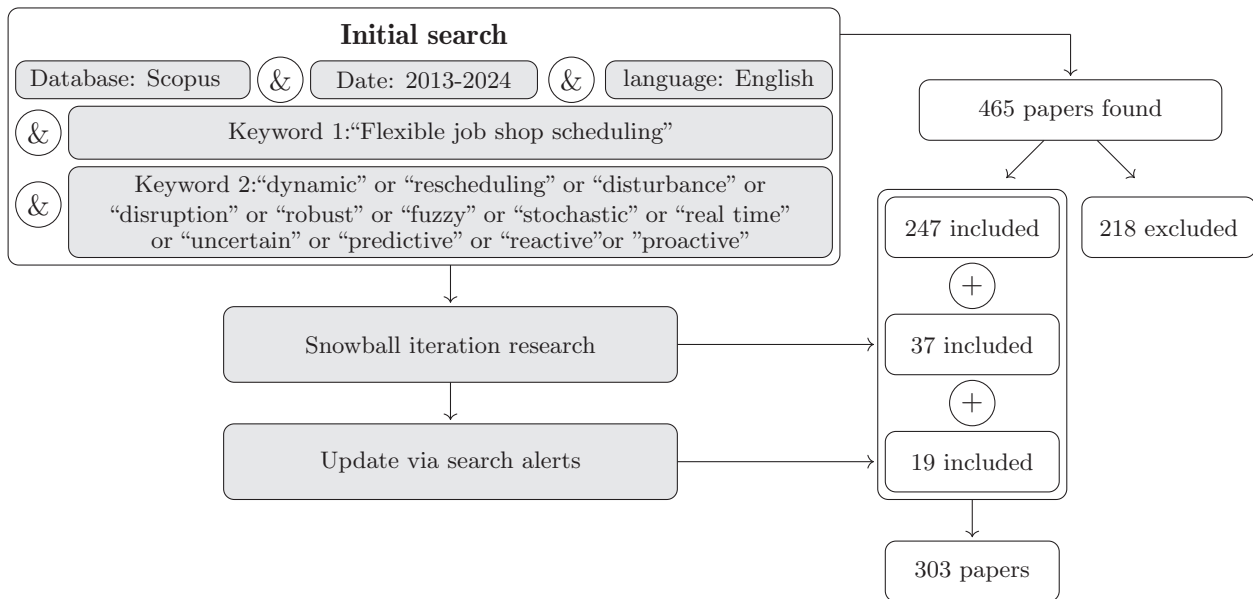


Figure 4.2: Research method

4.5 Results and Analysis

In this section, we present the 303 papers identified as mentioned in the previous section, along with an analysis. In the papers examined, authors utilize various datasets to validate their models. These datasets can either be generated specifically for the study or sourced from existing literature and studies. Utilizing existing datasets provides the advantage of facilitating result comparisons. When adopting data from previous studies, proper attribution is given to the original source. All datasets

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Zhu20 [312]	[5-12]	[24-150]	[32-200]		x			
Li21 [151]	[6-10]	[20-100]	[60-1000]			x x x	x	
Li21b [313]	8	15	[45-150]		x		x	x x x
An22 [314]		Gao15			x			
Gomez22 [315]	[8-10]	[15-20]	[225-500]		x	x x		x
Li22 [209]		Mk93					x	
Sun22 [316]	[6-15]	[10-20]		x	x			
Gomez23 [317]	[8-10]	[15-20]	[225-500]		x	x x		
Song23 [318]	[6-15]	[10-20]	[55-225]		x			

Mach.:Machines, W.:Workers, SU:setup, R:release date, D:due date, P:processing operation, T:Transport, MS:Machine Speed, I:Idle, TO:Turn on/off, S:Stand by, FP: fuzzy processing times, FD: fuzzy due dates, CP; change in processing times

Table 4.7: References and characteristics for data

4.5.1 Dynamic scheduling strategies

The 303 papers were categorized into three distinct strategies of dynamic scheduling. Specifically, we identified 92 papers (30%) focused on completely reactive models, 93 papers (31%) on proactive models, and 118 papers (39%) on predictive-reactive models (see Figure 4.3). The most frequently employed strategy is the predictive-reactive approach. Among the reviewed papers, we identified 10 articles that also exhibit proactive characteristics. However, for the purpose of our analysis, we classified them under the predictive-reactive paradigm due to their ability to adapt and reschedule in response to disruptions. Within predictive-reactive models, 2 primary types of rescheduling policies are distinguished: event-driven and periodic-driven. Event-driven policies, wherein rescheduling occurs in response to disruptions, are the most commonly utilized [319, 164]. However, periodic-driven policies are also employed, as demonstrated in studies such as [320] and [321]. Some research incorporates both approaches, resulting in hybrid policies [258]. Notably, [322] conducted a comparative analysis of these policies, revealing that while periodic rescheduling can yield better schedules in certain instances, it may be less responsive overall.

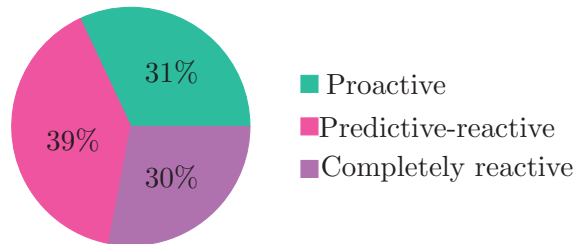


Figure 4.3: Percentages of dynamic types

To inventory the reviewed papers with the perspective of the three dynamic scheduling strategies, comprehensive lists of referenced papers are provided. These lists include the characterization of their specific features in terms of objective functions, disruption types, solving methods, and utilized data, as shown in the following tables: Table 4.8 for completely reactive studies, Table 4.9 for proactive studies, Table 4.10 for predictive-reactive studies, and Table 4.11 for proactive-reactive studies. In cases where a study considers multiple objectives related to the same criteria, they are noted into a

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single objective in the tables. For example, if a study evaluates both maximum tardiness and mean tardiness, it will be denoted as “T” for tardiness.

References	Objective	Disruption types	Solving methods	Instance used
[323, 267]	Cmax	JA	DRL(QL)/MAS	RGD
[324]	Cmax	JA	DRL(QL/Po)	RGD
[325]	Cmax	JA	DRL(Po)/DR	CS
[326]	Cmax	JA	MAS/RL(Po)/DR	RGD
[327]	Cmax	JA	GEP/VNS	RGD
[328]	Cmax	JA	MCTS	CS
[329]	Cmax	JA/UPT	DRL(QL)/DR	RGD
[330]	Cmax	JA/MB	DRL(QL)/GA/DR	RGD
[331]	Cmax	MB	MAS/PSO	Kcm02/RGD
[332]	Cmax	MB	DRL(Po)	-
[16]	Cmax	MB/UTT	DRL(Po)	Hurink94
[333]	Cmax	UTT	DRL(QL)/DR	CS
[334]	Cmax	NP	PR	Fattahi07/Mk93
[335]	Cmax	NP	DRL(Po)/MAS/DR	Hurink94/RGD
[266, 336]	Cmax/T	JA	DRL(QL)/DR	CS
[337]	Cmax/T	JA	DRL(QL)/DR	RGD
[338]	Cmax/T	NP	DRL(QL)/DES	RGD
[339]	Cmax/EC	JA	DRL(Po)/MAS	RGD
[165]	Cmax/EC	JA/MB	DRL(QL)/DR	RGD
[340]	Cmax/EC	JA/MB/OC	DRL(Po)/MAS	Mk93/Hurink94
[273]	Cmax/MW	JA/MB	GEP/DR	Mk93/RGD
[341]	Cmax/T/Fw	JA	GP/DR/HH	RGD
[342]	Cmax/T/Fw	JA	GEP/PR	TayHo08/Baker84
[303, 343]	Cmax/T/Fw	JA	GEP/H	RGD
[344]	Cmax/T/SU	JA	NSGA	Mk93/RGD
[345]	Cmax/E/T/Tr/Wt	NP	simulation	RGD
[346]	Cmax/C/MW	JA/MB	DRL(Po)/MAS	CS
[174]	Cmax/EC/MW	JA/MB	GT	Chan06/Wang20/CS
[347]	T	JA	DRL(Po)/DR	Luo20/Nie13/RGD
[348]	T	JA	DRL(Po)/DR/DES	Luo20
[52, 349, 350]	T	JA	DRL(QL)/DR	RGD
[351]	T	JA	DRL/GP/DR	RGD
[352]	T	JA	RL/DR/MAS	RGD/CS
[353, 354]	T	JA	GP/DES	RGD
[355]	T	JA/CDD/OM	DRL(Po)/DR	RGD
[356]	T/Fw	JA	GP/EAD	RGD
[357]	T/Fw	JA	GP/NSGAI	RGD
[358, 359, 360, 361, 362, 363, 364, 365, 366, 367, 368, 369, 370, 371]	T/Fw	JA	GP	RGD
[372, 373]	T/Fw	JA	GP/HH	RGD
[374]	T/Fw	JA	GP/HH/DR	RGD
[375]	T/Fw	JA	HH	RGD
[276]	T/Fw	JA/UPT	DES	RGD
[199]	T/EC	JA/MB	MAS/DR	He15/RGD
[200, 376]	T/EC	JA	GP/HH/DR	RGD
[53]	T/MW	JA	DRL(QL)/DR	RGD
[377]	T/MW	JA/MB	DRL(Po)/DR	RGD
[378]	T/MW	NP	DRL(QL)/MAS/DR	Mk93/RGD
[379]	T/Wt	DA/OC	MAS/HH	CS
[23]	E/T	JA	DRL(QL)/DR	RGD
[80]	E/T	JA	H/DR	CS/RGD
[380]	E/T/MW	JA	DRL(QL)/DR	CS
[381, 382, 383, 384, 385, 386]	Fw	JA	GP	RGD
[387, 388]	Fw	JA	GP/DR	RGD
[389, 390]	Fw	JA	GP/HH	RGD
[391, 392, 393]	Fw	JA	GP/HH/DR	RGD
[394]	Fw	JA	DES/GA	RGD
[395]	Fw	JA	GA/Sim.	RGD
[396]	Fw	JA	DRL(QL)/MAS	RGD
[397]	Fw/MW/EC	NP	HA/Sim.	CS

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[398]	Fw/MW/WiP	JA	DRL(QL)/DR	CS
[399]	MW	MB	GT	CS

RGD: generated, CS: case study

Table 4.8: Completely reactive

References	Objective	Disruption types	Solving methods	Data used
[400]	Cmax	UPT	GA	RGD
[401]	Cmax	UPT	GA	CS
[402]	Cmax	UPT	GA/PSO	Mk93/Hurink94/Chamb96
[270]	Cmax	UPT	GA/PSO	RGD
[403]	Cmax	UPT	GA/TS	Lei10/Lei12/Lei12b
[404]	Cmax	UPT	PSO	Lei10/Lei12
[405]	Cmax	UPT	PSO	Mk93
[406]	Cmax	UPT	PSO/BA/FA/CS	Mk93/Kcm02
[310]	Cmax	UPT	MVO	Lei10/Lei12/Gao15
[407]	Cmax	UPT	MVO/VNS	Lin19/Lei10/Lei12/Gao15
[408]	Cmax	UPT	ABC/VNS	Lei10
[409]	Cmax	UPT	JA/MC	Kcm02/Mk93/DP97/ Chamb96
[106]	Cmax	UPT	BSA/MC	Mk93/Kcm02/Chamb96
[410]	Cmax	UPT	BSA/HH	Lei10/Lei12/Gao15
[411]	Cmax	UPT	HH	Lei10/Lei12
[412]	Cmax	UPT	TL	Lei10/Lei12
[413]	Cmax	UPT	TL	Kim03
[414]	Cmax	UPT	Hybrid	Lei10/Lei12/Gao15/Mk93
[415]	Cmax	UPT	Hybrid	Fattahi07
[307]	Cmax	UPT	HS	CS
[416, 417]	Cmax	UPT	CCA	Lei10/Lei12
[418]	Cmax	UPT	NSGAI/TS	Muth63/Lawr84
[419]	Cmax	UPT	EDA	Lei10/Lei12
[420]	Cmax	UPT	BO	Lei10/Lei12
[421]	Cmax	UPT	GNHC	Lei10/Lei12
[422]	Cmax	UPT	FPA	Lei10
[423]	Cmax	UPT	ACO	CS
[268]	Cmax	UPT	MS	Zhu20/CS
[424]	Cmax	UPT	DRL(Po)/DR	Mk93/Hurink94
[425]	Cmax	UPT/UDD	GA	RGD
[426]	Cmax	UPT/UDD	QPSO	-
[427]	Cmax	UPT/MB	GA/VDO	CS
[428]	Cmax	MB	GA	-
[429]	Cmax	MB	DRL(Po)	CS
[90]	Cmax/R	UPT	EDA	Muth63/CS
[430]	Cmax/R	MB	QPSO	Kcm02/DP97/Mk93
[305]	Cmax/R	MB	NSGAI	Kcm02/Mk93/Li11
[431]	Cmax/R	MB	NSGAI	Mk93/Hinai11/RGD
[256]	Cmax/R	MB	NSGAI/ICA/NN	Mk93/RGD
[432]	Cmax/R	OC	solver	RGD
[433]	Cmax/R/S	MB	GA	Mk93
[434]	Cmax/R/S	MB	PSO	Jia07/Motag10/Mk93
[435]	Cmax/R/S	MB	TL	Mk93/Kcm02/RGD
[262]	Cmax/R/S	MB	BSA	Mk93/Kcm02/RGD
[436]	Cmax/R/T	URT	EAD	Kcm02/Xiong13
[269]	Cmax/R/MW	UPT	EAD	Mk93/Kcm02/Xiong13
[437]	Cmax/R/T/MW	NP	PSO	Mk93
[438]	Cmax/S	UPT	EAD/PSO	Mk93/Hurink94/DP97
[319]	Cmax/S	MB	simulation/NSGAI/ EA	Mk93/Kcm02
[209]	Cmax/MW	UPT	EAD	Lei10/Lei12/Gao15/Mk93
[439]	Cmax/MW	UPT	EAD	Jolai13/Lei10/Lei12
[237]	Cmax/MW	UPT	EAD/RL(QL)/VNS	Lei10/Lei12/Gao15/Mk93
[440]	Cmax/MW	UPT	EA	Gao15/Li22
[441]	Cmax/MW	UPT	NSGAI/PSO	Lei12
[442]	Cmax/MW	UPT	ABC	CS
[443]	Cmax/MW	UPT	BFO	Mk93

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[444]	Cmax/MW	UPT/UTT	MA	Lei10/Lei12/Mk93
[445]	Cmax/MW	JA/MB	MAS/DRL(QL)/GT	Mk93/Hurink94
[446]	Cmax/MW	MB	TL	Mk93
[261]	Cmax/MW/T	UPT/UDD	MS	Zhu20
[447]	Cmax/MW/Ag	UPT	ABC/VNS	Lei10/Lei12/CS
[448]	Cmax/T/E	UPT	NSGAI/simulation	-
[449]	Cmax/MW/C/S	OM/MB	GA	-
[450]	Cmax/C/E/T	UPT	Hybrid	RGD
[451]	Cmax/C/E/T/CE/ NP/Tr	MB/UPT	LR	RGD
[452]	Cmax/C/CE/CS	UPT/UDD/Ma	PSO/VNS	CS
[155]	Cmax/EC	UPT	EA	Li21
[453]	Cmax/EC	UPT	EA	Liu19/Li22
[454]	Cmax/EC	UPT	EA/IA	Mk93/Lei10/Lei12/Gao15
[455, 456, 457]	Cmax/EC	UPT	MA	Li21
[458]	Cmax/EC	UPT	MA/TS	Gomez22/23
[151]	Cmax/EC	UPT	AISA	Liu19/RGD
[146]	Cmax/EC	UPT	NSGAI	CS
[459]	Cmax/EC	UPT/UEC	WOA	-
[460]	Cmax/EC/MBP	MB	NSGAI	-
[461]	Cmax/EC/IC/Id	UPT/UTT	OFA	Adams88/Muth63/Mk93
[462]	Cmax/SL	UPT	TS/MC	Hurink94/Mk93
[463]	Cmax/SL	UPT	TS/MC	Hurink94/DP97
[464]	Cmax/Ag	UPT/UDD	MA	Wang12/Wang13
[304]	Cmax/Ag	UPT/UDD	NSGAI	-
[465]	Cmax/Fw	UPT	TL/GA	Lei10
[466]	Cmax/Q	UPT	SMO	CS
[467]	Cmax/Ag	UPT	GA/MC	CS
[468]	T	UPT/UDD	SA/MC	RGD
[469]	T	RP/URT	GA/simulation	RGD
[470]	T/Ot/R	NP	NSGA/TS	RGD
[471]	R	UPT	EDA	Mk93
[472]	E/T	UPT/UST	GA	CS
[473]	E/T/R	UPT	NSGAI/MC	Mk93/Hurink94
[317]	EC	UPT	MA	Gomez22/23
[315]	EC	UPT	MA	Lei10/Lei12/Lei12b/Mk93

RGD: generated, CS: case study

Table 4.9: Proactive

References	Objective	Disruption types	Solving methods	Data used
[474]	Cmax	JA	GA	RGD
[475]	Cmax	JA	GA	CS
[476]	Cmax	JA	GA/TS	Mk93
[477]	Cmax	JA	GA/DES/NN/ DR/PR	RGD
[478]	Cmax	JA	ABC	Kcm02/Mk93
[479]	Cmax	JA	ABC/RL(QL)	Mk93
[480]	Cmax	JA	DRL(Po)/DR	Mk93/Song23
[481]	Cmax	JA	DRL(QL)	RGD/CS
[482]	Cmax	JA	H	Birgin15
[483]	Cmax	JA	H/ML/TS	CS
[484]	Cmax	JA/MB	GA	Wu15
[485]	Cmax	JA/MB	GA/DRL(QL)	CS
[486]	Cmax	JA/MB	GA/SA/VNS	Lawr84/Wang17
[487]	Cmax	JA/MB	DR	RGD
[488]	Cmax	JA/MB/UPT	EDA	Lei10/Lei12
[489]	Cmax	JA/MB/OC	MAS/ACO	Kim03
[490]	Cmax	JA/MB/OC	ABC/TS	Kcm02/Gao15
[313]	Cmax	JA/MB/OC/CPT	MCTS	Mk93
[491]	Cmax	JA/MB/Ma	MA/GA/VNS	Mk93
[492]	Cmax	JA/MB/Ma/CPT	TS/MAS	CS
[493]	Cmax	JA/MB/TB	GA/VNS/MA	Mk93
[309]	Cmax	JA/MB/RP	GA	Wu15
[494]	Cmax	JA/UPT	ABC	CS

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[495]	Cmax	JA/OC	ABC	Hong03/Mk93
[496]	Cmax	JA/CEP	GA	CS
[497]	Cmax	JA/RP/Ma	GA	CS
[498, 499, 500]	Cmax	MB	GA	Mk93
[501]	Cmax	MB	GA	RGD
[502]	Cmax	MB	GA/ICA	Mk93
[503]	Cmax	MB	ACO	Mk93/Chamb96
[504]	Cmax	MB	ACO	DP97/CS
[505]	Cmax	MB	RL(QL)	Mk93
[506]	Cmax	UPT	ABC	Kcm02/Mk93
[507]	Cmax	NP	WOA	RGD
[508]	Cmax	NP	RL(QL)	CS
[162]	Cmax/EC	JA/MB	NSGAI	RGD
[163]	Cmax/EC	JA/MB	PSO	Jia07/Motag10/Mk93/ Lei18
[509]	Cmax/EC	JA/MB	SA	CS
[164]	Cmax/EC	MB	NSGAI	Wu18/Li21b
[166]	Cmax/EC	MB	GA/RL(QL)	Mk93
[161]	Cmax/EC	MB	PSO	He15
[510]	Cmax/EC	MB	MA	Wu18/Li21
[321]	Cmax/EC	MB/TB/LM/CPT	GA/simulation	CS
[511]	Cmax/EC	OI	MA	RGD/Chamb96/Mk93/ DP97
[512]	Cmax/EC	OC	MA	RGD
[120]	Cmax/EC/MW	JA	GT	Kcm02/He15
[513]	Cmax/EC/MW	JA/MB	NSGAI	Mk93
[514]	Cmax/EC/MW	MB	NSGAI	Mk93
[173]	Cmax/EC/MW	JA/MB/OC/RP	GT	Kcm02
[180]	Cmax/EC/S	JA	BSA	RGD
[247]	Cmax/EC/S	MB	RL(QL)/NSGAI	Meng20/Luo20b
[178]	Cmax/EC/S	RP/MD	NSGAI	Mk93/Wu18
[179]	Cmax/EC/R	JA/MB	PSO	Mk93/Wu18
[183]	Cmax/EC/T	MB/UPT	IA/GA	-
[515]	Cmax/EC/Q	RP/JA/MB	VVA	Mk93
[516]	Cmax/EC/C	MB/JA	ABC	CS
[517]	Cmax/EC/C/Q	MB	GA	RGD
[238]	Cmax/EC/Ag	JA/MB/UPT	IA/RL(QL)	An22
[48]	Cmax/EC/Ft	JA	GA	RGD
[518]	Cmax/S	JA/MB/CPT	simulation	CS
[258]	Cmax/S	JA/MB/CDD	QPSO	Mk93
[519]	Cmax/S	MB	MBO/GT	Kcm02/Mk93
[520]	Cmax/S	MB	TSO	Mk93/Kcm02
[521]	Cmax/S	MA	JA	CS
[522]	Cmax/S/MW	JA	NSGA	Mk93
[523]	Cmax/S/MW	MB	NSGAI	RGD
[524]	Cmax/S/MW/C	JA	QPSO	Kcm02/Mk93
[525]	Cmax/S/MW/C	JA/Ma	NSGAI	Gao15
[526]	Cmax/S/MW/Fw	JA	JA	CS
[527]	Cmax/S/MW/Fw	JA	JA	CS
[528]	Cmax/S/MW/T	MB/JA	MAS/IA	Kcm02/Mk93
[529]	Cmax/S/T	MB	NSGAI	Xia05
[322]	Cmax/S/T/Fw	JA/MB/CDD/OC	GRAS	Mk93/Kcm02/DP97
[530]	Cmax/S/T/Fw	JA/MB/CDD/OC	GRAS	Mk93/Lawr84/Gao06
[320]	Cmax/S/C	JA	EA	An22
[40]	Cmax/S/C/CE/Q	MB	LSA	-
[127]	Cmax/S/CE	UPT	ML	Hurink94/Mk93
[314]	Cmax/S/P	JA	NSGAI	Gao15
[531]	Cmax/S/R	MB	GT	Kcm02/Mk93/CS
[22]	Cmax/S/R	MB	GA	Kcm02/Mk93/Hinai11
[532]	Cmax/MW	JA/OC/MB/RP/ CPT/LM	BFO	Mk93/CS
[533]	Cmax/MW	NP	DEA	-
[239]	Cmax/MW/T	JA/OC/MA/Ma/MB	DRL(QL)/DR	RGD
[534]	Cmax/MW/C	JA	GA/SA	RGD
[259]	Cmax/MW/C	JA	NSGAI	Rui12
[535]	Cmax/MW/E/T	JA	H	CS
[536]	Cmax/C	JA	NSGAI/SA	RGD

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[537]	Cmax/C	JA	QPSO	CS
[538]	Cmax/C/Q	JA/MB/WA	GA	RGD
[539]	Cmax/Q	UPT	PR/simulation	CS
[102]	Cmax/T	CDD/DA/CPT/JA	DR	CS/RGD
[540]	Cmax/E/T/RP	JA/MB/OC	NSGAI	RGD
[541]	Cmax/St	JA	GA	Kcm02
[542]	T	JA	DRL(Po)	Hurink94
[543]	T/EC	JA	DRL(QL)/DR	Mk93
[175]	T/C/EC	UPT/URT/MB/ OM/OC/JA/CDD	NSGAI	CS
[544]	E/T	UPT	GA	-
[545]	E/T	Ma	GA	CS
[546]	E/T/WiP	JA	H	CS
[547]	E/T/MW/EC/S	NP	PSO	-
[548]	MW	JA	JA	CS
[549]	MW	JA	DRL (QL)	CS
[550]	EC	MB/JA	ACO	CS
[551]	S/R	MB	GT	Mk93/Lee94/Mesgh97/ Kcm02
[552]	C	OC/MB/RP/OM	H	RGD

RGD: generated, CS: case study

Table 4.10: Predictive-reactive

References	Objective	Disruption types	Solving methods	Data used
[553]	Cmax	MB	GA	-
[554]	Cmax	MB/UPT	GA	CS
[555]	Cmax	JA/MB/TB/TC	PSO/GA	CS
[556]	Cmax	JA/MB/OC/WA	RL(QL)	Sun22
[557]	Cmax/R/S	MB	GA	Kcm02/Mesgh97/Lee94/ Mk93
[264]	Cmax/R/S	MB	GA/H	CS
[558]	Cmax/T/MW, S	JA/MB	EA	RGD
[559]	T	JA/MB	H	Fattahi07
[560]	T/Fw	JA/MB/OC	simulation	-
[561]	T/M	JA/MB/CDD/MD/Ma	GA	Fattahi07

RGD: generated, CS: case study

Table 4.11: Proactive-reactive

The 303 papers identified and reviewed in this article come from 134 different scientific journals. We highlight the top 10 journals publishing DFJSSP in Figure 4.4. These selected journals account for 7.5% of the total number of journals but have collectively published 104 out of 303 papers, or 34.3%. The figure shows that certain journals tend to favor certain strategies of dynamic scheduling over others. For instance, IEEE Congress on Evolutionary Computation and IEEE Transactions on Evolutionary Computation have a higher concentration of publications on completely reactive models, whereas Computers & Operations Research predominantly focuses on proactive and predictive-reactive approaches, with no publications on completely reactive models. This discrepancy underscores the diversity in methodologies and applications associated with the three dynamic strategies.

Figure 4.5 illustrates the evolution of the number of articles published over the years, revealing a clear upward trend. Notably, the study of completely reactive models was limited before 2019, but an increasing number of papers have since begun to focus on these models. This reflects the need for real-time information and advanced technology for this kind of dynamic scheduling, making such models more relevant today. Similarly, proactive and predictive-reactive models have also seen an upward trajectory, with a peak in publications observed in 2022 and 2023. This trend underscores the increasing significance attributed to dynamic scenarios and disruptions during the process. Note that

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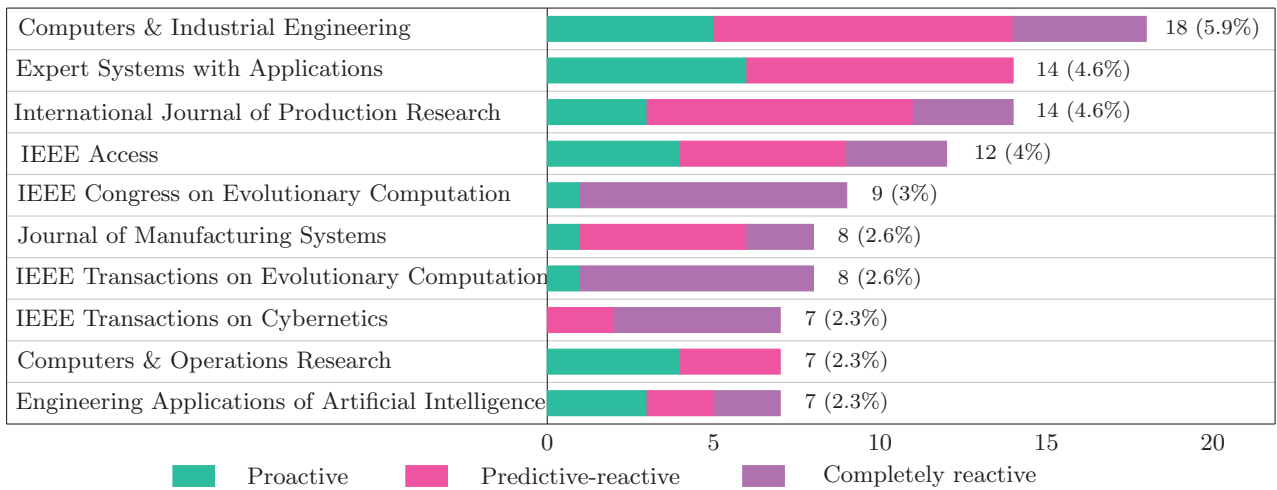


Figure 4.4: Top 10 journals publishing dynamic flexible job shop

the small number of articles from 2024 is because the year has just begun, so this does not indicate a decline in dynamic scheduling models in any category.

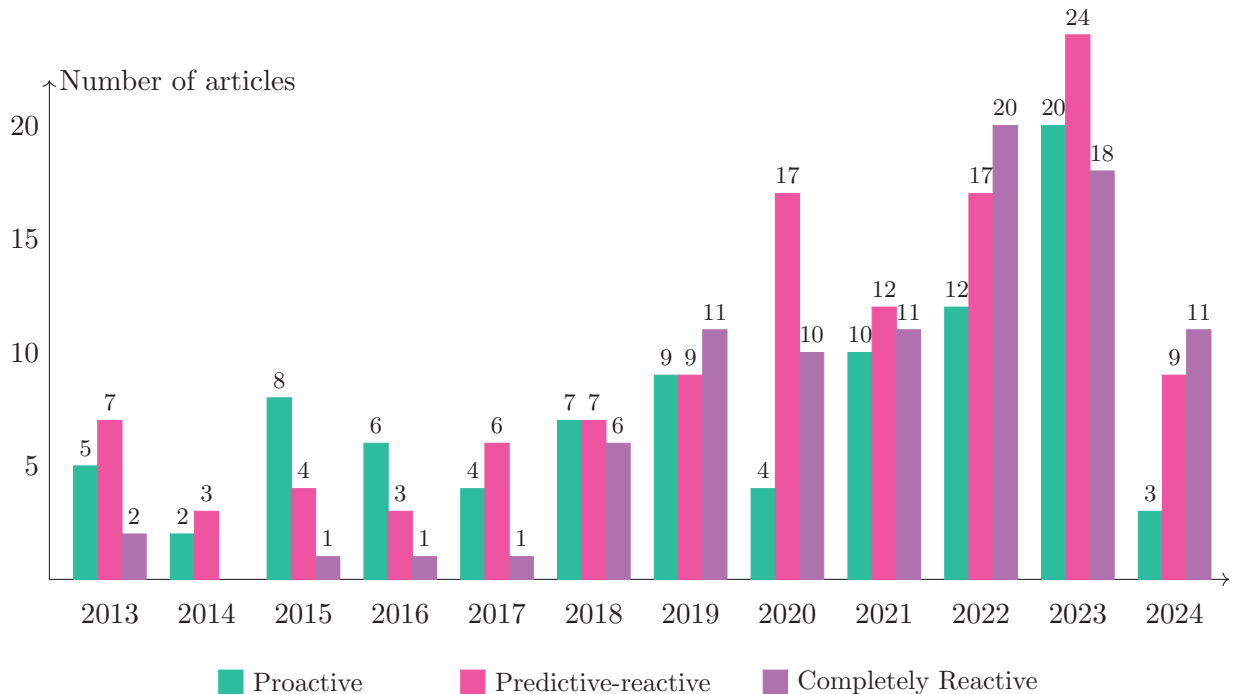


Figure 4.5: Enumeration of the surveyed literature

4.5.2 Disruption types

Among the 21 disruption types (see Table 4.2) identified in the reviewed articles, the top 10 most studied disruptions are illustrated in Figure 4.6. Notably, job arrival (JA) event emerges as the most studied disruption in both predictive-reactive and completely reactive models. In the context of completely reactive models, jobs often arrive during the processing and are not predetermined. Consequently, they are scheduled upon arrival in the system. Conversely, in predictive-reactive models, some jobs are known during the initial scheduling, and if new jobs arrive during the process, a rescheduling mechanism is employed to integrate the new arrivals. In predictive-reactive models, machine breakdown emerges as the second most studied disruption. Similar to job arrival, machine breakdowns are unpredictable and not known in advance. Consequently, a rescheduling process is initiated in response to breakdown occurrences. The most studied disruptions in proactive models are uncertain processing times of operations. These disruptions entail representing processing times using methods such as fuzzy numbers, stochastic models, gray intervals, etc. The actual processing times are revealed during the execution process, requiring the model to accommodate the various potential processing time scenarios. Moreover, 7 papers focus on the uncertain due dates of operations, employing proactive approaches. Furthermore, proactive strategies are employed to manage machine breakdowns. In these scenarios, the probability of breakdowns is considered to anticipate and mitigate potential disruptions. Additionally, preventive maintenance activities may be incorporated to proactively address and minimize the occurrence of breakdowns. Another disruption that is often studied is order cancellation, particularly in predictive-reactive approaches. In such scenarios, a job is initially scheduled but is later canceled during the processing, causing disruptions to the system. A rescheduling may be effective in minimizing idle times on the machines concerned. Besides, reprocessing operations [178], maintenance activities [497], changes in due dates [258], and changes in processing times [102] are also frequently studied. Moreover, there are 12 studies that do not explicitly detail the disruptions considered, particularly in completely reactive models. In such instances, where jobs are processed upon arrival in the system, all disruptions are managed in real-time.

In summary, job arrivals, machine breakdowns, and uncertain processing times are the three disruptions that have been the most widely studied. Conversely, other disturbances have received much less attention. Among the 303 papers, 70% exclusively focus on a single disruption type, while 26% consider multiple disruption types within the same model. The remaining 4% do not specify the disruptions considered. More specifically, 77% of the completely reactive models, 80% of the proactive models, and 54% of the predictive-reactive models concentrate on a single disruption. In contrast, 15% of the completely reactive models, 18% of the proactive models, and 42% of the predictive-reactive models explore multiple disruptions.

4.5.3 Objective types

Regarding objective types (see Table 4.1), the makespan (C_{max}) is undoubtedly the most extensively studied in the literature and is widely recognized and utilized in scheduling problems. Figure 4.7 emphasizes the significant disparity between the makespan and other objectives under consideration. Out of the 303 papers, 73% focus on optimizing the makespan. Among these, 43% are mono-objective studies solely concentrating on the makespan, representing 31% of the 303 studies. However, for completely reactive models, the criteria of tardiness and flow time exceed the makespan in terms of the number of considerations. Specifically, researchers from Victoria University of Wellington in Kelburn,

4.5. RESULTS AND ANALYSIS

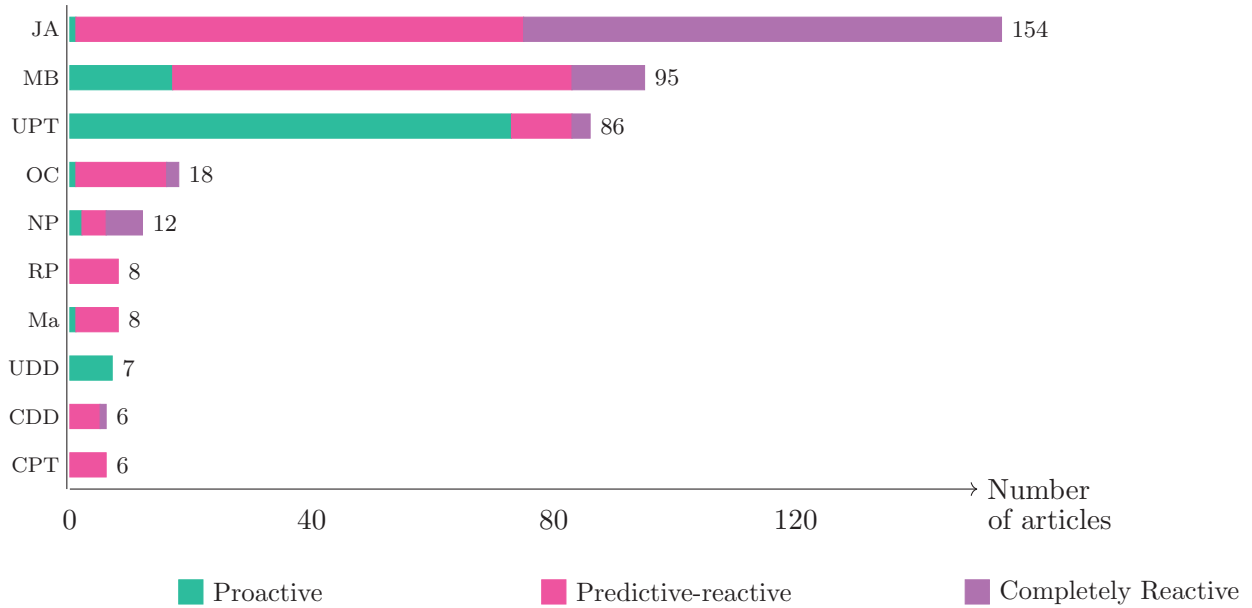


Figure 4.6: Enumeration of the 10 most studied disruptions type

New Zealand, and another group from Beihang University in Beijing, China, have extensively studied these two criteria and published numerous papers on completely reactive models [359, 375]. These researchers have particularly focused on metrics such as mean flow time, maximum flow time, mean weighted flow time, mean tardiness, maximum tardiness, and maximum weighted tardiness. In proactive and predictive-reactive models, respectively 91% and 88% of studies consider the makespan, either as a single-objective function or as one of the objectives in a multi-objective function.

Machine workload (MW) is extensively investigated across all three strategies, particularly focusing on the minimization of either the maximum or mean machine workload.

Another extensively studied objective function involves minimizing energy consumption throughout the process, encompassing energy consumed by machines, transportation equipment, auxiliary machinery, setup, loading, and power cycling. This criterion has received significant attention over the past 4 years, reflecting a growing awareness of environmental concerns [26]. However, studies focusing on the minimization of energy consumption in completely reactive models remain relatively rare. Less frequently, another environmental criterion, namely carbon emissions, is minimized in proactive or predictive-reactive models [452, 127].

Robustness criteria are primarily incorporated into proactive models, where the ability to anticipate and mitigate disruptions during the process is crucial. Conversely, stability measures are predominantly integrated into predictive-reactive models, where rescheduling occurs in response to disruptions. Stability aims to ensure that the rescheduled plan closely resembles the initial schedule, minimizing disruptions to the process as much as possible.

The following two criteria that receive considerable attention are costs (including machinery, energy, tardiness, etc.) and earliness. Less commonly, production quality is considered as an objective function, as evidenced by a few studies [515, 40]. Additionally, the agreement index, examined in studies by [447, 464, 467], aims to maximize either the minimal agreement index or the average agreement

index. The work by [462, 463] focuses on optimizing the service level, corresponding to the probability of a classical criterion (the makespan in their studies) to be smaller than a specified threshold. The authors believe that this criterion is relevant for real life applications and should be analyzed with other criteria such as tardiness. Two papers [451, 345] focus on minimizing transportation time or distance, while the second study also incorporates the waiting time of operations, a criterion also studied in [379]. Additional criteria such as idle resources, worker fatigue or stress, space utilization, profit, etc., are rare and considered in a limited number of studies.

In summary, the makespan is the most commonly used objective in predictive-reactive and proactive models, while flow time and tardiness are prevalent in completely reactive models. Certain other criteria receive considerable attention, including energy consumption, machine workload, stability, robustness, and costs. However, the exploration of other criteria remains relatively limited in the literature.

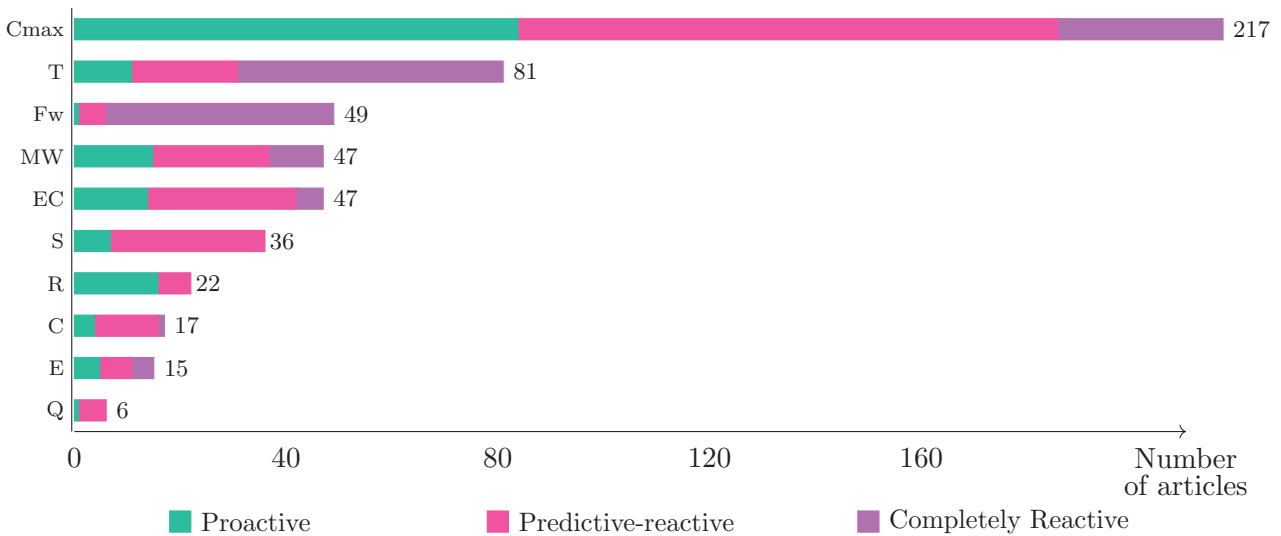


Figure 4.7: Enumeration of the 10 most used objective

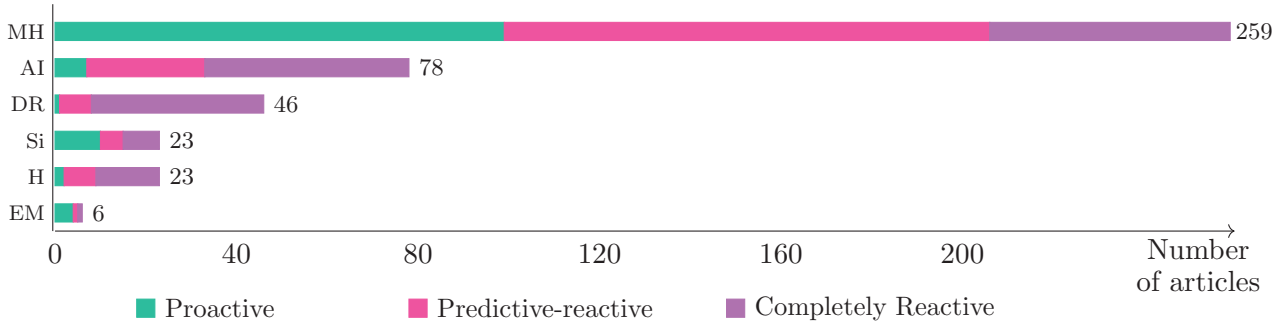
4.5.4 Solving methods

Various solving methods, detailed in Table 4.3, have been proposed in the reviewed articles. In 35% of them, hybrid methods are employed, which combine multiple approaches. Among these approaches, we can find exact methods (EM), heuristics (He), metaheuristics (MH), rules (DR), simulation (Si), and artificial intelligence (AI) methods. The distribution of the utilized approaches according to these types and according to the different dynamic scheduling strategies is described in Figure 4.8. Metaheuristic approaches are the most prevalent, used in 85% of the 303 papers. Artificial intelligence algorithms constitute the second most common method, present in 26% of the papers, particularly prevalent in 49% of the completely reactive models. Dispatching and priority rules are found in 15% of the papers, also prevalent in completely reactive models, while simulation and heuristic methods are utilized in 7.6% of them. In particular, Monte Carlo simulation is employed in 7 proactive models [106, 462, 467], and discrete event simulation in 5 completely reactive models [338, 353, 354].

Exact methods are employed in only a small fraction, around 2%, of the published papers on this

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topic. This is due to the inherent complexity of the scheduling problems being considered, which often involve a large number of variables and constraints. The most applied is backtracking search algorithm, mostly in proactive models [106, 410]. Specifically, completely reactive models often leverage artificial intelligence or metaheuristics in conjunction with rules or heuristics. Metaheuristics are prevalent in proactive models, while predictive-reactive models also commonly utilize metaheuristics, occasionally in combination with artificial intelligence methods.



MH: metaheuristics, AI: artificial intelligence, DR: rules, Si: simulation, H: heuristics/hyper heuristics, EM: exact methods

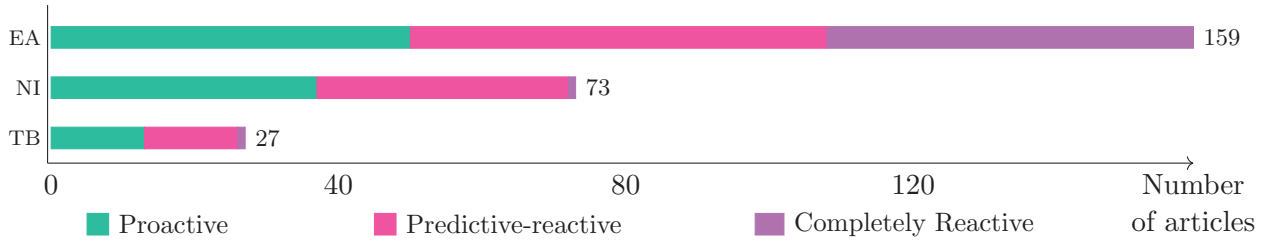
Figure 4.8: Solving methods used

Metaheuristics can be categorized into three main groups: evolutionary-based, nature-inspired, and trajectory-based algorithms. As depicted in Figure 4.9, evolutionary algorithms are the most frequently utilized across all three strategies. Particularly, in completely reactive models, this category of metaheuristic is predominantly employed, with genetic programming being utilized in 45% of cases. Notably, researchers from Victoria University of Wellington in Kelburn, New Zealand, have extensively focused on genetic programming for these models [359], often integrating hyper-heuristics [372] or dispatching rules [393].

Additionally, other evolutionary algorithms such as gene expression programming, non-dominated sorting genetic algorithms, genetic algorithms, and evolutionary algorithms based on decomposition are also employed to solve these models. Proactive models also heavily rely evolutionary algorithms, particularly genetic algorithms [400, 401], non-dominated sorting genetic algorithms [444, 455], and memetic algorithms [418, 305]. Nature-inspired algorithms are also widely employed to solve proactive models, with notable usage of particle swarm optimization [404, 405], teaching learning optimization [412, 413], and artificial bee colony algorithms [408, 447]. Trajectory-based algorithms, such as local search methods, are often combined with other techniques. In proactive models, tabu search [403, 418] and variable neighborhood search [407, 237] are among the most commonly found.

Finally, in predictive-reactive models, evolutionary algorithms remain prevalent, with genetic algorithms [474, 475], non-dominated sorting genetic algorithms [162, 164], and memetic algorithms [510, 512] being widely utilized. Nature-inspired metaheuristics such as artificial bee colony algorithms [478, 479], particle swarm optimization [179, 547], ant colony optimization [489, 503], and the Jaya algorithm [526, 527] are commonly employed. Trajectory-based methods, including simulated annealing [486, 509] and tabu search [490, 492], are also utilized for predictive-reactive strategies.

Figure 4.10 provides a detailed overview of the various artificial intelligence methods employed in the three strategies:



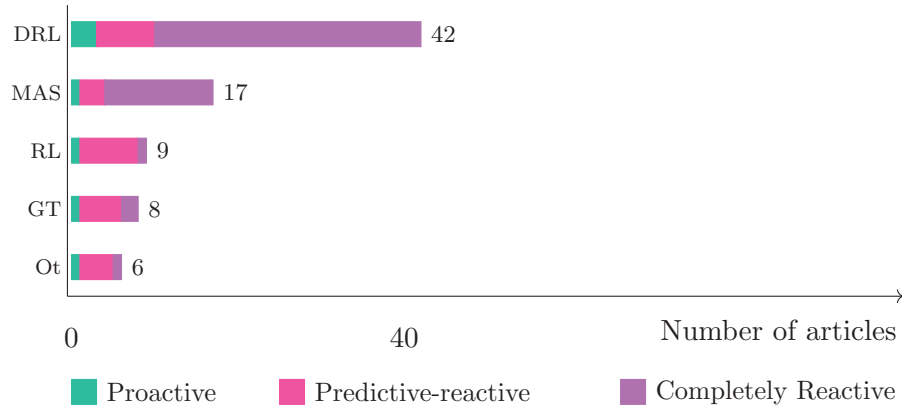
EA: evolutionary algorithms, NI: Nature inspired, TB: trajectory based

Figure 4.9: Details on the metaheuristics used

- In completely reactive models, deep reinforcement learning is extensively utilized. Specifically, we observe that 21 papers utilize a combination of value-based methods (such as Q-Learning) with neural networks [323, 267], while 11 studies integrate policy-based methods with neural networks [332, 325]. Many of these studies employ deep reinforcement learning to train models in selecting optimal dispatching rules based on the current system state. Additionally, 13 studies leverage multi-agent systems, where multiple autonomous agents (such as products, machines, etc.) collaborate to achieve a common goal [199, 378]. These approaches are often combined with metaheuristics, dispatching rules, or other artificial intelligence methods to address the challenges of completely reactive FJSSP.
- In the case of predictive-reactive models, 8 studies utilize Q-Learning techniques to train systems to respond to disruptions. Specifically, Q-Learning is employed to select the best rescheduling strategy [166] or adjust algorithm parameters dynamically based on system states [247]. Deep reinforcement learning algorithms find application in predictive-reactive models, using both value-based and policy-based approaches. For instance, [549] employ deep reinforcement learning with Q-Learning to optimize rule selection, while [480] utilize proximal policy optimization to determine the optimal pairing of machines and AGVs for each operation. Furthermore, 5 predictive-reactive studies incorporate game theory approaches to achieve effective rescheduling, aiming to identify the Nash equilibrium [173, 519, 531, 551]. Notably, [120] employ an infinitely repeated game framework, allowing players to interact repeatedly over time and make strategic decisions in each round. In the context of FJSSP, players are analogous to objective functions, each with its utility function and strategies. In the category “other”, we classified algorithms such as random forest classifier, support machine vector, multi-layer perceptron [483] and ensemble deep forest [127], deep learning with neural networks [477] and Monte-Carlo tree search algorithms [313].
- Regarding proactive models, the artificial intelligence methods are not commonly used.

In summary, metaheuristic methods are extensively employed in solving DFJSSP across all three strategies, frequently in combination with other approaches. Among these, evolutionary algorithms are the most prevalent. Artificial intelligence methods also play a significant role, frequently utilized to train models in selecting optimal dispatching rules or rescheduling strategies in completely reactive and predictive-reactive models respectively.

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RL: Reinforcement learning, DRL: Deep RL, MAS: Multi-agent systems, GT: Game theory, Ot: other

Figure 4.10: Details on the artificial intelligence methods used

4.5.5 Sustainable criteria

In the current context of Industry 5.0, the integration of environmental and social considerations is increasingly recognized as essential [9]. Minimizing energy consumption and carbon emissions during industrial processes form a significant focus in the effort of integrating environmental factors into operational decision-making. However, addressing social factors presents a more intricate challenge, encompassing not only workers’ skills but also their safety and overall well-being in the workplace [27]. To truly foster prosperity, industries must incorporate social, environmental, and economic considerations [70]. In Figure 4.11, the 303 reviewed studies are categorized into four groups: those focusing solely on economic aspects, those integrating environmental criteria, those incorporating social aspects, and those encompassing all three.

Economic considerations are naturally addressed in all papers, reflecting their fundamental importance. While the environmental aspect has garnered increasing attention, particularly in recent years, the social factor remains relatively underexplored in the domain of DFJSSP. Notably, both environmental and social aspects receive limited attention in completely reactive models. The works of [48, 40, 451, 459] integrate the three factors—economic, environmental, and social—into sustainable scheduling practices.

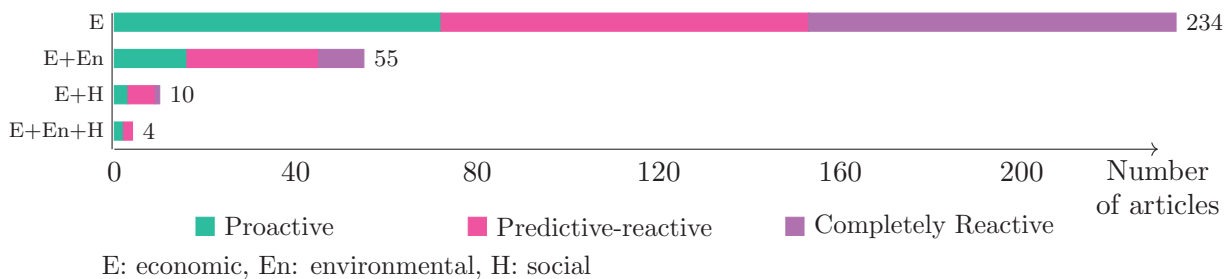


Figure 4.11: Sustainable factors used

Concerning the environmental aspect, only one disruption type has been identified: uncertain power consumption for a machine to perform a task [459]. In terms of the objective function, the environmental aspect is extensively explored among the 303 papers. Specifically, 44 studies—comprising 3 completely reactive, 14 proactive, and 27 predictive-reactive models—focus on minimizing energy consumption during the process. Furthermore, 4 proactive and predictive-reactive models aim to minimize carbon emissions, which are closely associated with energy consumption.

In terms of social factors, [540] and [48] look into human fatigue. In [540], the authors aim to minimize rejected products resulting from worker errors, impacted by worker fatigue. In [48], the study focuses on directly minimizing the maximum human fatigue rate. Another study incorporates worker stress levels into the objective function, correlating them with various rescheduling strategies [541]. The underlying assumption is that reducing potential disruptions to the existing schedule will lead to a reduction in workers' stress levels. Among the disruption types studied, only two are related to workers: worker absence [538, 556] and changes in worker proficiency [496]. These disruptions are examined in just 3 papers. Worker absence is treated similarly to machine breakdown, considering the worker as an unavailable resource. Changes in worker proficiency may occur due to fatigue or prolonged engagement in repetitive tasks.

In summary, among the three sustainability criteria, economic and environmental considerations are prevalent in DFJSSP. In contrast, disruptions caused by workers and the optimization of workers' safety and well-being are at an early stage of research. However, considering that operator errors are responsible for about 60%–90% of failures in a system [17], focusing on workers skills, safety and well-being could enhance the resilience and the robustness of the system.

4.6 Conclusion and future research perspectives

The dynamic nature of production scheduling has led to a surge of research interest in the DFJSSP over the past decades. This interest continues to increase, driven by advancements in technology that enable greater responsiveness and data collection capabilities. DFJSSP extends the classical job shop scheduling problem by incorporating flexibility in machine assignments and accommodating dynamic changes in the production environment. These complexities necessitate sophisticated optimization techniques and real-time decision-making capabilities.

By exploring diverse scheduling strategies and policies, different disturbances types, various objective functions, and numerous solving methods, this paper synthesizes findings from 303 studies on DFJSP since 2013. The aim is to provide a comprehensive overview of the current state-of-the-art in this domain, highlighting emerging trends and identifying challenges that merit further investigation in future research.

As stated in the introduction, our survey aims to answer the following questions:

- Q1: The DFJSSP can be categorized into three main strategies: predictive-reactive, proactive, and completely-reactive scheduling. The predictive-reactive strategy involves creating an initial schedule with the option to reschedule if needed. The proactive strategy aims to anticipate and mitigate disruptions in advance. The completely-reactive strategy does not rely on a pre-schedule but makes scheduling decisions in real-time as the process unfolds. Each strategy has its advantages and drawbacks: the completely-reactive approach is more responsive and simple but tends to be shortsighted; the predictive-reactive approach is near-optimal and capable of

responsiveness but can be complex to implement; and the proactive approach is more stable and robust but involves high complexity. Among these strategies, various disturbances can be considered, including abrupt and gradual disruptions. In the literature, the most studied DFJSSP approach is the predictive-reactive strategy, with a focus on disturbances such as job arrivals and machine breakdowns.

- Q2: Various approaches, policies, and solving methods are used in addressing DFJSSP. The most effective methods vary according to the strategy employed, but hybrid methods, which combine multiple solving techniques, are widely used. For completely-reactive models, artificial intelligence, particularly deep reinforcement learning, is often combined with dispatching rules. In proactive and predictive-reactive models, metaheuristics, especially evolutionary algorithms, are the most common. In predictive-reactive scheduling, combining event-driven and periodic-driven rescheduling tends to yield good results by leveraging the advantages of both. Proactive models frequently manage disruptions using fuzzy logic or stochastic models.
- Q3: Currently, DFJSSP encompasses several challenges. First, handling multiple uncertainties and disturbances within the same model remains difficult, as different types of disruptions require different treatments. For instance, gradual disruptions and abrupt disruptions are not managed in the same way. Selecting the appropriate dynamic strategy, approach, policy, or solving method is still a complex issue. Secondly, as the complexity of the scheduling problem grows exponentially, developing solutions that can efficiently handle large-scale instances remains a persistent challenge. Addressing these challenges requires continuous research and innovation in algorithms, technologies, and methodologies to improve the efficiency and effectiveness of DFJSSP solutions.
- Q4: Among the emerging ideas and trends in DFJSSP research, we pointed out the following:
 - Integration of sustainability and human-centric approaches: The current focus on Industry 5.0 emphasizes reducing energy consumption, pollution, and waste while optimizing resource utilization to achieve greener manufacturing processes. Enhancing human-machine collaboration, prioritizing human safety, and ensuring well-being at work are also key trends. As workers are unique, their potential to introduce uncertainties and disruptions requires further consideration.
 - Developing robust and resilient scheduling: There is a growing trend towards creating scheduling systems that are both robust and resilient. This involves anticipating disruptions as accurately as possible while also being capable of quickly returning to a state close to the initial schedule when disruptions occur.
 - Continual integration of new technologies: Ongoing research focuses on integrating emerging technologies into scheduling problems, including advancements in artificial intelligence, real-time data analytics, and the Internet of Things (IoT). These emerging ideas and trends are driving the evolution of DFJSSP research, leading to more advanced, flexible, and efficient scheduling solutions that can better meet the demands of modern manufacturing environments.

Machine Learning-Driven Solutions for Sustainable and Dynamic Flexible Job Shop Scheduling under Worker Absences and Energy Disruptions

Abstract

This paper addresses the Dynamic Sustainable Flexible Job Shop Scheduling Problem (DSFJSSP) by considering the human and environmental factors along with their associated disturbances. It specifically focuses on disruptions caused by worker absences and fluctuations in renewable energy production. Furthermore, this paper integrates human skills, energy consumption (including operational, transport, and auxiliary equipment), as well as setup, transport, and travel times. We modeled the considered DSFJSSP as a multi-objective non-linear integer programming model and employed three machine learning-based methods to compare its effectiveness in adapting to changes caused by disruptions. Obtained results highlight the importance of incorporating both human-related disruptions and renewable energy variability to improve resilience and sustainability of job shop scheduling systems.

Keywords: Dynamic scheduling, Flexible job-shops, Machine learning, Sustainability, Worker absences, Energy variation

5.1 Introduction

Industrial globalization and growing demand for customized, high-quality products have compelled industries to continually improve their processes to meet customer expectations. Historically, these improvements have been primarily driven by economic reasons, often at the expense of environmental sustainability [14]. As a result, significant amounts of non-renewable resources have been consumed, especially over recent decades, leading to significant production of waste and pollution across all levels: soil, water, and air. Today, many developed nations are expressing serious concerns about global warming, the depletion of fossil fuels and overall environmental degradation. Consequently, optimizing energy use and reducing greenhouse gas (GHG) emissions have become critical objectives in the industrial sector. In response to these challenges, manufacturing companies are increasingly investing in energy-saving technologies and sustainable practices that can balance financial gains with

environmental consideration [562]. This shift towards a sustainable industrial paradigm is now a necessity in a context of accelerated climate change and its growing impacts.

In addition to environmental considerations, human well-being is a cornerstone in sustainable manufacturing. Today, a strong emphasis is placed on worker health and safety, promoting for ergonomic work environments that reduce physical strain and protect against occupational hazards. By prioritizing human well-being, industries can improve productivity and foster a culture of safety and inclusion, where employees and machines collaborate together harmoniously. This approach not only safeguards the workforce, but also strengthens the long-term sustainability of industrial operations by fostering a more resilient and motivated workforce.

In this context, the concept of Industry 5.0 has emerged as a revolutionary approach, focusing not only on automation and efficiency, but also on human-machine collaboration, innovation and environmental harmony [12]. At the heart of Industry 5.0 are the principles of sustainability, resilience and human-centricity, which collectively address the urgent need for industries to operate in a more environmentally responsible manner. This approach promotes the adoption of processes that are not only economically sound but also beneficial to consumers, employees, the environment, and society as a whole [10]. The aim is to manufacture goods using methods that minimize environmental impacts, conserve energy and resources, and ensure safety for all stakeholders. Initially, sustainable manufacturing was seen as a strategy to reduce the environmental footprint of production processes. However, it is now recognized as a comprehensive initiative that promotes sustainability across its economic, environmental, and social dimensions, aligning industrial practices with the broader goals of preserving the planet for future generations.

At the operational level of an industrial organization, production scheduling plays a crucial role in impacting sustainability. Scheduling involves allocating and the coordinating machines, consuming raw materials and energy, and workers operating these machines. Historically, most scheduling models have overlooked the consideration of workers, simplifying constraints and ignoring factors that could improve their safety and well-being. Moreover, although a growing body of research focusing on energy consumption in response to the environmental crisis, much works remain to be done to fully integrate these considerations into production scheduling models [26].

In this paper, we study a Dynamic Sustainable Flexible Job Shop Scheduling Problem (DSFJSSP). We propose a model that simultaneously integrates the social dimension of worker safety, the environmental impact through carbon emissions, and the economic factor of production efficiency. Our model aims to promote a more sustainable approach by considering all three pillar aspects: social, environmental, and economic. The objective is to strike a balance between worker well-being, environmental conservation, and operational efficiency. Respecting these three pillars strengthens the system's resilience and supports its long-term sustainability. Additionally, our model is dynamic and capable of adapting to disruptions, in real time. Specifically, we focus on two types of disruptions: unplanned worker absences and fluctuations in renewable energy availability. While many disruptions can affect production processes, our study focus on these specific challenges due to their growing relevance in modern manufacturing environments and because they are seldom addressed, particularly in combination. By addressing these factors, we aim to demonstrate the model's ability to maintain operational efficiency across economic, environmental and human criteria, promoting resilience in the face of these and similar critical disruptions.

In the following sections of this manuscript, a literature review is presented in Section 5.2, with a focus on social and environmental considerations in FJSSP and dynamic models. The problem

description is detailed in Section 5.3. Section 5.4 provides detailed explanations of the proposed solving approach. First, we apply an improved Non-dominated Sorting Genetic Algorithm (INSGA-III) to obtain an initial solution. Following this, compare three machine learning approaches for addressing disruptions linked to workers and energies within the dynamic model. The results and analysis are provided in Section 5.5, while Section 5.6 summarizes this study and its findings, discusses limitations, and suggests future research directions.

5.2 Literature review

As previously mentioned, our focus is on the Flexible Job Shop Scheduling Problem (FJSSP), a widely adopted framework, especially in contemporary manufacturing systems. Traditionally, classic FJSSP models assign tasks to machines, often overlooking the critical role and constraints associated with workers. In the first sub-section of this review, we highlight studies that incorporate worker-related constraints into scheduling models and/or addresses environmental considerations, particularly through the minimization of energy consumption and carbon emissions. In the second sub-section, we review recent advancements in dynamic FJSSP, examining how these models adapt to disruptions and changing conditions. A focus is made on studies that integrate artificial intelligence, particularly machine learning techniques, to solve the problem.

5.2.1 Flexible Job Shops Scheduling Problem under Industry 5.0

In the context of Industry 5.0, integrating human factors into FJSSP has become increasingly important. This shift highlights the crucial role humans play in enhancing both technological advancements and business processes. Industry 5.0 envisions a synergy between advanced automation and human expertise, with the goal of not only improving productivity and innovation but also safeguarding worker well-being and protecting the environment. Human-centered approaches, which empower operators by enhancing their skills and fostering collaboration with smart technologies, are essential for maintaining systemic efficiency in production [12]. However, despite the recognized importance of human factors, early stages of production system development have often overlooked ergonomics, due to challenges in quantifying human issues and assumptions that humans can naturally adapt to technical systems [43]. Nonetheless, the literature strongly advocates for the consideration of human factors such as skills, safety, and ergonomics, which are indispensable for optimizing production goals. Recent studies emphasize the impact of work-related stress on workers' health and productivity. They demonstrate that stress increases errors and distractions, thereby reducing output quality and driving up costs, which considerably degrades the competitiveness of a company [563]. To address these issues, [564] incorporate unpredictable human behavior into production scheduling, using simulations to measure the impact of worker behavior profiles on productivity, and optimizing job assignments. Similarly, [565] explore a multi-objective FJSSP that considers worker behaviors, focusing on learning, forgetting, fatigue, and recovery in relation to processing time. [566] examine worker shifts, aiming to respect rest periods and avoid overtime, while [567] propose a multi-objective model that accounts for ergonomic factors such as worker energy expenditure, makespan, workload, and energy use. Furthermore, [568] address worker factors such as random resignations, optimizing makespan and minimizing deviations from production goals. In another study, [569] develop a multi-objective model that accounts for multi-skilled workers and aims to minimize total tardiness, earliness, maximum workload,

5.2. LITERATURE REVIEW

and costs, including idle worker costs. Addressing these human factors in FJSSP, particularly in the context of smart manufacturing systems, is crucial for optimizing both worker performance and overall production outcomes [14].

In parallel, there has been an emphasis, in the literature, on integrating environmental considerations into FJSSP. [570] review recent literature on energy-efficient scheduling in job shop manufacturing systems and provide data sets specifically tailored for these types of problems. A common approach is to minimize energy consumption throughout the production process, as highlighted in some studies, such as [550, 181, 140, 167]. This energy usage stems from various sources, including machining operations, transportation, loading and unloading products, machine setup, and even auxiliary systems such as lighting, heating, and air conditioning [26]. Minimizing energy consumption not only contributes to environmental sustainability but also offers companies the opportunity to reduce their energy expenses, thereby lowering overall production costs, which allows to increase the margin and serves as a lever of competitiveness. To further incentivize energy savings, time-of-use pricing imposed by energy suppliers has been incorporated into recent studies. This pricing model encourages high electricity consumers, particularly factories, to shift their energy consumption from peak hours to mid-peak or off-peak periods, optimizing costs while reducing pressure on the power grid due to increased load [571]. In [572], the proposed model aids in scheduling energy-intensive processes, ensuring that such processes are carried out when the carbon intensity of the energy used is at its lowest, thereby supporting decarbonization efforts. Additionally, renewable energy sources have garnered increasing attention due to their potential to reduce carbon emissions. On-site renewable energy production, regardless of its type, such as wind, solar, geothermal, or hydroelectric, represents a valuable resource for companies with energy-intensive production processes. Beyond the environmental benefits, renewable energy can also significantly lower energy costs for manufacturers. For instance, [562, 573] explore the use of photovoltaic panels to generate solar energy. The electricity produced can be used immediately to meet operational needs or stored in batteries for later use. Factories can also draw power from the grid when necessary, and surplus energy from the grid can be stored in batteries. This dual system allows factories to purchase electricity at lower rates during off-peak hours and use stored energy during periods of high electricity prices, creating a more cost-efficient and sustainable energy management system. In conclusion, incorporating environmental considerations into FJSSP is decisive not only for meeting sustainability goals, but also for offering economic benefits through reduced energy costs and enhanced process efficiency. As industries move toward decarbonization and energy-efficient practices, such strategies will become increasingly important in shaping the future of sustainable manufacturing.

Recent studies have integrated both environmental considerations and worker-related aspects into scheduling models. For instance, [28] examine the SFJSSP by considering makespan, energy consumption for transportation, auxiliary operations, and machining, along with an index for ergonomic risks. Furthermore, [27] incorporate worker preferences related to shifts, machine assignments, and variations in operations. Similarly, [48] focus on minimizing three objectives simultaneously: the makespan, the energy consumption, and the ergonomic risks. In another study, [41] analyze makespan, worker costs, and energy consumption, taking into account workers with varying skill levels across different machines. Furthermore, [43] propose a multi-objective model that not only considers makespan and worker costs, but also includes a “green factor” that encompasses safety, noise, energy consumption, and tool recycling. The incorporation of both environmental and worker considerations in scheduling models is essential for optimizing production efficiency while promoting sustainability and enhancing worker well-being. These studies underscore the importance of balancing multiple objectives to create

a more sustainable and equitable manufacturing environment.

5.2.2 Dynamic Flexible Job Shops and Machine Learning

In recent years, the dynamic FJSSP (DFJSSP) has attracted significant attention due to its ability to handle real-world complexities such as new job insertions, urgent orders, machine failures, and variable processing times [424]. This dynamic approach brings the problem closer to practical applications. Solving the DFJSSP with exact methods is often impractical, as these methods struggle with the computational complexity inherent in real-world scenarios. Instead, approximate approaches are often preferred for providing near-optimal solutions in a shorter time frame, striking a balance between speed and solution quality [271]. Among these approaches, several categories stand out, including heuristics [559], metaheuristics [400], rule-based methods [376], simulation approaches [518], and artificial intelligence algorithms [424]. Notably, AI-based approaches, particularly reinforcement learning (RL) and deep reinforcement learning (DRL), have emerged as compelling solutions to the DFJSSP. Traditional optimization techniques often struggle to adapt to the ever-changing nature of these problems, but AI-driven methods are proving to be more effective. Particularly, RL excels in handling environmental uncertainties and enables autonomous learning throughout the scheduling process, including the monitoring and adjustment of the actual schedule. In RL, the system's state represents the current environment, actions are the decisions made by the agent at each step, and rewards are the outcomes of those decisions. RL agents learn by maximizing rewards, reinforcing successful actions while discouraging poor ones. RL algorithms fall into three main categories: model-free, model-based, and hybrid methods that combine the two. Within model-free methods, there are value-based approaches like Q-Learning, and policy-based approaches such as Proximal Policy Optimization (PPO) [274]. DRL, an advanced form of RL, enhances these methods by replacing traditional action-state tables with neural networks, which allows for more efficient decision-making in complex environments. However, DRL also introduces challenges, such as increased computational complexity and the need for large datasets [275]. Recent studies have successfully applied Q-Learning techniques to train systems for handling disruptions. Specifically, Q-Learning has been used to select optimal rescheduling strategies [166, 29] or dynamically adjust algorithm parameters based on the system's state [247]. DRL algorithms have also been implemented in various models, using both value-based and policy-based methods. For example, [549, 323, 267] utilize DRL with Q-Learning to optimize rule selection, while [480] apply PPO to determine the optimal pairing of machines and Automated Guided Vehicles (AGVs) for each operation. Other studies integrate policy-based methods with neural networks [332, 325], often using DRL to select the best dispatching rules based on the system's current state. These AI approaches are frequently combined with metaheuristics, dispatching rules, or other advanced methods to address the challenges of fully reactive FJSSP.

5.3 Problem description

In this study, we propose a multi-objective non-linear integer programming model to solve the considered Sustainable Flexible Job Shop Scheduling Problem (SFJSSP). The objective is to minimize three key criteria simultaneously: the makespan (f_1), the total carbon emissions (f_2), and the maximum OCRA index across all workers (f_3).

The OCRA method is recommended for analyzing, predicting, and preventing musculoskeletal dis-

5.3. PROBLEM DESCRIPTION

orders, as per European standard EN 1005 and international standard ISO 11228-3. The OCRA index is calculated for each worker and shift, considering the number of technical actions and multiplying factors such as posture, applied force, repetitiveness, additional risks (e.g., vibration or temperature), lack of rest, and the overall duration of the process. According to ISO 11228-3, an OCRA index below 2.2 indicates an acceptable level of risk exposure for workers, while an index above 3.5 signifies a high risk.

We measure the carbon emissions from three types of energy consumption: i) the executing operations on machines, which depend on the specific operation types as well as the machines and workers involved, ii) the internal product transportation, determined solely by the distance between machines and remaining consistent across all products, and iii) the operation of auxiliary installations, which is tied to the makespan, as longer processing times require more energy for lighting, heating, and other utilities. We consider that the factory has access to two energy sources: on-site renewable solar energy generated by photovoltaic (PV) panels, and conventional energy. Solar energy can be stored in a battery with limited capacity, and its availability varies throughout the day. Since solar energy emits significantly less carbon than conventional energy, the model must decide which energy source to use for each operation, aiming to minimize overall carbon emissions while considering energy availability. We assume that only operations can use solar energy while auxiliaries equipment and transport can only use conventional energy.

The FJSSP is commonly defined by a set of jobs $\mathcal{J} = j_1, j_2, \dots, j_J$, where each job consists of a series of operations $\mathcal{O}j = O_{j1}, O_{j2}, \dots, O_{jK_j}$ to be performed on a set of machines $\mathcal{M} = m_1, m_2, \dots, m_M$ in a specific sequence. In the variation of FJSSP considered in this paper, operations must also be assigned to workers. We assume that all workers are capable of performing any task, but the time required to complete a task depends on the skill level of the assigned worker; more skilled workers can complete tasks faster. Therefore, the problem involves two key sub-problems: optimizing the assignment of both machines and workers for each operation, and determining the optimal sequence of operations for both machines and workers. Section 5.3.1 outlines the mathematical model we suggested to minimize the three objectives simultaneously. In Section 5.3.2, we introduce the various disruptions that can occur during the process and impact the initial schedule, along with the rescheduling strategies employed to address these challenges when disruptions arise.

5.3.1 Mathematical model

Notations

The notations used to formalizing our mathematical models are detailed below.

Sets, indices and parameters

\mathcal{W}	set of workers, $w = 1..W$.
\mathcal{M}	set of machines, $m = 1..M$.
\mathcal{J}	set of jobs, $j = 1..J$.
\mathcal{E}	set of energies, $e = s$ (solar), $e = c$ (classic).
\mathcal{K}_j	set of operations of j noted O_{kj} , with $k = 1..K_j \forall j \in \mathcal{J}$.
\mathcal{T}	set of periods, $t = 1..T$.
$start_t, end_t$	starting and ending time of period t .
p_{kjwm}	processing time of operation O_{kj} on machine m with worker w .

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$s_{kjm k'j'}$	setup time of machine m between operations o_{kj} and $o_{k'j'}$.
$tp_{mm'}$	transport time of a product between machines m and m' .
$t_{mm'}$	travel time for a worker between machines m and m' .
e_{jkwm}	energy consumption to execute operation O_{kj} on machine m with worker w .
$e_{mm'}^{trans}$	energy consumption to transport a product from machine m to machine m' .
e^{aux}	energy consumption for auxiliary installations by time unit.
e_t^s	energy produced by the solar energy during period t in kWh.
c	battery capacity.
ce_e	carbon emission factor of energy e by kWh.
ata_{kjm}	number of technical actions to execute operation O_{kj} on machine m .
pm_{kjm}	posture multiplier when executing O_{kj} on machine m .
rm_{kjm}	repetitiveness multiplier for executing O_{kj} on machine m .
fm_{kjm}	strength multiplier for executing O_{kj} on machine m .
arf_{kji}	additional risks multiplier for executing O_{kj} on machine m .
rcm	recovery period multiplier.
dum	duration of repetitive task multiplier.
cf	constant frequency of technical actions per minute.
M	a big number.

Decision variables

S_{kj}	starting time of operation O_{kj} ;
C_{kj}	ending time of operation O_{kj} ;
$Cmax$	total processing time, makespan.
R_{kjwt}	rest time of worker w after operation O_{kj} .
X_{kjwt}^e	binary variable equal to 1 if O_{kj} is executed on machine m by worker w in period t with energy e .
$Y_{kjwt'j'}$	binary variable equal to 1 if O_{kj} is executed by worker w before $O_{k'j'}$.
$Z_{kjm k'j'}$	binary variable equal to 1 if O_{kj} is executed on machine m before $O_{k'j'}$.
$N_{kjm k'j' m'}$	binary variable equal to 1 if O_{kj} is executed on machine m and $O_{k'j'}$ on machine m' .
ET	total energy consumption for transport.
EA	total energy consumption for auxiliaries installation.
CEM	total carbon emission for operations.
CEA	total carbon emission for auxiliaries installation.
CET	total carbon emission for transport.
C_t	energy stored in the battery at the beginning of period t .
ATA_{wt}	real number of technical actions for worker w in period t .
RTA_{wt}	recommended number of technical actions for worker w on period t .
$OCRA^{max}$	OCRA maximum for all workers and all periods.
$U_{kjk'j't}$	binary variable equals to 1 if $O_{k'j'}$ is executed before O_{kj} in period t .

Objective functions

We study three objectives function simultaneously:

$$f_1 : Cmax \tag{5.1}$$

$$f_2 : CET + CEA + CEM \tag{5.2}$$

$$f_3 : OCRA^{max} \tag{5.3}$$

Constraints

Constraint (5.4) defines the makespan as the completion time of the final operation in the schedule. Constraints (5.5) calculate the energy consumption for internal transport operations and the corresponding carbon emissions. Similarly, constraints (5.6) compute the energy consumption for auxiliary installations and their associated carbon emissions. Constraint (5.7) determines the carbon emissions generated by machines during operations, accounting for both solar and conventional energy sources. Constraints (5.8), (5.9), and (5.10) serve as capacity constraints: they ensure that the energy drawn from the battery does not exceed its storage capacity, that solar energy usage in each period t does not surpass the amount stored at that time, and that the energy stored at time t equals the energy stored at time $t - 1$ minus the energy consumed, plus the energy produced. Constraints (5.11) ensure that, in each period, all available solar energy is fully utilized before any transition to conventional energy occurs.

$$Cmax \geq C_{kj} \quad \forall j \in \mathcal{J}, k \in \mathcal{K}_j \tag{5.4}$$

$$CET = \sum_j \sum_k \sum_m \sum_{m'} N_{kjm(k+1)jm'} \times e_{mm'}^{trans} \times ce_c \tag{5.5}$$

$$CEA = Cmax \times e^{aux} \times ce_c \tag{5.6}$$

$$CEM = \sum_e \sum_j \sum_k \sum_m \sum_w \sum_t X_{k'jwmt}^e \times e_{kjwm} \times ce_e \tag{5.7}$$

$$C_t \leq c \quad \forall t \in \mathcal{T} \tag{5.8}$$

$$C_t \leq C_{t-1} + e_{t-1}^s - \sum_j \sum_k \sum_m \sum_w X_{k'jwmt}^s \times e_{kjwm} \quad \forall t \in \mathcal{T} \tag{5.9}$$

$$\sum_j \sum_k \sum_m \sum_w X_{k'jwmt}^s \times e_{kjwm} \leq C_t \quad \forall t \in \mathcal{T} \tag{5.10}$$

$$U_{k'j'kjt} + \sum_w \sum_m X_{k'jwmt}^s - 1 \leq \sum_w \sum_m X_{k'j'wmt}^s \quad \forall j, j' \in \mathcal{J}, k \in \mathcal{K}_{j,j'}, t \in \mathcal{T} \tag{5.11}$$

Equations (5.12) to (5.15) represent the constraints applicable to workers, shared across both models. Equation (5.12) ensures their rest time after each operation performed, Equations (5.13) and (5.14) compute the real and recommended number of technical actions for each worker at each period, with the ratio between these counts representing the OCRA index, and Equation (5.15) defines the $OCRA^{max}$ as the maximum OCRA index reached among all workers during all time periods.

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$$R_{kjwt} = 0.08 \times \sum_m \sum_e X_{kjwmt}^e \times p_{kjwm} \quad \forall t \in \mathcal{T}, w \in \mathcal{W}, j \in \mathcal{J}, k \in \mathcal{K}_j \quad (5.12)$$

$$ATA_{wt} = \sum_j \sum_k \sum_m \sum_e ata_{kjm} X_{kjwmt}^e \quad \forall w \in \mathcal{W}, t \in \mathcal{T} \quad (5.13)$$

$$RTA_{wt} = rc_m \times dum \times \sum_j \sum_k \sum_m \sum_e cf \times pm_{kjm} rm_{kjm} fm_{kjm} ar_{kjm} \times X_{kjwmt}^e p_{kjwm} \quad \forall t \in \mathcal{T}, w \in \mathcal{W} \quad (5.14)$$

$$OCRA^{max} \geq \frac{ATA_{wt}}{RTA_{wt}} \quad \forall t \in \mathcal{T}, w \in \mathcal{W} \quad (5.15)$$

Equations (5.16), (5.17) and (5.18) are precedence-related constraints linked to, respectively, two operations of the same job, two operations assigned to the same machine, and two operations assigned to the same worker.

$$S_{(k+1)j} \geq C_{kj} + \sum_m \sum_{m'} N_{kjm(k+1)jm'} \times tp_{mm'} \quad \forall j \in \mathcal{J}, k \in \mathcal{K}_j \quad (5.16)$$

$$S_{k'j'} + (1 - \sum_m Z_{kjm k'j'})M \geq C_{kj} + s_{kjm k'j'} \quad \forall j, j' \in \mathcal{J}, k, k' \in \mathcal{K}_j, \mathcal{K}_{j'} \quad (5.17)$$

$$S_{k'j'} + (1 - \sum_w Y_{kjwk'j'})M \geq C_{kj} + \sum_w \sum_t R_{kjwt} + \sum_m \sum_{m'} N_{kjm(k+1)jm'} \times t_{mm'} \quad \forall j, j' \in \mathcal{J}, k, k' \in \mathcal{K}_j, \mathcal{K}_{j'} \quad (5.18)$$

Finally, constraint (5.19) states that an operation is executed exactly by one worker and one machine, and constraints (5.20) and (5.21) find the period when each task is assigned.

$$\sum_w \sum_m \sum_t \sum_e X_{kjwmt}^e = 1 \quad \forall j \in \mathcal{J}, k \in \mathcal{K}_j \quad (5.19)$$

$$S_{kj} \leq end_t + (1 - \sum_w \sum_m \sum_e X_{kjwmt}^e)M \quad \forall j \in \mathcal{J}, k \in \mathcal{K}_j, t \in \mathcal{T} \quad (5.20)$$

$$S_{kj} + (1 - \sum_w \sum_m \sum_e X_{kjwmt}^e)M \geq start_t \quad \forall j \in \mathcal{J}, k \in \mathcal{K}_j, t \in \mathcal{T} \quad (5.21)$$

5.3.2 Disruptions and rescheduling strategies

When a disruption occurs during the process, the initial schedule can become inefficient or even unfeasible, requiring rescheduling to help the system adapt and maintain efficiency. With a focus on sustainability, this study addresses disruptions involving both workforce availability and renewable energy sources. The first type of disruption is operator absences, as workers availability often plays a major role in process interruptions. Operators may arrive late, leave early, or miss an entire shift due to personal reasons or unexpected events, such as injuries or fatigue. When an operator is absent, all operations assigned to him during his absence are interrupted, causing a domino effect which disrupts subsequent operations.

5.4. RESOLUTION METHODS

The second type of disruption stems from the variability of renewable energy sources, particularly solar power. Energy generated by the photovoltaic panels is forecasted based on weather conditions; however, actual production can deviate from these estimates. In cases where production is lower than expected, some operations relying on solar energy may need to be switched to conventional energy sources, leading to higher carbon emissions. Rescheduling strategies can help mitigate these issues by reallocating operations to different energy sources, thus optimizing the schedule in response to disruptions and reducing the carbon emissions.

If any of these disruptions occur within the system, prompt rescheduling becomes imperative. According to the occurred disruption, we consider three different rescheduling strategies as presented in Table 5.3.

We group the operations to be scheduled into three distinct categories: completed operations, incomplete operations, and operations yet to begin. The completed operations remain unchanged, while those that have not yet started or are incomplete require rescheduling.

Disruptions/ strategies	Total rescheduling	Partial rescheduling	Adaptive rescheduling
Worker absence	Tasks not started or incomplete are rescheduled.	Tasks not started or incomplete not assigned to the absent worker: assignments are retained but starting times may be adjusted. Tasks not started or incomplete assigned to the absent worker: re-assigned to a new worker/machine pair, starting times may be adjusted.	Right shift rescheduling: tasks assigned to the absent worker: postponed until he is available again. All tasks: sequence, machine, and worker assignments remain unchanged, but starting times may be adjusted.
Energy variation	Tasks not started or incomplete are rescheduled.	If energy production is lower than expected, tasks assigned to solar energy are rescheduled. If production is higher, tasks assigned to conventional energy are rescheduled. In both scenarios the assignments may change.	If energy production is below expectations, solar energy tasks are shifted to conventional sources until limits are met. If production exceeds expectations, conventional tasks are redirected to solar energy. In both scenarios, the assignments remain unchanged.

Table 5.3: Overview of strategies based on disruption types

Depending on the specific circumstances, the most effective strategy may vary. For our problem, it is crucial to select a strategy that minimizes disruption across three key aspects related to our objectives: the makespan, the total carbon emission, and the maximum OCRA index. To determine a strategy selection based on the circumstances, we adopted a machine learning based approach, which is detailed in Section 5.4.

5.4 Resolution methods

The literature on scheduling problems has shown that the FJSSP is NP-hard, and thus, it can be deduced that SFJSSP shares this NP-hardness [46]. Since we are considering different sustainability

criteria, the model will have to make the trade-off between them. Indeed, it must seek a solution that goes beyond mere economic efficiency, as in classical models; it should also prioritize the health and well-being of workers and the planet. Solving such a complex problem with an exact method is feasible only for small-scale instances. To obtain a high-quality solution close to the optimal one in a reasonable time, we implemented the Improved Non-dominated Sorting Genetic Algorithm (INSGA-III) for the initial schedule, and used machine learning based methods for the dynamic model.

5.4.1 Improved Non-dominated Sorting Genetic Algorithm

To address the static model and derive an initial schedule, we employ an improved version of the Non-dominated Sorting Genetic Algorithm III referred to as INSGA-III, as previously outlined. Non-dominated sorting genetic algorithms are well-known for their effectiveness in solving multi-objective optimization problems, especially in the field of scheduling. These algorithms operate based on the Pareto-dominance principle, managing a population of solutions while effectively handling multiple objectives. The goal is to converge toward a set of non-dominated solutions, identifying the most optimal outcomes. The core structure of these algorithms begins with an initial population P_0 , comprising N solutions. At each iteration, an offspring population Q_t of size N is generated using crossover and mutation operators. The combined population $R_t = P_t \cup Q_t$ contains $2N$ solutions, from which the N best solutions are selected for the next generation P_{t+1} . Selection is based on dominance levels to ensure elitism, while additional mechanisms maintain diversity. In NSGA-III, diversity is preserved through normalization, association, and niche preservation strategies. In [27], we introduce several key improvements to the standard NSGA-III:

- Enhanced initialization: The initial population is optimized by generating 25% of the solutions randomly, while the remaining 75% are derived from heuristic methods that aim to approach optimal solutions for each considered objective;
- Adaptive parameter tuning: A Q-Learning method dynamically adjusts parameters for the crossover and mutation operators at each iteration, improving convergence and maintaining solution diversity;
- Local search enhancement: At the end of each iteration, a local search is applied to refine the solutions. This local search employs five distinct rules based on the current solution state, with a reinforcement learning algorithm determining the most effective rule to apply.

For final implementation, we select the solution that minimizes the average of the three objectives from the final population. For further details on the improved algorithm and its application to our SFJSSP, refer to [27].

5.4.2 Machine learning methods: Q-Learning, Deep Learning, and Deep Reinforcement Learning

In the event of disruptions, we use machine learning methods to train the model to effectively react to these disruptions. We compare three different machine learning methods: the Q-Learning (QL), the Deep Learning (DL), and a combination of both, the Deep Q-Learning (DQL).

Q-Learning

Q-Learning is a model-free reinforcement learning algorithm used to solve decision-making problems where the environment can be described by discrete states and actions. It aims to find an optimal policy for an agent by learning the best action to take in each state to maximize cumulative rewards. The agent interacts with an environment, observes the results of its actions, and updates its knowledge based on these experiences. Then, a Q-Table is created and updated at each iteration. The Q-Table is a matrix where each row corresponds to a state and each column to an action. The value in the table represent the "Q-value", an estimate of the expected reward for taking a certain action in a given state. The agent updates the Q-values using the Bellman equation:

$$Q(s_t, a_t) = (1 - \alpha) \times Q(s_t, a_t) + \alpha(r_t + \lambda \times \max_a Q(s_{t+1}, a)), \quad (5.22)$$

where α represents the learning rate and λ represents the discount factor. The learning rate α typically ranges between 0 and 1. A value of α close to 1 can render the Q-value highly volatile, making it extremely responsive to fluctuations. Conversely, a value of α approaching 0 tends to favor historical information, resulting in a conservative Q-value. The discount factor λ plays a critical role in temporal reward considerations. A value of λ near 0 primarily emphasizes immediate rewards, whereas a value closer to 1 places greater significance on rewards in the distant future. It has been proved that Q-Learning works well with small or moderately sized problems but struggles with high-dimensional or continuous action spaces.

For the DFJSSP, the states represent various scenarios. In the case of a disruption, we define 15 distinct states. These states are based on two key factors: the timing of the disruption (whether it occurs at the beginning, middle, or end of the process) and the proportion of the disruption. For a worker absence, it corresponds to the proportion of the disruption duration, and in the event of a disruption in energy availability it corresponds to the proportion of energy variations. These states are outlined in Table 5.4.

	Proportion of disruption (%)				
	0-20	20-40	40-60	60-80	80-100
Beginning	s1	s2	s3	s4	s5
Middle	s6	s7	s8	s9	s10
End	s11	s12	s13	s14	s15

Table 5.4: States definition

The Q-agent selects a rescheduling strategy from three available options: total rescheduling ($a1$), partial rescheduling ($a2$), or right shift rescheduling ($a3$). These strategies represent the actions the agent can take. Action selection is governed by an epsilon-greedy policy, which encourages exploration in the early stages of the algorithm, gradually shifting towards exploitation of learned knowledge as the process progresses. The reward function evaluates the effectiveness of the rescheduling based on three key objectives: the updated makespan (C_{max}^*), the updated carbon emissions (CE^*), and the updated maximum OCRA level ($OCRA_{max}^*$) achieved with the new schedule. The temporary reward r^{temp} is calculated as follows:

$$r^{temp} = \frac{1}{3} \times \frac{C_{max}^*}{C_{max}} + \frac{1}{3} \times \frac{CE^*}{CE} + \frac{1}{3} \times \frac{OCRA_{max}^*}{OCRA_{max}} \quad (5.23)$$

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It is important to note that the coefficient $\frac{1}{3}$ can be adjusted depending on the scenario, allowing more emphasis to be placed on one objective over another. The reward r_t is then derived from r^{temp} , which is scaled between -5 and 5 , with smaller r^{temp} values corresponding to larger rewards. The Q-table is updated using the equation (5.22) with $\lambda = 0$ meaning only immediate rewards are considered, and $\alpha_t = 1 - 0.9 \times \frac{t}{T}$, where T is the total number of iterations. This adaptive α ensures a stronger influence on the Q-table during the initial stages, gradually stabilizing as the process advances. Table 5.5 shows the Q-table representation.

action/state	s1	s2	...	s15
a1	$Q(s1, a1)$	$Q(s2, a1)$...	$Q(s15, a1)$
a2	$Q(s1, a2)$	$Q(s2, a2)$...	$Q(s15, a2)$
a3	$Q(s1, a3)$	$Q(s2, a3)$...	$Q(s15, a3)$

Table 5.5: Q-table visualization

The training phase of the QL is presented in Figure 5.1.

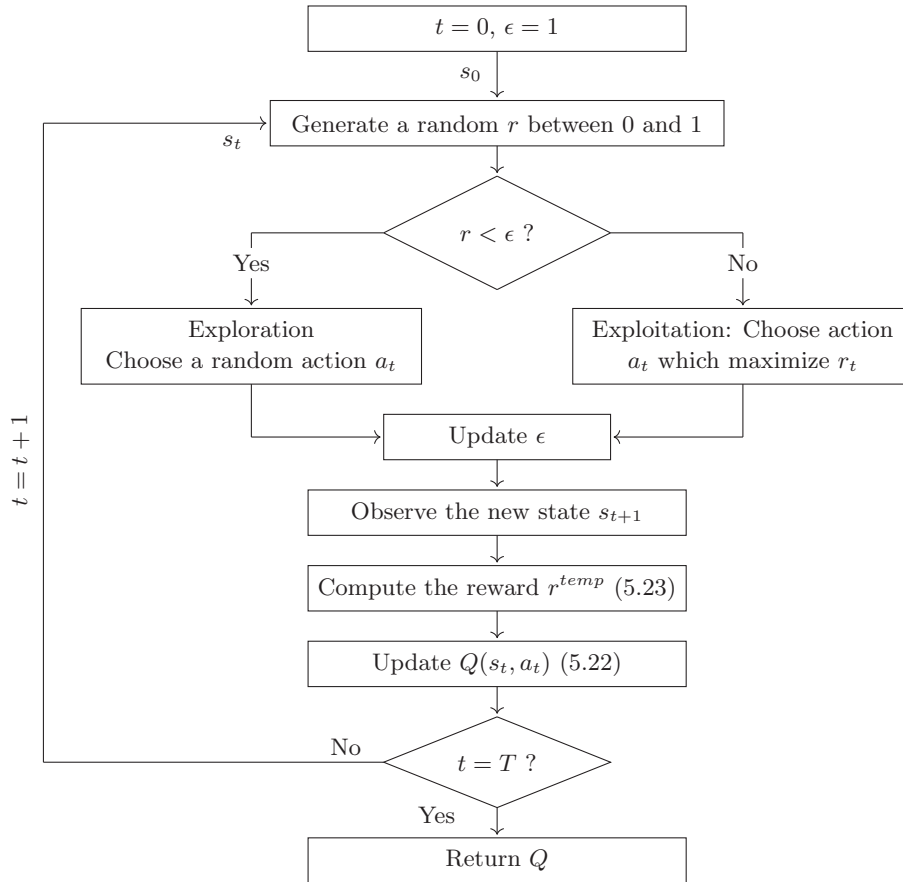


Figure 5.1: Q-learning framework

Deep Learning

DL is a subset of machine learning that uses artificial neural networks with many layers to model complex patterns in data. Unlike Q-Learning, which operates in discrete state-action pairs, deep learning focuses on function approximation and representation learning to solve tasks like classification, regression, and prediction. The neural networks is composed of layers of neurons connected by weight, where each neuron performs a mathematical operation on the inputs. The network learns by adjusting the weights during training to minimize a loss function. It uses the back propagation process to update the weights based on the error by calculating gradients and adjusting the weights using optimization techniques. DL is powerful in handling large, complex datasets with non-linear relationships, but the models lack direct decision-making capabilities and do not easily adapt to a constantly changing or dynamic environment. They are often used for prediction or classification but not for planning or scheduling actions without additional reinforcement learning.

For the DFJSSP, we use an input layer consisting of two neurons: one representing the timing of the disruption and the other reflecting either the proportion of disruption duration (in the case of a worker absence) or the proportion of energy variations (in the case of an energy disruption). The output layer is composed of three neurons corresponding to the probabilities of selecting actions a_1 , a_2 and a_3 respectively. The neural network structure is presented in Figure 5.2.

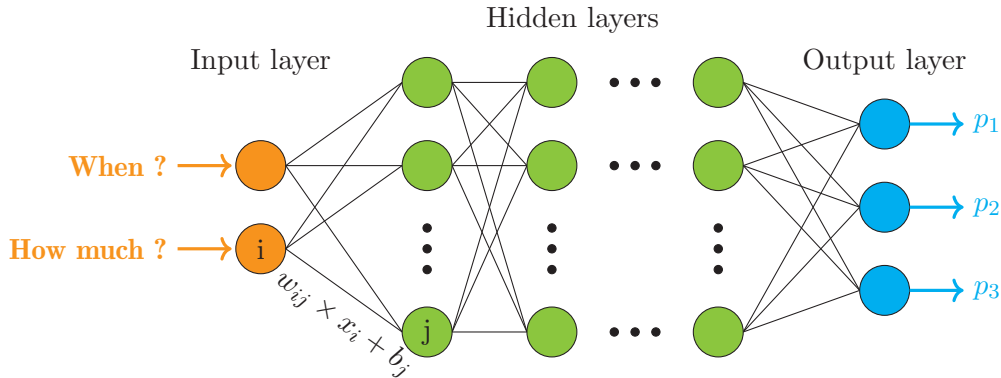


Figure 5.2: Neural network structure

As a loss function, we use the cross-entropy to measure the performance of the neural network, defined as follows:

$$L(y, \hat{y}) = -\frac{1}{N} \sum_{i=1}^N \sum_{j=1}^C y_{ij} \times \log(\hat{y}_{ij})$$

where y_{ij} represents the true label, \hat{y}_{ij} denotes the predicted probability, N is the number of samples and C the number of classes (here 3). This loss function quantifies the difference between the predicted probabilities and the actual labels, providing a robust framework for optimizing the model during training. The model is penalized appropriately for incorrect predictions, leading to improved accuracy and convergence. This approach is particularly suitable for multi-class classification problems. Regarding the hidden layers, we use the ReLU (Rectified Linear Unit) activation function, defined as $Relu_x = \max(0, x)$ where x represents the weighted sum of the inputs to the neuron plus a bias. ReLU helps the model learn faster by mitigating the vanishing gradient problem often encountered in deep networks. ReLU is particularly useful for its simplicity and efficiency, especially in

tasks with large datasets. For the output layer, a softmax activation function is used to obtain the probability distribution over the possible actions. These activation functions are critical for ensuring the model learns effectively and makes accurate decisions. The training phase of DL is presented in Figure 5.3.

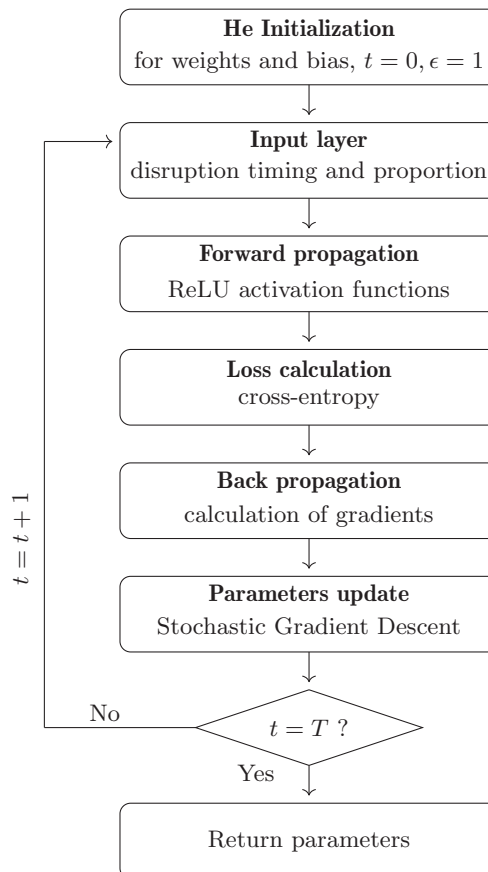


Figure 5.3: Deep learning framework

Deep Q-Learning

DQL combines the strengths of Q-Learning and deep learning to overcome the limitations of using a Q-table in complex, high-dimensional environments. Instead of using a table to store Q-values for each state-action pair, DQL uses two neural networks to approximate the Q-values: the primary network and the target network. The primary network is responsible for predicting the Q-values for each state-action pair and is updated at every training step through back propagation. The target network, on the other hand, is a copy of the primary network but is updated less frequently. It is used to calculate the Q-value target during the learning process, which helps stabilize the training by providing more consistent targets. By updating the target network periodically rather than at every step, the system avoids instability caused by rapid changes in the Q-value targets. DQL can be used to handle complex, dynamic environments where the state-action space is too large for traditional QL. However, DQL requires a large amount of training data and computational power, especially when

the scheduling environment is highly dynamic or uncertain.

As for the DL models, the input layer for DQL models consists of two neurons: one representing the timing of the disruption and the other reflecting either the proportion of disruption duration (in the case of a worker absence) or the proportion of energy variations (in the case of an energy disruption). The model has an output layer with three neurons, corresponding to the Q-value approximations for each action. The reward function used in DQL is the same as the standard QL approach, defined in equation (5.22). The reward is updated using a weighted combination of the current reward prediction and the actual reward, allowing the model to balance past knowledge with new information. Once the reward is calculated, the loss function is computed using the Mean Squared Error (MSE) between the predicted Q-value and the target Q-value. The formula for the loss at each iteration is:

$$L = \frac{1}{N} \sum_{i=1}^N (Q(s_t, a_t; \theta)_i - Q(s_t, a_t; \theta')_i)^2 \quad (5.24)$$

where N is the number of samples, $Q(s_t, a_t; \theta)_i$ represents the predicted Q-value for example i at time t given action a_t in state s_t , and $Q(s_t, a_t; \theta')_i$ is the target Q-value obtained from the environment after executing action a_t in state s_t . This averaging process ensures that the model updates based on the cumulative error over the entire batch, improving the model's stability and decision-making over time. The hidden layers also use the ReLU activation function. The output layer is linear, providing direct Q-value approximations for each action. These activation functions are critical for ensuring the model learns effectively and makes accurate decisions. The training phase of DL is presented in Figure 5.4.

The three models are trained offline prior to implementation. Table 5.6 summarizes the features and limitations of the three methods. The overall framework of the method is illustrated in Figure 5.5.

	QL	DL	DQL
Representation	Q-Table	Neural network approximates predictions	Neural network approximates Q-values
Learning methods	Directly updates Q-values based on reward	Learns patterns in data	Learns policies through neural network Q-value approximation
Limitation	Struggles with large state-action spaces	No decision-making or dynamic adaptation	Computationally expensive, requires large data

Table 5.6: Summary of differences between QL, RL and DQL

5.5 Results and analysis

5.5.1 Instances

To evaluate our model, we use various instance sets, inspired by [248] for small instances and [180] for larger ones. These datasets include jobs, tasks, machines, and their associated processing

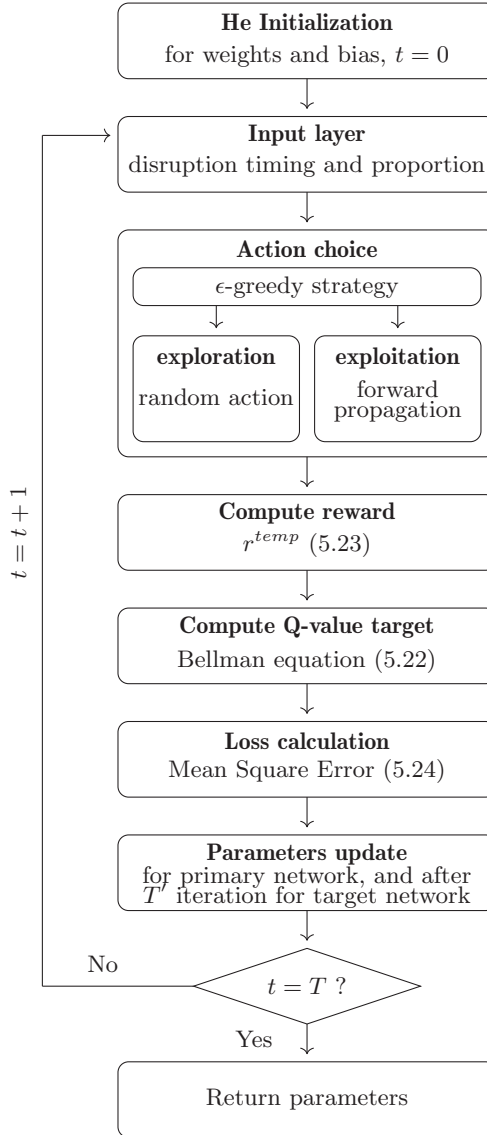


Figure 5.4: Deep Q-Learning framework

times. For our study, we augmented these instances with additional data on workers (including skills and factors to compute OCRA), energy consumption (covering operations, transportation, and auxiliary equipment), as well as transport, setup, and travel times. These datasets are detailed in [27]. Additional information on renewable energy sources, specifically solar power, is also required for our study. We used data collected by [562] regarding electrical energy generated by photovoltaic (PV) panels at different time slots of the day. These data, sourced from the European Commission [574] and adjusted to fit our instance sizes, reflects the average energy produced during different hours in July 2015 in California. Table 5.7 presents the data for each instance, detailing the hourly energy production in kWh, with “ c ” denoting the battery capacity.

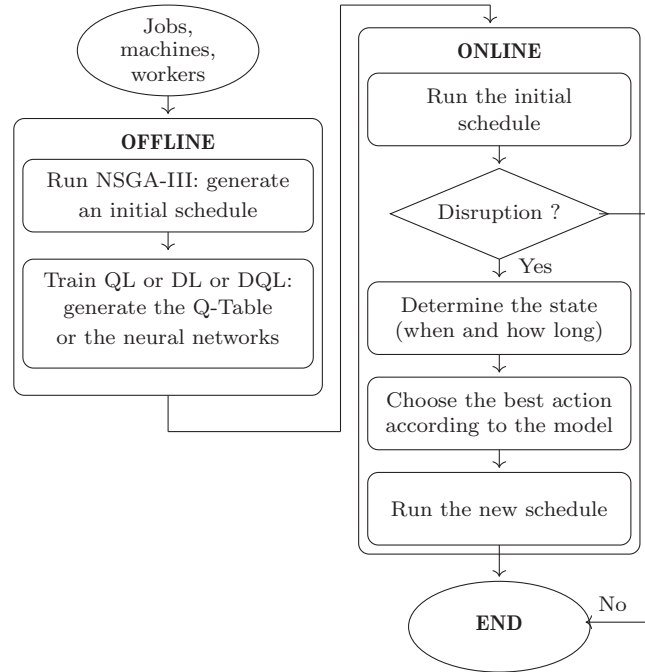


Figure 5.5: Global framework

Instances	c	Time slot												
		7-8	8-9	9-10	10-11	11-12	12-13	13-14	14-15	15-16	16-17	17-18	18-19	19-20
kcm_1	25	0.5	4	8.5	12.7	14.8	16.8	17.5	16.8	15	11.6	8	3.3	0.5
kcm_2	50	1	8	17	25.4	29.6	33.6	35	33.6	30	23.2	16	6.6	1
kcm_3	50	1	8	17	25.4	29.6	33.6	35	33.6	30	23.2	16	6.6	1
kcm_4	100	2	16	34	50.8	59.2	67.2	70	67.2	60	46.4	32	13.2	2
FJ_{05}	100	3	24	51	76.2	88.8	100.8	105	100.8	90	69.6	48	19.8	3
FJ_{10}	100	5	40	85	127	148	168	175	168	150	116	80	33	5
FJ_{15}	200	7,5	60	127,5	190,5	222	252	262,5	252	225	174	120	49,5	7,5
FJ_{20}	200	7,5	60	127,5	190,5	222	252	262,5	252	225	174	120	49,5	7,5

Table 5.7: Data used for solar energy generation and storage in each instance

5.5.2 Static results

First, we employed the GUROBI solver [575] with an ϵ -constraint method to validate our model and identify the Pareto front. The obtained solutions are plotted in Figure 5.6. The GUROBI solutions are represented in green while NSGA-III are shown in orange color. After conducting several runs of INSGA-III, we calculated the mean distance to the Pareto front (based on the GUROBI solutions), which was found to be 0.05. Additionally, the mean gap in hypervolume between the two methods was 2.2%, highlighting strong performance of our algorithm as demonstrated in [27].

Figures 5.7 and 5.8 show obtained results for kcm_4 and FJ_{15} instances. Results for these instances are plotted on two-dimensional axes with a population size of 60 and 40 iterations respectively. These results highlight that the correlation between objectives varies depending on the instance. In the

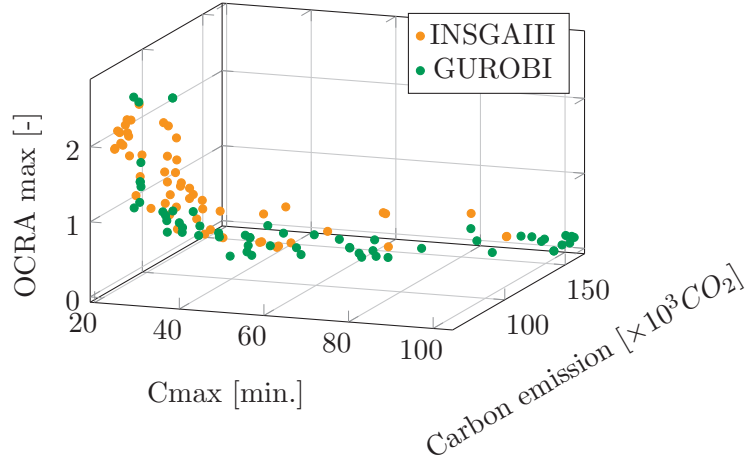
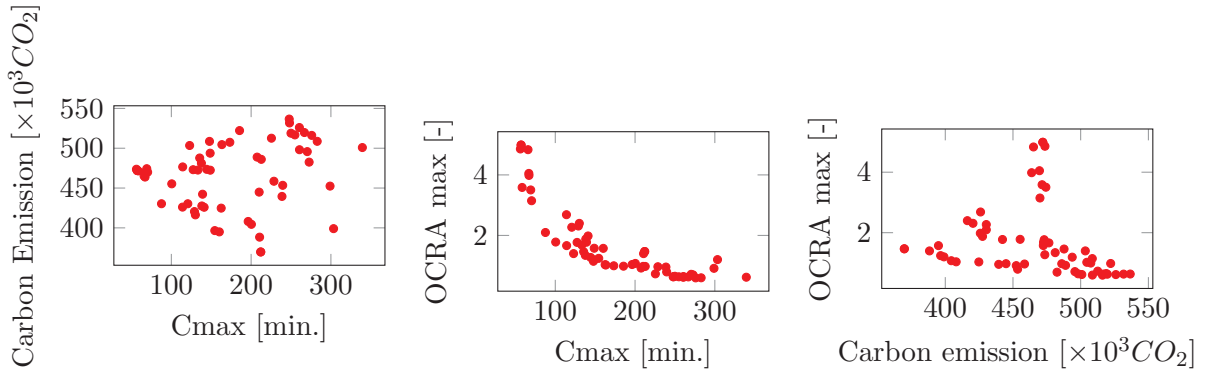


Figure 5.6: Comparison of INSGAIII and GUROBI using the kcm_1 instance

larger instance, FJ_{15} , the makespan and carbon emissions are inversely correlated: a shorter makespan results in higher carbon emissions, and vice versa. This can be attributed to two factors: (i) machines operating at higher speeds tend to consume more energy, and (ii) the use of solar energy at the start of each period may alter the task sequence, thereby extending the makespan. In the case of kcm_4 , carbon emissions are neither positively nor negatively correlated with the makespan or $OCRA_{max}$. However, in both instances, makespan and worker safety are inversely correlated, meaning that a shorter makespan poses greater risks to worker safety. To find an initial schedule based on these sets of solutions, we use the minimum average of the three normalized objectives, as presented in [27].

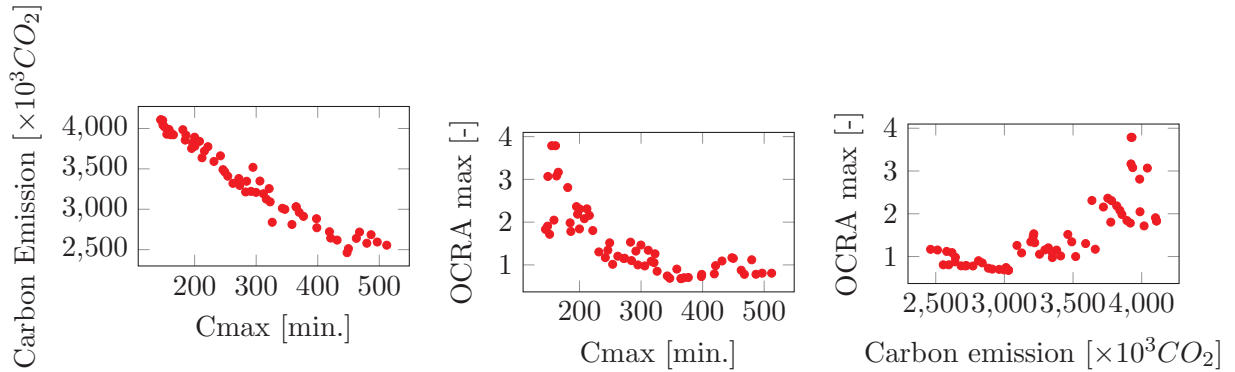


(a) Makespan and carbon emission (b) Makespan vs OCRA max (c) Carbon emission vs OCRA max

Figure 5.7: Display of the solutions of kcm_4 on two-by-two axes

Table 5.8 presents the average percentage of carbon emissions saved for each instance when incorporating solar energy, compared to using only conventional energy sources. The results clearly demonstrate that the integration of solar energy has a significant impact, leading to substantial carbon emission reductions throughout the entire process. This highlights the importance of renewable energy in reducing the environmental footprint, as even a partial reliance on solar energy can signifi-

5.5. RESULTS AND ANALYSIS



(a) Makespan and carbon emission (b) Makespan vs OCRA max (c) Carbon emission vs OCRA max

Figure 5.8: Display of the solutions of FJ_{15} on two-by-two axes

cantly reduce emissions, making it a crucial factor in sustainable production.

Instances	kcm_1	kcm_2	kcm_3	kcm_4	FJ_{05}	FJ_{10}	FJ_{15}	FJ_{20}
Carbon emission saved	19%	15,4%	15%	17,8%	7,8%	15%	14,6%	19,5%

Table 5.8: Proportion of carbon emission saved on the different instances

As an example, Figure 5.9 presents an initial schedule for kcm_4 , where each color represents a job. The makespan is equal to 100, the total carbon emission is equal to 404281 and the $OCRA^{max}$ to 1.62.

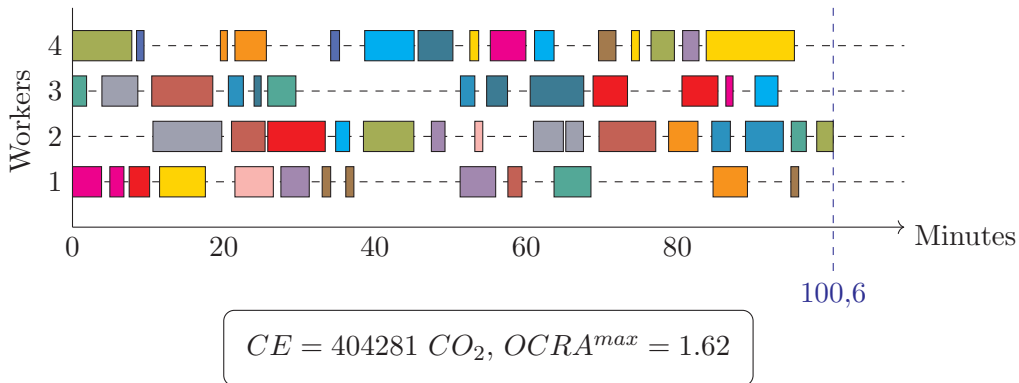


Figure 5.9: Initial schedule for kcm_4

To illustrate the energy distribution, Figure 5.10 shows the initial schedule mentioned above, where conventional energy usage is represented in grey and solar energy in green. In this case, all the solar energy stored at the beginning of the process is used for operations during the initial phase. However, in the second period, no operations are powered by solar energy due to insufficient accumulation in the first phase. Figure 5.11 presents an example of an initial schedule for FJ_{15} . In this case, solar energy is available at the beginning of each period to power operations, ensuring an utilization of renewable energy throughout the scheduling process.

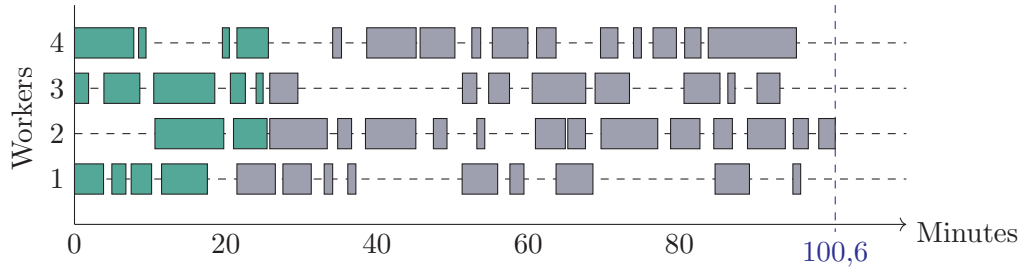


Figure 5.10: Initial schedule for kcm_4

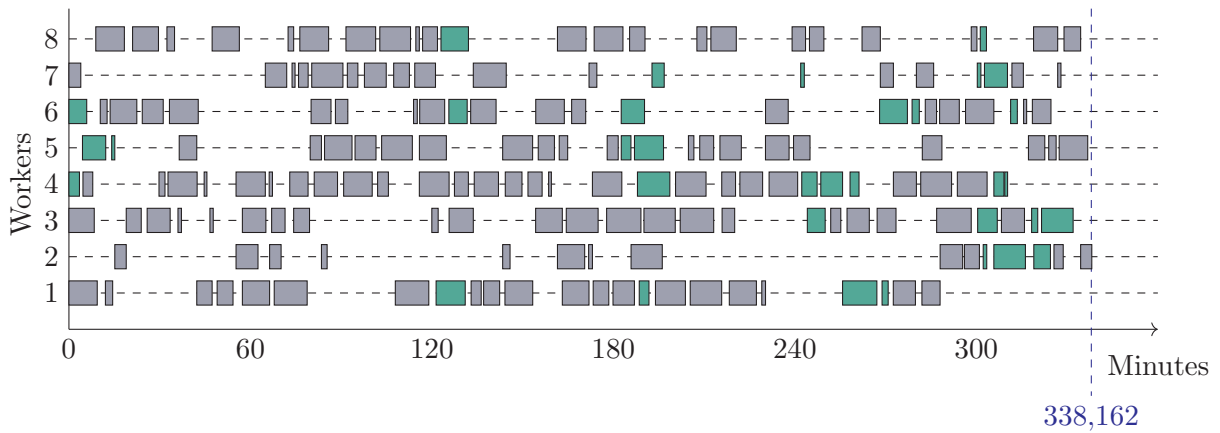


Figure 5.11: Initial schedule for FJ_{15}

5.5.3 Results considering disruptions

This section presents the rescheduling results in the event of disruptions. Table 5.9 outlines the various parameters used to solve the DFJSSP, including those critical for training the QL, DL, and DQL models. These parameters were selected after extensive testing to identify the optimal trade-off between the speed and efficiency of the models. In particular, for the DL and DQL models, tuning these parameters is crucial to prevent overfitting, which can lead to a model that performs well on training data but poorly on unseen data. Careful calibration enhances the model's generalization capabilities but also ensures robust performance. Additionally, we aim to strike a balance that maximizes predictive accuracy while minimizing computational time of the training. Furthermore, for both total and partial rescheduling, we employ the INSGA-III algorithm, utilizing lower parameter settings to prioritize speed in overcoming disruptions. In our model, we configure a population size of 10 and set the number of iterations to 10.

Table 5.10 presents the time required to train the three different models across all instances, utilizing the specified parameters. The data reveals that training the DL model is less computationally intensive than the other two models, QL and DQL. Although the difference in training time is modest for smaller instances, it becomes significantly more pronounced as the size of the instances increases. In fact, the computational time for all three models increases significantly as the size of the instances grows, leading to substantially higher resource costs.

We evaluate the efficiency of the models across 1000 simulations of random disruptions in the

Number of training data	100
Number of disruptions test	1000
Number of iteration for QL	10
Number of iteration for DL/DQL	10
Number of hidden layers for DL/DQL	3
Number of neurons by hidden layers for DL/DQL	8
Learning rate for DL/DQL	0.0001

Table 5.9: Parameters considered for the DFJSSP

Instances	kcm_1	kcm_2	kcm_3	kcm_4	FJ_{05}	FJ_{10}	FJ_{15}	FJ_{20}
QL	265	759	1297	2534	1860	22311	57878	103782
DL	75	195	354	736	476	5709	17912	23456
DQL	181	659	1107	2266	1576	19511	61130	102675

Table 5.10: Training durations for models (in seconds)

process for each instance. Table 5.11 presents the frequency of optimal solutions achieved by each model. Each time a disruption occurs within the system, the models generate the best rescheduling strategy based on their training. In some cases, all three models converge on the same solution; in others, two models may provide identical strategies while the third diverges, or all three may suggest different approaches. By simulating the outcomes of each rescheduling strategy, we compute the frequency with which each model identifies the best solution. The results clearly demonstrate that the DQL method consistently yields the best solutions across most instances, highlighting its effectiveness in handling disruptions in complex environments.

Instances	kcm_1	kcm_2	kcm_3	kcm_4	FJ_{05}	FJ_{10}	FJ_{15}	FJ_{20}
QL	63, 9%	63, 3%	46, 9%	82, 2%	68, 9%	81, 5%	18, 9%	20, 6%
DL	29, 1%	27, 6%	58%	35, 8%	34, 6%	89, 1%	42, 1%	34, 6%
DQL	67.6%	74, 4%	68, 7%	63, 8%	70, 4%	95, 5%	73, 3%	87, 5%

Table 5.11: Frequency of optimal solutions: best models in 1000 simulations

As an example, Figure 5.12 illustrates the three strategies implemented when worker 1 arrives late, specifically at the 23rd minute in the scenario presented in Figure 5.9. The total rescheduling strategy demonstrates the weakest performance for the three criteria. It's worth mentioning that during rescheduling, NSGA-III is run with suboptimal parameters compared to those used for the initial schedule, with a focus on speed to quickly address the disruption, explaining the poor performance. This approach can introduce significant deviations from the original schedule. Partial rescheduling, on the other hand, delivers favorable results across all three objectives, especially in minimizing both makespan and carbon emission, while keeping the deviations from the initial schedule to a minimum. In this case, the machine/worker pair remains unchanged for all tasks not assigned to the absent worker, though task sequences may be adjusted to accommodate the disruption. The right shift strategy maintains the same $OCRA^{max}$ since the machine/worker pairs remain unchanged for all tasks. However, the disruption still affects the makespan and carbon emission, despite efforts to minimize

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deviations from the original schedule. This strategy can be particularly effective in the case of minor disruptions.

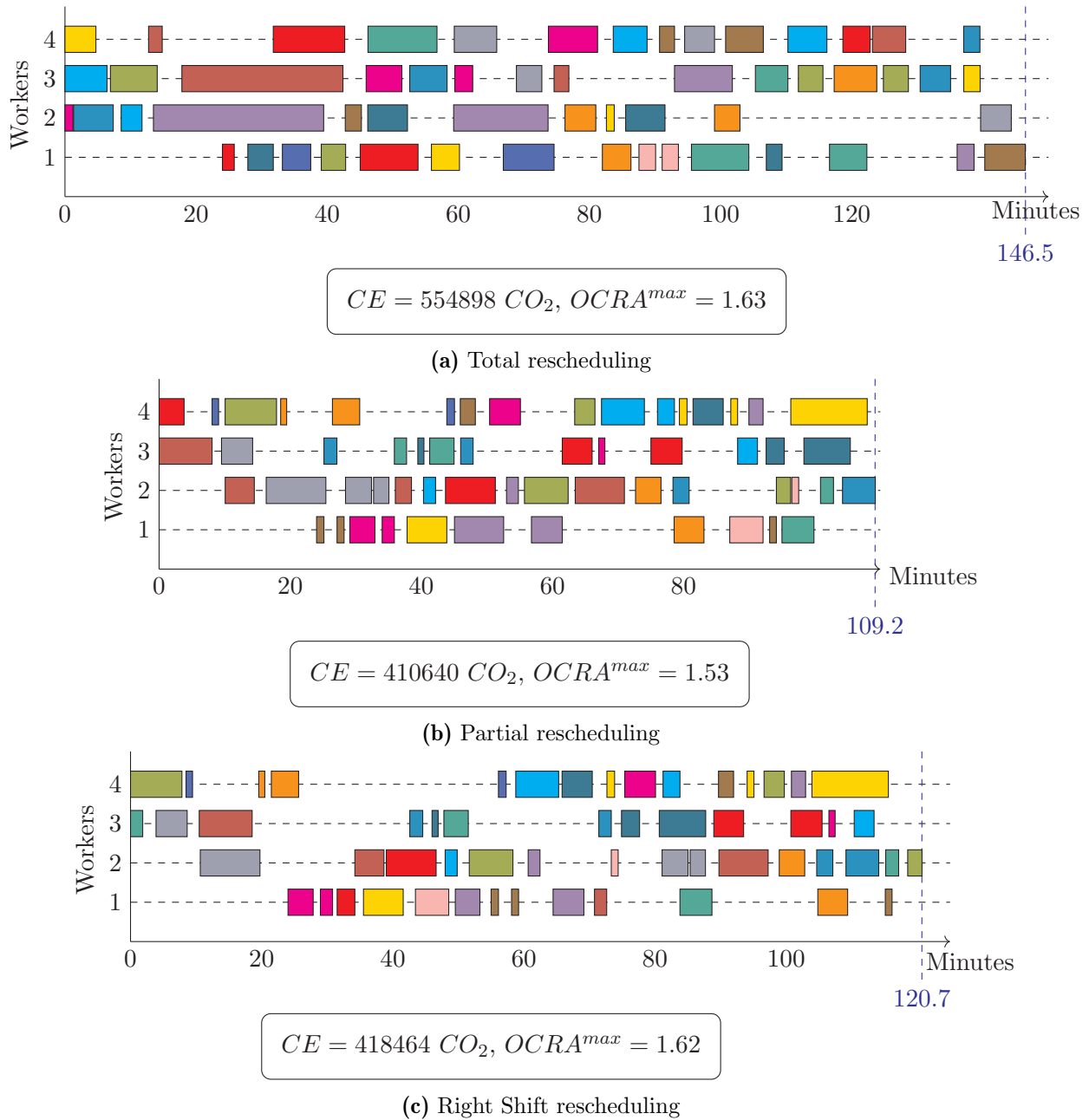


Figure 5.12: The three strategy applied if worker 1 late for 40 minutes

Tables 5.12, 5.13, and 5.14 summarize the percentage of times each action results in the best solution across various scenarios. These percentages are derived from 2000 disruptions on instance FJ_{15} . For worker absences, partial rescheduling consistently provides the best results across most scenarios. However, right-shift rescheduling tends to perform better for minor disruptions or those

5.6. CONCLUSION AND FUTURE RESEARCH PERSPECTIVES

occurring towards the end of the process. Notably, total rescheduling is rarely the optimal choice in these cases, suggesting that parameter adjustments may be necessary to enhance its performance. Regarding energy variations, adaptive rescheduling proves to be highly effective, emerging as the best option in the majority of scenarios. Interestingly, total rescheduling demonstrates better efficiency for disruptions occurring early in the process. These findings highlight the importance of tailoring rescheduling strategies to the specific characteristics of the disruption, such as timing and proportion. The results also underscore the value of learning-based approaches in dynamically identifying and selecting the most appropriate rescheduling strategy for each scenario.

Timing/actions	a1	a2	a3
Beginning	1,2 %	94,7 %	4,2 %
Middle	0,9 %	59,3 %	39,8 %
End	0,6 %	47,4 %	52 %

(a) Worker absence

Timing/actions	a1	a2	a3
Beginning	75.3%	13.6%	11.1%
Middle	23.3%	31.6%	45.1%
End	0%	46.7%	53.3%

(b) Energy variation

Table 5.12: Percentage of optimal actions based on disruption timing

Proportion/actions	a1	a2	a3
0-20	0,5 %	29,1 %	70,4 %
20-40	0 %	82,3 %	17,7 %
40-60	1,9 %	52,8 %	45,3 %
60-80	1,4 %	85,5 %	13 %
80-100	0,5 %	90 %	9,5 %

(a) Worker absence

Proportion/actions	a1	a2	a3
0-20	38%	17.6%	44.4%
20-40	40.8%	14.8%	44.4%
40-60	37.6%	18.5%	439%
60-80	24.3%	36,6%	39,1%
80-100	16%	72.9%	11%

(b) Energy variation

Table 5.13: Percentage of optimal actions based on disruption proportion

5.6 Conclusion and future research perspectives

In this study, we explored a dynamic flexible job shop scheduling problem that integrates human factors, in particular their safety through the $OCRA^{max}$ metric, alongside environmental factors, particularly the variability in renewable energy production. We formulated this problem as a multi-objective non-linear integer programming model and applied three machine learning-based methods to evaluate its effectiveness in adapting to disruptions.

By analyzing disruptions like operator absences and fluctuations in energy availability, we demonstrated the effectiveness of three different rescheduling strategies: total rescheduling, partial rescheduling and the right shift strategy. Our results showed that while total rescheduling can lead to significant deviations from the original schedule, partial rescheduling strikes a balance across all objectives, effectively maintaining a close adherence to the initial plan. The right shift strategy can be efficient for small disruptions proportion. These findings highlight the importance of adaptive scheduling approaches in real-world manufacturing environments where human and environmental factors are increasingly critical to operational efficiency and sustainability. Furthermore, our comparison of Q-learning (QL), deep learning (DL), and deep Q-learning (DQL) approaches for selecting optimal rescheduling strategies

5.6. CONCLUSION AND FUTURE RESEARCH PERSPECTIVES

States/actions	a1	a2	a3
s1	0 %	79,7%	20,3 %
s2	0 %	100 %	0 %
s3	3,6 %	96,4 %	0 %
s4	1,8 %	98,2 %	0 %
s5	0 %	100 %	0 %
s6	0 %	3,4 %	96,6 %
s7	0 %	77,2 %	22,8 %
s8	1,5 %	16,4 %	82,1 %
s9	2,4 %	88 %	9,6 %
s10	0 %	100 %	0 %
s11	1,3 %	3,8 %	94,9 %
s12	0 %	63,3 %	36,7 %
s13	0 %	33,9 %	66,1 %
s14	0 %	72,1 %	27,9 %
s15	1,4 %	72,2 %	26,4 %

(a) Worker absence

States/actions	a1	a2	a3
s1	91%	0%	9%
s2	90.4%	0%	9.6%
s3	70.2%	15.8%	14%
s4	52.9%	33.8%	13.2%
s5	62.5%	27.5%	10%
s6	16.9%	0%	83.1%
s7	27.5%	0%	72.5%
s8	50%	12.2%	37.8%
s9	17.1%	42.1%	40.8%
s10	5.5%	90.4%	4.1%
s11	0%	52.1%	47.9%
s12	0%	40.3%	59.7%
s13	0%	27%	73%
s14	0%	32.8%	67.2%
s15	0%	80.9%	19.1%

(b) Energy variation

Table 5.14: Percentage of optimal actions based on the states

based on disruption states revealed that DQL is the most effective approach, outperforming the other methods in terms of adaptability and solution quality.

Despite these insights, several limitations remain. First, the human factors considered are limited to operator absence, without addressing other potential disruptions such as varying levels of worker efficiency or health-related constraints. Also, our approach has only been tested on simulated instances. Future research should validate the results by applying the model to real-world case studies to better understand its practical applicability. It would also be beneficial to incorporate a wider range of renewable energy sources, such as wind, solar, and hydroelectric power, to evaluate their impacts on scheduling efficiency. Finally, the scope of this study is restricted to a specific range of disruptions, while in real scenarios more disruptions can occur such as job insertion or machine breakdowns.

Chapter 6

Conclusion

6.1 Summary of key findings

Our research addresses the Sustainable Flexible Job Shop Scheduling Problem (SFJSSP) within the framework of Industry 5.0, aiming to optimize a delicate balance between economic, environmental, and social objectives. Industry 5.0 emphasizes the integration of human-centric and sustainable practices, positioning our work at the intersection of operational efficiency and sustainability. Chapter 2 of this thesis highlights a significant gap in the existing literature, where few studies have successfully integrated all three criteria—economic, environmental, and social—into a single cohesive model. In Chapter 3, we present the development of two multi-objective models designed to address this gap. The first model (MOP1) focuses on minimizing the makespan, energy consumption, and ergonomic risks, aiming for a comprehensive optimization of operational and environmental performance while safeguarding worker well-being. The second model (MOP2) further incorporates worker preferences, providing a more human-centric approach to scheduling. As shown in Figure 6.1, the Pareto Front for both models demonstrates a broad and diverse solution space, highlighting their ability to deliver strong performance across all objectives. However, as is often the case with multi-objective optimization, these objectives do not always align perfectly, necessitating a careful navigation of trade-offs between the competing goals of efficiency, sustainability, and worker satisfaction. Achieving an optimal solution involves striking a delicate balance between these sometimes conflicting objectives, a challenge that is central to the dynamic nature of our approach.

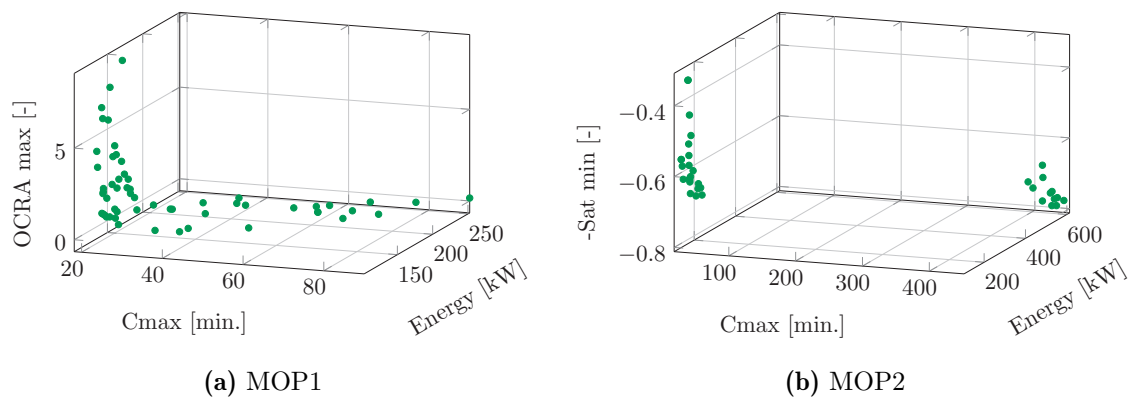


Figure 6.1: Results through the kcm_1 instance for MOP1 and MOP2

By leveraging the IQNSGA-III algorithm, we were able to effectively approximate the Pareto

Front, an essential task in multi-objective optimization. Specifically, for example kcm_1 , the algorithm demonstrated its effectiveness by yielding a minimal gap of only 1.31% in hypervolume between the Pareto Front and the solution obtained through IQNSGA-III. This small gap indicates that the algorithm is capable of accurately identifying high-quality solutions. The strength of IQNSGA-III lies in its ability to explore a wide solution space efficiently, offering a robust means of obtaining reliable initial solutions. By using the average of the normalized fitness function across multiple objectives, a schedule ensuring a balanced consideration of all criteria in the optimization process can be obtained.

Chapter 4 provides a comprehensive overview of the existing literature on the Dynamic Flexible Job Shop Scheduling Problem (DFJSSP), further emphasizing the notable gap in studies that integrate both environmental and social considerations, particularly in terms of model development and the types of disruptions addressed.

In response, Chapter 5 extends the previously developed model by integrating renewable energy sources and addressing the disruptions associated with their availability, as well as the potential for worker absenteeism. Specifically, we incorporate solar energy, which becomes available at the beginning of each production period. For each tested instance, we observed a significant reduction in carbon emissions due to the utilization of solar power, as detailed in Table 6.1. This not only showcases the environmental benefits of renewable energy integration but also reinforces the importance of sustainable energy practices in modern manufacturing systems.

Instances	kcm_1	kcm_2	kcm_3	kcm_4	FJ_{05}	FJ_{10}	FJ_{15}	FJ_{20}
Carbon emission saved	19%	15, 4%	15%	17, 8%	7, 8%	15%	14, 6%	19, 5%

Table 6.1: Proportion of carbon emission saved on the different instances

Additionally, in addressing dynamic disruptions like worker absences and energy fluctuations, machine learning-driven solutions were developed to optimize rescheduling decisions. Three distinct rescheduling strategies were tested—total rescheduling, partial rescheduling, and adaptive rescheduling—to identify the most effective approach for managing these disruptions. To guide the selection of the appropriate strategy based on the timing and proportion of disruptions, several machine learning techniques were implemented and compared. Among the approaches tested, including Q-learning, deep learning, and deep Q-learning, deep Q-learning proved to be the most effective. This technique enabled the system to dynamically adapt to disruptions while maintaining a focus on sustainability and minimizing production impacts. These results underscore the potential of combining optimization techniques with machine learning to build more resilient, adaptable, and sustainable manufacturing systems that can respond effectively to both operational and environmental challenges. The next section will summarize the key contributions of this thesis.

6.2 Contributions of the thesis

This thesis set out to address the Sustainable and Dynamic Flexible Job Shop Scheduling Problem by integrating human and environmental considerations within AI-driven scheduling solutions. The main objectives were to balance economic, social, and environmental criteria, address disruptions through adaptive rescheduling strategies, and leverage advanced AI techniques for decision-making. The thesis was guided by the following research questions, presented in Section 1:

- **Q1: Realism in modeling**
- **Q2: Integration of new criteria**
- **Q3: Balancing objectives**
- **Q4: Incorporating dynamic events**
- **Q5: Resolution methods**

The key contributions of this thesis, which address the above questions, are summarized as follows:

- **Realistic FJSSP Modeling:** We developed a model for the FJSSP that incorporates multiple real-world constraints, including setup times, transport durations, due dates, and processing precedence. This ensures the model closely aligns with practical manufacturing systems.
- **Integration of Environmental and Human Considerations:** Environmental considerations were integrated by minimizing energy consumption from transport, auxiliary equipment, and processing operations. Additionally, renewable energy sources were incorporated with constraints on production capacities and energy storage. For human factors, workers were modeled as resources with distinct skill sets and complex requirements, including ergonomic safety (quantified through the $OCRA^{max}$ index), rest times, travel durations between machines, and preferences related to tasks, task variety, and shifts.
- **Multi-Objective Optimization:** We proposed multi-objective optimization models to balance economic, environmental, and social criteria. Specifically, makespan was minimized for the economic aspect, energy consumption for the environmental aspect, and worker well-being was addressed by minimizing the $OCRA^{max}$ index or maximizing worker satisfaction. These objectives collectively ensure a trade-off among the three pillars of sustainability.
- **Dynamic Scheduling Strategies:** To address disruptions, such as worker absences and variations in renewable energy production, we developed adaptive scheduling strategies. Depending on the nature and timing of the disruption, we employed total rescheduling, partial rescheduling, and adaptive (right-shift) rescheduling strategies, ensuring flexibility and responsiveness.
- **AI-Driven Solution Methods:** An enhanced NSGA-III algorithm, improved through Q-learning and reinforcement learning, was proposed for static scheduling problems and demonstrated its effectiveness in finding high-quality solutions. For dynamic scheduling, AI-based approaches, including Q-Learning, Deep Learning, and Deep Q-Learning (DQL), were implemented to select optimal rescheduling strategies. Among these, DQL emerged as the most effective, demonstrating superior adaptability and solution quality in dynamic contexts.

These contributions are visually summarized in Figure 6.2. The figure illustrates in some way our overall approach, which consists of approaching research questions progressively and inclusively, gradually increasing the complexity of the problems tackled and the tools and methods developed.

Our results demonstrate that integrating human and environmental consideration into scheduling systems significantly enhances their resilience and overall sustainability. By addressing human-centric factors, such as reducing ergonomic risks and respecting worker preferences for task variety, shift assignments, and machine allocation, the proposed models mitigate risks such as fatigue, absenteeism, and injuries. This integration not only improves worker well-being but also ensures smoother production flows by minimizing disruptions linked to workforce dissatisfaction and health issues.

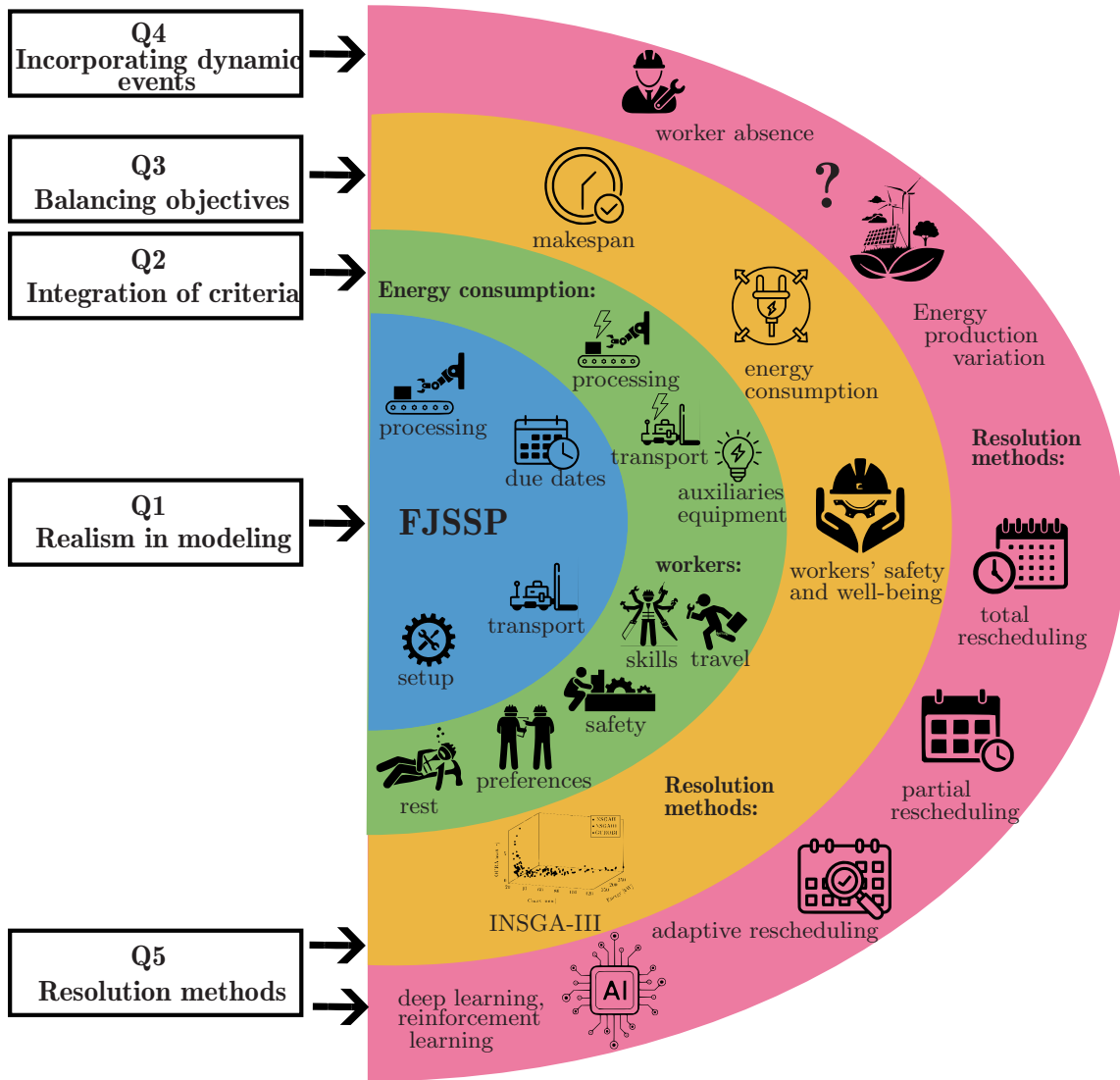


Figure 6.2: Overview of thesis contribution

On the environmental front, incorporating energy consumption constraints and renewable energy variability into the scheduling process reduces the system’s carbon footprint while maintaining operational efficiency. Results highlight that energy-aware scheduling strategies can effectively balance production goals with environmental sustainability, demonstrating the feasibility of renewable energy integration in dynamic manufacturing systems.

Regarding dynamic disruptions, our analysis reveals that choosing a good rescheduling strategies—total rescheduling, partial rescheduling, or adaptive rescheduling—play a critical role in managing unforeseen events, such as worker absences and fluctuations in renewable energy production. Among these, partial rescheduling emerges as the most balanced approach, effectively minimizing deviations from the original schedule while maintaining system performance. The adaptive strategy is particularly effective for handling small-scale disruptions with minimal computational effort, while

total rescheduling, although robust, often introduces larger schedule deviations.

Finally, leveraging AI-driven techniques for dynamic decision-making has proven highly effective. The comparison of Q-Learning, Deep Learning, and Deep Q-Learning (DQL) shows that DQL outperforms other methods in terms of solution quality. DQL enables the system to quickly identify the most appropriate rescheduling strategy based on the nature and timing of disruptions, thereby reducing recovery times and enhancing overall system stability.

In conclusion, this work highlights the importance of integrating economic, environmental, and social criteria in both static and dynamic scheduling contexts, using the flexible job shop as a representative example of modern production environments in the Industry 5.0 era. By accounting for real-world constraints, human well-being, and energy variability, the proposed approaches contribute to building more resilient, adaptive, and sustainable manufacturing systems that align with the primary goals of Industry 5.0.

6.3 Perspectives

Although this study presents valuable insights through the developed models and analyzed results, it also has certain limitations regarding some aspects that should be identified and recognized. These limitations not only highlight areas for improvement, but also present significant opportunities for future work:

- **Data aspects:** A significant limitation of this study lies in its reliance on instances derived from existing literature and artificially generated data. While these instances provide a foundation for testing and validating the models, they may not fully capture the intricacies, variability, and unforeseen challenges inherent in real-world manufacturing environments. Real-world scenarios often involve additional complexities, such as unstructured disruptions—where the duration of the disruption, like the sudden absence of key workers or unexpected machine failures, is unknown in advance—varying levels of data quality, and unique constraints, such as regulatory requirements specific to certain industries, which may not be reflected in simulated cases.

Moreover, the instance sizes used in this research, though suitable for initial testing, are smaller than those typically encountered in industrial settings. Applying the models to real-world cases would not only expose them to larger, more complex problem instances, but would also allow them to benefit from professional-grade equipment and advanced operational approaches. Addressing this gap is critical to ensuring the practical applicability of the proposed models and methods. A key perspective for future work involves finding real-world applications to validate and refine the proposed solutions. Collaboration with industry partners could enable access to real manufacturing data, providing an opportunity to test the models in operational settings. This step is essential to bridge the gap between theoretical development and practical implementation, ensuring the solutions' robustness, adaptability, and relevance to modern manufacturing challenges.

- **Social aspects:** A potential extension of the current model could involve integrating a more nuanced representation of worker fatigue. While the OCRA index provides valuable insights into ergonomic risks, it assesses fatigue on a broader scale by considering the overall process. A more refined approach could involve implementing dynamic fatigue models, such as fatigue

curves, with predefined thresholds to ensure worker safety and productivity are not compromised. Additionally, while the current model focuses on upper-limb risks through the OCRA index, exploring alternative or complementary ergonomic indices could provide a broader perspective on worker well-being and their potential impact on scheduling. For instance, indices addressing lower-limb fatigue or whole-body strain might be tested and compared to evaluate their effect on operational outcomes.

Future research could also investigate additional worker characteristics, such as age, physical stature, experience, or health conditions, all of which influence performance, fatigue rates, and recovery times. These factors are particularly relevant in ensuring inclusivity and efficiency in human-centered manufacturing systems. It is worth noting that other studies have begun exploring these areas, particularly integrating personalized worker attributes and dynamic fatigue modeling. However, this research is still in its early stages, leaving significant room for advancements. Furthermore, the integration of individual and collective human behavior models, as well as human-machine and even human-humanoid interactions, represents a crucial avenue for future investigation. These interactions, especially in environments incorporating advanced robotics, can significantly impact worker well-being, productivity, and system adaptability. The complexity of human factors in scheduling emphasizes the need for ongoing studies to enhance worker well-being, productivity, and adaptability in increasingly human-centric manufacturing environments.

- **Environmental Aspects:** While this study introduced the example of solar energy as a complementary renewable source into the scheduling model, further exploration of renewable energy sources and their specificities is needed to create a more robust and sustainable framework. Other energy sources, such as wind power, geothermal energy, or bioenergy, could be incorporated to provide a diversified and dynamic energy supply system.

Additionally, the temporal variability and storage constraints of renewable energies should be further analyzed to ensure seamless integration into manufacturing processes. It is worth noting that some studies have already begun to explore the integration of renewable energy in scheduling and manufacturing systems. However, this area of research is still in its early stages, with much work needed to address the complex challenges associated with renewable energy variability, grid dependency, and long-term sustainability in production environments.

Beyond energy considerations, the inclusion of recycling strategies could significantly enhance the environmental sustainability of the system. For instance, the recycling of tooling materials, by-products, or waste generated during production could be modeled to minimize resource consumption and reduce the ecological footprint. This could involve not only optimizing production schedules but also scheduling recycling activities in parallel with manufacturing processes to ensure efficient resource use. Moreover, integrating the scheduling of logistics, quality control, and maintenance activities with production could further improve efficiency and reduce environmental impact. These enhancements would move the scheduling model closer to the goals of a circular economy, emphasizing resource efficiency and environmental responsibility.

- **Dynamic events:** This study specifically focused on dynamic events related to human and environmental factors to investigate their impacts on scheduling outcomes and how to deal with them intelligently. While this approach allowed for an in-depth exploration of these critical aspects, there are several areas for improvement and expansion.

Firstly, the scope of disruptions could be broadened to include additional worker-related dynamics, such as variations in processing times due to human errors, learning curves, or changes in task complexity. The characterization of these variations can be based on advanced models combining physiological aspects with individual and collective worker behaviors in a manufacturing environment. Incorporating these variations could provide a more accurate representation of real-world scenarios.

Secondly, in the current model, worker absences are assumed to have a known duration. However, in practical settings, absence durations are often uncertain and may evolve unpredictably. Incorporating undetermined or stochastic absence durations into the scheduling model would significantly enhance its realism and robustness.

Finally, the model does not currently account for other common disruptions frequently encountered in manufacturing systems. For example, literature extensively highlights the importance of addressing machine breakdowns, unexpected job arrivals, material shortages, or delayed deliveries, as these can have cascading effects on the production schedule. Integrating such disruptions into the scheduling framework would create a more comprehensive and precise model, better suited to the complex and dynamic nature of real-world manufacturing environments. This represents an important avenue for future research, with the potential to further enhance the adaptability and resilience of dynamic scheduling systems.

- **Resolution methods:** While the resolution methods employed in this study, such as NSGA-III and AI-driven approaches like QL, DQL, and DL, have demonstrated significant advantages, they are not without limitations. NSGA-III, for instance, is effective for solving multi-objective optimization problems, but its scalability can be a challenge for large-scale industrial problems. The computational cost of maintaining a diverse Pareto front grows substantially as the problem size increases. A potential improvement would involve hybridizing NSGA-III with other metaheuristics, such as particle swarm optimization (PSO), to enhance convergence speed and scalability. By combining NSGA-III's ability to maintain a diverse set of high-quality solutions across multiple objectives with PSO's strengths in rapid local search and fine-tuning of solutions, the hybrid approach could achieve faster convergence toward the Pareto-optimal front. PSO, for example, could be used during the refinement stages of the search process to accelerate the exploitation of promising regions in the solution space, while NSGA-III continues to ensure exploration and diversity. Additionally, the hybridization could improve scalability, as the cooperative use of these methods allows for better handling of larger problem instances by distributing the computational effort more effectively between exploration and exploitation phases.

For AI-based methods, QL and DQL have shown promise in dynamic scheduling, but their reliance on extensive training data and computational resources limits their applicability in real-time environments. To address these issues, Transfer Learning seems a promising approach that could be explored to leverage pre-trained models from similar scheduling contexts, thereby reducing the training burden. Additionally, the integration of distributed reinforcement learning techniques could enhance computational efficiency by parallelizing the learning process. Another avenue for improvement involves designing reward functions that are more nuanced and multi-dimensional, capturing not just immediate objectives but also long-term sustainability and resilience. Lastly, the black-box nature of AI models remains a significant challenge. Improving the interpretability of RL-based approaches is crucial for their adoption in industry. These improvements would address current limitations while paving the way for more robust, scalable,

and user-friendly scheduling solutions tailored to Industry 5.0 standards. Moreover, the potential integration of generative AI could provide an avenue for further advancements. By using generative models to predict and create novel scheduling scenarios, or to simulate disruptions and alternative solutions, it may enhance the system's adaptability and decision-making capabilities, thus offering a more dynamic approach to complex manufacturing environments.

- **More general aspects:** One limitation of the current model is the oversimplification of transportation logistics. Currently, transportation equipment is assumed to be unlimited in both number and capacity, which does not accurately represent the operational constraints typical in real-world manufacturing systems. A more refined transportation model could be developed to include realistic constraints, such as the limited number of Automated Guided Vehicles (AGVs), their capacity, battery life, and charging requirements. Additionally, incorporating AGV traffic management, collision avoidance mechanisms, and dynamic rerouting strategies to address congestion would significantly improve the model's realism.

Another area for improvement is the inclusion of multiple factories. In modern supply chains, operations are frequently distributed across various facilities. Extending the model to facilitate coordination between factories, manage transportation between sites, and optimize shared resource allocation could offer valuable insights into the complexities of inter-factory scheduling.

Finally, integrating resource maintenance is another potential enhancement. While workers' fatigue is accounted for, machine maintenance is not currently incorporated. Including both preventive and corrective maintenance tasks scheduling would further increase the model's applicability and accuracy in real-world scenarios.

In conclusion, this thesis has made significant contributions to addressing the dynamic and sustainable Flexible Job Shop Scheduling Problem by integrating human and environmental factors into AI-driven scheduling solutions. By considering factors such as energy consumption, renewable energy variability, and worker well-being, this research proposes scheduling models that not only enhance economic and environmental efficiency but also improve employee safety and satisfaction. The multi-objective optimization, coupled with dynamic rescheduling strategies, has enabled the development of scheduling systems capable of adapting to unforeseen disruptions, such as worker absences and fluctuations in energy production. The AI methods proposed, particularly Deep Q-Learning, have proven effective in selecting appropriate rescheduling strategies in real-time, contributing to more resilient and flexible disruption management. However, improvements are possible, including extending the model to incorporate more complex scenarios, enhancing worker fatigue representation, integrating additional renewable energy sources, and managing unforeseen dynamic events. Future research perspectives include validating the models in real-world industrial settings, improving the scalability of the proposed methods, and exploring new approaches to further optimize production systems within the Industry 5.0 framework. This work paves the way for transitioning towards more sustainable, adaptive, and human-centered production systems, in line with the goals of the future industry.

6.3. PERSPECTIVES

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Appendix A

Update of Chapter 2 completing the state-of-the-art on SFJSSP

This appendix supplements the state-of-the-art on SFJSSP presented in Chapter 2. Since the original paper was published in early 2023, this section covers works from the end of 2022 and 2024 that focus on the FJSSP incorporating human or environmental factors. Tables A.1, A.2, and A.3 categorize these papers, extending the tables presented in Chapter 2. Specifically, Table A.1 lists papers that incorporate only human factors, Table A.2 focuses on papers addressing only environmental factors, and Table A.3 covers papers that integrate both.

References	Human Factors						Objective(s)		
	Ag	Lc	Er	Lr	Re	Sk	Eco.	Env.	Hum.
[576, 577]				×	×		Cmax;mW		wW
[578]				×	×		Cmax;mW		
[579]						×	Cmax;mW		wW
[580, 581, 582, 583, 584]						×	Cmax		
[585]						×	Cmax;T		
[586]						×	Cmax;mW		
[569]		×			×		C, mW, E/T		
[540]*					×		Cmax;T		EF
[541]*							Cmax		S
[566]**							T		O
[587]**							Cmax;mW;C		
[588, 589, 590, 591]**							Cmax		
[568]*							Cmax;R		
[592]**							Cmax;Tr;SU		
[593]**							Cmax;T		

Ag: Age; Lc: labor cost; Er: Ergonomic risks; Lr: Learning rate; Re: Rest; Sk: Skill; Cmax: makespan; mW: Machine workload; C: Cost; R: Reliability; E/T: Earliness/Tardiness; wW: Workers workload; O: Overtime of workers *: dynamic scheduling; Tr: Transport time; SU: Setup time; EF: Error due to human fatigue; S: Stress level; **: Human is considered as a dual resource and no specific factor is indicated.

Table A.1: Articles on FJSSP integrating the human factor from 2023 to 2024

References	Env. factors				Objective(s)		
	Ce	Ec	Ne	Rc	Eco.	Env.	Hum.
[594]	×	×	×		Cmax;E/T	Ce;Ne	

[595]	× ×	Cmax;C	Ce
[596, 597, 598, 599]	× ×	Cmax	Ce
[600, 601, 602, 603, 604, 605, 606, 607, 608, 609, 610, 611, 612, 613, 614, 615, 616, 453, 617, 618, 454, 619, 620, 621, 622, 456, 456, 623, 624, 455, 625, 626, 627, 628, 629, 630, 631, 632, 633, 634] [635, 636, 637, 321, 638, 510, 238, 511]*	×	Cmax	Ec
[639, 513]*	×	Cmax;R	Ec
[640, 641]	×	Cmax;EC	
[642]	×	T,EC	
[643, 644, 645, 646]	×		Ec
[647]	×	F	Ec
[648, 649] [650]*	×	Cmax;E/T;mW	Ec
[376], [543]*	×	T	Ec
[651, 652]	×	Cmax;mW	Ec
[653, 654]	×	Cmax;T	Ec
[655]	×	Cmax;T;C	Ec
[656]	×	Cmax, MC	Ec
[657]	×	Cmax;C	Ec
[658]	×	Cmax;mW;IO	Ec
[659]	×	C	
[660, 661, 662] [663]*	×	Cmax;mW	Ec

Ce: Carbon emission; Ec: Energy consumption; Ne: Noise emission; Rc: Recycling; C: Cost; EC: Energy cost; Cmax: makespan; R: Reliability; mW: Machine workload; E/T: Earliness/Tardiness; Ec: Energy consumption; Ce: Carbon emission/footprint; F: Flow time; IO: Turn On/Off; MC: Maintenance cost; *: dynamic scheduling

Table A.2: Articles on FJSSP integrating the environmental factor from 2023 to 2024

References	Human Factors					Env. factors				Objective(s)			
	Ag	Lc	Er	Lr	Re	Sk	Ce	Ec	Ne	Rc	Eco.	Env.	Hum.
[40]*			×		×	×	×	×			Cmax;C;Q	Ce	
[36]			×		×	×	×				Cmax	Ce	
[27, 28] [29]*			×		×	×	×				Cmax	Ec	Er
[41]*		×			×	×	×				Cmax;Lc;R	Ec	
[33]					×	×	×					Ec	
[42, 664]						×	×				Cmax	Ec	
[565]		×	×	×			×				Cmax;C	Ec	
[48]*					×		×				Cmax	Ec	F

Ag: Age; Lc: labor cost; Er: Ergonomic risks; Lr: Learning rate; Re: Rest; Sk: Skill; Ce: Carbon emission; Ec: Energy consumption; Ne: Noise emission; Rc: Recycling; EC: Energy cost; Cmax: makespan; C: Cost; Ce: Carbon emission/footprint; Ec: Energy consumption; R: Reliability; Q: Quality; F: Fatigue.

Table A.3: Articles on FJSSP integrating both human and environmental factors from 2023 to 2024

Figure A.1 complements the chronological analysis shown in Figure 2.8. It highlights trends in the literature, demonstrating a continuous rise in studies, particularly with regard to environmental factors. The two most commonly investigated objectives are makespan and energy consumption. In contrast, human factors, such as ergonomic risks, fatigue, and well-being, remain significantly underexplored.

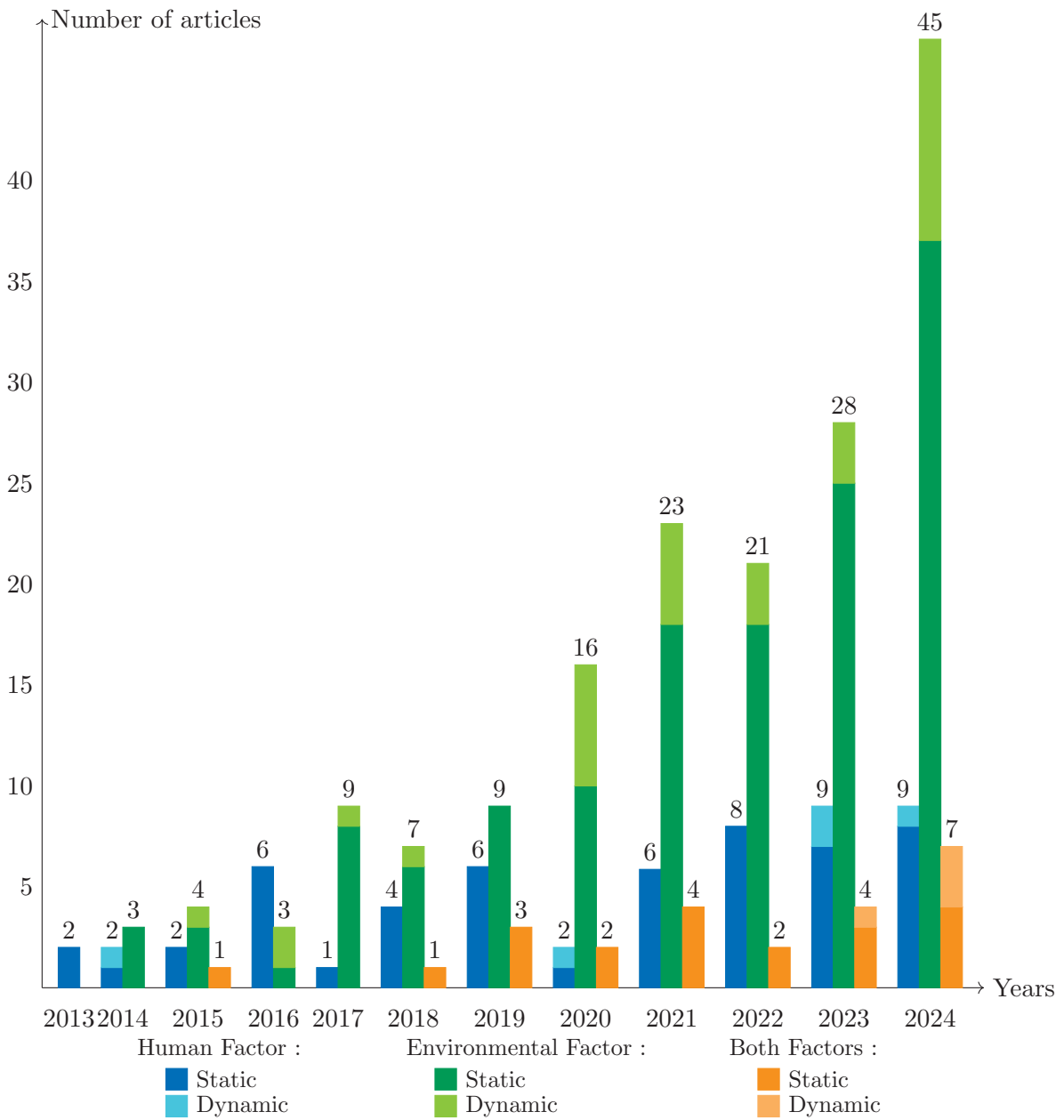


Figure A.1: Enumeration of the surveyed literature integrating human and/or environmental factors

Appendix B

Preliminary mono-objective MILP model for Green Scheduling Integrating Human Factors

This appendix presents a preliminary study conducted at the start of the thesis, which was presented at *ROADEF 2023* and is available at the following link: [665]. At this stage, the model was single-objective, focusing solely on minimizing energy consumption. The purpose of this work was to illustrate the potential impact of integrating environmental and social considerations on a small-scale case study.

B.1 Proposed model

We propose a FJSSP model taking into account economic, environmental, and human aspects. The principal assumptions of the model are: i) each operation needs one operator and one machine to be processed, ii) machines and operators can perform one operation at a time, iii) an operator rests *REST* of his working time after each operation, and iv) the time horizon is composed of two 7-hour shifts per day. The objective function minimizes the total energy consumption as follows:

$$\min_{\mathbf{X}} EM(\mathbf{X}) + ET(\mathbf{X}) + EC(\mathbf{X}) \quad (\text{B.1})$$

where \mathbf{X} is a multidimensional vector of binary decision variables defining the schedule, $EM(\mathbf{X})$ the total energy consumption for processing operations on machines, $ET(\mathbf{X})$ the total energy consumption associated to the transport of products between machines, and $EC(\mathbf{X})$ the auxiliary energy consumption, such as lighting or heating, directly linked to the makespan. For human consideration, we use the OCRA index, which predicts the risk of work-related musculoskeletal disorders associated with a given schedule of tasks performed by an operator. In our model, jobs, tasks, workers, machines, and periods are respectively denoted by j , k , w , i , and t . The decision variable X_{kjwit} indicates if the k -th operation of job j is assigned to worker w and machine i in period t . We defined other intermediary decision variables, which are linear functions of \mathbf{X} : \mathbf{R} for rest time, \mathbf{OCRA} for OCRA index, \mathbf{V} for the assignment of workers on periods, \mathbf{S} and \mathbf{C} for starting and completion times of operations, \mathbf{Y} for the assignment of operations to the same worker, and \mathbf{N} for the assignment of operations on machines. The parameters of the model are: p for the processing time, tv for the travel time, tp for the transport time, s for the the setup time, b and f for, respectively, the beginning and the ending of a period, and d for the due dates. In addition to classical FJSSP constraints, we have the following additional

B.1. PROPOSED MODEL

workers-related constraints:

- OCRA index threshold:

$$OCRA_{wt} \leq OCRA^{max} \quad \forall w, t \quad (2)$$

- Rest time for workers:

$$R_{kjw} = REST \times \sum_i X_{kjwit} \times p_{kjwi} \quad \forall t, w, j, k \quad (3)$$

- Assignment of workers to periods:

$$V_{tw} + V_{(t+1)w} = 1 \quad \forall t, w \quad (4)$$

- Worker-related precedence constraints:

$$S_{k'j'} + (1 - \sum_w Y_{k'j'w})M \geq C_{k'j'} + \sum_{w,i,t} R_{kjwit} + \sum_{i,i'} tv_{ii'} \times N_{k'j'k'j'i'} \quad \forall j, j', k, k' \quad (5)$$

Figure B.1 shows the first results of our model on a small instance, inspired by [248] and completed with information for workers and energy consumption. The instance is composed of 5 machines, 3 workers, and 4 jobs composed of a total of 12 tasks. The model is implemented and solved using GUROBI solver. As expected, energy consumption is reduced when considered in the objective. When we incorporate the worker factors, the OCRA index is better and the tasks are not allocated in the same way. At this point, we can say that the consideration of these two factors is not negligible. More tests have to be done to confirm this analysis, especially on real data.

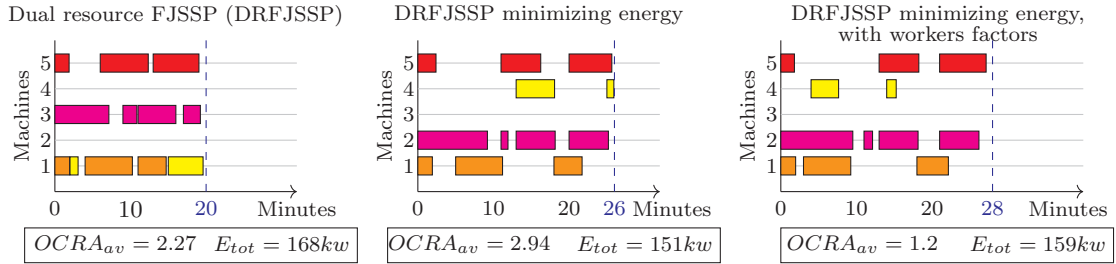


Figure B.1: Tasks allocation under different FJSSP model

Appendix C

Evaluating the results sensitivity to parameter variations

This appendix aims to assess the sensitivity of the three objective results to variations in different model parameters. The range of parameter values can influence each objective differently, potentially altering the shape of the Pareto front and affecting the correlations between objectives. To explore these dynamics, we first vary parameters related to energy consumption, including the energy required for task operations, product transportation, and auxiliary equipment. Next, we analyze the impact of workforce-related factors such as the number of workers, their skill levels, the number of technical actions per operation, and rest periods. The initial instance, described in Section C.1, serves as the baseline for comparison, allowing us to quantify the effects of these parameter changes on overall performance and trade-offs among the objectives.

C.1 Initial instance

Number of jobs	46	Transport time	1-3 (min)
Number of tasks	182	Energy consumption	15-40 (kW)
Number of machines	15	Energy transport	2 (kW)
Number of workers	8	Energy auxiliaries	1 (kW)
Processing times	1-20 (min)	Workers skills	0.9-1.3
Setup time	0-1 (min)	Technical actions	10-70
Travel time	0.5-2 (min)	Rest time	8 (%)

Table C.1: Initial instance composition

This instance is the FJ_{15} instance presented in Section 3.5.

Figure C.1 presents the solution obtained with INSGA-III on the initial instance. In this case, the makespan is inversely correlated with both energy consumption and $OCRA^{max}$. Meanwhile, energy consumption and $OCRA^{max}$ appear to be positively correlated: as energy consumption increases, $OCRA^{max}$ tends to rise as well.

C.2. ENERGY CONSUMPTION VARIATION

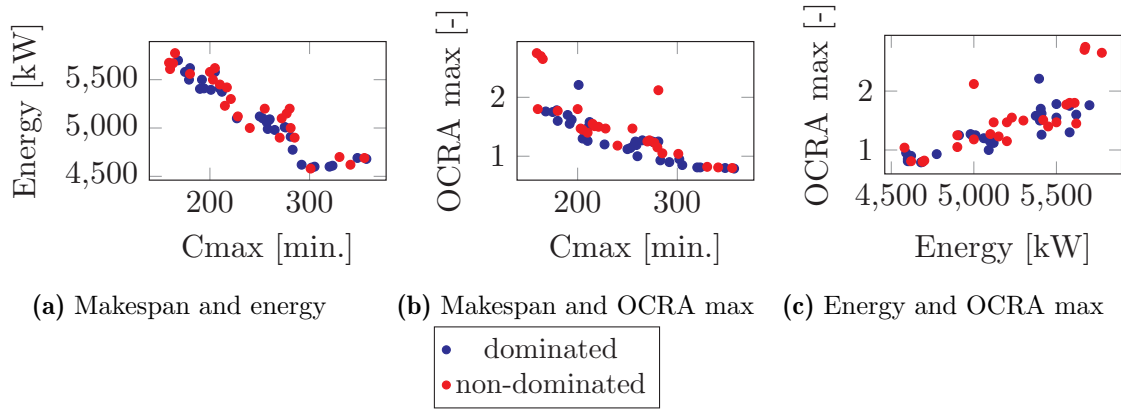


Figure C.1: Display of the solutions of FJ_{15} on two-by-two axes

C.2 Energy consumption variation

C.2.1 Auxiliary energy consumption

First, we assess the impact on all objective functions when auxiliary energy consumption is increased compared to the initial instance. As expected, the total energy consumption rises with the higher auxiliary energy per time unit. However, both the makespan and $OCRA^{max}$ remain largely unaffected, staying within the same range as before.

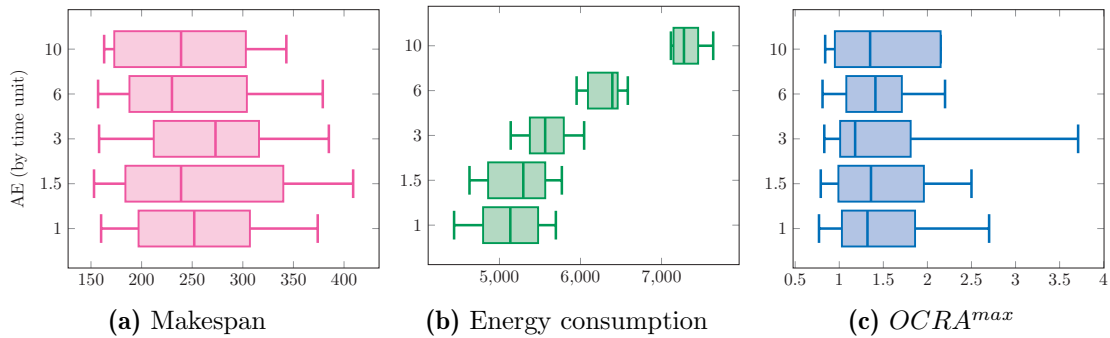


Figure C.2: Impact of auxiliaries energies variations on FJ_{15}

Figure C.3 illustrates the solutions with an auxiliary energy consumption of 10 kW per time unit. Here, we observe that the relationship between makespan and energy consumption begins to reverse. This can be explained by the fact that total auxiliary energy consumption is directly tied to the overall process duration: longer makespan lead to higher auxiliary energy consumption, which is influenced by the per-time-unit value. The relationship between makespan and $OCRA^{max}$ remains unchanged, while the correlation between energy consumption and $OCRA^{max}$ disappears.

C.2. ENERGY CONSUMPTION VARIATION

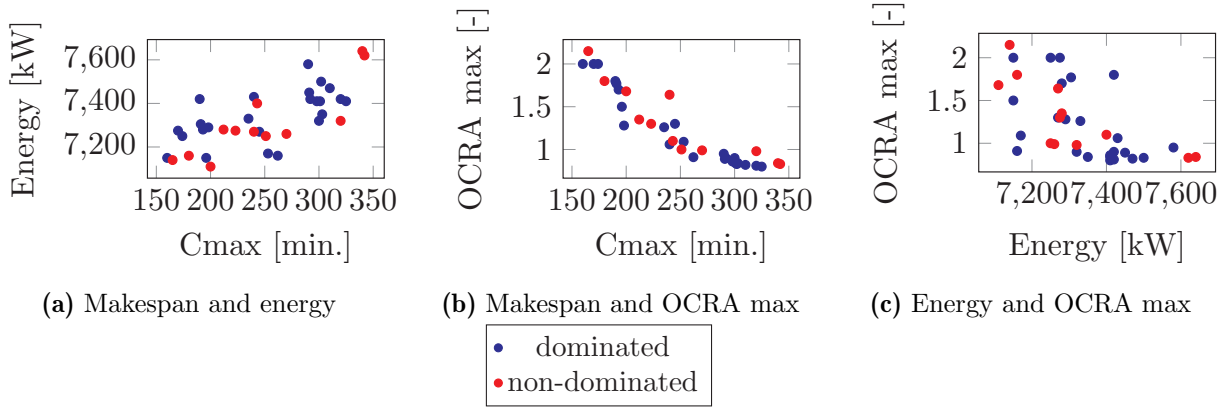


Figure C.3: Display of FJ_{15} solutions with 10 auxiliary energy consumption per time unit

C.2.2 Transport energy consumption

In this section, we assess the impact of energy consumption for transporting products between machines, focusing on the consumption per time unit. As anticipated, an increase in this value results in a proportional rise in total energy consumption. However, the other two objectives—makespan and $OCRA^{max}$ —remain largely unaffected by this variation, demonstrating minimal sensitivity to changes in transportation energy. This is further illustrated in Figure C.4, where the boxplot for these objectives show little deviation.

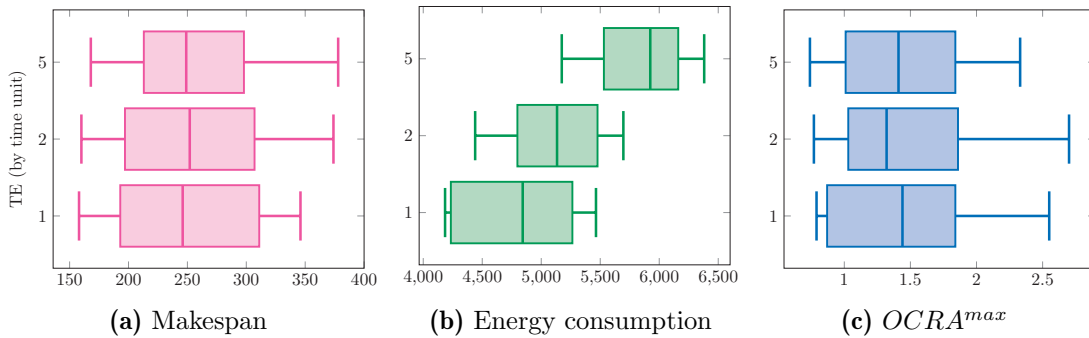


Figure C.4: Impact of transport energies variations on FJ_{15}

C.2.3 Processing energies

This section evaluates the impact of varying the range of energy consumption for processing operations. We test three different ranges: from 0 to 25 kW, from 40 to 65 kW, and from 60 to 90 kW. The initial scenario is from 15 to 40 kW. Figure C.5 illustrates the impact of these ranges on each objective function. Notably, we observe that the makespan remains unaffected across the first three scenarios, but in the fourth scenario (60 – 90 kW), the worst solution found is significantly higher than in the other ranges. As expected, total energy consumption increases with the rising parameter values. Regarding $OCRA^{max}$, no major changes are observed, although the diversity of solutions

C.3. VARIATION WORKERS

becomes greater as energy consumption increases, indicating a broader spread in possible outcomes.

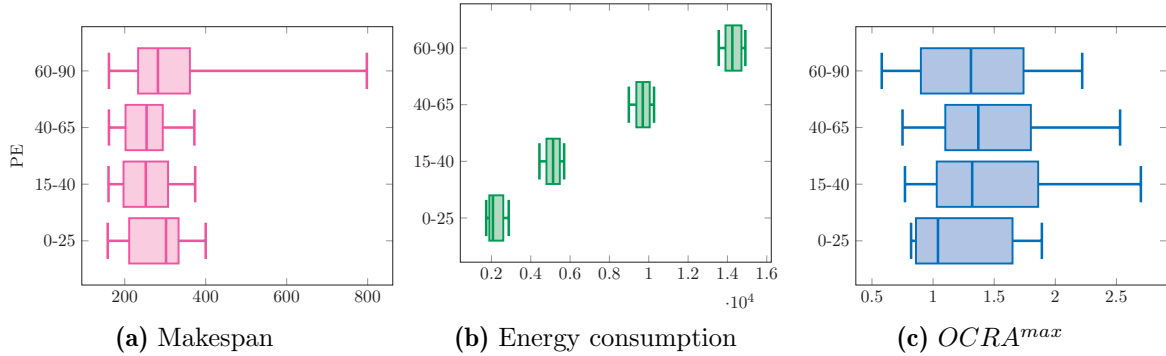


Figure C.5: Impact of processing energies variations on FJ_{15}

Figure C.6 illustrates the differences in the solution visualizations for the fourth scenario (60 – 90 kW). We again observe high values for both energy consumption and makespan, as noted in Figure C.5. For most solutions, makespan and energy consumption remain inversely correlated, though we identify a few isolated solutions where both objectives are high. The relationship between makespan and $OCRA^{max}$ continues to be inversely correlated, but no significant correlation is observed between energy consumption and $OCRA^{max}$ in this scenario.

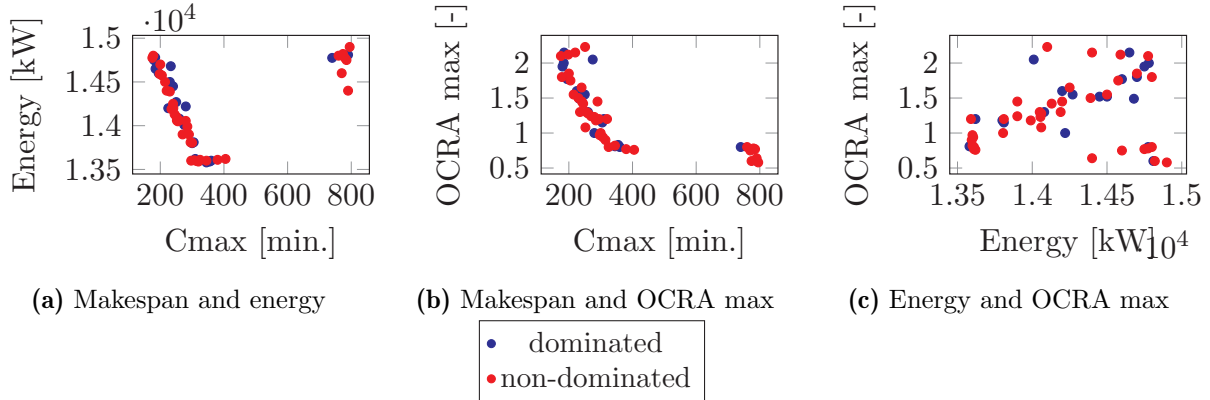


Figure C.6: Solutions with energy consumption for processing operations ranging from 60 to 90 kW

C.3 Variation workers

C.3.1 Number of workers

Secondly, we evaluate the impact of worker-related parameters on the three objective functions. First, the number of workers is varied from 4 to 12. As shown in Figure C.7, the number of workers has a significant impact on the makespan, which decreases as the number of workers increases. The solution space for the makespan narrows considerably with the increasing number of workers. Regarding energy consumption, we observe higher values when the number of workers is smallest (4), but the energy

C.3. VARIATION WORKERS

consumption remains relatively stable for the other scenarios. For $OCRA^{max}$, the smallest number of workers also leads to an increase value and a wider range of possible solutions. Once again, the four other scenarios are less affected.

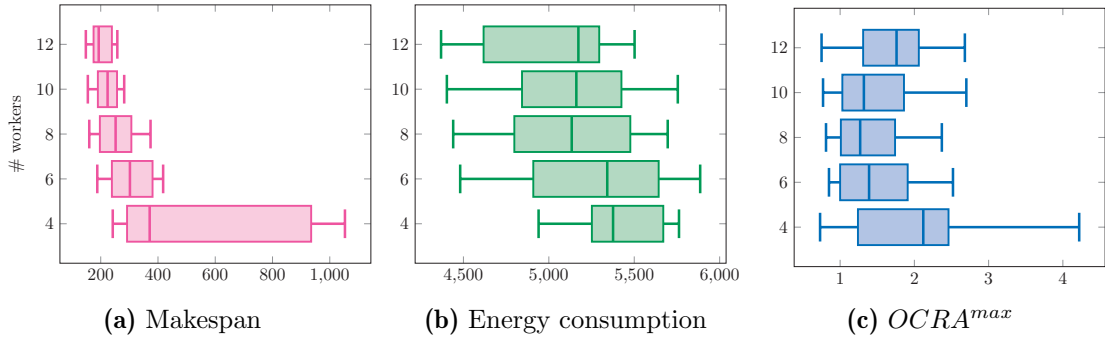


Figure C.7: Impact of number of workers on FJ_{15}

C.3.2 Workers skills

Worker skill is represented by a parameter that acts as a time factor. For instance, if the worker skill of an operator for a specific task is 0.9, the initial processing time for that task is multiplied by 0.9, meaning the worker completes the task faster. In the initial scenario, worker skills range from 0.9 to 1.3. We tested two scenarios where all operators have the same skill: in the first scenario, the skill is set to 0.9, and in the second, it is set to 1.3. As shown in Figure C.8, assigning a skill of 0.9 to all workers reduces the range of possible solutions but yields good results across all three objectives. In the scenario where all workers have a skill of 1.3, the solution space expands, leading to potential significant increases in makespan and energy consumption, though $OCRA^{max}$ remains unaffected.

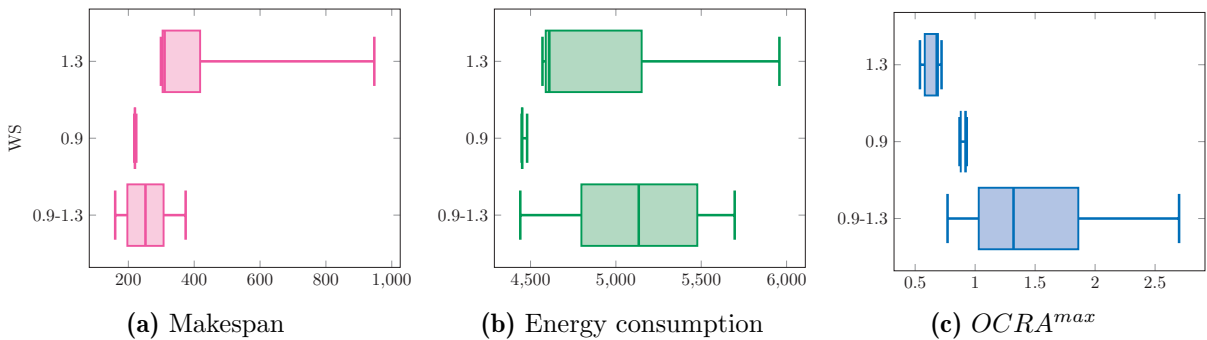


Figure C.8: Impact of workers skills variations on FJ_{15}

C.3.3 Number of technical actions

The number of technical actions per task initially ranges between 10 and 70. Figure C.9 illustrates the impact of varying this interval on the three objectives, with a particular focus on $OCRA^{max}$. Since $OCRA$ is directly influenced by the number of technical actions, any variation in this parameter

C.3. VARIATION WORKERS

significantly affects the $OCRA^{max}$ objective. Specifically, increasing the number of technical actions leads to a rise in $OCRA^{max}$, while reducing the number of actions results in a decrease. Additionally, a higher number of technical actions broadens the range of possible values, indicating more diverse outcomes. Conversely, when the number of technical actions is smaller, the makespan tends to increase.

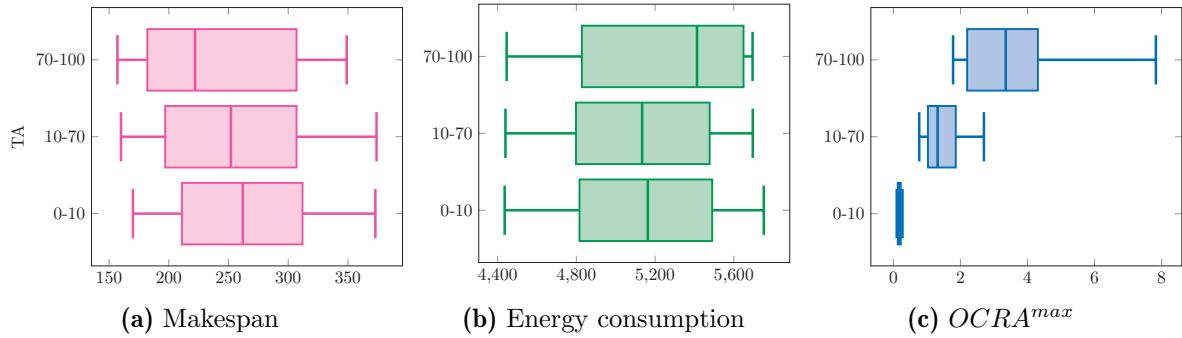


Figure C.9: Impact of number of technical actions variations on FJ_{15}

C.3.4 Rest time

Initially, the rest time for all workers is set to be at least 8% of their total working time. This section evaluates the impact of varying this rest time on the three objectives. Once again, Figure C.10 shows that $OCRA^{max}$ is the most affected objective, as there is a direct link between $OCRA$ and rest time. Naturally, increasing rest time leads to an improvement in $OCRA^{max}$ values. On the other hand, a longer rest time results in a higher makespan, as extended breaks between operations slow down the overall process. Energy consumption, however, remains largely unaffected by changes in rest time, suggesting that rest time has minimal influence on the total energy used during production.

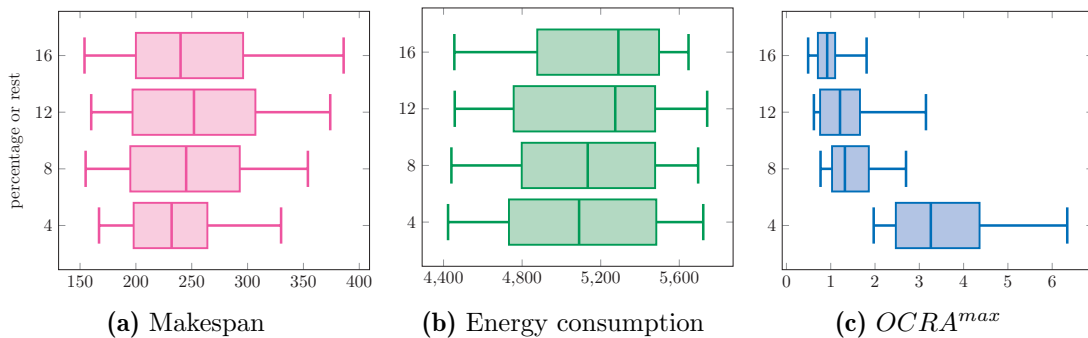


Figure C.10: Impact of rest times variations on FJ_{15}

In conclusion, this study demonstrates that variations in the parameters of different instances have a significant impact on the outcomes and the resulting Pareto front. It is crucial to acknowledge that the nature of the instance and the specific case study heavily influence the final results and the optimal solution. For example, in one scenario, energy consumption might play a decisive role in shaping the outcomes, while in another, it may have a less pronounced effect. Similarly, human factors, such as worker skills or rest times, can greatly impact the results in certain instances but be less influential in

C.3. VARIATION WORKERS

others. This highlights the importance of tailoring the model and parameter settings to the specific context of each case study, as the sensitivity of the objectives to these variations can differ significantly. Therefore, understanding the relationships between parameters and objectives is essential for achieving the most accurate and relevant solutions.

Appendix D

Evaluating model complexity and algorithm performance

This appendix evaluates the performance of the IQNSGA-III algorithm with respect to various parameter settings and instance sizes. Table D.1 provides an overview of the composition of the instances.

Instances	# machines	# workers	# jobs	# tasks
kcm_1	5	3	4	12
kcm_2	7	5	10	29
kcm_3	10	7	10	30
kcm_4	10	4	15	56
FJ_{05}	6	4	18	78
FJ_{10}	15	8	31	125
FJ_{15}	15	8	46	182
FJ_{20}	30	20	60	234
$DFMC$	8	8	40	570

Table D.1: Instances composition (#: number of)

First, we assess the impact of population size on the algorithm’s execution time. We test five different population sizes—20, 40, 60, 80, and 100—and record the average execution time in seconds, as shown in Table D.2.

Instances/ population size	20	40	60	80	100
kcm_1	7.5	15	25	35	45
kcm_2	21	43	68	92	119
kcm_3	30	61	92	130	163
kcm_4	76	154	232	305	397

Table D.2: Calculation time depending on the population size (seconds)

Next, we test five different iteration counts and record the average execution time in seconds, as shown in Table D.3.

Figure D.1 presents these results as a curve, highlighting that the computation time increases with instance size. It also shows that both population size and the number of iterations appear to have a similar impact on the algorithm’s execution time.

Instances/iteration number	20	40	60	80	100
kcm_1	9.2	17.5	25.5	33	41
kcm_2	24.5	47	69	90	112
kcm_3	34	65	95	124.5	157.5
kcm_4	84	158	232	309.5	380

Table D.3: Calculation time depending on the number of iteration (seconds)

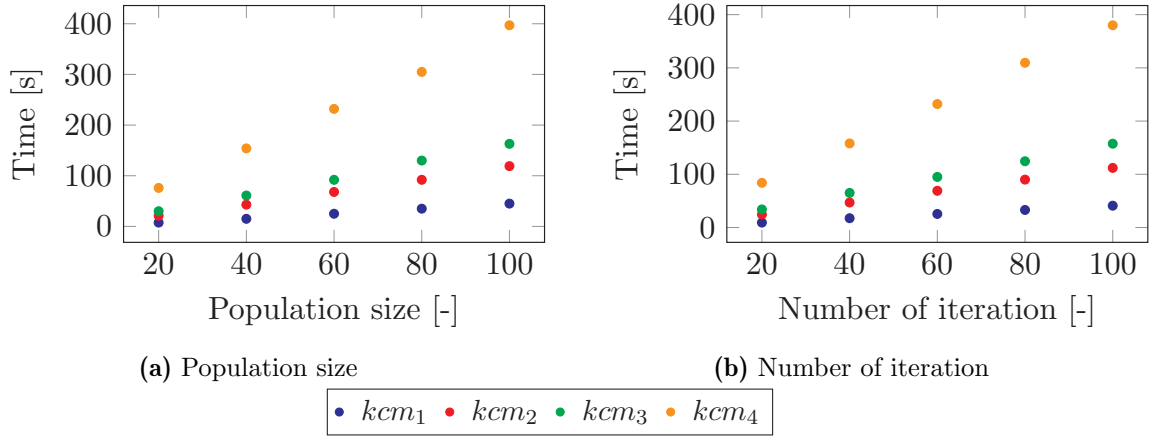


Figure D.1: Calculation time depending on different instances and algorithm parameters

Next, we analyze the impact of population size on the algorithm’s performance. To do so, we calculate the averages of the minimum, first quartile (q1), second quartile (q2), and third quartile (q3) for each objective, considering both population size and the number of iterations. These results for kcm_1 are presented in Figure D.2 and D.3, but we remark the same tendencies for each instances. For greater clarity, we compute the relative error for each value, comparing it to the best value obtained with other population sizes and iteration counts.

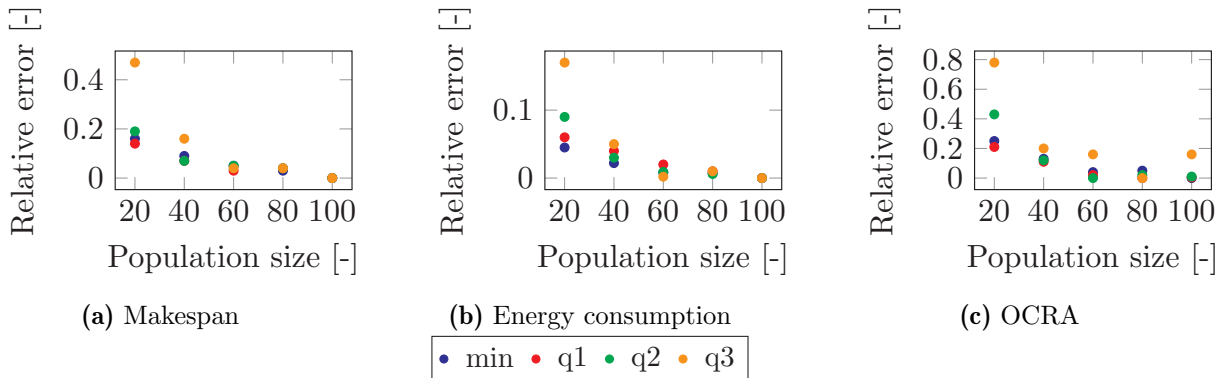


Figure D.2: Algorithm performance depending on different instances and different population size

Both figures demonstrate that population size and the number of iterations have a significant impact on the algorithm’s performance and the final results. Increasing the population size expands

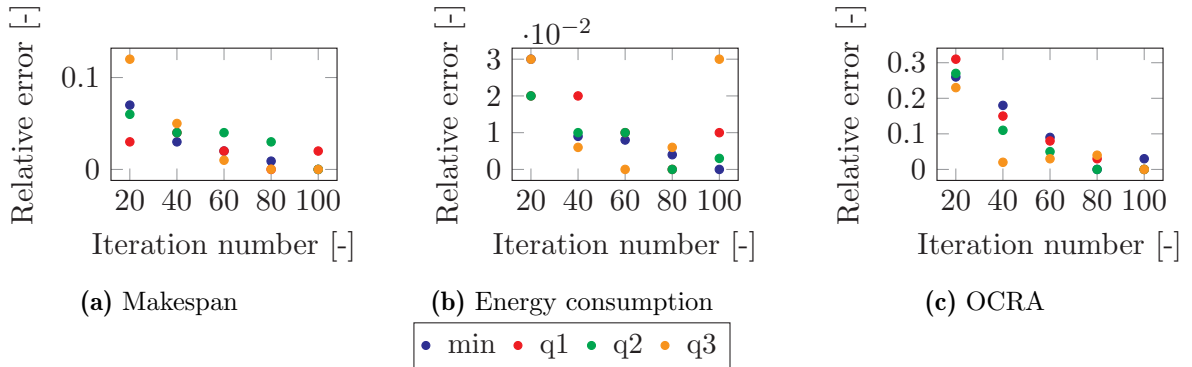


Figure D.3: Algorithm performance depending on different instances and different number of iteration

the search space, while a higher number of iterations increases the likelihood of converging to an optimal solution. For our study, we selected a population size and iteration count of 60, balancing both performance and computation time. Table D.4 presents the algorithm's computation time for each instance using the selected parameters.

Instances	Time (s)
kcm_1	25
kcm_2	70
kcm_3	91
kcm_4	234
FJ_{05}	220
FJ_{10}	1440
FJ_{15}	4535
FJ_{20}	4195
$DFMC$	14000

Table D.4: Computation time for different instances

Figure D.4 shows the computation time for each instance based on their characteristics, particularly the number of tasks, machines, and workers. As expected, the computation time increases with the number of workers and machines, but the most impactful factor appears to be the number of tasks. Indeed, the trends in the computation time curve closely follow those of the task count. This is particularly evident in the last instance, $DFMC$, where the number of tasks is significantly higher, while the number of workers and machines remains similar to other instances, yet the computation time is substantially longer.

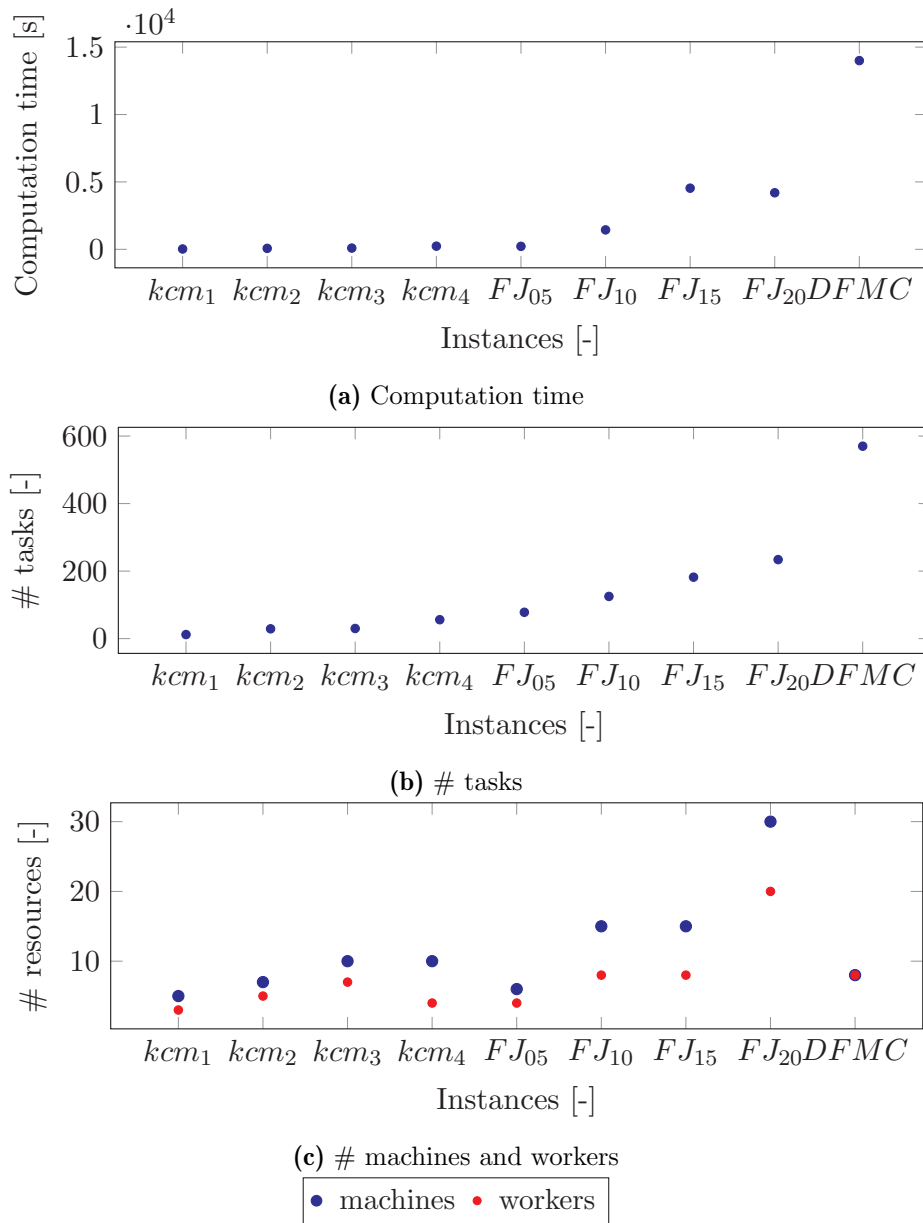


Figure D.4: Computation time and characteristics for different instances

Appendix E

Complementary model constraints

This appendix presents the model constraints that were not presented from the articles for the sake of clarity. These constraints, while essential for the implementation, do not contribute to a better understanding of the model's logic. The following constraints serve to complete the model described in Chapter 3.

$$\sum_m X_{kjwmt} \leq V_{tw} \quad \forall t \in \mathcal{T}, w \in \mathcal{W}, j \in \mathcal{J}, k \in \mathcal{K}_j \quad (\text{E.1})$$

$$C_{kj} = S_{kj} + \sum_w \sum_m \sum_t p_{kjwm} \times X_{kjwmt} \quad \forall j \in \mathcal{J}, k \in \mathcal{K}_j \quad (\text{E.2})$$

$$R_{kjwt} \leq \sum_m X_{kjwmt} \times M \quad \forall j \in \mathcal{J}, k \in \mathcal{K}_j, w \in \mathcal{W}, t \in \mathcal{T} \quad (\text{E.3})$$

$$Y_{k'jwk'j'} \leq \sum_m \sum_t X_{kjwmt} \quad \forall j, j' \in \mathcal{J}, k \in \mathcal{K}_j, k' \in \mathcal{K}_{j'}, w \in \mathcal{W} \quad (\text{E.4})$$

$$Y_{k'jwk'j'} \leq \sum_m \sum_t X_{k'j'wmt} \quad \forall j, j' \in \mathcal{J}, k \in \mathcal{K}_j, k' \in \mathcal{K}_{j'}, w \in \mathcal{W} \quad (\text{E.5})$$

$$Y_{k'jwk'j'} + Y_{k'j'wkj} \leq 1 \quad \forall j, j' \in \mathcal{J}, k \in \mathcal{K}_j, k' \in \mathcal{K}_{j'}, w \in \mathcal{W} \quad (\text{E.6})$$

$$Y_{k'jwk'j'} + Y_{k'j'wkj} \geq \sum_m \sum_t X_{kjwmt} + \sum_{m'} \sum_t X_{k'j'wm't} - 1 \quad \forall j, j' \in \mathcal{J}, k \in \mathcal{K}_j, k' \in \mathcal{K}_{j'}, w \in \mathcal{W} \quad (\text{E.7})$$

$$Z_{k'jmk'j'} \leq \sum_w \sum_t X_{kjwmt} \quad \forall j, j' \in \mathcal{J}, k \in \mathcal{K}_j, k' \in \mathcal{K}_{j'}, m \in \mathcal{M} \quad (\text{E.8})$$

$$Z_{k'jmk'j'} \leq \sum_w \sum_t X_{k'j'wmt} \quad \forall j, j' \in \mathcal{J}, k \in \mathcal{K}_j, k' \in \mathcal{K}_{j'}, m \in \mathcal{M} \quad (\text{E.9})$$

$$Z_{k'jmk'j'} + Z_{k'j'mkj} \leq 1 \quad \forall j, j' \in \mathcal{J}, k \in \mathcal{K}_j, k' \in \mathcal{K}_{j'}, m \in \mathcal{M} \quad (\text{E.10})$$

$$Z_{k'jmk'j'} + Z_{k'j'mkj} \geq \sum_w \sum_t X_{kjwmt} + \sum_w \sum_t X_{k'j'wmt} - 1 \quad \forall j, j' \in \mathcal{J}, k, k' \in \mathcal{K}_{j,j'}, m \in \mathcal{M} \quad (\text{E.11})$$

$$\sum_m Z_{k'jmkj} = 0 \quad \forall j \in \mathcal{J}, k \in \mathcal{K}_j \quad (\text{E.12})$$

$$\sum_w Y_{k'jwkj} = 0 \quad \forall j \in \mathcal{J}, k \in \mathcal{K}_j \quad (\text{E.13})$$

$$N_{k'jmk'j'm'} \geq \sum_w \sum_t X_{kjwmt} + \sum_w \sum_t X_{k'j'wm't} - 1 \quad \forall j, j' \in \mathcal{J}, k, k' \in \mathcal{K}_{j,j'}, m, m' \in \mathcal{M} \quad (\text{E.14})$$

$$\sum_{j'} \sum_{k'} \sum_m N_{k'jmk'j'm'} \leq \sum_w \sum_t X_{kjwmt} \times M \quad \forall j \in \mathcal{J}, k \in \mathcal{K}_j, m \in \mathcal{M} \quad (\text{E.15})$$

$$\sum_j \sum_k \sum_m N_{kjm k' j' m'} \leq \sum_w \sum_t X_{k' j' w m' t} \times M \quad \forall j' \in \mathcal{J}, k' \in \mathcal{K}_{j'}, m' \in \mathcal{M} \quad (\text{E.16})$$

$$A_{wm} = \sum_k \sum_j \sum_t X_{k j w m t} \quad \forall w \in \mathcal{W}, m \in \mathcal{M} \quad (\text{E.17})$$

$$B_{wm} \geq X_{k j w m t} \quad \forall j \in \mathcal{J}, k \in \mathcal{K}_j, w \in \mathcal{W}, m \in \mathcal{M}, t \in \mathcal{T} \quad (\text{E.18})$$

$$B_{wm} \leq \sum_k \sum_j \sum_t X_{k j w m t} \quad \forall w \in \mathcal{W}, m \in \mathcal{M} \quad (\text{E.19})$$

Equation (E.1) ensures that a worker can perform a task in a given period only if he is assigned to that period. Equation (E.2) calculates the completion time of each task by adding the processing time to the start time. Constraint (E.3) ensures that a worker can rest after a task only if they have operated that task. Constraints (E.4) to (E.13) declare the variables Y and Z . Equations (E.4) and (E.5) set $Y_{k_j w k'_{j'}}$ to 0 if either operation O_{k_j} or $O_{k'_{j'}}$ is not performed by worker w . Equation (E.6) states that if operation O_{k_j} is processed before operation $O_{k'_{j'}}$ by worker w , the reverse is not possible. Equation (E.7) asserts that if both operations O_{k_j} and $O_{k'_{j'}}$ are processed by worker w , one must precede the other. Similarly, Equations (E.8) and (E.9) set $Z_{k_j m k'_{j'}}$ to 0 if either operation O_{k_j} or $O_{k'_{j'}}$ is not processed on machine m . Equation (E.10) states that if operation O_{k_j} is processed before operation $O_{k'_{j'}}$ on machine m , the reverse is not possible. Equation (E.11) asserts that if operations O_{k_j} and $O_{k'_{j'}}$ are both processed on machine m , one must precede the other. Equations (E.12) and (E.13) ensure that Z and Y are equal to 0 when $k_j = k'_{j'}$. Equation (E.14) states that if operation O_{k_j} is on machine m and operation $O_{k'_{j'}}$ on machine m' , then $N_{k_j m k'_{j' m'}}$ equals 1. Equations (E.15) and (E.16) set $N_{k_j m k'_{j' m'}}$ to 0 if operation O_{k_j} is not assigned to machine m or if operation $O_{k'_{j'}}$ is not assigned to machine m' . Equation (E.17) calculates how many times worker w is assigned to machine m . Equation (E.18) ensures that if worker w is assigned to machine m at least once, B_{wm} equals 1, and equation (E.19) ensures that if worker w is never assigned to machine m , B_{wm} equals 0.

