Contribution to Key Techologies of Integrated Process Planning and Scheduling in Job Shops

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Contribution aux Technologies Clés de l'Intégration de la Planification des Processus et l'Ordonnancement dans les Ateliers d'Usinage

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Résumé en Français

1 Le contexte

Du point de vue du mode de la production dans les entreprises modernes, la compétition du marché mondial et les demandes personnalisées et diversifiées des clients ont entraîné la prévalence de la production en petites quantités de pièces mono-bloc pour répondre plus rapidement aux demandes variables du marché et pour mieux satisfaire les besoins des clients au niveau de la variété, de la qualité, du prix et du service personnalisé des produits. Dans un tel environnement, la conception des produits et de la planification des processus devraient faire plus étroitement coopérer la production pour permettre aux administrateurs dans les entreprises et les ateliers d'usinage de saisir les changements sur le site de production dans les meilleurs délais afin qu'ils puissent porter un jugement précis et donner une réponse rapide pour ajuster raisonnablement les plans de production.

Du point de vue du mode d'opération d'entreprises modernes, pour gagner la compétition dans un marché dynamique, stimulant et exigeant une réponse plus rapide à l'évolution des marchés et l'agilité de la production, les fabricants ont besoin de changer leurs systèmes de fabrication d'un environnement centralisé à un environnement distribué (Wang et Shen, 2007). Dans une telle situation, le système de fabrication distribué (DMS : Distributed Manufacturing System) devrait être le principal concept de système de fabrication (Wu et al., 2002). Un DMS est normalement constitué de plusieurs partenaires (éléments du système) qui peuvent être distribués géographiquement dans des endroits différents. Cela leur permet de se rapprocher de leurs clients potentiels, de se conformer aux lois locales, de se concentrer sur quelques types de produits, de produire et de commercialiser leurs produits plus efficacement, et de répondre aux changements du marché plus rapidement (Chan et al., 2006, Schniederjans 1999, Sule 2001). Dans l'environnement de DMS, chaque partenaire est généralement capable de fabriquer une variété de types de produits. En outre, ils peuvent avoir une efficacité différente de la production et des contraintes diverses en fonction des machines, des compétences de la main-d'œuvre et de leur niveau d'éducation, du coût de l'emploi, de la politique du gouvernement, des taxes, des fournisseurs à proximité, des moyens de transport, etc. (Chan et al., 2006). Comme les partenaires sont différents au niveau des coûts d'opération, des délais de production, des services aux clients, des contraintes, etc., les outils de modélisation et de simulation distribuée sont de plus en plus importants pour évaluer et améliorer la production, mieux utiliser les ressources de production et améliorer la flexibilité, le dynamisme, l'adaptabilité, l'agilité et la productivité des systèmes de fabrication distribués.

La planification du processus est l'acte de préparer les instructions d'opérations détaillées pour transformer une conception technique en une pièce finale. Un plan de processus spécifie les ressources de fabrication et les opérations/routes techniques qui sont nécessaires pour fabriquer un produit. Le résultat de la planification de processus comprend l'identification des outils d'usinage et des accessoires applicables à un job, et la séquence des opérations pour traiter le job. Typiquement, un job peut avoir un ou plusieurs plans de processus alternatifs. L'ordonnancement reçoit des plans de processus comme input et a pour tâche d'allouer les opérations de tous les jobs dans un ordre à ressources limitées dans le temps pour satisfaire ou optimiser plusieurs critères tout en respectant les relations de précédence indiquées dans les

plans de processus. L'ordonnancement est non seulement le séquençage, mais également la détermination du début et de la fin du temps de traitement pour chaque opération sur la base de la séquence (Li et al., 2010a).

Il est évident que la planification des processus et l'ordonnancement sont fortement interdépendants comme tous les deux sont liés à l'allocation des ressources (Lv et Qiao, 2013). Cependant, dans les approches traditionnelles, ces deux fonctions sont exécutées séquentiellement par des départements différents dans un système de fabrication (Jain et al., 2006). L'ordonnancement est effectué après que le plan de processus ait été généré. Cette approche séquentielle crée souvent des obstacles à l'amélioration de la productivité des systèmes de fabrication et il est difficile de fournir une réactivité aux incertitudes de production (Shao et al, 2009; Lian et al, 2012). Dans le même temps, il peut apporter quelques autres problèmes, tels que les conflits d'objectifs entre la planification des processus et l'ordonnancement, le déséquilibre de charge des ressources de production et l'infaisabilité du plan de processus (Lv et Qiao, 2013; Li et al, 2010d; Li et al, 2010b; Li et al, 2010c; Li et al, 2012a; Li et al, 2012b; Shao et al, 2009).

Pour répondre à ces problèmes, il est nécessaire d'intégrer plus étroitement la planification des processus et l'ordonnancement. Chryssolouris et Chan (Chryssolouris et Chan, 1984) ont été les premiers à proposer l'idée préliminaire de l'intégration de la planification des processus et de l'ordonnancement (IPPS).

IPPS est le concept d'effectuer la planification des processus et l'ordonnancement de façon concourante avec les objectifs d'éliminer ou réduire les conflits d'objectifs entre la planification des processus et l'ordonnancement, de réduire le makespan et les pièces dans le processus, d'améliorer l'utilisation des ressources et d'améliorer la flexibilité pour s'adapter à des incertitudes irrégulières dans les ateliers d'usinage (Lee et Kim, 2001;. Wan et al, 2013). D'ailleurs, dans la recherche au début des Computer Integrated Manufacturing Systems (CIMS), certains chercheurs ont constaté que l'intégration de la planification des processus et de l'ordonnancement (IPPS) est très importante pour le développement des CIMS. Sans l'IPPS, un vrai CIMS cherchant à intégrer les phases différentes de la fabrication dans un système unique et complet ne peut pas être réalisé (Li et al., 2010c). L'IPPS peut fournir des plans des processus et des plans de l'ordonnancement mieux que les systèmes traditionnels de fabrication pour améliorer considérablement la productivité du système de fabrication. De plus, l'IPPS peut également améliorer la fabrication distribuée et collaborative au niveau de la flexibilité, l'adaptabilité, l'agilité et l'optimisation globale (Wang et Shen, 2007).

2 Concept associés

2.1 La planification des processus

2.1.1 Concept

Comme une composante essentielle reliant la conception et les procédés de fabrication en aval, la planification de processus consiste à préparer les instructions d'opérations détaillées pour transformer une conception technique en une pièce finale (Chang et Wysk, 1984). La planification des processus est la détermination systématique des méthodes par lesquelles un produit doit être fabriqué de façon économique et compétitive. La planification de processus

comprend les activités et fonctions permettant de préparer un ensemble de plans et instructions détaillés pour produire une pièce visant à atteindre la qualité correcte, le coût de fabrication minimes et assurer une bonne fabricabilité (Guo et al., 2009). La planification commence par des dessins techniques, des spécifications, des pièces ou des listes de matériaux et des prévisions de la demande. La première étape de la conception du plan de processus est de reconnaître un ensemble de caractéristiques géométriques et leurs interrelations à partir de la conception de la pièce. Basé sur les caractéristiques géométriques identifiées, un ensemble de fonctions d'usinage est sélectionné. Une fonction d'usinage peut être traitée comme un processus d'usinage général sans les méthodes d'usinage détaillées ou spécifiées. Les processus d'usinage peuvent être restreints par les relations de priorité, qui sont imposées par les exigences technologiques de la pièce (Moon et al., 2002a). Les principales considérations dans la planification des processus comprennent (Zhang, et Gen, 2010):

- Générer les opérations d'usinage basées sur les caractéristiques d'une pièce en se conformant aux spécifications fonctionnelles désirées et pour obtenir une bonne fabricabilité;
- Identifier les ressources d'usinage applicables aux opérations;
- Déterminer le plan de set-up et la séquence d'opérations selon certains critères liés au ratio coût-efficacité et aux exigences technologiques.

Par conséquent, un plan des processus pour une pièce peut être représenté par une série d'opérations d'usinage, des ressources applicables pour les opérations, des plans de set-up, la séquence d'opération, etc.

2.1. 2 Modèle de l'information de fabrication dans la planification du processus

L'information principale de fabrication impliquée dans la planification des processus comprend des informations sur les matériaux, les activités de fabrication, des ressources de fabrication et les organisations de fabrication (Zhang, 2009), comme montré sur la Figure 1. Ces quatre groupes d'informations de base peuvent être décrits comme suit :

- Matériel: les produits à fabriquer, les matières premières et les matières produites dans la planification des processus. Les informations de matériau comprennent les informations des pièces, des assemblages, des produits, des matières premières et des matériaux supplémentaires.
- Activité : les activités de fabrication, y compris les activités d'usinage et les activités d'assemblage et ainsi de suite.
- Ressources de fabrication : les équipements et les outils qui seront utilisés dans le processus de fabrication.
- Organisation : les unités qui exécutent des activités de fabrication, y compris les services et le personnel.

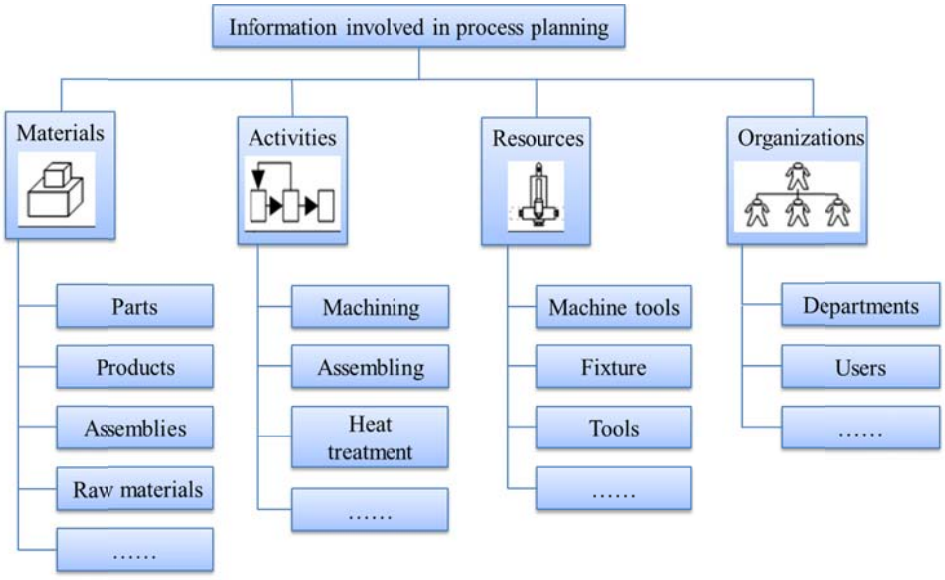

Figure 1 The information involved in process planning

2.2 L'ordonnancement

2.2.1 Concept

L'ordonnancement consiste à décomposer la tâche de production dans les plans de production déterminés selon les commandes ou les prévisions du marché en termes du temps, d'espace, et de spécifications. En termes de spécification de production, les variétés, la quantité et la qualité du produit seront établis ; quant à l'espace, l'unité de production sera attribuée aux ateliers d'usinage, à la section des ateliers d'usinage, à l'équipe et même à l'équipement ; pour le temps des jobs, il sera affiné en mois, jours et heures en assurant que les plans de la production des plans peuvent être pratiquement exécutés.

En résumé, l'ordonnancement consiste à déterminer le moment le plus approprié pour exécuter chaque opération des ordres de production lancés, en tenant compte de la date due de ces commandes, un makespan minimum, une utilisation équilibrée des ressources, etc., afin d'obtenir une productivité élevée dans le travail d'atelier (Guo et al, 2009;. Aldakhilallah et Ramesh, 1999).

2.2.2 La tâche principale de l'ordonnancement

D'une part, les plans de production sont reçus par les systèmes d'ordonnancement des systèmes de planification supérieure et ensuite décomposés en niveau de l'opération de traitement pour développer le plan d'emploi atelier selon lequel les tâches d'atelier sont spécifiquement et raisonnablement attribuées à chaque unité de production et les instructions de planification sont délivrées aux systèmes de contrôle de l'atelier.

D'autre part, le système d'ordonnancement reçoit en temps réel les informations de traitement rapportées par les systèmes de contrôle dans l'atelier, et se préoccupe des incidents aléatoires causés par les incertitudes telles que la modification de l'ordre, pour ajuster la planification de la production et mener un ré-ordonnancement lorsque cela est nécessaire. En outre, il offre des rétroactions des informations de progression de traitement pour les systèmes de planification supérieurs afin de contrôler efficacement le traitement des jobs.

L'organigramme de l'ordonnancement des jobs dans les ateliers d'usinage est illustré dans la figure 2.

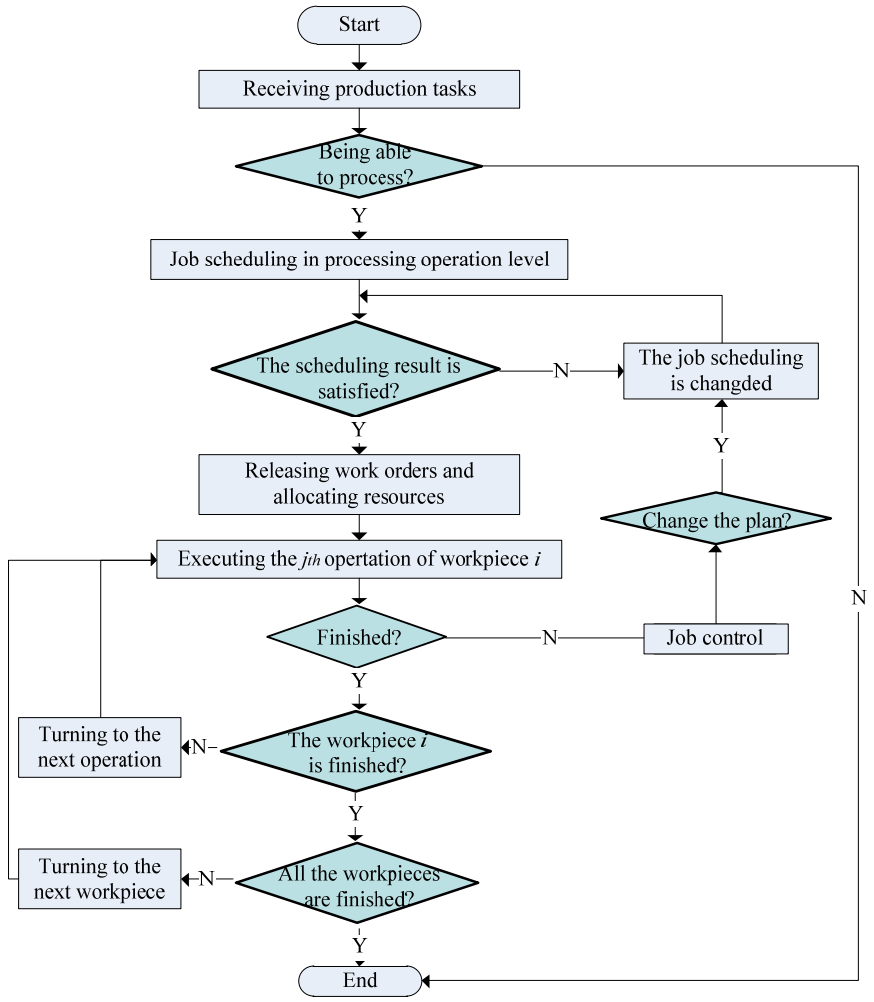

Figure 2 The flow chart of job planning and scheduling

En théorie, l'ordonnancement des jobs doit satisfaire aux exigences suivantes :

• Assurer la livraison du produit;

• Réduire le temps d'attente pour les personnels et les équipements;

• Prendre le temps de traitement de la pièce pour être le plus court;

• Réduire le nombre de produits en cours de traitement et le temps de stationnement;

• Effectuer un contrôle de la production.

2.3 La relation entre la planification de processus et l'ordonnancement

La planification du processus et l'ordonnancement sont deux des modules les plus importants dans un système de fabrication. Leurs tâches influencent fortement la rentabilité des entreprises de fabrication, de l'utilisation des ressources et de délai de livraison du produit (Yang et al., 2001). La planification de processus et l'ordonnancement ont non seulement des liens étroits au niveau du transfert de données, mais aussi partagent des tâches et objectifs communs dans l'allocation des ressources (Lv, 2012; Lv et Qiao, 2014).

(1) Le transfert de données existe entre la planification des processus et l'ordonnancement

D'une part, l'objectif principal de la fonction de planification du processus est de générer des plans de processus précisant les matières premières/composants nécessaires pour fabriquer un produit ainsi que les processus et les opérations nécessaires pour transformer les matières premières au produit final, et le résultat de la planification des processus sera transféré aux ateliers d'usinage pour guider les procédures de production.

Normalement, en raison de la flexibilité d'opération, la flexibilité de séquence et la flexibilité de traitement, il y a des plans de processus alternatifs pour chaque pièce. Et pour l'ordonnancement, il existe un processus de prise de décisions qui prend les plans de processus des pièces comme entrée et détermine l'allocation optimale des tâches ou près optimale en respectant les contraintes sur les précédences des opérations et les ressources des procédures afin de maximiser ou minimiser un ou plusieurs objectifs. Par conséquent, il existe une relation étroite entre la planification des processus et l'ordonnancement en raison du transfert de données entre les deux.

(2) Tous les deux impliquent l'affectation des ressources et leurs fonctions sont complémentaires.

D'autre part, pour la planification de processus et l'ordonnancement, tous les deux sont responsables de la répartition et de l'utilisation efficace des ressources dans les ateliers d'usinage. L'une des tâches principales de la planification des processus est d'identifier les ressources d'usinage (y compris l'identification des machines, outils et installations) applicables pour les opérations basées sur l'analyse des caractéristiques des pièces, tandis que l'ordonnancement assigne une tâche spécifique à une machine spécifique afin de satisfaire une mesure de performance donnée, et cela est restreint par les instructions de séquençage dictées dans les plans des processus et par la disponibilité des ressources de production. Ainsi, à la fois la planification des processus et l'ordonnancement impliquent l'affectation des ressources et sont complémentaires au niveau de leurs fonctions (Phanden et al., 2011).

La planification du processus est indépendant du temps, tandis que l'ordonnancement est considéré comme une activité dépendant du temps (Wu et al, 2002).

2.4 La nécessité d'intégrer la planification des processus et l'ordonnancement

Les systèmes de Computer Aided Process Planning (CAPP) ont été développés au cours des dernières décennies avec l'intention de combler l'écart entre la FAO et la CAO et de fournir une rétroaction rapide pour les concepteurs concernant l'information détaillée de la fabrication (i.e., la fabricabilité) et l'estimation des coûts liés, et de réduire substantiellement le temps de cycle de développement pour un produit (Tan et Khoshnevis, 2000).

La plupart de ces systèmes sont capables de générer de nombreux plans de processus alternatif dont un bon plan est choisi selon certains critères établis. Cependant, traditionnellement seulement l'intégration statique hors ligne entre CAPP et CAD est soulignée. Ils négligent généralement le potentiel d'intégration en aval avec l'ordonnancement et d'autres fonctions de production et prêtent peu d'attention à l'effet que les changements des conditions dans les ateliers peuvent avoir sur le choix des plans de processus. Il est assez

fréquent que les plans de processus générés par ces systèmes ne soient pas rigidement suivis dans la mise en œuvre dans les ateliers en raison des conflits possibles avec l'ordonnancement, la contention de ressources et l'indisponibilité, etc.

En même temps, étant donné un plan de processus fixe, l'activité de planification doit souvent résoudre les conflits entre les ressources disponibles en raison des évolutions de l'environnement. Le plan de processus original doit être modifié fréquemment pour tenir compte des changements dans l'atelier. Certains chercheurs ont constaté qu'environ autant que 30 pour cent des plans de processus doivent être modifiés (Detand et al., 1992). Ces événements répétés vont inévitablement conduire à des plans de processus moins pertinents et peu suivis, ce qui entraîne l'insuffisance de collaboration entre la fonction la planification des processus et la fonction d'ordonnancement.

En tant que tel, conventionnellement basée sur le concept de subdiviser les tâches en fonctions plus petites et séparées pour satisfaire les exigences de la sous-optimisation et appropriées pour la production de masse (Larsen et Alting, 1992), la planification des processus et l'ordonnancement sont effectuées en deux phases distinctes et séquentielles, où l'ordonnancement est faite séparément après la planification du processus. Être confronté à l'environnement de fabrication caractérisé par la diminution du temps, des normes rigoureuses de qualité, une plus grande variété et des coûts compétitifs aujourd'hui, l'approche traditionnelle ne peut généralement pas obtenir un résultat satisfaisant pour les raisons suivantes (Phanden, et al, 2011;. Larsen et Alting , 1992; Morad et Zalzala, 1999; Li et al, 2010a, b, c; Kumar et Rajotia, 2003) :

- Dans la pratique de fabrication, les planificateurs de processus planifient les jobs individuellement et supposent que l'atelier est idéal et les ressources avec les capacités illimitées sont toujours disponibles dans l'atelier. Pour chaque job, les ressources de fabrication dans l'atelier sont généralement affectées à ce job sans tenir compte de la concurrence des ressources d'autres jobs (Usher et Fernandes K, 1996a, b). Cela peut conduire des planificateurs de processus à sélectionner les machines souhaitables pour chaque job à plusieurs reprises. En outre, les ressources ne sont jamais toujours disponibles dans l'atelier. Par conséquent, les plans de processus générés sont en quelque sorte irréalistes et ne peuvent pas être facilement exécutés dans l'atelier pour un groupe de jobs (Lee et Kim, 2001). En conséquence, les plans des processus optimaux obtenus deviennent souvent impossibles quand ils sont effectués dans la pratique à un stade ultérieur.
- Les plans d'ordonnancement sont souvent déterminés après des plans de processus. Les plans des processus fixes peuvent conduire les plans d'ordonnancement à finir avec une charge sévèrement déséquilibrée entre les ressources et créer des goulets d'étranglement inutiles.
- Même si les planificateurs de processus considèrent la restriction des ressources actuelles dans l'atelier, les contraintes dans la phase de planification de processus peuvent avoir déjà changé en raison du retard entre la phase de planification et la phase d'exécution. Cela peut conduire à l'infaisabilité du plan de processus optimisé (Kumar et Rajotia, 2002). Des enquêtes ont montré que 20-30% des plans de production totaux dans une période

donnée doivent être modifiés pour s'adapter au changement dynamique dans un environnement de production (Kumar et Rajotia, 2003).

- La cible de débit des commandes dans un atelier souffre souvent de perturbations causées par des machines goulots d'étranglement, la non-disponibilité des outils et du personnel, ou une panne de machines et équipements. Un plan de l'ordonnancement généré peut s'avérer invalide et être régénéré.
- Dans la plupart des cas, à la fois pour la planification des processus et l'ordonnancement, une technique d'optimisation avec un critère unique est utilisée pour déterminer la meilleure solution. Cependant, l'environnement de production réel est mieux représenté en considérant plusieurs critères simultanément (Kumar et Rajotia, 2003). En outre, la planification de processus et l'ordonnancement peuvent avoir des objectifs contradictoires. La planification de processus souligne les exigences technologiques d'un job, tandis que l'ordonnancement implique les aspects du temps et les ressources et leur partage pour tous les jobs. S'il n'y a pas de coordination appropriée, cela peut créer des problèmes contradictoires.

2.5 L'intégration de la planification des processus et l'ordonnancement

Pour surmonter les problèmes ci-dessus, il y a un besoin croissant pour la recherche profonde sur l'intégration de la planification des processus et de l'ordonnancement (IPPS). L'IPPS est le concept permettant d'effectuer la planification des processus et l'ordonnancement de manière concourante avec les objectifs d'éliminer ou réduire les conflits d'horaire, de réduire les temps d'écoulement et le travail dans le processus, d'améliorer l'utilisation des ressources et d'améliorer la flexibilité nécessaire pour s'adapter à des incertitudes dans les ateliers tels que les perturbations irrégulières (Lee et Kim, 2001; Wan et al, 2013). Sans IPPS, un véritable système de fabrication intégrée par ordinateur (CIMS), qui vise à intégrer les différentes phases de la fabrication dans un système unique et complet, ne peut être efficacement réalisé (Li et al., 2012). Par l'intégration de ces deux systèmes, l'IPPS peut fournir de meilleurs plans des processus et l'ordonnancement que les systèmes de fabrication traditionnels pour améliorer grandement la productivité du système de fabrication. Les mérites de l'IPPS sont d'augmenter la faisabilité de la production et l'optimalité en combinant à la fois des problèmes de la planification des processus et de l'ordonnancement (Wong et al., 2006a, b).

Le problème de l'IPPS peut être généralement défini comme (Kim et al., 2003) : Étant donné un ensemble de N jobs qui doivent être effectués sur M machines avec la flexibilité d'opération, la flexibilité de séquence et la flexibilité de traitement, trouver une séquence d'opérations et la séquence de machines-outils correspondante pour chaque job et un plan d'ordonnancement dans lequel les opérations sur les mêmes machines sont traités telles qu'elles satisfassent les contraintes de précédence et il est optimal par rapport à certains critères pertinents, par exemple makespan minimum et débit moyen minimum dans le temps et ainsi de suite.

La Figure 3 est utilisée pour illustrer ce problème (Guo et al., 2009b). Par exemple, il y a trois pièces pouvant être usinées par trois, deux et trois opérations sur trois machines,

respectivement. Pour les différentes pièces, il y a des contraintes de précédence entre les opérations à usiner (Part1: Oper1→Oper2→Oper3, Part2: Oper4→Oper5, Part3: Oper6→Oper7→Oper8). Quand toutes ces 8 opérations sont séquencées (Oper1→Oper4→Oper2→ Oper6→Oper3→Oper7→Oper8→Oper5 comme il est montré dans la figure 2-3) et les ressources de fabrication sont spécifiées, le plan de l'ordonnancement peut être déterminé en conséquence. Le problème d'optimisation consiste à déterminer la séquence d'opérations et sélectionner les ressources de fabrication de manière à atteindre les objectifs d'optimisation (de makespan dans la Figure 3, par exemple), tout en maintenant l'ordonnancement et la planification des processus faisable.

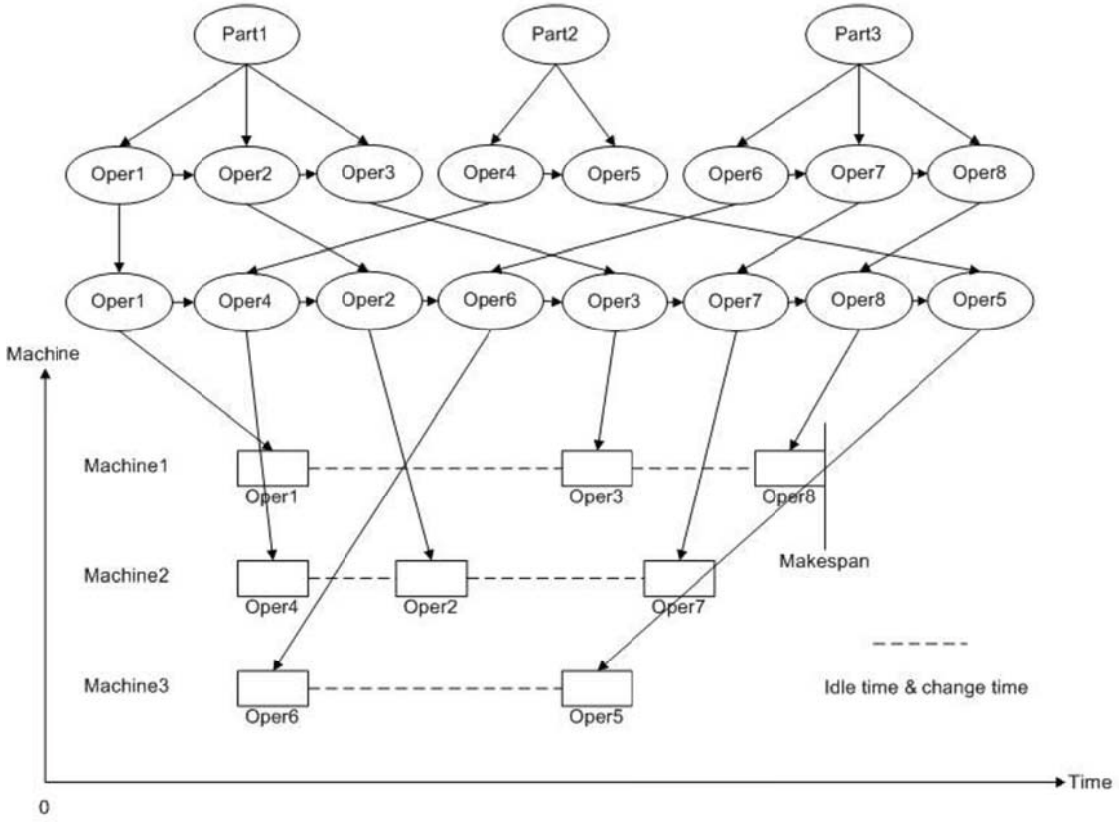

Figure 3 Illustration of the IPPS problem (Guo et al., 2009b)

3 Problèmes de l'IPPS

Bien que la recherche sur l'IPPS ait été largement abordée depuis près de trois décennies eu égard au cadre, la modélisation, l'élaboration de système et ainsi de suite, il y a encore quelques problèmes cruciaux qui doivent être résolus comme décrit dans ce qui suit.

(1) Le Modèle d'intégration améliorée de l'IPPS devrait être proposé

Les modèles d'intégration qui existent actuellement (NLPP, CLPP et DPP) ont leurs propres avantages et inconvénients. Tout modèle unique d'intégration existant ne peut pas résoudre le problème d'IPPS de manière efficiente ou efficace. Par conséquent, un modèle d'intégration hybride, meilleur et plus pratique, combinant leurs avantages et éliminant leurs inconvénients, devrait être davantage étudié et amélioré.

(2) L'IPPS dans les systèmes de fabrication distribués devrait être plus étudié

Le système de fabrication distribué (DMS) est un concept de système de premier plan dans l'avenir. Par conséquent, la recherche sur les problèmes de l'IPPS dans ces systèmes est avec une signification pratique. Cependant, les littératures existantes se concentrent principalement sur un atelier d'usinage unique, et il n'y a pas de recherche systématique sur les problèmes de l'IPPS dans un environnement de DMS, où plusieurs entreprises et job shops seront impliqués. Les problèmes de l'IPPS dans le DMS sont beaucoup plus compliqués que les problèmes classiques car ils impliquent non seulement les problèmes de l'IPPS dans chaque atelier d'usinage, mais aussi les problèmes dans un niveau supérieur, afin de savoir comment attribuer les jobs à une entreprise adaptée pour optimiser l'utilisation des ressources de fabrication. Par conséquent, il est urgent de proposer un modèle d'intégration efficace et fiable et faire des études supplémentaires sur le mécanisme d'intégration de l'IPPS dans le DMS afin d'utiliser de manière optimale les ressources de l'entreprise, d'équilibrer la charge de travail des ressources et de mieux en faire profiter à la fois les entreprises et les clients.

(3) La recherche sur l'optimisation multi-objectif de l'IPPS devrait être étendue

L'optimisation de l'IPPS est un problème multi-objectif. Une grande partie de la recherche actuelle sur l'IPPS a été concentrée sur le seul objectif. Cependant, parce que les différents départements d'une entreprise ont des attentes différentes afin de maximiser leurs propres profits (par exemple, le département de fabrication prévoit de réduire les coûts et d'améliorer l'efficacité du travail), les gestionnaires veulent maximiser l'utilisation des ressources existantes, et le département de vente espère mieux répondre aux exigences de livraison des clients. Dans ce cas, considérer uniquement cet objectif ne peut pas répondre aux exigences de la production dans le monde réel. Par conséquent, de nouvelles études sur les problèmes d'optimisation multi-objectifs de problèmes de l'IPPS sont toujours très demandées pour aider efficacement les administrateurs dans les entreprises et les ateliers d'usinage dans les processus de décision.

De plus, la pollution de l'environnement a exercé une forte pression sur les entreprises manufacturières tandis que l'ordonnancement dans les ateliers d'usinage pourraient affecter de manière significative la consommation d'énergie ainsi que d'autres impacts sur l'environnement d'une machine individuelle (Fang et al., 2011). L'ordonnancement d'opération optimisé pourrait encore réduire les coûts énergétiques. Malheureusement, bien qu'une variété de mesures de performance ait été considérée pour l'ordonnancement dans les ateliers, ces efforts ont surtout porté sur le développement économique, le temps ou les considérations opérationnelles. En revanche, la recherche sur l'ordonnancement avec des objectifs axés sur l'environnement est relativement rare. Rarement des études précédentes visaient des objectifs liés à l'énergie dans la modélisation du problème d'ordonnancement. Par conséquent, il est d'une grande importance d'examiner la définition quantifiée de la consommation d'énergie de chaque machine-outil dans l'optimisation multi-objectif des problèmes de l'IPPS pour soutenir la protection de l'environnement et le développement durable tout en répondant aux exigences des clients et des marchés.

(4) La capacité de ré-ordonnancement dans l'IPPS

Dans les environnements de fabrication dynamiques et stochastiques, les gestionnaires, les planificateurs de production, et les superviseurs doivent non seulement générer des

plannings de haute qualité, mais aussi réagir rapidement à des événements inattendus et réviser le plan de l'ordonnancement d'une manière économique (Guilherme et al., 2003). Des événements inattendus peuvent générer des différences considérables entre le plan prédéterminé et sa réalisation effective dans l'atelier. Un des buts les plus importants de la recherche sur les problèmes d'IPPS est d'améliorer la flexibilité et la capacité de réaction rapide du système de fabrication en utilisant la flexibilité du plan de processus. Par conséquent, le ré-ordonnancement est pratiquement obligatoire pour que l'effet de ces perturbations aux performances du système puisse être minimisé. Les recherches actuelles sur les problèmes de l'IPPS dans la littérature sont principalement axées sur l'ordonnancement statique, et les méthodes de ré-ordonnancement permettant à la fois de répondre efficacement aux événements dynamiques et de maintenir la stabilité du système en même temps devraient être étudiées.

4 Objectifs de recherche

(1) Établir un nouveau modèle hybride de l'intégration de la planification de processus et de l'ordonnancement dans les systèmes de fabrication distribués

Les problèmes 1 et 2 prénommés sera résolus dans cette partie. Un nouveau modèle hybride de l'intégration de la planification de processus et de l'ordonnancement dans un système de fabrication distribué (HMIPPS_DMS) sera proposé pour faciliter à la fois l'échange d'informations et la collaboration fonctionnelle en combinant la flexibilité du plan de processus fourni par l'intégration interface-orientée de NLPP (planification de processus non linéaire) et la structure hiérarchique de la DPP (planification de processus distribués) dans un environnement de DMS.

Dans HMIPPS_DMS, l'intégration hiérarchique de la planification des processus et de l'ordonnancement est réalisée par trois hiérarchies d'intégration. D'abord, au niveau de l'Entreprise, on a une phase d'intégration initiale/grossière. A ce niveau, l'entreprise optimale pour fabriquer les pièces sera choisie basée sur l'analyse concurrente de la capacité et de la possibilité des ressources ainsi que l'estimation grossière des performances du coût/temps d'usinage dans toutes les entreprises candidates. Ensuite, le niveau d'intégration au niveau des ateliers d'usinage est une deuxième phase d'intégration, par laquelle les ateliers d'usinage optimaux dans l'entreprise sélectionnée seront choisis en fonction de l'estimation détaillée du coût/temps d'usinage et de l'analyse concurrente de la capacité et de la possibilité des ressources dans tous les ateliers dans cette entreprise. Finalement le niveau d'intégration des ressources est une intégration finale/détaillée, et le plan du processus finalement choisi pour chaque pièce et le plan de l'ordonnancement seront déterminés.

(2) Étendre le problème d'optimisation multi-objectif de l'IPPS

Le problème 3 prénommé sera résolu dans cette partie. Basé sur le concept de problème d'optimisation multi-objectif (MOOP), le modèle mathématique complet pour expliquer et décrire le MOOP de l'IPPS sera construit, dans lequel certains nouveaux paramètres et objectifs concernant la consommation d'énergie dans l'usinage des pièces seront étudiés et adoptés. Puis la méthode NSGA-II (non-dominé Tri GA-II) sera améliorée pour résoudre efficacement les problèmes d'optimisation multi-objectifs de l'IPPS afin que les décideurs

dans les entreprises et les ateliers d'usinage puissent faire des choix raisonnables en fonction de leurs préférences pour les objectifs d'optimisation.

(3) Améliorer la capacité de ré-ordonnancement de l'IPPS

Le problème 4 prénommé sera résolu dans cette partie. Un cadre et un modèle de ré-ordonnancement unifié de l'IPPS avec trois types typiques d'incertitudes normalement rencontrées dans les ateliers d'usinage, à savoir l'arrivée de nouveaux jobs, la panne des machines-outils et l'annulation de commande, seront construits. Pour accroître la flexibilité du système, les trois types de flexibilité (la flexibilité d'opération, la flexibilité de séquence et la flexibilité de traitement) seront utilisés dans le processus de ré-ordonnancement. Pour répondre aux changements dynamiques et maintenir la stabilité du système dans les ateliers en même temps, le modèle considérera simultanément l'efficacité et la stabilité de production. Les mesures seront adoptées pour l'optimisation de l'efficacité de la production sont makespan, le coût d'usinage, et la consommation d'énergie; tandis que les mesures seront prises en compte dans l'optimisation de la stabilité de la production sont le coût de la déviation liée à la machine et le coût de la déviation liée au job causée dans le ré-ordonnancement. Une fonction d'objectif final sera proposée par la méthode de pondération tenant compte à la fois des mesures appliquées à l'efficacité et la stabilité, ce qui est plus pratique dans la prise de décision dans les systèmes de fabrication réels.

5 Plan de la thèse

Le contour de la thèse est illustré dans la Figure 4.

Dans le chapitre 1, l'introduction générale de la thèse est présentée, y compris le contexte de la thèse, les problèmes actuels de l'IPPS, les objectifs de recherche et le contour de la thèse.

Chapitre 2 offert une revue de la littérature globale basée sur une étude de la littérature profonde et étendue. Dans les dernières décennies, l'idée de l'intégration de la planification des processus et l'ordonnancement (IPPS) dans les ateliers d'usinage a reçu un intérêt croissant de la communauté scientifique, en particulier les problèmes d'optimisation impliqués dans l'IPPS. Focalisés sur la recherche concernée de cette thèse, ce chapitre présente les concepts relatifs et un état de l'art pour les problèmes de l'IPPS, ainsi que d'une vaste revue de la littérature sur les problèmes étroitement apparentés, tels que le mécanisme d'intégration de l'IPPS, les approches d'exécution d'optimisation de l'IPPS et les deux principaux problèmes étendus dans l'IPPS, y compris le problème d'optimisation multi-objectif de l'IPPS et les problèmes de ré-ordonnancement de l'IPPS.

Dans le chapitre 3, sur la base de le modèle des informations d'intégration proposé pour le problème de l'IPPS dans un système de fabrication distribué (DMS), un nouveau modèle hybride de l'intégration de la planification des processus et l'ordonnancement dans les systèmes de fabrication distribués (HMIPPS_DMS) est établi en adoptant à la fois l'idée interface-orientée du NLPP et l'idée fonction-orientée du DPP.

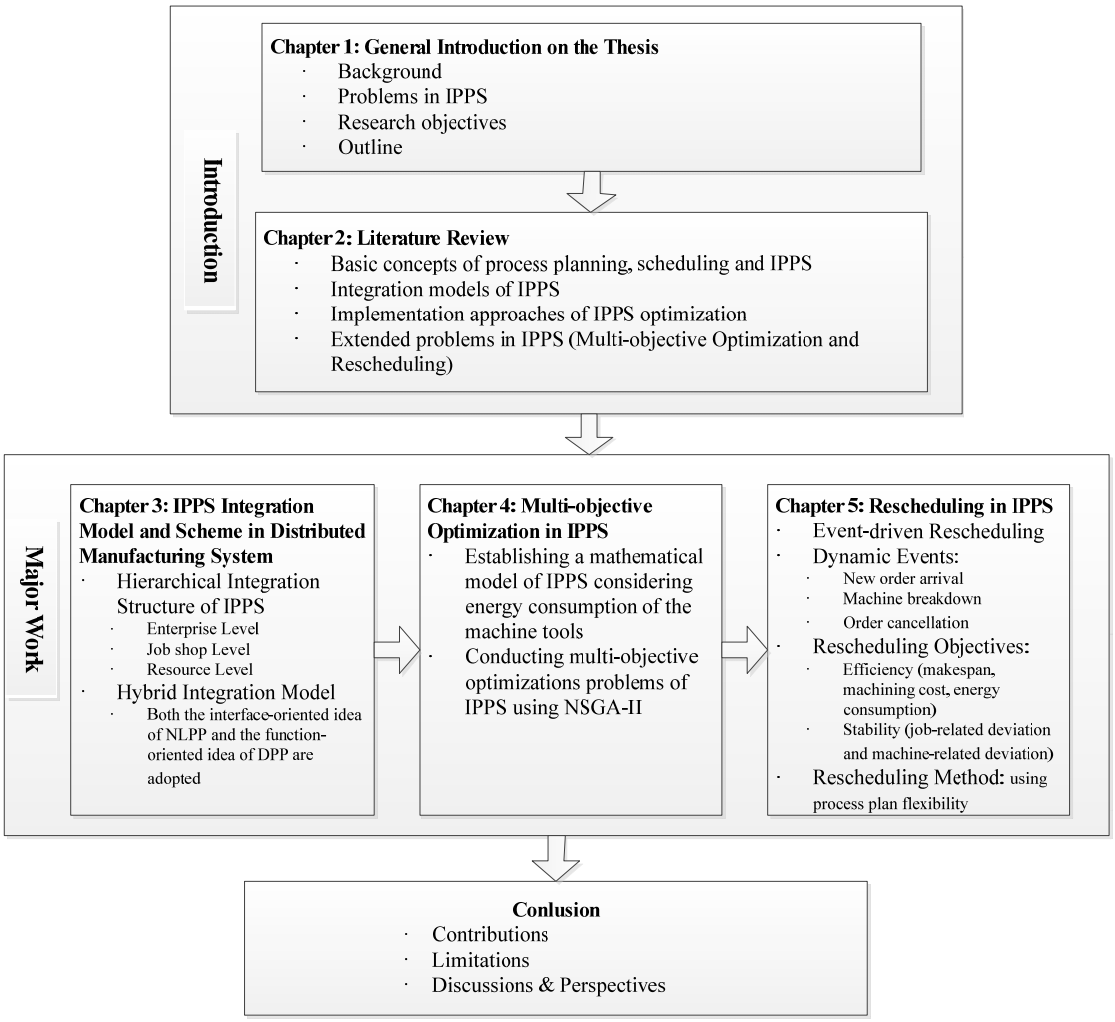

Figure 4 The outline of the thesis

Comme les modèles d'intégration actuels de l'IPPS (NLPP, CLPP et DPP) ont leurs propres avantages et inconvénients et aucun modèle unique d'intégration ne peut résoudre le problème IPPS de façon efficiente ou efficace, le mieux et plus pratique modèle d'intégration hybride combinant leurs avantages et éliminant leurs inconvénients devrait être proposé. Pendant ce temps, la compétition dans un marché dynamique et stimulant qui exige peu de temps de réponse aux changements des marchés et l'agilité dans la production a conduit à la prévalence du système de fabrication distribué (DMS). Un DMS est constitué de plusieurs partenaires (éléments du système) qui peuvent être distribués géographiquement dans des endroits différents et chaque partenaire peut être constitué de plusieurs ateliers d'usinage qui sont différents au niveau de la capacité, de la possibilité et des performances de la production. Dans une telle situation, la recherche sur les problèmes de l'IPPS dans DMS est avec signification pratique pour allouer de manière optimale les ressources de l'entreprise et de mieux en faire profiter à la fois les entreprises et les clients. Par conséquent, dans ce chapitre, sur la base du modèle des informations d'intégration proposé pour le problème de l'IPPS dans DMS, un nouveau modèle hybride de l'intégration de la planification des processus et l'ordonnancement dans DMS sera mis en place en adoptant à la fois l'idée interface-orientée du NLPP et l'idée fonction-orientée du DPP. Hiérarchiquement constitué de trois niveaux d'intégration, le nouveau modèle de HMIPPS_DMS facilitera l'optimisation de l'intégration en

couches de l'IPPS à chaque niveau par la phase de l'intégration initiale au niveau d'Enterprise, la phase de l'intégration correspondante au niveau d'atelier d'usinage et la phase d'intégration finale/détaillée au niveau de ressources.

Dans le chapitre 4, basé sur le concept du problème d'optimisation multi-objectif (MOOP), le modèle mathématique complet pour expliquer et décrire la MOOP dans l'IPPS dans un atelier d'usinage unique est construit, dans lequel certains nouveaux paramètres et objectifs concernant la consommation d'énergie dans l'usinage des pièces sont étudiés et adoptés. Puis NSGA-II (non-dominé Tri GA-II) est améliorée pour résoudre efficacement les problèmes d'optimisation multi-objectifs dans l'IPPS.

Jusqu'ici, la plupart des chercheurs actuels sur l'optimisation de l'IPPS ont été concentrés sur l'objectif single, qui ne peut pas répondre aux exigences de la production dans le monde réel, où les différents départements ont des attentes différentes afin de maximiser leurs propres profits, par exemple, la fabrication prévoit de réduire les coûts et d'améliorer l'efficacité du travail ; quant à eux, les gestionnaires veulent maximiser l'utilisation des ressources existantes ; et le département de la vente poursuit pour mieux répondre aux exigences de livraison des clients. De plus, l'ordonnancement dans les ateliers d'usinage pourrait affecter de manière significative la consommation d'énergie ainsi que d'autres impacts sur l'environnement d'une machine individuelle. L'ordonnancement optimisé d'opérations pourrait encore réduire les coûts énergétiques. Dans ce chapitre, basé sur le concept du problème d'optimisation multi-objectif (MOOP), le modèle mathématique complet pour expliquer et décrire le MOOP dans l'IPPS dans un atelier d'usinage est construit, dans lequel certains nouveaux paramètres et objectifs concernant la consommation d'énergie dans l'usinage des pièces sont étudiés et adoptés. Puis NSGA-II (non-dominé Tri GA-II) est améliorée pour résoudre efficacement les problèmes d'optimisation multi-objectifs dans l'IPPS afin que les décideurs dans les entreprises et les ateliers d'usinage puissent faire des choix raisonnables en fonction de leurs préférences pour les objectifs d'optimisation.

Dans le chapitre 5, un modèle de ré-ordonnancement considérant simultanément l'efficacité et la stabilité de la production est proposé. Un processus de ré-ordonnancement sera nécessaire dans l'IPPS dans les ateliers dynamiques (IPPS_DJS) lorsque les perturbations inattendues se produisent.

Dans ce chapitre, un modèle de ré-ordonnancement considérant simultanément l'efficacité et la stabilité de la production est proposé. Les mesures adoptées en fonction de l'optimisation de l'efficacité sont le makespan, le coût d'usinage et la consommation d'énergie ; tandis que les mesures définies pour l'optimisation de la stabilité sont le coût de la déviation liée à la machine et le coût de la déviation liée à l'emploi en cause dans le plan de ré-ordonnancement. Dans le cadre de l'IPPS_DJS, les trois types de flexibilité de la production (la flexibilité de l'opération, la flexibilité de la séquence et la flexibilité de traitement) sont utilisés dans le processus du ré-ordonnancement pour maintenir la flexibilité du ré-ordonnancement. Ensuite, le modèle mathématique du problème du ré-ordonnancement dans l'IPPS_DJS est construit, dans lequel une fonction objectif finale est proposée par la méthode de pondération tenant compte à la fois des mesures liées à l'efficacité et à la stabilité, ce qui est plus pratique pour la prise de décision dans les systèmes réels de fabrication. Des études

de cas sont présentées afin de vérifier le modèle proposé pour le ré-ordonnancement en utilisant les GA.

6 Contributions:

Les compétitions du marché mondial et les demandes personnalisées et diversifiées des clients ont apporté de la prévalence de la production en monobloc ou en petits lots à réagir, plus rapidement aux demandes variables du marché et aux autres besoins des utilisateurs sur la variété des produits, la qualité, le prix et un service personnalisé. Dans un tel environnement, la conception des produits et de la planification des processus devraient être plus étroitement liés avec la production pour permettre aux administrateurs dans les entreprises et les ateliers d'usinage de saisir les changements du site de production dans les plus brefs délais afin qu'ils puissent porter un jugement précis et donner une réponse rapide pour ajuster raisonnablement les plans de production.

La planification de processus et l'ordonnancement dans l'atelier d'usinage sont fortement interdépendants comme tous les deux sont liés à l'allocation des ressources. La planification du processus consiste à préparer des instructions d'opération détaillées pour transformer une conception technique en une pièce finale. Un plan de processus spécifie les ressources de fabrication et les opérations/routes techniques qui sont nécessaires pour fabriquer un produit. Typiquement, un job peut avoir un ou plusieurs plans de processus alternatifs en raison de la flexibilité de la production.

L'ordonnancement reçoit des plans de processus comme entrées et sa tâche est d'allouer les opérations de tous les jobs dans un certain ordre dans un cadre à ressources limitées dans le temps pour satisfaire ou optimiser plusieurs critères tout en respectant les relations de précédence indiquées dans les plans de processus. L'ordonnancement est non seulement le séquençage, mais également la détermination du temps de début et d'achèvement de chaque opération sur la base de la séquence.

Évidemment, la planification des processus et l'ordonnancement dans les ateliers d'usinage sont deux modules très importants qui sont interdépendants et interagissent mutuellement. Il est très important d'intégrer les deux fonctions car cela peut améliorer les performances de la production dans les systèmes de fabrication. En outre, l'IPPS est très important pour le développement de CIMS.

Pendant les trois dernières décennies, de nombreux chercheurs ont mené les études vastes et en profondeur sur les problèmes de l'IPPS et obtenu de bons résultats. Basé sur l'analyse complète des résultats et déficiences de la recherche existante, cette thèse a effectué des recherches détaillées et plus profondes dans les aspects suivants.

(1) L'étude d'état de l'art

Un état de l'art sur les problèmes liés à l'IPPS a été donné sur la base des travaux actuellement publiés, ainsi que d'une revue de la littérature de problèmes étroitement apparentés. Les concepts et les définitions liés à la planification des processus, l'ordonnancement de jobs et l'IPPS ont été introduits. Basée sur l'analyse de la relation entre la planification des processus et l'ordonnancement, la nécessité d'intégrer les deux a été illustrée. Les trois mécanismes d'intégration traditionnelles de l'IPPS ont été étudiés et la

comparaison entre ces trois mécanismes a été réalisée pour décrire clairement les avantages et les inconvénients de chaque mécanisme d'intégration traditionnel, sur la base duquel le mécanisme d'intégration améliorée pour l'IPPS a été étudié pour faciliter la proposition d'un nouveau modèle dans cette thèse. Les méthodes d'exécution d'optimisation de l'IPPS dans la littérature ont été étudiées et résumées. Les deux principaux problèmes étendus dans l'IPPS ont été étudiés, qui sont le problème d'optimisation multi-objectifs et le problème de ré-ordonnancement. Les techniques clés impliquées dans ces deux problèmes ont été prolongées, sur la base de l'étude de la littérature, de l'analyse et de la synthèse.

(2) La proposition d'un nouveau modèle hybride de l'intégration de la planification des processus et de l'ordonnancement dans les systèmes de fabrication distribués (HMIPPS_DMS)

Le modèle de l'information d'intégration pour le problème de l'IPPS dans DMS a été établi sur la base de la définition de DMS et sa structure. Ensuite, pour résoudre les problèmes d'optimisation de l'IPPS dans un environnement DMS, un nouveau modèle hybride de l'IPPS dans DMS (HMIPPS_DMS) facilitant à la fois l'échange d'informations et la collaboration fonctionnelle en combinant NLPP et DPP dans un environnement DMS a été proposé.

Dans le HMIPPS_DMS, l'intégration hiérarchique de la planification des processus et de l'ordonnancement est réalisée par trois hiérarchies d'intégration : la phase d'intégration initiale/ grossière au niveau d'Enterprise, la phase d'intégration correspondante au niveau d'atelier d'usinage et la phase d'intégration finale/détaillée au niveau de ressource.

De plus, dans l'intégration au niveau d'atelier d'usinage, *s* plans de processus alternatifs près optimaux sont sélectionnés pour être intégrés à l'ordonnancement, ce qui améliore les performances de production et offre la flexibilité des plans des processus en même temps. La planification des capacités et la planification des capacités des ressources de la production de façon concurrente évitent les conflits entre les ressources et l'utilisation déséquilibrée des ressources, assurant la stabilité de la production et de l'efficacité dans les ateliers d'usinage. Une étude de cas a été conçue et réalisée sur la base de la description mathématique du problème IPPS dans DMS pour démontrer la fiabilité et décrire les procédures détaillées de HMIPPS_DMS, montrant que les HMIPPS_DMS proposés peuvent être très efficaces dans la résolution des problèmes d'optimisation de l'IPPS dans un environnement DMS.

Notez que le mécanisme d'intégration au niveau d'atelier d'usinage et celui au niveau de ressources sont adaptatifs pour l'IPPS dans une entreprise unique et dans l'environnement de l'atelier. Par conséquent, dans la recherche suivante sur les problèmes étendus de l'IPPS dans l'atelier d'usinage, ce mécanisme d'intégration a été adopté.

(3) L'Optimisation multi-objectif dans l'IPPS est réalisé en tenant compte des nouveaux paramètres et objectifs liés à la consommation d'énergie

Basé sur le concept du problème d'optimisation multi-Objectif (MOOP), le modèle mathématique complet pour expliquer et décrire le MOOP dans l'IPPS dans un atelier d'usinage a été créé, dans lequel certains nouveaux paramètres et objectifs concernant la consommation d'énergie dans l'usinage des pièces ont été adoptés selon l'étude et l'analyse connexe. Ensuite, sur la base du modèle mathématique, l'optimisation multi-objectif pour les problèmes de l'IPPS a été réalisée en utilisant la méthode NSGA-II améliorée, afin que les

décideurs dans les entreprises et les ateliers d'usinage puissent faire des choix raisonnables en fonction de leurs préférences pour les objectifs. L'encodage, le décodage et les opérateurs génétiques adoptés dans cette méthode améliorée de NSGA-II ont été expliqués en détail. Enfin, deux études de cas ont été menées pour mesurer la capacité d'adaptation de l'algorithme NSGA-II amélioré et pour vérifier le modèle mathématique proposé pour résoudre les problèmes du MOOP de l'IPPS.

(4) L'optimisation de l'IPPS dans l'atelier d'usinage dynamique est réalisée

Dans le but de faciliter le ré-ordonnancement dans l'intégration de la planification des processus et l'ordonnancement dans les ateliers d'usinage dynamiques, le modèle de ré-ordonnancement pour l'IPPS_DJS a d'abord été proposé pour illustrer le processus de ré-ordonnancement lorsque les perturbations de l'annulation de l'emploi, la panne de la machine et la nouvelle arrivée de la commande se produisent lors de l'exécution du plan d'ordonnancement initial.

Et puis, un modèle mathématique pour décrire le problème de l'IPPS_DJS considérant simultanément l'efficacité et la stabilité a été établi. Les mesures adoptées en fonction de l'optimisation de l'efficacité sont le makespan, le coût d'usinage, et la consommation d'énergie ; tandis que les mesures envisagées dans l'optimisation de la stabilité sont le coût de la déviation liée à la machine et le coût de la déviation liée à la pièce causés dans le plan de ré-ordonnancement. Une fonction multi-objectif est proposée par la méthode de pondération tenant compte à la fois des mesures participant à l'efficacité et à la stabilité, ce qui est plus pratique dans les processus de prise de décision dans les systèmes de fabrication réels. Enfin, des études de cas ont été faites pour vérifier l'efficacité et l'efficience du cadre et le modèle de l'IPPS_DJS proposé.

7 Limitations:

Comme le montre la recherche dans cette thèse, l'auteur a approfondi la compréhension et élargi la connaissance des problèmes concernant l'IPPS. Les futurs travaux concernant cette recherche devraient être davantage réalisés sur les aspects suivants.

(1) La planification des processus devrait également être intégrée avec la conception du produit lorsque l'ordonnancement dans l'atelier d'usinage devrait être intégré à la planification des ressources d'entreprise (ERP) et le système de contrôle, sur la base duquel CIMS peut être réalisé.

(2) De plus, il faut encore étudier et quantifier de façon plus pratique le mécanisme et les paramètres concernant la consommation d'énergie par les machines-outils pendant les processus de fabrication dans les ateliers, afin d'essayer de diminuer la consommation d'énergie et les effets sur l'environnement dans les ateliers.

(3) Par ailleurs, il faut aussi incorporer les paramètres plus pratiques et liés au site de production au modèle de l'IPPO pour améliorer la production aux niveaux de la flexibilité, la stabilité et l'efficacité.

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Nomenclature

ACO	Ant Colony Optimization
AI	Artificial Intelligence
AIS	Artificial Immune System
APPS	advanced process planning and scheduling
APS	Advanced Planning and Scheduling
ASP	Adaptive Setup Planning
CAD	Computer Aided Design
CAM	Computer Aided Manufacturing
CAPP	Computer Aided Process Planning
CE- NSGA-II	Controlled Elitist- NSGA-II
CIMS	Computer Integrated Manufacturing System
CLPP	Close-Loop Process Planning
CMPSO	Cooperative Multiple Particle Swarm Optimization
CNC	Computerized Numerical Control
CP	Constraint Programming
DAI	Distributed Artificial Intelligence
DD	Delivery Date
DEP	Design Environment Parameter
DJS	Dynamic Job Shop
DKM	Dynamic Key Machine
DMS	Distributed Manufacturing System
DP	Dynamic Programming
DPP	Distributed Process Planning
D-Space	Decision Space
DV	Design Variable
EA	Evolutionary Algorithm
EC	European Commission
ERP	Enterprise Resource Planning
ESCSA	Enhanced Swift Converging Simulated Annealing
FLC	Fuzzy Logic Control
FMS	Flexible Manufacturing System
fmoGA-A	Fast Multi-Objective Genetic Algorithm with Archive Mechanism
GA	Genetic Algorithm
GHG	GreenHouse Gas
GPP	Generic Process Plan
HAN	Hybrid-based Agent Negotiation
HD-DNA	Hybrid Dynamic DNA
HMIPPS_DMS	Hybrid Model of Integrated Process and Planning in Distributed Manufacturing System
ID	Identification
IGA	Improved Genetic Algorithm
IPPS	Integrated Process Planning and Scheduling

IPPS_DJS	Integrated Process Planning and Scheduling in Dynamic Job Shop
JSP	Job-shop Scheduling Problem
M1	Machine 1
MAS	Multi-Agent System
MAN	Multi-Agent Negotiation
MF	Manufacturing Feature
MOEAs	Multi-Objective Evolutionary Algorithms
MOOP	Multi-Objective Optimization Problem
MPP	Multiple Process Plans
MPSC	Multi Plant Supply Chain
MRP	Material Requirement Planning
NC	Numerical Control
NLPP	Non-Linear Process Planning
NSGA-II	Non-dominated Sorting Genetic Algorithm-II
PF-Space	Pareto Front Space
PPSM	Process Plans Selection Module
P-Space	Parameter Space
PSO	Particle Swarm Optimization
SAA	Simulate Anneal Arithmetic
SAM	Scheduling Analysis Module
SEA	symbiotic evolutionary algorithm
SM	Scheduling Module
SOOP	Single-Objective Optimization Problem
TAD	Tool Approach Direction
TS	Tabu Search
TST	Topological Sort Technique
TSP	Travelling Salesman Problem
TDEA	Territory Defining Evolutionary Algorithm
UML	Unified Modelling Language

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Chapter 1 General Introduction

1.1 Background

From the point of view of production mode of modern enterprises, the global market competition and diversified, personalized customer demands have brought about the prevalence of single-piece & small batch production to more quickly respond to the variable market demands and further meet user requirements on product variety, quality, price and personalized service. Under such environment, product design and process planning should be more closely cooperated with practical production to enable the administrators in the enterprises and job shops to grasp the changes in the production site in the shortest time so that they can make accurate judgment and give rapid response to reasonably adjust the production plans.

From the point of view of operation mode of modern enterprises, to win the competition in a dynamic and challenging marketplace demanding shorter response time to changing markets and agility in production, the manufacturers need to change their manufacturing systems from centralized environment to a distributed environment (Wang and Shen, 2007). In such situation, Distributed Manufacturing Systems (DMS) are expected to be the leading manufacturing system concepts (Wu et al., 2002). A DMS normally consists of several partners (system elements) that may geographically be distributed in different locations. This allows them to be closer to their potential customers, to comply with the local laws, to focus on a few product types, to produce and market their products more effectively, and to be responsive to market changes more quickly (Chan et al. 2006, Schniederjans 1999, Sule 2001). In DMS environment, each partner is usually capable of manufacturing a variety of product types. In addition, they may have different production efficiency and various constraints depending on the machines, labor skills and their education level, labor cost, government policy, tax, nearby suppliers, transportation facilities, etc. (Chan et al., 2006). Since different partners have different operating costs, production lead time, customer service levels, constraints, etc., how to apply distributed modeling and simulation tools to evaluate and improve products and processes, better utilize production resources and improve flexibility, dynamism, adaptability, agility and productivity of distributed manufacturing systems has become significant.

Process planning is the act of preparing detailed operation instructions to transform an engineering design to a final part. A process plan specifies the manufacturing resources and the technical operations/routes that are needed to produce a product. The outcome of process planning includes the identification of machining tools and fixtures applicable to a job, and the arrangement of operations and processes to machine the job. Typically, a job may have one or more alternative process plans. Scheduling receives process plans as their input and its task is to allocate the operations of all the jobs in an order to limited resources in time aspect to satisfy or optimize several criteria while respecting the precedence relations given in the process plans. Scheduling is not only the sequencing, but also the determining of the starting and completing time of each operation based on the sequence (Li et al., 2010a).

It is obvious that process planning and job shop scheduling are highly interrelated as both of them are related with resource assignment (Lv and Qiao, 2013). However, in traditional

approaches, these two functions are performed sequentially by different departments in a manufacturing system (Jain et al., 2006). Scheduling was conducted after the process plan had been generated. This sequential approach often creates obstacles in productivity enhancement of manufacturing systems and it is difficult to provide agile responsiveness to the production uncertainties (Shao et al., 2009; Lian et al., 2012). Meanwhile, it may bring some other problems, such as objective conflicts between process planning and scheduling, load unbalance for production resources and process plan infeasibility after dispatched to the production system (Lv and Qiao, 2013; Li et al., 2010d; Li et al., 2010b; Li et al., 2010c; Li et al., 2012a; Li et al., 2012b; Shao et al., 2009).

In response to these problems, it is necessary to integrate process planning and scheduling more closely. Chryssolouris and Chan (Chryssolouris and Chan, 1984) were the first to propose the preliminary idea of the integration of process planning and scheduling (IPPS).

IPPS is the concept of conducting process planning and scheduling concurrently with the objectives to eliminate or reduce scheduling conflicts, to reduce flow time and work in process, to improve resources utilization and to enhance the flexibility to adapt to uncertainties such as irregular shop floor disturbance (Lee and Kim, 2001; Wan et al., 2013). The IPPS can introduce significant improvements to the efficiency of manufacturing resources through eliminating or reducing scheduling conflicts, reducing flow-time and work-in-process, improving production resources utilizing and adapting to irregular shop floor disturbances (Lee and Kim, 2001). Besides, in the beginning research of Computer Integrated Manufacturing System (CIMS), some researchers have found that the integration of process planning and scheduling (IPPS) is very important to the development of CIMS. Without IPPS, a true CIMS striving to integrate the various phases of manufacturing in a single comprehensive system may not be effectively realized (Li et al., 2010c). IPPS can provide better process plans and schedules than the traditional manufacturing systems to greatly improve the productivity of the manufacturing system. What's more, IPPS can also improve the flexibility, adaptability, agility and global optimization of the distributed and collaborative manufacturing (Wang and Shen, 2007).

1.2 Problems in IPPS

Although the research on IPPS has been extensively conducted over the past nearly three decades in the respects of framework, modelling, system building and so on, there are still some crucial problems need to be solved as following.

(1) Improved integration model of IPPS should be proposed

The currently existing integration models (NLPP, CLPP and DPP) have their own advantages and disadvantages. Any single existing integration model cannot solve the IPPS problem efficiently or effectively. Therefore, better and more practical hybrid integration model combining their advantages and eliminating their disadvantages should be further researched and improved.

(2) IPPS in Distributed Manufacturing Systems should be further studied

Distributed Manufacturing System (DMS) is a leading system concept in future. Therefore, the research on IPPS problems in such systems is with practical significance. However, existing literatures are mainly focused on a single given job shop environment, and there is no systematic research on IPPS problems in DMS environment, where several enterprises and job shops will be involved in. IPPS problems in DMS are much more complicated than classical ones because they involve not only the IPPS problems in each job shop, but also the problems in an upper level of how to allocate the jobs to a suitable enterprise to optimize the utilization of manufacturing resources. Therefore, it is urgent to propose effective and reliable integration model and further study integration mechanism of IPPS in DMS to optimally use enterprise resources, balance resource workload and better profit both the enterprises and the clients.

(3) Research on multi-objective optimization in IPPS should be extended

The IPPS is a multi-objective problem. A great deal of current research on IPPS has been concentrated on the single objective. However, because different departments in an enterprise have different expectations in order to maximize their own profits, for example, the manufacturing department expects to reduce costs and improve work efficiency, the managers want to maximize the utilization of the existing resources, and the sale department hopes to better meet the delivery requirements of the customers. In this case, only considering the single objective cannot meet the requirements from the real-world production. Therefore, further studies on multi-objective optimization problems in IPPS problem are still highly demanded to effectively and efficiently help the administrators in the enterprises and job shops in decision-making processes.

What's more, environmental pollution has exerted heavy pressure to manufacturing enterprises while job shop schedules could significantly affect energy consumption as well as other environment impacts of an individual machine (Fang et al., 2011). Optimized operation schedules could further reduce energy costs. Unfortunately, although a variety of performance measures have been considered for shop scheduling, these efforts have largely focused on economic, time, or operational considerations. In contrast, research on scheduling with environmentally-oriented objectives is relatively scarce. Seldom of the previous studies addressed energy related objectives in modelling the scheduling problem. Therefore, it is of great significance to consider the quantified definition of energy consumption of each machine tool in multi-objective optimization of IPPS problems to support environment protection and sustainable development while meeting demands from customers and markets.

(4) Rescheduling capability in IPPS

In dynamic, stochastic manufacturing environments, managers, production planners, and supervisors must not only generate high-quality schedules but also react quickly to unexpected events and revise schedule in a cost-effective manner (Guilherme et al., 2003). Unexpected events can generate considerable differences between the predetermined schedule and its actual realization on the shop floor. One of the most important purposes to research on IPPS problems is to enhance the flexibility and rapid response capability of the manufacturing

system using process plan flexibility. Therefore, rescheduling is practically mandatory so that the effect of such disturbances in the performance of the system can be minimized. Current research on IPPS problems in the literature is mostly focused on static scheduling, and rescheduling methods and mechanism both effectively responding to dynamic events and maintaining system stability at the same time should be further studied.

1.3 Research Objectives

(1) Establishing Hybrid Model of Integrated Process Planning and Scheduling in Distributed Manufacturing Systems

The fore-mentioned problem 1and 2 will be solved in this part. A new Hybrid Model of Integrated Process Planning and Scheduling in Distributed Manufacturing System (HMIPPS_DMS) will be proposed to facilitate both information exchange and functional collaboration by combining the process plan flexibility provided by the interface-oriented integration of NLPP (Non-linear Process Planning) and the hierarchical structure of DPP (Distributed Process Planning) in DMS environment. In HMIPPS_DMS, the hierarchical integration of process planning and scheduling is realized through three integration hierarchies: initial/rough integration phase in Enterprise Level Integration to optimally determine an enterprise partner to process the jobs based on concurrent resource capability and capacity analysis as well as production performances in all candidate enterprises, matching integration phase in Job Shop Level Integration to select the most appropriate job shops to allocate the jobs based on concurrent resource capability and capacity analysis as well as production performances in the feasible jobs of the determined enterprise, and final/detailed integration phase in Resource Level Integration to obtain the detailed process plan for each job and the scheduling plan in the selected job shops.

(2) Extending Multi-Objective Optimization Problem in IPPS

The fore-mentioned problem 3 will be solved in this part. Based on the concept of Multi-Objective Optimization Problem (MOOP), the complete mathematical model to explain and describe the MOOP in IPPS will be constructed, in which some new parameters and objectives relating energy consumption in machining the parts will be studied and adopted. Then NSGA-II (Non-dominated Sorting GA-II) will be improved to effectively solve the multi-objective optimization problems in IPPS so that the decision-makers in the enterprises and job shops can make reasonable choices according to their preferences for the optimization objectives.

(3) Improving rescheduling capability in IPPS

The fore-mentioned problem 4 will be solved in this part. A framework and a unified rescheduling model in IPPS with three typical types of uncertainties normally encountered in job shops, i.e. arrival of new jobs, machine breakdown and order cancellation will be constructed. To enhance system flexibility, the three types of flexibility (routing flexibility, sequence flexibility and process flexibility) will be used in the rescheduling process. To respond to dynamic changes and meanwhile maintain system stability in the job shops, the model will simultaneously consider production efficiency and stability. The measurements

will be adopted in production efficiency optimization are makespan, machining cost, and energy consumption; while the measurements will be considered in production stability optimization are the machine-related deviation cost and job-related deviation cost caused in the rescheduling. A final objective function will be proposed by weighting method considering both the measurements involved in efficiency and stability, which is more practical in decision-making in real manufacturing systems.

1.4 Thesis Outline

The outline of the thesis is shown as Figure 1-1.

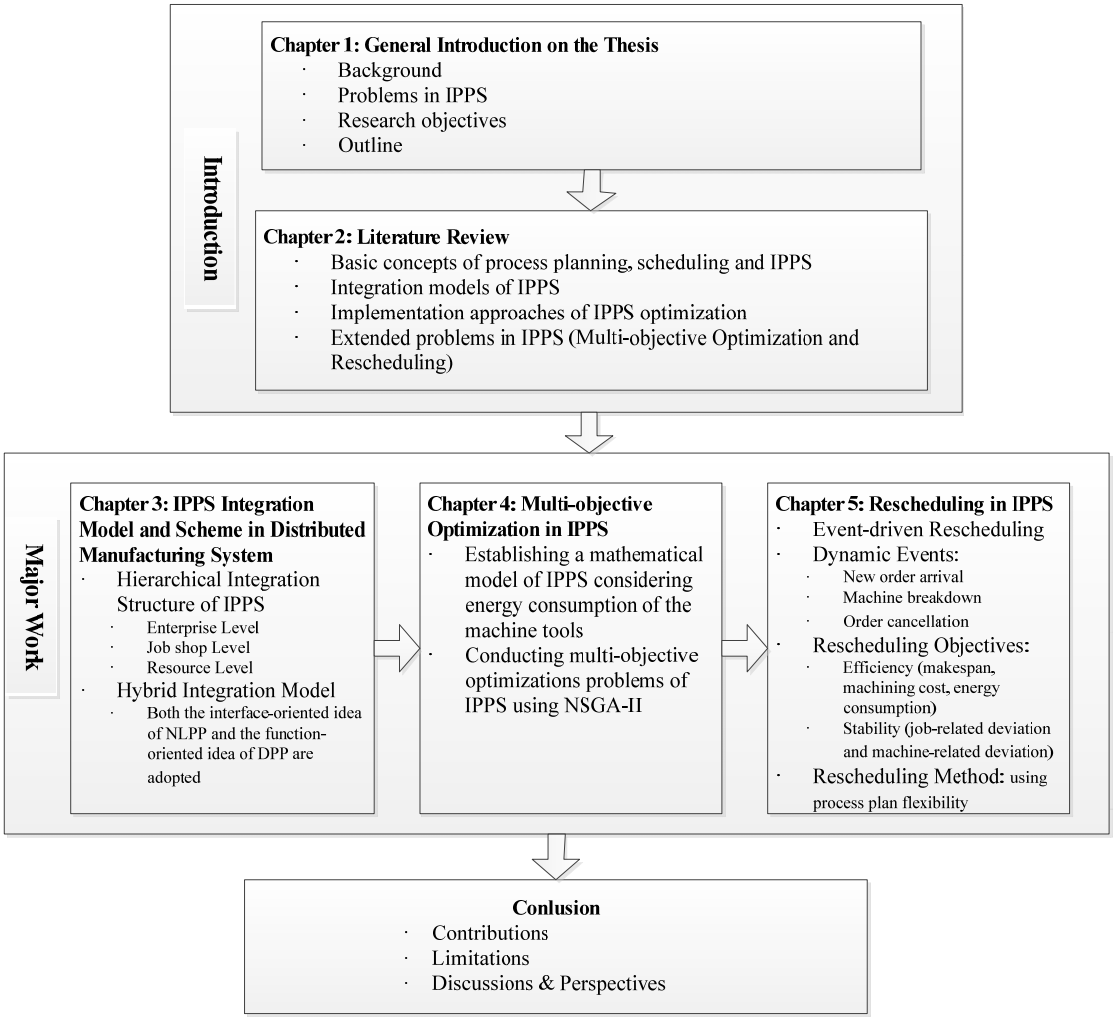


Figure 1-1 The outline of the thesis

In Chapter 1, the general introduction of the thesis is presented, including the background of the thesis, current problems in IPPS, research objectives and the outline of the thesis.

Chapter 2 offered a literature review summary based on a deep and extensive literature study. Firstly, the basic concepts of process planning, scheduling and IPPS are introduced. Then the traditional integration models of IPPS are studied. Next the implementation approaches of IPPS optimization are enumerated and compared. Finally the extended

problems in IPPS including Multi-objective Optimization Problem (MOOP) and rescheduling problem in dynamic job shops are explored.

In chapter 3, based on the proposed information integration model for IPPS problem in Distributed Manufacturing System (DMS), a new Hybrid Model of Integrated Process Planning and Scheduling in Distributed Manufacturing System (HMIPPS_DMS) is established by adopting both the interface-oriented idea of NLPP and the function-oriented idea of DPP. Hierarchically constituted of three integration levels, the new model of HMIPPS_DMS will facilitate the layered integration optimization of IPPS in each level through Initial Integration Phase in Enterprise Integration Level, Matching Integration Phase in Job Shop Integration Level and Final/Detailed Integration Phase in Resource Integration Level.

In Chapter 4, based on the concept of Multi-Objective Optimization Problem (MOOP), the complete mathematical model to explain and describe the MOOP in IPPS in a single job shop is constructed, in which some new parameters and objectives relating energy consumption in machining the parts will be studied and adopted. Then NSGA-II (Non-dominated Sorting GA-II) is improved to effectively solve the multi-objective optimization problems in IPPS.

In chapter 5, a rescheduling model simultaneously considering production efficiency and stability is proposed. The measurements adopted in light of efficiency optimization will be makespan, machining cost, and energy consumption; while the measurements defined in stability optimization will be the machine-related deviation cost and job-related deviation cost caused in the rescheduling plan. In conducting IPPS_DJS, the three types of production flexibility (routing flexibility, sequence flexibility and process flexibility) will be used in the rescheduling process to maintain rescheduling flexibility.

Chapter 2 Literature Review

Introduction:

In the past decades, the idea of integrated process planning and scheduling (IPPS) in the job shops has received an increasing interest from the scientific community, especially the optimization problems involved in IPPS. Focused on the concerned research of this thesis, this chapter provides the related concepts and a state of the art for IPPS problems, as well as an extensive literature review on closely related problems, such as integration mechanism of IPPS, implementation approaches of IPPS optimization and the major two extended problems in IPPS including multi-objective optimization problem of IPPS and rescheduling problems of IPPS.

2.1 Related Concept

2.1.1 Process Planning

2.1.1.1 Concept

Process planning as an essential component linking design and downstream manufacturing processes, is the act of preparing detailed operation instructions to transform an engineering design to a final part (Chang and Wysk, 1984). Process planning is the systematic determination of methods by which a product is to be manufactured economically and competitively.

Process planning encompasses the activities and functions to prepare a detailed set of plans and instructions to produce a part aiming at achieving the correct quality, the minimal manufacturing cost and ensuring good manufacturability (Guo, et al., 2009). The planning begins with engineering drawings, specifications, parts or material lists and a forecast of demand. The first step to design process plan is to recognize a set of geometric features and their interrelationships from the part design. Based on the geometric features identified, a set of machining functions are selected, which can be treated as a general machining process without detail machining methods specified. The set of machining processes can be constrained by the precedence relations, which are imposed by the technological requirements of the part (Moon et al., 2002a). The main considerations in process planning include (Zhang, and Gen, 2010):

- Generating machining operations based on the features of a part to meet desired functional specifications and achieve good manufacturability;
- Identifying machining resources applicable to the operations;
- Determining the set-up plan and operation sequence according to some cost-effective criteria and technological requirements.

Therefore, a process plan for a part can be represented by a series of machining operations, applicable resources for the operations, set-up plans, operation sequence, etc.

2.1.1.2 Manufacturing Information Model in Process Planning

The main manufacturing information involved in process planning includes information on materials, manufacturing activities, manufacturing resources and manufacturing

organizations (Zhang, 2009), as shown in Figure 2-1. These four groups of basic information can be described as following:

- Material refers to the products to be produced, raw materials and the materials produced in process planning. The material information includes the information of parts, assemblies, products, raw materials and supplemental materials.
- Activity refers to the manufacuring activities, including machining activities and assembling activities and so on.
- Manufacturing resource mainly refers to the equipments and tools will be used in product processing.
- Organization refers to the units executing the manufacturing activities, including departments and staff.

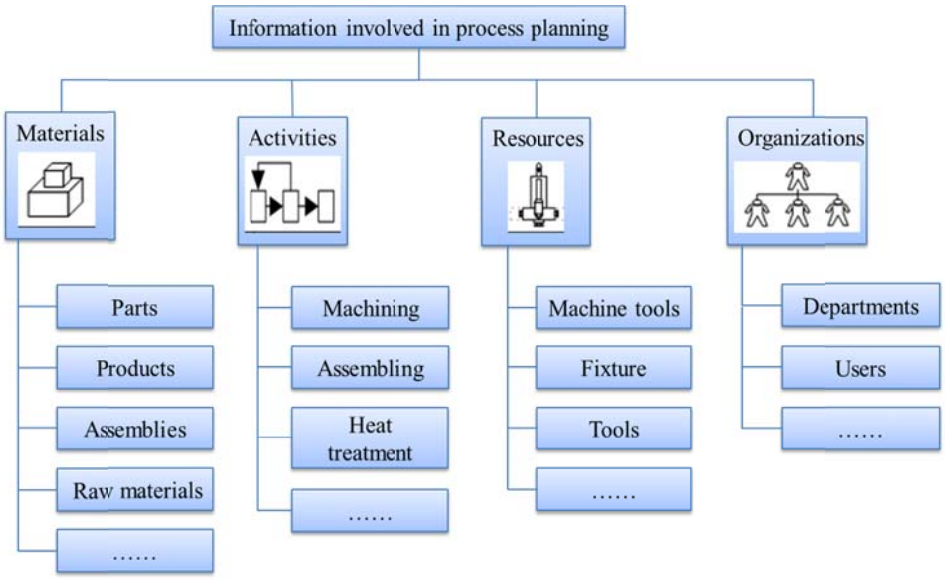


Figure 2-1 The information involved in process planning

2.1.2 Job Scheduling

2.1.2.1 Concept

Job scheduling is to decompose the production task in the production plans determined according to the orders or market-forecast in terms of timing, space, specifications. As for production specification, the varieties, quantity and quality of the product will be set; as for space, the production unit will be allocated to job shops, job shop section, working team and even to equipment; as for job timing, it will be refined into month, days and hours; assuring the production plans to be executed practically.

In summary, scheduling is to determine the most appropriate moment to execute each operation for the launched production orders, taking into account the due date of these orders, a minimum makespan, a balanced resource utilization ,etc., to obtain high productivity in the job shop (Guo et al., 2009; Aldakhilallah and Ramesh, 1999).

2.1.2.2 The Main Task of Job Scheduling

On the one hand, the production plans are received by scheduling systems from the upper planning systems and then decomposed into processing operation level to develop the job shop scheduling plan, according to which the job shop tasks are specifically and reasonably allocated to each production unit and scheduling instructions are issued to job shop control systems.

On the other hand, scheduling system receives the real-time processing information reported by the shop floor control systems, and concerns about the random incidents caused by the uncertainties such as order changing, to adjust the job planning and conduct rescheduling when necessary. Besides, it offers feedbacks of processing progress information to the upper planning systems to effectively control job processing.

The flow chart of the job scheduling in job shops is shown in Figure 2-2.

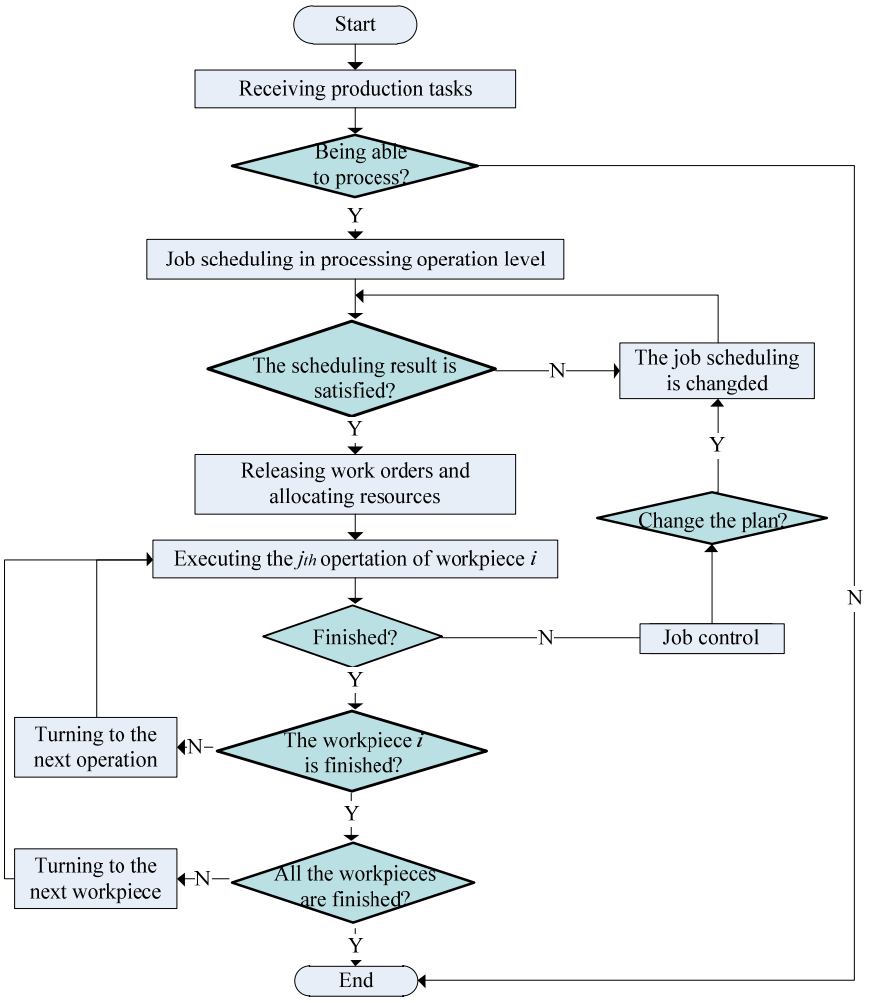


Figure 2-2 The flow chart of job planning and scheduling

In theory, job scheduling should satisfy the following requirements:

- Ensure product delivery;
- Reduce the waiting time of the operating staff and equipment;
- Make the processing time of the work piece to be shortest;
- Reduce the number of products being processes and the parking time;
- Conduct production control.

2.1.3 The Relationship between Process Planning and Scheduling

Process planning and scheduling are two of the most important modules in a manufacturing system. These tasks strongly influence the profitability of manufacturing enterprises, resource utilization and product delivery time (Yang et al., 2001). Process planning and scheduling not only have close relationship in light of data transfer, but also share the common tasks and objectives in resource allocation (Lv, 2012; Lv and Qiao, 2014).

(1) Close relationship on data transfer exists between process planning and scheduling

On the one hand, the primary goal of process planning function is to generate process plans specifying raw material/components needed to produce a product as well as processes and operations necessary to transform raw materials into the final product, and the outcome of process planning will be transferred to job shops to guide the production procedures. Normally, because of the routing flexibility, sequencing flexibility and processing flexibility, there are alternative process plans for each job. And as for scheduling, it is a decision-making process which takes the process plans of the jobs as the input, and determines the optimal or near optimal task allocation by satisfying the constraints on operation precedence and procedure resources to maximize or minimize one or some objectives. Therefore, close relationship on data transfer exists between process planning and scheduling.

(2) Both process planning and scheduling involve assignment of resources and are complementary in functions

On the other hand, both of process planning and scheduling are responsible for the efficient allocation and utilization of resources in the job shops. One of the main tasks of process planning is to identify machining resources (including identification of machines, tools and fixtures) applicable for operations based on the analysis of the features of the parts, while scheduling assigns a specific task to a specific machine in order to satisfy a given performance measure, which is bound by process sequencing instructions that the process plan dictate and by the time-phased availability of production resources. Thus, both process planning and scheduling involve assignment of resources and are complementary in functions (Phanden et al., 2011).

Process planning is time-independent, while scheduling is considered as time-dependent activities (Wu et al, 2002).

2.1.4 The Necessity to Integrate Process Planning and Scheduling

Computer Aided Process Planning (CAPP) systems has been developed in the past decades, intending to bridge the gap between CAM and CAD and to provide fast feedback to designers regarding detailed manufacturing information (i.e., manufacturability) and related cost estimation, and to substantially reduce product development cycle time (Tan and Khoshnevis, 2000). Most of these systems are capable of generating numerous feasible alternative process plans from which a good plan is chosen according to some established criterion. However, traditionally only the static off-line integration between CAPP and CAD is emphasized. They generally overlook the potential of downstream integration with scheduling and other production functions and pay limited attention to the effect that changing shop floor conditions may have effect on the desirability of process plans. It is not uncommon that the process plans generated from such systems are not rigidly followed in shop floor implementation because of possible scheduling conflicts, resource contention and unavailability, etc.

Meanwhile, given a fixed process plan, scheduling activity often has to resolve conflicts between available resources due to changing environment. The original process plan has to be modified frequently to accommodate changes in the shop floor. Some researchers have found that approximately as much as 30 percent of the process plans needs modifications (Detand et al., 1992). Such repeated events will inevitably lead to disrespected and loosely followed process plans, resulting in inadequate collaboration between process planning function and scheduling function.

As such, conventionally, based on the concept of subdividing the tasks into smaller and separated duties to satisfy the requirements of sub-optimization and suitable for mass production (Larsen and Alting, 1992), process planning and scheduling are carried out in two distinct, sequential phases, where scheduling is done separately after the process planning. Being faced with today's manufacturing environment characterized by decreasing lead time, exacting standards of quality, larger part variety and competitive costs, the traditional approach usually cannot get a satisfactory result due to the following reasons (Phanden, et al., 2011; Larsen and Alting, 1992; Morad and Zalzala, 1999; Li et al., 2010a, b, c; Kumar and Rajotia, 2003):

- In manufacturing practice, process planners plan jobs individually and assume that shop floor is ideal and unlimited capacities of resources are always available in the shop. For each job, manufacturing resources on the shop floor are usually assigned on it without considering the competition for the resources from other jobs (Usher and Fernandes K, 1996a, b). This may lead to the process planners favoring to select the desirable machines for each job repeatedly. Moreover, the resources are never always available on shop floor. Therefore, the generated process plans are somehow unrealistic and cannot be readily executed on the shop floor for a group of jobs (Lee and Kim , 2001). Accordingly, the resulting optimal process plans often become infeasible when they are carried out in practice at the later stage.
- Scheduling plans are often determined after process plans. Fixed process plans may drive scheduling plans to end up with severely unbalanced resource load and create superfluous

bottlenecks.

- Even if process planners consider the restriction of the current resources on the shop floor, the constraints in the process planning phase may have already changed owing to the time delay between the planning phase and execution phase. This may lead to the infeasibility of the optimized process plan (Kumar and Rajotia, 2002). Investigations have shown that 20-30% of the total production plans in a given period have to be modified to adapt to the dynamic change in a production environment (Kumar and Rajotia, 2003).
- The throughput target of orders in a workshop often suffers from disruptions caused by bottleneck machines, non-availability of tools and personnel, or breakdown of machines and equipment. A readily generated schedule becomes invalid and has to be regenerated.
- In most cases, both for process planning and scheduling, a single criterion optimization technique is used for determining the best solution. However, the real production environment is best represented by considering more than one criterion simultaneously (Kumar and Rajotia, 2003). Furthermore, the process planning and scheduling may have conflicting objectives. Process planning emphasizes the technological requirements of a job, while scheduling involves the timing aspects and resources and resources sharing of all jobs. If there is no appropriate coordination, it may create conflicting problems.

2.1.5 Integrated Process Planning and Scheduling

To overcome the above problems, there is an increasing need for deep research on the integration of process planning and scheduling (IPPS). IPPS is the concept of conducting process planning and scheduling concurrently with the objectives to eliminate or reduce scheduling conflicts, to reduce flow time and work in process, to improve resources utilization and to enhance the flexibility to adapt to uncertainties such as irregular shop floor disturbance (Lee and Kim, 2001; Wan et al., 2013). Without IPPS, a true computer integrated manufacturing system (CIMS) which strives to integrated the various phases of manufacturing in a single comprehensive system, may not be effectively realized (Li et al., 2012).Through the integration of these two systems, IPPS can provide better process plans and schedules than the traditional manufacturing systems to improve the productivity of the manufacturing system greatly. The merits of IPPS is to increase production feasibility and optimality by combining both the process planning and scheduling problems (Wong et al., 2006a, b).

The IPPS problem can be generally defined as (Kim et al., 2003): Given a set of N jobs which are to be performed on M machines with routing flexibility, sequence flexibility and process flexibility, find an operation sequence and corresponding machine tool sequence for each job and a schedule in which operations on the same machines are processed such that it satisfies the precedence constraints and it is optimal with respect to some relevant criteria, e.g. minimum makespan and minimum mean flow time and so on.

Figure 2-3 is used to illustrate this problem (Guo et al., 2009b). For instance, there are 3 parts that can be machined by 3, 2 and 3 operations on 3 machines, respectively. For the different parts, there are precedence constraints among the operations to machine them (Part1:

Oper1→Oper2→Oper3, Part2: Oper4→Oper5, Part3: Oper6→Oper7→Oper8). When all these 8 operations are sequenced (Oper1→Oper4→Oper2→ Oper6→Oper3→Oper7→Oper8→Oper5 as shown in Figure 2-3) and the manufacturing resources are specified, the schedule can be determined accordingly. The optimization problem is to determine the operation sequence and select the manufacturing resources so as to achieve the optimization objectives (makespan in Figure 2-3, for example) whilst maintaining the schedule and process planning feasible.

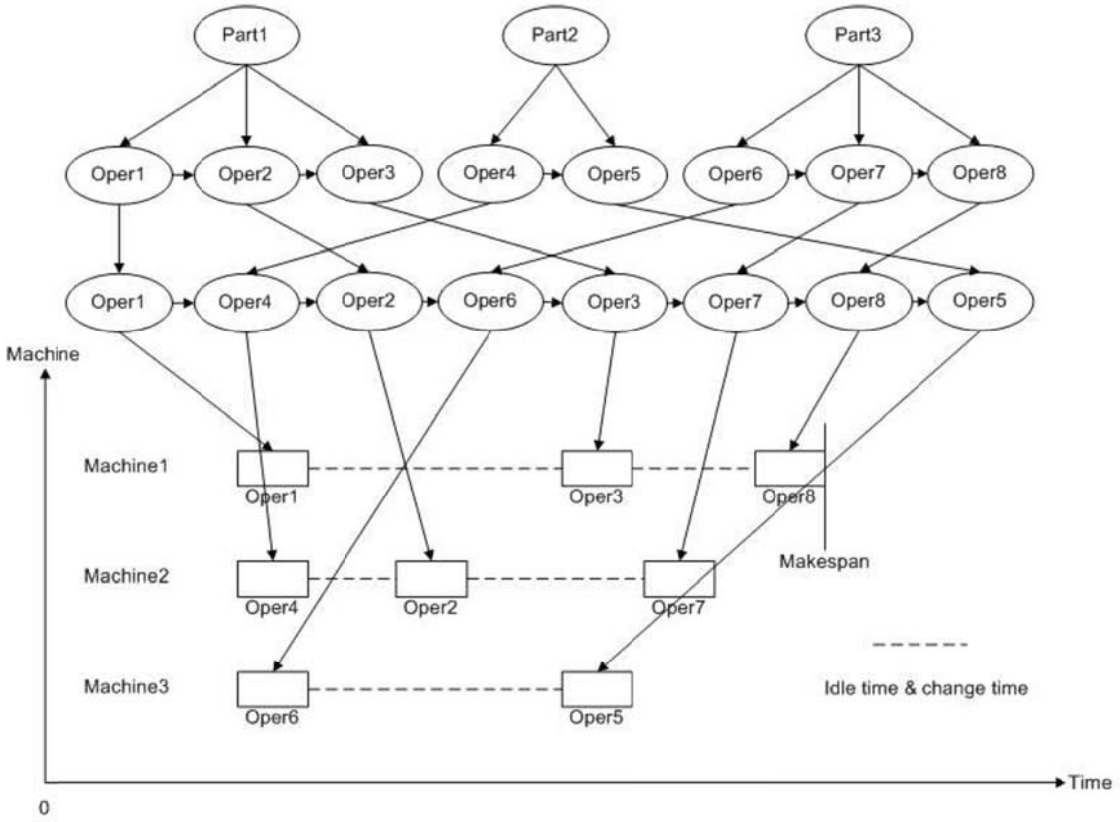


Figure 2-3 Illustration of the IPPS problem (Guo et al., 2009b)

2.2 Literature Review on Integration Mechanism of IPPS

The research on IPPS was firstly proposed by (Chryssolourisa et al., 1984; Chryssolourisa et al., 1985), and afterwards, there have been numerous research efforts towards the integration of process planning and scheduling from all over the world. Different integration models and optimization methods have been proposed and researched, identifying that the integration of process planning and scheduling can effectively resolve the problem of objective-conflict between the two, reducing work flow time, makespan, etc., improving the profitability of resource utilization and enhancing the ability to flexibly response to the uncertain conditions of the job shops (Shao et al., 2009; Kumar and Rajotia, 2003).

The integration models of IPPS was summarized and divided into the following three types in (Larsen and Alting, 1992; Larsen, 1993): Nonlinear Process Planning (NLPP), Closed Loop Process Planning (CLPP) and Distributed Process Planning (DPP). This taxonomic approach has been widely used and cited by most of the researchers in this filed, i.e. in (Jain et

al., 2006; Phanden et al., 2013; Baykasoglu and Ozbakir, 2009; Li et al., 2012a, b; Zhang et al., 2003). Besides, the main literature reviews on IPPS is also conducted based on this taxonomy (Li et al., 2010(a); Phande et al., 2011). The detailed introduction of these three integration mechanism is as following.

2.2.1 Non-linear Process Planning

In Non-Linear Process Planning (NLPP) (Rakesh et al., 2011; Rakesh et al., 2013; Kruth and Detand, 1992; Lee and Kim, 2001; Li et al., 2010 (c); Li et al., 2010 (b)):

- Multiple process plans (MPP) for each part before it enters to shop floor are firtly created by considering operation flexibility (possibility of performing an operation on more than one machine), sequencing flexibility (possibility of interchanging the sequence in which required manufacturing operations are performed) and processing flexibility (possibility of producing the same manufacturing feature with alternative operations or sequence of operations).
- All these possible process plans are ranked according to process planning criterion (such as total machining time and total production time) and stored in a process planning database.
- The first priority plan is always ready for submission when the job is required and then scheduling makes the real time decision.
- If the first priority plan does not fit well in the current status of shop floor, the second priority plan is provided to scheduling.
- This procedure is repeated until a suitable plan is identified from already generated process plans.

NLPP can be also called as flexible process planning (Saygin and Kilic, 1999; Zhang et al., 2003; Gan and Lee, 2002; Kim et al., 1997), multi-process planning (Li et al., 2010(a)) or alternative process planning (Yang et al., 2001; Kim and Egbelu, 1998; Kim and Egbelu, 1999; Usher, 2003; Kis, 2003; Nasr and Elsayed, 1990). Figure 2-4 shows the basic flow chart of NLPP.

The underlying assumption is that all problems that can be solved ahead of time should be solved before the manufacturing starts. Thus, NLPP is based on static shop floor situations (Zhang and Merchant, 1993; Gaalman et al., 1999).

The information flow is a one-way type in NLPP, i.e. from process planning to production planning, and thus, it may be impossible to achieve full optimal results in integrating the two functions (Kempenaers et al., 1996; Gaalman et al., 1999). Moreover, modern production systems maintain MPP (Kim K. H., Egbelu P. J., 1999), and it seems to be a proper means to realize the integration between process planning and scheduling (Kempenaers et al., 1996). Also, it can be implemented in a company with existing process planning and scheduling department. However, when there are large numbers of parts, the number of process plans tends to increase exponentially and can cause a storage problem (Usher, 2003). Besides, some of the process plans created are not feasible according to real-time shop status and considering all possible process alternatives for resource allocation may

enormously increase the complexity of process plan representation (Zhang and Merchant, 1993; Huang et al., 1995).

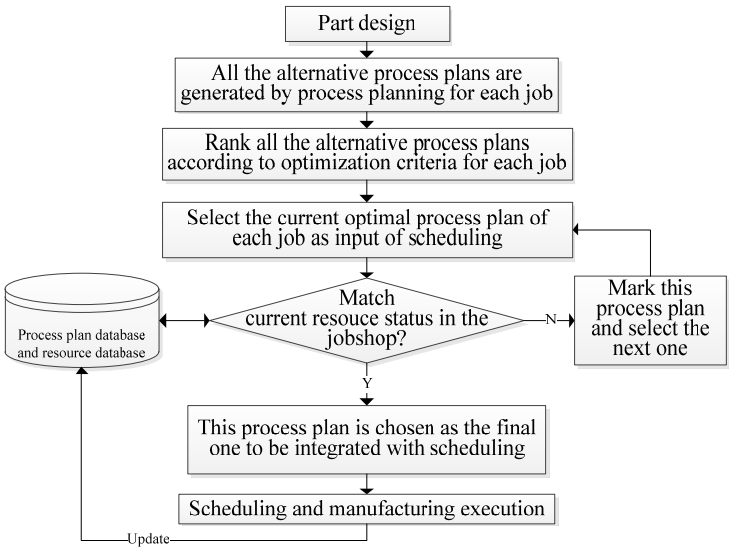


Figure 2-4 The basic flow chart of NLPP

2.2.2 Closed-Loop Process Planning

In Closed-Loop Process Planning (CLPP) (Phanden et al., 2011, 2013), process plans are generated by means of a dynamic feedback from production scheduling and available resources. Production scheduling tells process planning regarding availability of different machines on shop floor for the coming job, so that every plan is feasible with respect to current availability of production facilities. Every time an operation is completed on shop floor, a feature-based work piece description is studied in order to determine next operation and allocate the resources. This approach takes dynamic behavior of the manufacturing system into consideration. Thus, real-time status is crucial for CLPP (Zhang and Merchant, 1993). It is also referred to as on-line process planning (Kumar and Rajotia, 2003, 2006; Mamalis et al., 1996; Baker and Maropoulos, 2000), real-time process planning (Phanden et al., 2011, 2013) or dynamic process planning (Jian et al., 1992; Usher and Fernandes, 1996a, b; Seethaler and Yellowley, 2000; Chang and Chen, 2002; Lim and Zhang, 2000). Figure 2-5 shows the basic flow chart of CLPP.

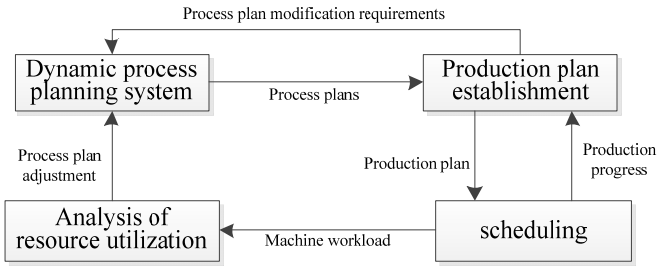


Figure 2-5 The basic flow chart of CLPP

In order to take full advantage of CLPP, process planning and scheduling departments in a company may have to be dismantled and reorganized (Iwata and Fukuda, 1989). Moreover,

it requires high-capacity software and hardware (Zhang and Merchant, 1993) and adaptation of step-by-step local view that limits the solution space for subsequent operations (Gaalman et al., 1999). However, this approach is unrealistic as the complexity of manufacturing processes might be unavoidable in achieving real-time process plan generation (Joo et al., 2001).

2.2.3 Distributed Process Planning

Distributed process planning (DPP) (Phanden et al., 2011, 2013) performs both process planning and production scheduling simultaneously. It divides process planning and production scheduling tasks into two phases. The first phase is preplanning. In this phase, process planning function analyses the job based on the product data. The features and feature relationships are recognized, and corresponding manufacturing processes are determined. The required machine capabilities are also estimated. The second phase is the final planning, which matches required job operations with the operation capabilities of available production resource. The integration occurs at the point when resources are available and the job was required. The result is dynamic process planning and production scheduling constrained by real-time events. This approach is also referred to as just-in-time approach or phased or progressive approach. Figure 2-6 shows the basic flow chart of DPP.

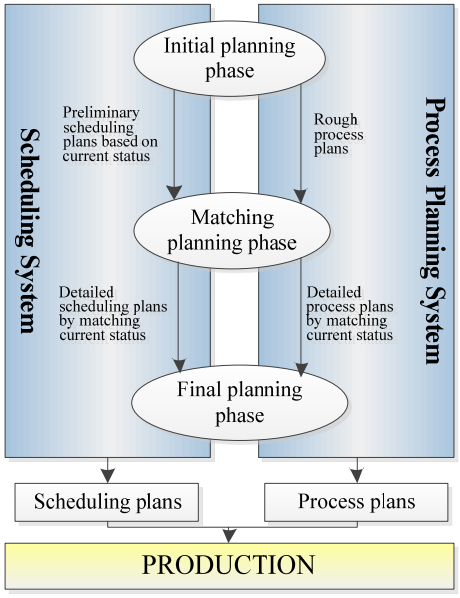


Figure 2-6 The basic flow chart of DPP

This approach is the only one that integrates the technical and capacity-related planning tasks into dynamic fabrication planning system (Larsen and Alting, 1990). However, this approach requires high capacity and capability from both hardware and software. Moreover, scope of DPP is limited within some specific CAPP functions such as process and machine selection as detailed process planning tasks are shifted down to manufacturing stages for enhancing flexibility (Joo et al., 2001). From implementation viewpoint, both process planning and scheduling departments in a company have to be dismantled and reorganized (Haddadzade et al., 2009).

2.2.4 Summary

The comparison and respective features of the integration mechanisms of IPPS is shown as Table 2-1.

Table 2-1 The comparison of the three integration mechanisms of IPPS

Integration Mechanism	Features
NLPP	Advantages: ▪ Process plans contain alternative routing, which offer high degree of flexibility to scheduling; ▪ It contains possibilities of improving off-line scheduling performances and can be quickly react to disturbances on the shop floor; ▪ It can be implemented in a company that has process planning and scheduling departments; Disadvantages: ▪ It has one-way of information flow, i.e. from process planning to production planning. Therefore, it may be impossible to achieve full optimal results in integrating two functions; ▪ Some of the process plans created are not feasible according to real time shop status; ▪ Considering all possible process alternatives for resource allocation may enormously increases complexity of process plan representation.
CLPP	Advantages: ▪ Each generated process plan is feasible and based on current shop floor conditions; ▪ It enhances real time, intuition and manipulability of process planning system; Disadvantages: ▪ It requires high-capacity software and hardware; ▪ The process planning and scheduling departments of a company may have to dismantle and reorganize to take the full advantage; ▪ The adaptation of a step-by-step local view limits the solution space for subsequent operations.
DPP	Advantages: ▪ It completely integrates process planning and scheduling functions and provides the reasonable schedules without generating superfluous process plans; ▪ It performs process planning and scheduling in parallel; ▪ The activities within each phase take place in different time periods; ▪ The interaction between process planning and scheduling starts from a more global level and ends at a more detailed level; Disadvantages: ▪ It requires high-capacity software and hardware; ▪ Process planning and scheduling departments of a company have to be dismantled and reorganized; ▪ It has limited scope within some specific CAPP function such as process and machine selection as ▪ detailed process planning tasks are shifted down to manufacturing stages for enhancing flexibility; ▪ It is truly integrated approach with whole solution space available but, due to vast solution space, finding a feasible solution in a reasonable amount of time is difficult.

The existing three traditional integration models are also categorized into two types according to their integration characteristics – *interface-oriented integration model* and *function-oriented integration model* (Lv, 2012; Lv and Qiao, 2014). In NLPP and CLPP, the flexibility of job shop scheduling has been enhanced by utilizing alternative process plans and the feedback on job shop resources. However, the integration activity is indeed conducted after process planning, and job shop scheduling plan is just selected and adjusted based on the generated process plans. Therefore, NLPP and CLPP are *interface-oriented integration*, where just data exchange is involved in the integration between process planning and scheduling, while the collaborative plan of their interrelated functions is not taken into consideration. In

DPP, the integrated functions of process planning and scheduling are deployed in different hierarchies, and it is a concurrent collaboration in functionality, therefore DPP is categorized as *function-oriented integration*.

As each of traditional integration models has its own advantages and disadvantages as shown in Table 2-1, any single existing integration model cannot solve the IPPS problem efficiently or effectively. A new trend is to syncretize the existing integration models to combine their merits and avoid their deficiencies. In the improved IPPS integration models, a common method is to combine NLPP (alternative process plans) and DPP (hierarchical approach) based on the concurrent engineering principle where process planning and scheduling systems are working simultaneously while maintaining process plan flexibility (Shao et al., 2009; Lv, 2012; Lv and Qiao, 2014). Especially, in (Lv, 2012; Lv and Qiao, 2014), in the improved IPPS integration model, both the information exchange based on interface-oriented integration idea of NLPP and function integration function-oriented integration idea of DPP are realized through three integration hierarchies: initial planning phase, matching planning phase and final planning phase. However, the improved and systematic integration model of IPPS in DMS has not been studied in any literature.

2.3 Literature Review on Implementation Approaches of IPPS Optimization

Job shop scheduling problem has been verified to be typically NP-hard, i.e., it is impossible to find an optimal solution without the use of an essentially enumerative algorithm, with computation time increasing exponentially with problem size. And it is one of the most complex combinational optimization problems (Graves, 1981; Gaery et al., 1976).

As for a classical jobs shop scheduling problem, there will be a set of jobs and a set of machines. Each machine can handle at most one job at a time. Each job consists of a chain of operations, each of which needs to be processed during an uninterrupted time period of given length on a given machine. The purpose is to find the best schedule, i.e., an allocation of the operations to time intervals on the machines, satisfying some given criteria. As for a job shop scheduling problem with N jobs, M machines, and k operations for each job, the total number of the possible combination solutions is $((N!)^M)^k$ (Lv, 2009; Shen et al., 2006). The constraints and solution space involved in IPPS are much more complex than those of process planning or job shop scheduling (Ho and Moodie, 1996), thus IPPS is an even more difficult combinational optimization problem. Therefore, it inspires a lot of scholars to create new approaches for IPPS problem. During the last decades, various Artificial Intelligence (AI) based approaches have been developed to solve IPPS. The typical methods are: agent-based approaches, petri-net-based approaches and optimization-algorithm-based approaches.

2.3.1 Agent-based Approaches of IPPS

Software agents date back to the early days of AI work (Nwana and Ndumu, 1997). It is firstly proposed in concurrent actor model in (Hewitt, 1977). In this model, Hewitt proposed the concept of a self-contained, interactive and concurrently-executing object which he termed an ‘actor’. Along with distributed problem solving and parallel AI, software agents

and Multi-Agent Systems (MAS) form collectively one of the three broad areas which fall under distributed AI (DAI) (Nwana and Ndumu, 1997). Hence, on the one hand, software agents inherit many of DAI's motivations, goals and potential benefits, i.e., modularity (which reduces complexity), speed (due to parallelism), reliability (due to redundancy) and flexibility (i.e. new tasks are composed more easily from the more modular organization); on the other hand, they also inherit benefits from AI such as operation at the knowledge level, easier maintenance, reusability and platform independence (Nwana and Ndumu, 1997; Huhns and Singh, 1994).

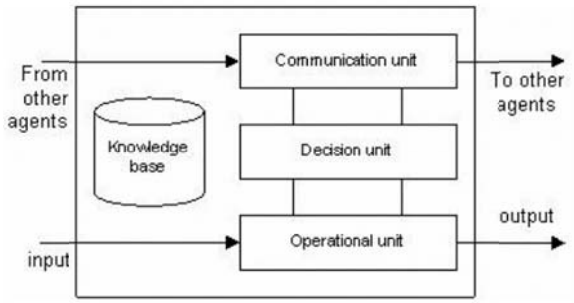


Figure 2-7 Common structure of an agent

A typical definition of an agent is given by (Nwana and Ndumu, 1997) as: an agent is defined as referring to a component of software and/or hardware which is capable of acting exactly in order to accomplish tasks on behalf of its user. When applied to manufacturing, an agent is a software object representing an element in a manufacturing system such as a product or a machine (Zhao et al, 2010). The internal structure of an agent usually comprises a communication unit, a decision unit, an operational unit and a knowledge base, as shown in Figure 2-7. These components represent different important features of an agent. Firstly, an agent should be able to interact with its environment of physical world via its operational unit. Secondly, an agent should be autonomous and be able to make decisions independently. An agent has to consider the statue of environment and consult its knowledge base during decision making. The knowledge base stores the production rules and the experience of the agent and it defines the preference of the agent. Thirdly, a communication unit is included in the architecture. An agent should be able to interact with other agents in communication activities such as information exchange, command and feedback, etc. (Wong et al., 2008). On the basis of the definition, one conclusion is that an agent is a software system that communicates and cooperates with other software systems to solve a complex problem that is beyond the capability of each individual software system (Shao et al., 2009; Wang et al., 2006).

The decentralized multi-agent control has been based on the idea that several distributed decision-makes (or agents) can cooperate and interact to obtain globally optimal performances (Wong et al., 2006a,b). During the last decades, the concept of MAS has been widely accepted in manufacturing applications because of its flexibility, re-configurability and scalability (Wong et al., 2006b). An MAS is a distributed artificial intelligence system

composed of a number of autonomous agents capable of communicating and collaborating with each other to achieve common goals (Shukla et al., 2008).

Wang et al. (2006) provided a literature review on the IPPS, particularly on the agent-based approaches for the problem. The advantages of the agent-based approach for scheduling were discussed. The agent technology for collaborative process planning was reviewed in (Zhang and Xie, 2007). The focus of this research was on how the agent technology can be further developed in support of collaborative process planning as well as its future research issues and directions in process planning.

Gu et al. (1997) proposed an MAS where process routes and schedules of a part were accomplished through the contract net bids. Lim and Zhang (2003, 2004) introduced a multi-agent-based framework for IPPS that could be also used to optimize the utilization of manufacturing resources dynamically as well as provide a platform on which alternative configurations of manufacturing systems could be assessed.

Wu et al. (2002) used a multi-agent approach to realize concurrent process planning and scheduling in distributed virtual manufacturing.

Leung et al. (2006a) presented a negotiation-based IPPS system multi-agent negotiation (MAN) whereby the actual process plan and schedule for producing a particular product were determined through negotiation between part agents and machine agents representing parts and machines respectively. MAN was then extended to hybrid-based agent negotiation (HAN) which was a hybrid MAS architecture with the addition of a supervisory agent, and the performance and effectiveness of the negotiation-based IPPS approach were found to be improved (Wong et al., 2006b ,c).

Nejad et al. (2008, 2010, 2011) proposed a multi-agent architecture of an IPPS system for multi-jobs in flexible manufacturing systems. A negotiation protocol was used to dynamically and incrementally generate the process plans and the schedules of the manufacturing resources and the individual jobs based on the alternative manufacturing processes.

Li et al. (2009, 2010d) proposed an agent-based approach with an optimization agent and a mathematical model for IPPS in a job shop environment. The system contained three agents and databases. Job agents and machine agents were used to optimize alternative process plan and schedule.

Zattar et al. (2010) proposed a heterarchical multi-agent model that allows the dynamic process planning while reducing makespan and flow time through the reduction of the set-up time between the jobs based on operation-based time-extended negotiation protocol.

Using a pheromone-based approach, Rajabinasab and Mnsour (Rajabinasab and Mnsour, 2011) developed a multi-agent scheduling system to solve the flexible job shop problem considering dynamic events such as stochastic job arrivals, uncertain processing time and unexpected machine breakdowns with good quality and robustness.

Agent-based approach is an effective method to solve IPPS. Because single-agent environments cannot solve the problem effectively, MAS is more suitable to solve it (Zhang

and Xie, 2007). However, when the number of the agents is large, agents will spend more time processing message than doing actual work, and it is often difficult to apply the generic agent architectures directly to IPPS systems. The recent research works are trying to combine the agent-based approach with other techniques such as GA, neural network and some mathematical modelling methods (Shen et al., 2006). Therefore, one future research trend is presenting more effective algorithms to improve the effectiveness of agent-based approaches.

2.3.2 Algorithm-based Approaches of IPPS

The basic steps of the algorithm-based approach are as follows:

- First, process-planning system is used to generate the alternative process plans for all jobs and select user-defined number optimal plans based on the simulation results.
- Then, the algorithm in the scheduling system is used to simulate scheduling plans based on the alternative process plans for all jobs.
- Finally, based on the simulation results, the process plan of each job and the scheduling plan are determined.

In this approach, the most researches focused on the Evolutionary Algorithm (EA), swarm intelligence and some other meta-heuristic methods, such as Genetic Algorithm (GA), Simulate Anneal Arithmetic (SAA), Particle Swarm Optimization (PSO), Tabu Search (TS), ant colony optimization (ACO) and Artificial Immune System (AIS), and some hybrid algorithms were also used to solve IPPS.

Morad and Zalzala (1999) described the integration of process planning and scheduling using GA in a cellular manufacturing environment.

Lee and Kim (2001) proposed a method for IPPS using simulation based on GA. Simulation module computes performance measures based on process plans combination created by GA instead of process plan alternatives and output the near-optimal process plan combination prior to execution on shop floor.

Moon et al., (2002a) proposed a GA approach based on a topological sort technique (TST) to solve an integrated machine tool selection and sequencing model for dynamic batch production. The model determined machine visiting sequences for all part types, such that the total production time for the production order was minimized and workloads among machine tools were balanced. Operations sequencing problem was formulated as a multiple travelling salesman problem (TSP) and each TSP determine machine operation sequences for each part type. A TST was used to obtain all flexible sequences in directed graph. Then in (Moon et al., 2002b), the authors extended the proposed GA-based IPPS model for multi-plant supply chain. A mathematical model was formulated with considerations of alternative machines and sequences, sequences dependent setup and due dates to minimize tardiness. Lee et al. (2002) produced an Advanced Planning and Scheduling (APS) model of a real manufacturing supply chain. This model integrated process planning, scheduling, and outsourcing to keep the due dates of each customer order. A GA-based approach was developed to minimize the makespan by considering alternative machines, alternative sequences of operations with

precedence constraints and outsourcing. Moon and Seo (2005a) developed an EA-based heuristic approach to solve the problem of advanced process planning and scheduling (APPS) for a multi-plant environment. The objective of the model was to decide the schedules for minimizing makespan and operation sequences with machine selections considering precedence constraints, flexible sequences and alternative machines. Then in (Moon and Seo, 2005b), the authors extended this problem to a multi-objective model simultaneously considering minimizing makespan and balancing machine load with an adaptive GA approach with the recombination functions and the revised adaptive weighted method. Moon et al. (2008) proposed an evolutionary search method based on TST for IPPS in supply chain. A mixed integer programming model was formulated, which incorporate process planning of resources selection and sequence of operations as well as determination or their schedule to optimize makespan.

Kim et al. (2003) proposed an AI search technique called symbiotic evolutionary algorithm (SEA) to simultaneously deal with process planning and job shop scheduling in Flexible Manufacturing System (FMS). SEA was based on the fact that parallel searches for different pieces of solution were more efficient than a single search for the entire solution. The job shop scheduling determines both process plan for each job and corresponding scheduling.

Zhang et al. (2003), Saravanan et al., Wang et al., (2008a) and Wang et al., (2009) proposed an iterative integration approach of process planning and scheduling for batch manufacturing problems in job shop environments, in which a process planning module, a scheduling module and an integrator module were included. The process planning module employed simulated annealing algorithm to generate the entire plan solution space and choose the optimal plan, while the scheduling module was based on commonly used heuristics; then the integration was achieved through the integrator module providing intuitive feedback to the process planning module in the form of extra constraints to process planning of a particular job based on the schedule performance measures.

Choi and Park (2006) proposed a GA-based method for IPPS that minimized makespan of each job order considering alternative machines and alternative operation sequences in integrated manufacturing environment.

Jain et al. (2006) proposed an integration scheme that can take advantage of flexibility on the shop floor and can be implemented in a company with existing process planning and scheduling departments. The proposed methodology was able to take advantage of MPP (Multiple Process Plans), while following a real-time strategy for scheduling suitable for changing workshop status. The proposed system was composed two basic modules: process plans selection module (PPSM) and scheduling module (SM). PPSM selects best four process plans for each part type and stores them in a database. SM performs part scheduling for using best four process plans. Then in (Phanden et al., 2013), the authors extended the integration scheme by adding two more modules to form a four-module-integration scheme of process planning and scheduling, they are process plans selection module (PPSM), scheduling module (SM), scheduling analysis module(SAM) and process plan modification module (PPMM)

respectively. The formalized approach was able to solve process planning and scheduling problem concurrently and effectively with the use of simulation-based GA optimization method and heuristics.

Li and McMahon (2007) proposed a SA-based approach for IPPS in a job shop environment. Processing, operation sequencing and scheduling flexibility were used to explore search space of proposed algorithm. The algorithm was defined in two sets of data structures. The first set represents process plans and the second set specifies the schedule of a group of parts.

Li et al. (2008) proposed a GA-based approach to facilitate IPPS targeting at minimizing makespan. They developed an efficient genetic representation and operator scheme.

Chan et al. (2008) proposed a new Cooperative Multiple Particle Swarm Optimization (CMPSO) algorithm to efficiently resolve the process planning and scheduling integration problems in a realistic Multi Plant Supply Chain (MPSC) model aiming at reducing the overall tardiness. The proposed algorithm is marked by the cooperation among 'sister swarms' that make it compatible to the problems pertaining to multiple dimensions.

Guo et al. (2009b) proposed a PSO algorithm and re-planning method for machine breakdown status and new order arrival. The solutions were encoded into PSO particles to search for best sequence of operations through optimization strategies of PSO algorithm.

Shao et al. (2009) suggested an approach by synthesizing integration methodology of NLPP and DPP in which process planning and scheduling system were working simultaneously. A simulation approach based modified GA was developed.

Targeting the potential adaptability of process plans associated with setups, Cai et al. (2009) proposed a cross-machine setup planning approach using GA for machines with different configurations to bridge the gap between process planning and scheduling.

Baykasoğlu and Özbakır (2009) proposed an IPPS model that comprises of two parts. First part was a generic process plan (GPP) generator to generate final process plan. Second part was dispatching rule based heuristic to generate feasible schedules. A multiport objective TS algorithm was employed to find an optimal schedule.

Li et al (2010c) conducted the research to develop a mathematical model with an evolutionary algorithm-based approach to facilitate the integration and optimization of process planning and scheduling in a NLPP scheme. To improve the optimization performance of the proposed approach, efficient genetic representation and operator schemes have been developed.

Wang et al. (2010) handled a multi-objective integrated process planning and scheduling problem with a particle swarm optimization in which a local search was incorporated.

Zhang and Wong (2012b) implemented constraint programming (CP) to solve a complex IPPS problem with alternative machines and processes in a job shop environment. Variables

and constraints being clearly defined, a method of constraint propagation was given to enhance the efficiency of the proposed approach.

Wan et al., (2013), and Zhang and Wong (2013b) proposed an ant colony optimization (ACO) and an enhanced ACO with several modifications (including quantification of convergence level, introduction of pheromone on nodes, new strategy of determining heuristic desirability and directive pheromone deposit strategy) respectively to accomplish the IPPS problem in the job shop environments.

Jain et al. (2006) and Phanden et al. (2013) solved the process planning and scheduling problem concurrently and effectively in a flexible manufacturing system with the use of simulation-based GA optimization method and heuristics.

Manupati et al. (2013) proposed and developed Multi-Objective Evolutionary Algorithms (MOEAs) such as Territory Defining Evolutionary Algorithm (TDEA), Non-dominated Sorting Genetic Algorithm (NSGA-II) and Controlled Elitist- NSGA-II (CE- NSGA-II) to resolve the multi objective problem of IPPS in a networked manufacturing environment. Considering that setup planning assumes an important position in a reconfigurable environment,

Mohapatra et al. (2013b) sequenced and grouped machining features of the part into certain setup based on tool approach direction (TAD) and addressed the adaptive characteristics of process plan associated with setup, i.e. a cross machine setup planning to capture the different configuration of machines to realize the integration of process planning and scheduling using artificial immune system (AIS).

The biggest shortcoming is that the simulation time may be long and the approach cannot be used in the real manufacturing system. Therefore, one important future research trend is to find effective algorithm for IPPS and developing effective systems.

2.3.3 Hybrid Approaches of IPPS

Agent-based approach is a good method to solve IPPS. However, when the number of the agents is large, agents will spend more time processing message than doing actual work, and it is often difficult to apply the generic agent architectures directly to IPPS systems. Therefore, one future research trend is proposing simpler, more effective and workable MAS approach for IPPS applications. As for the algorithm-based approach, the biggest shortcoming of this approach is that the simulation time may be long and it cannot be used in the real manufacturing system. Therefore, one important future research trend is researching and finding effective algorithm for I PPS and developing effective system.

As each pure algorithm optimization approach and agent-based methods has its own advantages and disadvantages, a various kinds of hybrid approaches were proposed by different scholars to maximize the favorable factors and minimize the unfavorable ones of different methods, obtaining better optimization results.

Sugimura et al. (2001, 2003, 2007) proposed a systematic method to select suitable machining sequences of the machining features and suitable sequences of the machining

equipment based on the combined method of GA and DP for process planning and scheduling integration problem in HMS.

Zhao et al. (2004) proposed a GA-based approach for IPPS in a job shop environment. A fuzzy inference system was used to select alternative machines. Based on the capability of machines, GA was used to balance load for all machines. Zhao et al. (2006) extended their earlier work and used PSO for balancing load on each machine. Moreover, Zhao et al. (2010) presented an integrated process planning and scheduling system aiming at realizing a flexible production control in holonic manufacturing systems, in which fuzzy logic was used to choose the most reliable machine and the hybrid PSO was applied to balance the load for all the machines.

Chan et al. (2006) presented an artificial immune system incorporated with the fuzzy logic controller (termed as AIS-FLC algorithm) to effectively solve the complex real world problems of process planning and scheduling integration considering outsourcing, reducing the computational time as well as convergence rate.

Fujii et al. (2008) proposed a multi-agent-learning-based integration method to solve the conflict between the optimality of the process plan and the production schedule. In this method, each machine made decisions about process planning and scheduling simultaneously, and it had been modeled as a learning agent using evolutionary artificial neural networks to realize proper decisions resulting from interactions between other machines.

Shukla et al. (2008) integrated process planning and scheduling by means of a bidding-based multi-agent system for facilitating manufacturing enterprises with high responsiveness in dynamic environment, in which the optimum process plan and schedule is computed by the optimization agent that is facilitated with the virtues of a hybrid tabu-SA algorithm.

Motivated by the drawbacks of the GA and SA-based approaches, Chan et al. (2009) studied a new Enhanced Swift Converging Simulated Annealing (ESCSA) algorithm, encapsulating the salient features of GA, SA, and Fuzzy Logic Control (FLC) and overcoming their shortcomings, to solve the integration problem of process planning and scheduling inheriting outsourcing and leagile concepts aiming at minimizing the makespan.

Leung et al. (2010), Wong et al. (2012), and Zhang et al. (2013a) implemented an ACO algorithm in an established agent-based platform to integrate process planning and shop floor scheduling. Artificial ants are implemented as software agents that run separately and simultaneously and they can be added or removed from the platform.

Li et al. (2010b) proposed a hybrid approach combining advantage of GA and TS to solve IPPS problem. To improve the optimization performance of the proposed approach, the efficient genetic representations, operator and local search strategy have been developed. The first part of chromosome was alternative process plan string, second part was scheduling plan string and third was machine string.

Li et al. (2012a) developed a novel approach to facilitate the multi-objective IPPS problem, in which a game theory based hybrid algorithm of GA and TS has been applied. In

the proposed approach, the Nash equilibrium in game theory has been used to deal with the multiple objectives. And a HA of GA and TS has been used to optimize the IPPS problem.

Li et al. (2012b) proposed an active learning genetic algorithm based method to facilitate the integration and optimization of process planning and scheduling. This algorithm can more accurately reflect the laws of the biological evolution. Therefore, it has better searching ability than the simple GA.

Wen et al. (2013) proposed an improved genetic algorithm (IGA) with external archive maintenance to optimize the multi-objective of IPPS problem. IGA was used to search for the Pareto optimal solutions, while the external archive is used to store and maintain the generated non-dominated solutions during the optimization procedure.

Zhang et al. (2012a) proposed an MAS architecture to solve the dynamic IPPS problem by combining with a variety of heuristic methods to support dynamic process planning, scheduling and rescheduling. Dynamic process planning and scheduling can be fulfilled with the interaction and negotiation between agents while no negotiation protocols are needed for heuristic algorithms to search near-optimal solution, greatly enhancing the adaptability and flexibility.

Manupati et al. (2012) developed a game theory approach to formulate the mathematical model to represent the game and incorporated a nature-inspired evolutionary algorithm known as HD-DNA (Hybrid Dynamic DNA) to solve the game in generating optimal process plans in the context of a network-based manufacturing environment.

Mohapatra et al. (2013a) dealt with a multi-objective optimization problem focusing on developing an adaptive setup planning (ASP) algorithm in accordance with the dynamic scheduling requirement and thus a niche attempt to bridge the gap between process planning and scheduling with NSGA-II; further, a fuzzy set theory approach is developed to extract one of the Pareto-optimal solutions as the best compromising one.

2.4 Literature Review on Extended Problems in IPPS

2.4.1 Multi-objective Optimization Problems of IPPS

So far, most of the current researchers on IPPS have been concentrated on the single objective, which cannot meet the requirements from the real-world production, where different departments have different expectations in order to maximize their own profits, for example, the manufacturing department expects to reduce costs and improve work efficiency; the managers want to maximize the utilization of the existing resources; and the sale department pursues to better meet the delivery requirements of the customers. However, only seldom papers focused on their research on the multi-objective IPPS problem.

Norhashimah et al. (1999) proposed a GA based on weighting-sum method to simultaneously minimize makespan, total rejects and total cost of production for IPPS problem. However, in their work, only routing flexibility was considered when generating alternative process plans for the jobs, which is far more simple than the modern real manufacturing systems.

Li and McMahon (2007) proposed a SA based approach for multi-objective IPPS problem, where the manufacturing cost (including: cost of machines utilization; cost of cutting tools utilization; number of machine changes; number of tool changes; number of set-ups; number of violated constraints), makespan, the balanced level of machine utilization and part tardiness are considered meanwhile using weighting method.

Li (2009) conducted multi-objective optimization for IPPS problem in his PhD thesis based on Pareto approach using NSGA-II method with the objectives of minimizing the makespan, the total processing cost, the lateness, the weighted number of tardy jobs and the total earliness plus the total tardiness.

Baykasoglu and Ozbakir (2009) proposed an approach which made use of grammatical representation of generic process plans with a multiple objective tabu search (TS) framework to solve multi-objective IPPS effectively.

Zhang and Gen (2010) proposed a Fast Multi Objective Genetic Algorithm with Archive Mechanism to solve process planning and scheduling problems with multiple objectives of minimizing both the maximum total processing time and the maximum variation of workload of machine in a distributed manufacturing system, where factories with various machines and tools at different geographical locations are combined to produce various parts with different resource constraints.

Li, et al. (2012a) proposed a game theory base hybrid algorithm to facilitate the multi-objective IPPS problem, in which the Nash equilibrium in game theory was used to deal with the multiple objectives, and a HA has been used to optimize the IPPS problem.

Appendix 1 shows a summary of the recent research work on multi-objective optimization of production scheduling problem.

2.4.2 Rescheduling Problems of IPPS

In dynamic, stochastic manufacturing environments, managers, production planners, and supervisors must not only generate high-quality schedules but also react quickly to unexpected events and revise schedule in a cost-effective manner (GUILHERME et al., 2003). Unexpected events can generate considerable differences between the predetermined schedule and its actual realization on the shop floor. Therefore, rescheduling is practically mandatory so that the effect of such disturbances in the performance of the system can be minimized. The events triggering rescheduling are called *rescheduling factors* (Dutta, 1990; Dhingraet al., 1992). The most common rescheduling factors are classified into two categories by (Djamila et al., 2009):

- **Resource-related**: machine breakdown, operator absenteeism, unavailability or tool failures, loading limits, delay in the arrival or shortage of materials, defective material (material with wrong specification), etc.
- **Job-related**: rush jobs, job cancellation, due date changes, early or late arrival of jobs, change in job priority, changes in job processing time, etc.

The rescheduling factors may trigger the following actions (Guilherme et al., 2003), where rescheduling will be necessary:

- Overtime;
- In-process subcontracting;
- Process change or re-routing;
- Machine substitution;
- Limited manpower;
- Setup times;
- Equipment release.

2.4.2.1 Rescheduling strategies

Two common strategies for controlling production in dynamic rescheduling environment are completely reactive scheduling and predictive-reactive scheduling. Predictive-reactive scheduling includes three types or rescheduling policies: periodic, event-driven, and hybrid.

(1) Completely reactive scheduling

Completely reactive scheduling does not create firm production schedules in advance and decisions are made locally in real-time. Decentralized production control methods dispatch jobs when necessary and use information available at the moment of dispatching. Such schemes use dispatching rules or other heuristics to prioritize jobs waiting for processing at a resource (Perking and Kumar, 1989; Church and Uzsoy, 1992; Fang and Xi, 1997). Some authors refer to completely scheduling schemes as *online scheduling* (Li, et al., 1993; Olumolade and Norrie, 1996; Sabuncuoglu and Karabuk, 1999).

Dispatching rules and pull mechanisms are used to control production without a production schedule. When a machine becomes available, it chooses from a set of jobs awaiting service by using a dispatching rule that prioritizes the jobs by some criteria. Common dispatching rules employ processing times and due dates in simple rules and complex combinations.

A variety of dispatching rules have been used to react to real-time events in completely reactive scheduling. And no rule performs well for all criteria. Therefore, many investigations were carried out towards recognizing a combination of several dispatching rules to find a range of system states in which the relative performance of each rule is highest. Panwalkar and Iskander (1997) provided an extensive list of dispatching rules. They categorize these rules into five classes: simple dispatching rules, combinations of simple rules, weighted priority indexes, heuristic scheduling rules, and other rules. Rajendran and Holthaus (1999) presented excellent state-of-the-art surveys of dispatching rules in dynamic job shops and flow shops. According to their classification, there are also five classes of dispatching rules: rules involving process times, rules involving due dates, simple rules involving neither process time nor due dates, rules involving shop floor conditions, and rules involving two or more of the first four classes.

Pull mechanisms such as kanban cards and constant WIP order release policies add production authorization cards to the system so that a resource can work only when both material and cards are available.

Completely reactive scheduling is closely related to real-time control, since decisions are made based on the current state of the manufacturing system. Controlling a manufacturing system so that it maintains a desired inventory position (in work-in-process or finished goods) is a common strategy when there is steady demand for each product.

Dispatching rules and pull mechanisms are quick, usually intuitive, and easy to implement. However, global scheduling has the potential to significantly improve shop performance compared to myopic dispatching rules, where it is hard to predict system performance as decisions are made locally in real-time (Ouelhadj and Petrovic, 2009).

(2) Predictive-reactive scheduling

Predictive-reactive scheduling is a common strategy to rescheduling dynamic manufacturing systems (Herrmann, 2006). It is a scheduling/rescheduling process in which schedules are revised in response to real time events. Predictive-reactive scheduling has two primary steps: the first step generates a production schedule; the second step updates the schedule in response to a disruption or other event to minimize its impact on system performance (Herrmann, 2006).

Predictive-reactive scheduling is an iterative process. Wu and Li (1995) have described rescheduling as an iterative process of three steps:

- The evaluation step evaluates the impact that a disruption causes. No further action is required if the impact is acceptably small.
- The solution step determines the rescheduling solutions that can enhance the performance of the existing schedule.
- The revision step updates the existing production schedule or generates a new one.

Yamamoto and Nof (1985) have proposed a rescheduling approach following a general three-phase scheme:

- The planning phase constructs an initial schedule just prior to the start of a new work period, based on all available production requirements. It prepares the information necessary for the operations during a given period.
- The control phase compares the actual progress of operations to the current schedule every time a new operation begins of finished. If the difference exceeds a specified limit, the rescheduling phase should begin.
- The rescheduling phase constructs a revised schedule considering the operational changes that have triggered the rescheduling.

In predictive-reactive scheduling, the new schedule may deviate significantly from the original one, which will seriously affect other planning activities that are based on the original

schedule and may lead to poor performance of the schedule. Therefore, to generate predictive-reactive schedules that are robust is desirable. Robust predictive-reactive scheduling focuses on building predictive-reactive schedules to minimize the effects of disruption on the performance measure value of the realized schedule (Ouelhadj and Petrovic, 2009). A typical solution to generate a robust schedule is to reschedule considering both shop efficiency and deviation from the original schedule (stability) simultaneously. Stability measures the deviation from the original predictive schedule caused by schedule revision to quantify the undesirability of making changes to the initial schedule (Wu et al. 1991, 1993; Cowling and Johansson 2002; Leus and Herroelen 2005). In many research, the stability is measured by starting time deviation (the deviation from the original job starting time) and sequence deviations (the deviation from the original sequences) (Wu et al. 1991, 1993; Abumaizar and Svestka, 1997).

Three types of rescheduling policies have been studied to implement a predictive-reactive scheduling strategy: periodic, event-driven and hybrid. As for periodic and hybrid policies, *rolling time horizon* technology has been widely studied and used. The overall scheduling problems can be decomposed into smaller and static scheduling problems by performing scheduling on a rolling time horizon.

Periodic policy

A periodic policy reschedules the facility periodically and implements the schedules on a rolling time horizon basis (Herrmann, 2006). By rolling the optimization horizon, satisfactory results will be obtained. Church and Uzsoy (1992) provided a good detailed explanation of this rescheduling policy. According to periodic policy, schedules are generated at regular intervals, which gather all available information from the shop floor. The dynamic scheduling problem is decomposed into a series of static problems that can be solved by using classical scheduling algorithms (Ouelhadj and Petrovic, 2009). The schedule will then be implemented and not revised until the next period begins with this strategy the impractical global optimization requirement is relaxed and the local optimum scheduling can be implemented in real-time with a rolling horizon.

The main concept in the rolling horizon scheduling is rolling horizon optimization. A number of jobs are selected from jobs waiting for processing, to form a *job window*. Only jobs in the jobs window are scheduled and partially processed according to the scheduling results. After a period of time (here is referred to the predictive period and is denoted as T_i, as shown in Figure 2-8), all jobs which have finished their operations are removed from the job window and some new jobs are selected for it. Then jobs in the job window are scheduled again. The procedure is repeated until all operations on all jobs have been finished.

The Job Window

While using the rolling horizon scheduling strategy, a rolling domain should first be defined. Here the rolling domain is taken as a job window, i.e. a number of jobs for scheduling and processing. The rolling of the job window is implemented by removing the finished jobs from, and adding new jobs to it.

At time T_i, the job set S_J can be divided into three subsets: i.e. the jobs which have finished their operations S_c, the jobs in current job window S_w and the available jobs waiting for being scheduled and process S_a.

When forming a job window, the number of jobs in the job window and the selection rule to choose the jobs to go into the window are the main factors for consideration which will affect the efficiency of the scheduling.

The predictive period T_i is the time interval between two successive rescheduling.

This policy is more suitable for the varying environment in a dynamic shop. Scheduling is performed on a rolling horizon basis, so the problem size becomes smaller and is suitable for complicated problems and real-time applications. Periodic approaches insure more schedule stability and less schedule nervousness than constant rescheduling. However, following an established schedule in the face of significant changes in the system status may compromise performance, and determining the optimal rescheduling period is also a difficult task when using this type of policy (Guilherme et al., 2003).

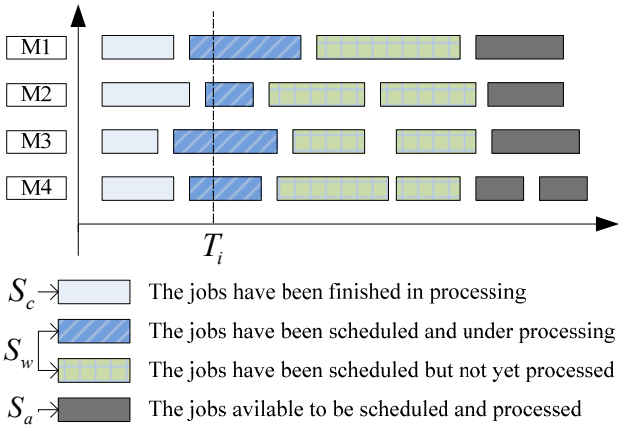


Figure 2-8 A job window

Event-driven policy

In event-driven policy, rescheduling is triggered in response to an unexpected event that alters the current system status.

In the extreme, a new schedule is created (or revised) every time an event that alters system status occurs (Church and Uzsoy, 1992). In such cases, the time spent on rescheduling can become excessive and it will definitely require a fast and reliable electronic data collection to quickly capture new events. Besides, in large facilities where many events occurring in rapid succession, the system may be in a permanent state of rescheduling, resulting in high nervousness (low stability) and excessive computational requirements (Guilherme et al., 2003).

Hybrid policy

A *hybrid policy* reschedules the system periodically and also when an exception occurs. Events usually considered are machine breakdowns, arrival of urgent jobs, cancellation of jobs, or job priority changes. When a critical event occurs, rescheduling is performed immediately, otherwise periodic rescheduling is adopted.

2.4.2.2 Rescheduling techniques

Rescheduling has been conducted using the following techniques: heuristics, meta-heuristics, knowledge-based systems, fuzzy logic, neural network, hybrid techniques and multi-agent systems.

Heuristics

Heuristics in this context are problem specific schedule repair methods, which do not guarantee to find an optimal schedule, but have the ability to find reasonably good solutions in a short time (Ouelhadj and Petrovic, 2009). The most common schedule repair heuristics are: right-shift schedule repair, match-up repair and partial schedule repair. Dispatching rules are also heuristics that have played a significant role in completely reactive scheduling.

When the problem becomes more complex, using heuristics can make the solution trapped in a poor local optimum.

Meta-heuristics: tabu search, simulated annealing and genetic algorithms

In recent years, meta-heuristics are increasingly used to solve production scheduling problems. Meta-heuristics are high level heuristics which guide local search heuristics to escape from local optima. Local search heuristics are neighborhood search methods based on the idea of searching neighborhoods. In local neighborhood search, the search starts from some given solution, and tries iteratively to move to a better solution in an appropriately defined neighborhood of the current solution using move operators (Ouelhadj and Petrovic, 2009). The search process stops when no better solution can be found in the neighborhood of the current solution, which is the local optimum. Meta-heuristics such as tabu search, simulate annealing, and genetic algorithms improve local search to escape local optima by wither accepting worse solutions, or by generating good starting solutions for the local search in a more intelligent way than just providing random initial solutions.

Multi-agent based dynamic scheduling

Today's systems must rapidly adapt to disturbances while maintaining shorter product cycles, improving productivity, and increasing operational flexibility. To face this challenge, the current trend has been towards highly automated systems intended to offer robustness, stability, adaptability and efficient use of available resources through a modular and distributed design (Herrmann, 2006). The primary motivation in designing these systems is to decentralize the control of the munufacturing system, thereby reducing the complexity and cost, increasing flexibility, and enhancing fault tolerance.

Literature study shows that multi-agent systems are one of the most promising approaches to build complex, robust and cost-effective next-generation manufacturing

scheduling systems because of their autonomous, distributed and dynamic nature, and robustness against failures (Verstraete et al., 2006, 2007a, 2007b; Rolon et al., 2012). A multi-agent system is a network of problem solvers that work together to solve problems that are beyond theil individual capabilities (O'Hare and Jennings, 1996). The use of multi-agent systems to solve the problem of dynamic scheduling is motivated by the following key points (Ouelhadj and Petrovic, 2009):

Firstly, multi-agent based scheduling systems recognize that data and control are distributed through the factory. These systems are composed of autonomous agents attached to each physical of functional manufacturing entity in the facility (resources, operators, parts, jobs, etc.). Local autonomy allows the agents to take the responsibility to carry out local scheduling for one or more entities in the production process and to respond locally and efficiently to local variarions, increasing the robustness and flexibility of the system.

Secondly, these individual agents have considerable latitude in responding to local conditions and interacting and cooperating with each other in order to achieve global optimal and robust schedules. The overall system performance is not globally planned, but emerges through the dynamic interaction of the agents in real-time. Thus, the system emerges from the concurrent independent local decisions of the agents.

Thirdly, the software for each agent is much shorter and simpler than it would be for a centralized approach, and as a result is easier to write, install and maintain. Further more, it is possible to integrate new resouces or remove existing ones with their attached agents to from the factory without making any changes to the existing software network.

Other artificial intelligence techniques

Many dynamic scheduling problems have adopted artificial intelligence techniques such as knowledge-based systems, neural networks, case-based reasoning, fuzzy logic, Petri nets, etc.

The basic motivation of knowledge-based approaches is that there is a wide variety of technical expertise on the corrective actions to undertake in the presence of real-time events. Knowledge-based systems focus on capturing the expertise or the experience of the expert in a specific domain and an inference mechanism is used to derive conclusions or recommendations regarding the corrective action to undertake.

Neural networks, Petri nets, and fuzzy logic have also been used to solve the problem of dynamic scheduling. Extensive discussions of these techniques can be found in Suresh and Chaudhuri (1993), Szelke and Kerr (1994), Zweben and Fox (1994), Kerr and Szelke (1995), and Meziane et al. (2000).

To derive better dynamic scheduling systems, some researchers developed hybrid systems which combine various artificial intelligence techniques

Comparison of solution techniques

The detailed comparion of the solution techniques of rescheduling in dynamic manufacturing environments was offered in (Ouelhadj and Petrovic, 2009).

Heuristics have been widely used to react to the presence of real-time events because of their simplicity, but they may become stuck in poor local optima. To overcome this, meta-heuristics such as tabu search, simulated annealing, and genetic algorithms have been proposed. Several comparative studies have been provided in the literature to compare the performance of tabu search, genetic algorithms, and simulated annealing. Unlike simulated annealing and tabu search based on manipulating one feasible solution, genetic algorithms manipulate a population of feasible solutions.

Knowledge-based systems possess the potential for automating human expert reasoning and heuristic knowledge to run production scheduling systems. However, they usually lack the ability to optimise the system and require considerable effort to build and maintain. They are aimed at generating feasible schedules conforming to the domain knowledge. In terms of effectiveness of the decision making capability, knowledge-based systems are limited by the quality and integrity of the specific domain knowledge.

Fuzzy logic has not yet been explored to its fullest potential. Neural networks cannot guarantee to provide optimal decisions, but their learning capability makes them ideally suited for rapidly changing systems. Integrating neural networks, simulation, and expert systems seems to have a lot of promise.

Centralised scheduling systems provide a consistent global view of the state of the enterprise and globally better schedules. However, practical experience has indicated that these systems tend to have problems with reactivity to disturbances.

A large research field, currently subject of many in depth studies, regards the use of multi-agent systems in dynamic scheduling. The primary motivation in designing these systems is to decentralise the control of manufacturing systems, thereby reducing the complexity, increasing flexibility, and enhancing fault tolerance. Refusing the traditional idea of a central scheduling system, which establishes a manufacturing plan for all the machines and jobs, multi-agent systems assume the presence of several agents with a good deal of decision making autonomy, distributed inside the manufacturing system. The agents interact and cooperate with each other in order to achieve effective global performances. Local autonomy allows the agents to take the responsibility for carrying out local scheduling for one or more functional or physical components in the production process (such as machines and jobs). Agents have the ability to observe their environment and to communicate and cooperate with each other in order to ensure that local schedules lead to globally desirable schedules. Local autonomy allows the agents to respond locally to local variations, increasing the robustness and the flexibility of the system.

According to the comparison of these techniques, the future work will be focused on meta-heuristics, hybrid methods of artificial technology, and multi-agent based approach to solve the rescheduling problems in dynamic manufacturing environments.

2.5 Conclusion

This chapter gave a detailed literature review on the problems related to IPPS. Firstly, the related concepts and definitions of process planning, job scheduling and IPPS were introduced. Based on the analysis of the relationship between process planning and scheduling as well as the problem in current job shops, the necessity to integrate the two was illustrated. Then the three traditional integration models of IPPS were studied and the comparison between these three models was conducted to clearly describe the advantages and disadvantages of each traditioanl integration model, based on which the improved integration model of IPPS was researched to facilitate the proposition of a better one in this thesis. Next, the implementation approaches of IPPS optimization in the literature were studies and summerized into three categories, which are agent-based approached, algorithm-based approaches and hybrid approaches of the two. Finally, the two major extended problems in IPPS were studied, which are multi-objective optimization problem and rescheduling problems. The key techniques involved in these two major extended problems were grasped based on the literature study, analysis and summary. This chapter provides a firm background, a deep insight and a wide perspective for the propositions of the main work of this thesis.

Chapter 3 Proposition of a New Hybrid Integration Model of IPPS in DMS

Introduction:

As current integration models of IPPS (NLPP, CLPP and DPP) have their own advantages and disadvantages and any single integration model cannot solve the IPPS problem efficiently or effectively, better and more practical hybrid integration model combining their advantages and eliminating their disadvantages should be proposed. Meanwhile, the competition in a dynamic and challenging marketplace demanding short response time to changing markets and agility in production has driven the prevalence of Distributed Manufacturing System (DMS). A DMS consists of several partners (system elements) that may geographically be distributed in different locations and each partner may be constituted of several job shops with different manufacturing capability, capacity and performances. In such situation, the research on IPPS problems in DMS is with practical significance to optimally allocate enterprise resources and better profit both the enterprises and the clients. Therefore, in this chapter, based on the proposed information integration model for IPPS problem in DMS, a new Hybrid Model of Integrated Process Planning and Scheduling in Distributed Manufacturing System (HMIPPS_DMS) will be established by adopting both the interface-oriented idea of NLPP and the function-oriented idea of DPP. Hierarchically constituted of three integration levels, the new model of HMIPPS_DMS will facilitate the layered integration optimization of IPPS in each level through Initial Integration Phase in Enterprise Integration Level, Matching Integration Phase in Job Shop Integration Level and Final/Detailed Integration Phase in Resource Integration Level.

3.1 Introduction on Distributed Manufacturing System (DMS)

3.3.1 Definition of Distributed Manufacturing System (DMS)

Distributed Manufacturing System is defined as the manufacturing system whose functionality and performance is independent of the physical distance between system elements (Putnik et al., 1998). Such systems have gained much attention in recent years and have widely been applied in many areas such as multimedia and production control (Kim et al. 1996; Wang 2003; Cicirello 2004; Chan et al., 2006). A DMS normally consists of several partners (system elements) that may geographically be distributed in different locations. This allows them to be closer to their potential customers, to comply with the local laws, to focus on a few product types, to produce and market their products more effectively, and to be responsive to market changes more quickly (Chan et al. 2006; Schniederjans 1999; Sule 2001). In DMS, each partner has to share efficiently the available resources in order to appropriately assign and schedule tasks to them. One of its aims is to apply distributed modeling and simulation tools to evaluate and improve products and processes, and to ensure a fast response to the changing market in a cost-effective way.

In DMS environment, each partner is usually capable of manufacturing a variety of product types. In addition, they may have different production efficiency and various constraints depending on the machines, labor skills and their education level, labor cost, government policy, tax, nearby suppliers, transportation facilities, etc. (Chan et al., 2006). Since different partners have different operating costs, production lead time, customer service

levels, constraints, etc., IPPS problems in DMS are much more complicated than classical ones because they involve not only the IPPS problems in each job shop, but also the problems in an upper level of how to allocate the jobs to a suitable enterprise (Jia et al. 2003; Chan et al. 2005a) to optimize the utilization of manufacturing resources. Once a job is allocated to a job shop and processed, it is usually unable or uneconomical to transfer this work-in-progress part to another factory for the remaining operations (Chan et al. 2006; Zhang and Gen 2010).

The target DMS structure is shown in Figure 3-1. A DMS consists of several different candidate enterprises that are geographically distributed in different locations. Each enterprise includes one or more different job shops with their own technologies, manufacturing capabilities and capacities as well as productions performances.

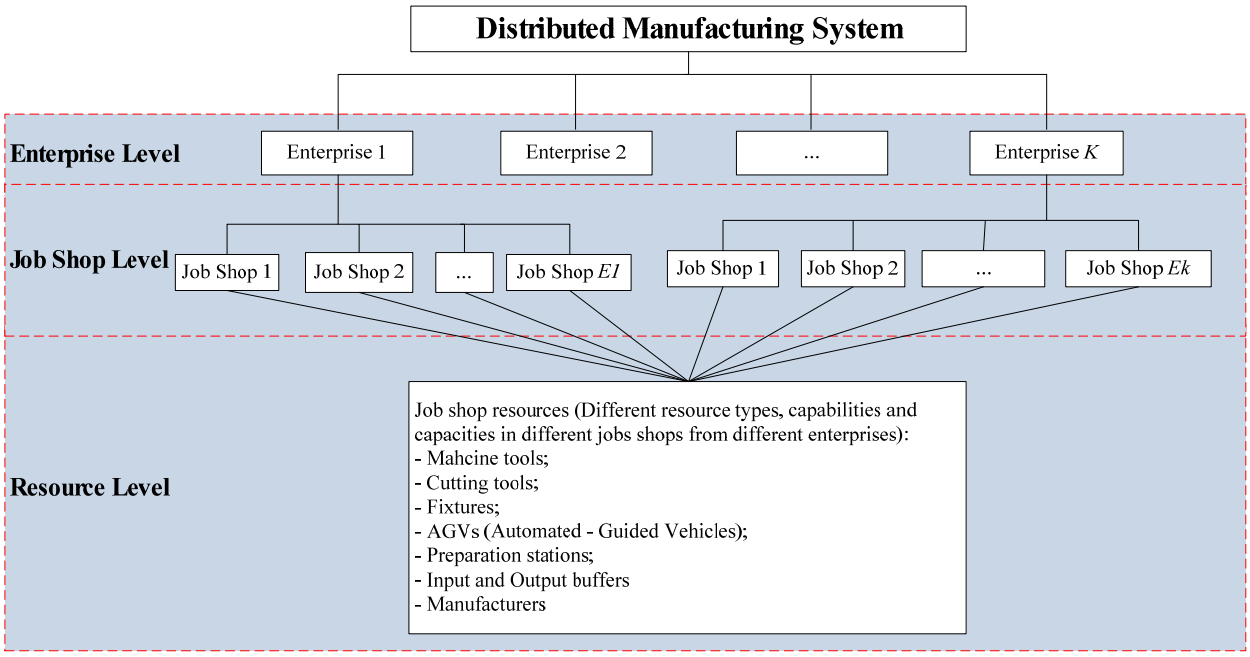


Figure 3-1 The structure of the Distributed Manufacturing System

3.3.2 Information Integration Model for IPPS Problem in Distributed Manufacturing System (DMS)

The UML class diagram of information integration model for IPPS problem in DMS is shown in Figure 3-2. This UML class diagram illustrates the related information classes and their relations in IPPS problem in DMS. The information integrated can be divided into two categories of information, which are *order-related information* and *resource-related information.*

(1) Order-related information

①Order information

Order information includes the ID of the order, job varieties, batch sizes and job priority in the order.

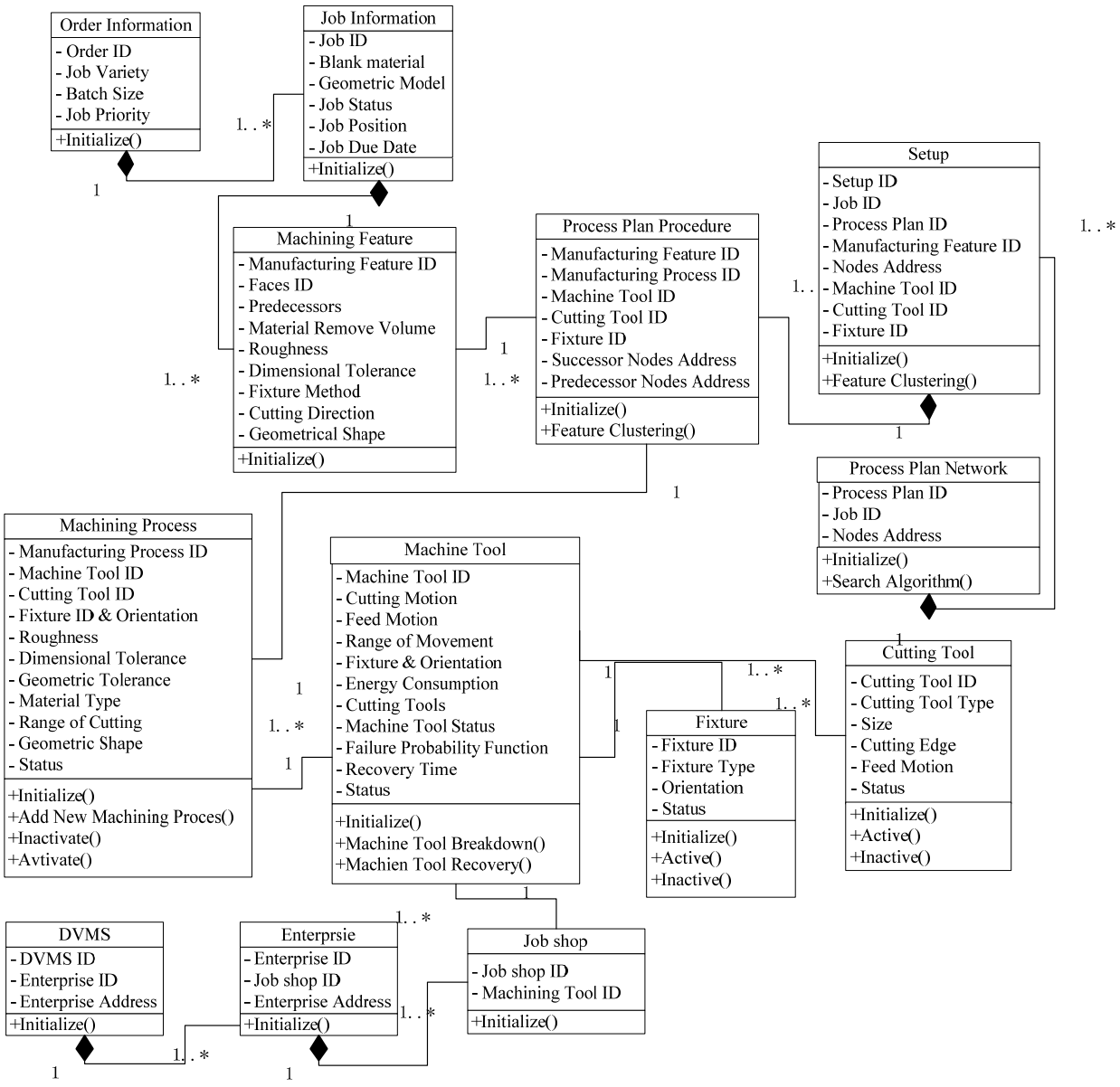


Figure 3-2 UML Class diagram of integrated information in IPPS

②Job information

The information related to the jobs is the job information, manufacturing features of the jobs and job status.

- Job information describes the job IDs, blank materials, geometrical models, the locations and the progresses of the machining processes of the jobs.
- Manufacturing feature information describes the manufacturing features of the jobs and their technical data such as manufacturing types, tolerances and the roughness, based on which the appropriated manufacturing operations and machining tools will be selected.
- The status of the jobs are as following:

- Idle: the job is idle and waiting for the next manufacturing operations.
- Manufacturing operation: the job is under manufacturing processes on a certain machine tool.
- Transportation and re-fixturing: the job is transported and/or re-fixtured for its next machining operations.

③ Process plan information

The information related to process plan includes process plan network information, setup information, process plan procedure information and manufacturing process information.

- The process plan networks represent the generated process plans in non-linear and hierarchical ways. It includes all the alternative process plans that satisfy the technological requirements of the jobs.
- Setup information generated for candidate machine tools is the important input for process planning, scheduling, process monitoring and their integration. The major constraints for setup planning come from design specifications of the jobs and manufacturing resources in the job shop.

Setup planning for machining a part is to determine the number and sequence of setups (including machining features grouping in setups) and part orientation of each setup.

Setup planning is the critical bridge between general process planning and detailed operation planning in a machine shop; it is also the intimate upstream of fixture planning.

The task of setup planning is as following:

- Determining the number and sequences of setups;
- Determining the machining features in each setup;
- Determining part locating orientation of each setup.

- Process plan procedure information describes the correspondent manufacturing feature ID of the machining procedure, the machining process, machine tool, cutting too and fixture adopted by the procedure, as well as the procedure sequence relations.
- Machining process information represents the machining processes of machining features of the jobs, which are carried out by the correspondently feasible machine tools. It mainly includes the following information:
  - Machining process ID which is the combination of the ID of the machine tools, the ID of the fixtures and the ID of the cutting tools.
  - Machining process types and machining feature types that each machining process type can be machined.
  - Technology requirements of the machining processes, such as surface roughness, tolerances and material removal rate, etc.
  - Machining process status, including inactive status (if one of the machine tool, the cutting tool and the fixture related to the machining process are broken down) and active status (otherwise).

(2) Resource-related information

①DMS information

DMS information class mainly describes the enterprises included in the DMS and the related information like enterprise address.

②Enterprise information

Enterprise information class mainly describes the job shops included in the enterprises and the related information on these job shops.

③Job shop resource information

The job shop resource information mainly considered in IPPS in one job shop includes the information on machine tool, cutting tools and fixtures.

- Machine tool information specified the shape generation functions, which are represented by the cutting motions, the spindle directions, the feed motions and the maximum product size. And also, the energy needed to finish a certain operation by the machine tool is also included.
- As for the status of the machine tools, the following situations are considered:
  - Idle: the machine tool is idle and waiting for next machining operation.
  - Manufacturing operation: the machine tool is machining a certain job.
  - Breakdown: the machine tool has been broken and is under recovery process.
- Cutting tool information describes the characteristics of the cutting tools, including the information about the cutting tool types, the tool sizes and the cutting edge types.
- Fixture information includes the fixture types, and the positions of the fixtures against the spindle axis.

3.3 Proposition of a New Integration Model of IPPS in DMS

The IPPS problems in DMS are much more complicated than classical IPPS problems because they involve not only the IPPS problems in each job shop but also the problems in an upper level of how to allocate the parts to a suitable job shop in the feasible enterprises. Once a part is allocated to a job shop and processed, it is usually unable or uneconomical to transfer this work-in-progress part to another job shop for the remaining operations. Moreover, the production scheduling(s) in the job shops have to depend on the parts allocated (Chan, 2006a).

Based on the summary of the traditional three integration mechanisms of IPPS, a Hybrid Model of IPPS in DMS (HMIPPS_DMS), which is a hybrid integration model facilitating both information exchange and function collaboration by combining the process plan flexibility provided by the interface-oriented integration of NLPP and the hierarchical structure of DPP (where hierarchical collaborative integration is conducted) is proposed for DMS as shown in Figure 3-3.

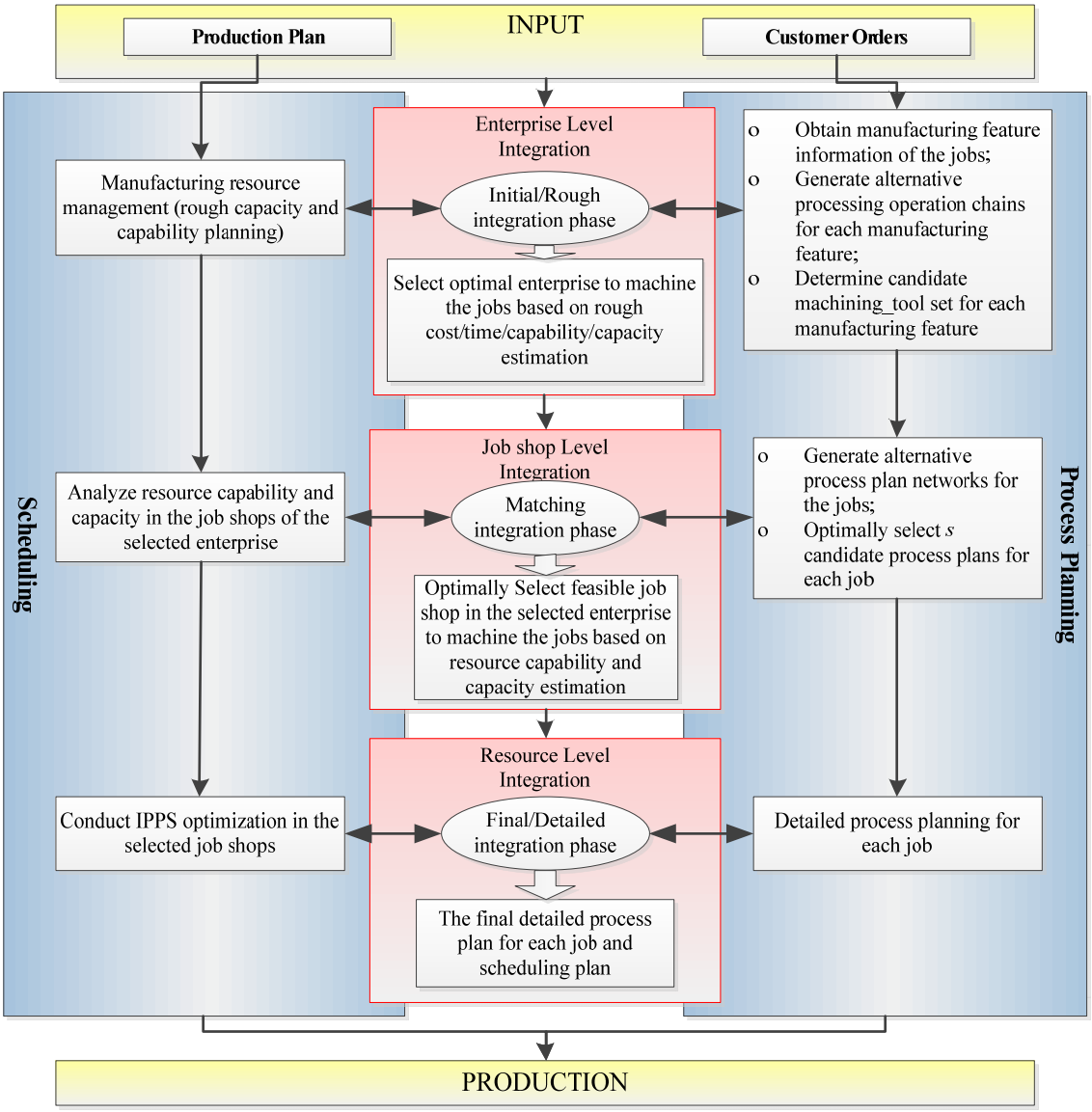


Figure 3-3 The HMIPPS_DMS framework

Production planning and scheduling are considered to be a processes that relates specific production events to a specific time or specific span of time. They both deal with the time-based allocation of orders to resources. Production planning deals with loading of the production orders to equipment groups for a relatively longer time period, e.g. 1 week, 1 month or more, while scheduling is concerned with short-term allocation and sequencing of jobs on the shop floor. Both scheduling and production plan are time-dependent, and production plan directly affects resource capacity in the job shops, therefore it is essential to take production plan into consideration when conducting job shop scheduling, given resource capacity is a premise to finish the orders before their due dates. Therefore, resource capacity analysis is considered in the HMIPPS_DMS.

As shown in Figure 3-3, in HMIPPS_DMS, the hierarchical integration of process planning and scheduling is realized through three integration hierarchies: initial/rough

integration phase in Enterprise Level Integration, matching integration phase in Job Shop Level Integration and final/detailed integration phase in Resource Level Integration

3.3.1 Enterprise level integration

The objective of enterprise level integration aims at selecting the optimal candidate enterprise in a DMS to process the orders. This level of IPPS is an initial/rough planning phase, where process planning module generates alternative processing operation chains and determine candidate machine tool set for each manufacturing feature of the jobs, while scheduling module estimates manufacturing resource capability and capacity based on current production plan in each job shop of the candidate enterprises to provide information on its process potential. Then by concurrent consideration of the specific capability, capacity and performance of the candidate enterprises, the optimal one will be selected to process the order.

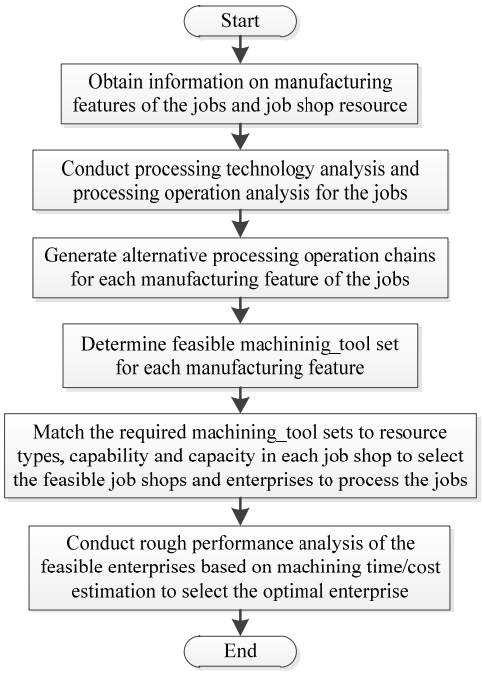


Figure 3-4 The integration procedures in the initial integration phase

In the *initial planning phase*, based on the *interface-oriented* idea, process plan system firstly analyzes process feasibility and manufacturability according to job feature information, machining resource availability and machining capability. And then the alternative process plan networks (feasible alternative process plans) satisfying feasibility constraints for each job will be generated. Meanwhile, receiving the production plan, scheduling system collaboratively offers information on catalogues of machining resources, machining capability and machining resources capacity to process planning systems. Then based on the rough estimation of manufacturing cost and time, the optimally feasible enterprise will be selected to machine the jobs. The integration procedures and the integration content in the initial planning phase are shown as Figure 3-4 and Figure 3-5 respectively.

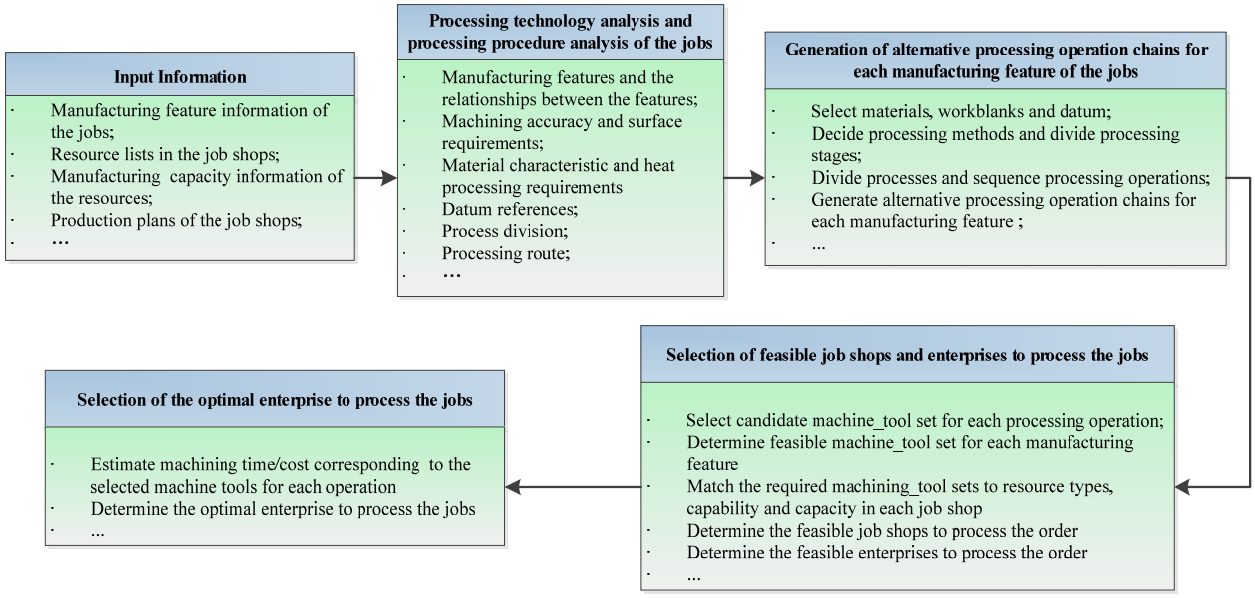


Figure 3-5 The integration contents in the initial integration phase

(1) Obtaining information on manufacturing features of the jobs and job shop resource

Firstly, the manufacturing feature information of the jobs is received from feature database, while the resource type information and the resource capability information are obtained from the resource database. Besides, the production plans in the job shops will be offered.

(2) Conducting processing technology analysis and processing procedure analysis of the jobs based

- Processing technology analysis includes: recognizing manufacturing features of the jobs and the relationships between manufacturing features, determining machining accuracy, surface requirements, material characteristic and heat processing, et al.
- Processing analysis includes: determining datum reference of the parts, process division, processing route and so on.

(3) Generating alternative processing operation chains for each manufacturing feature of the jobs

Based on the selection of materials, workblanks and datum for the jobs, the processing methods of each manufacturing feature will be decided and the processing stages will be divided. Then the processing operations and their sequence will be determined to generate alternative processing operation chains for each manufacturing feature.

(4) Selecting feasible job shops and enterprises to process the jobs

In the light of the processing requirements of each operation to machine the manufacturing features, the candidate machine tool set will be selected for each operation and the feasible machine tool set for each manufacturing will then be decided. Then the feasible job shops and enterprises will be chosen through matching the candidate machine tool sets

required by the manufacturing features of the jobs to resource types, capability and capacity in the job shops.

(5) Selecting the optimal enterprise to process the jobs

Finally the optimal feasible enterprise will be determined based on machining time/cost estimation in the feasible enterprises.

Generating alternative processing operation chains and determining the feasible machine tool set for each manufacturing feature is a prerequisite in initial process planning. The key task in determining feasible enterprises to process the jobs is to match the feasible machine tool sets to the manufacturing resource lists and their corresponding machining capability and capacity in the job shops of the enterprises. In general, initial/rough integration phase is a static interface-oriented integration of IPPS, which does not take the dynamic loading in the job shops.

3.3.2 Job Shop Level Integration

Job shop level integration aims at determining the optimal job shops to finish the orders. As shown in Figure 3-6. There are a number of job shops in the enterprise, and a number of parts in an order are received. Each job shop has a different number of machine tools and can produce various product types with different efficiency, machining capability and capacity. Each part has several numbers of operations, and each operation can be performed on at least one feasible machine tool and different machine tools are with different machining time and cost. So the problem here to be solved are to determine how to allocate these parts to suitable job shops and then determine the production scheduling and process planning in each job shop in order to realize optimization objectives.

From Figure 3-6, I parts need to be processed in F job shops in the selected optimal enterprise. For each Job Shop f, such as factory 1, they have M_1 machines and L_1 tools can be used. All of operations of one part have precedence relationships which are not violated in manufacturing process. Each operation has machine tool candidates, cutting tool candidates, tool access directions (TADs) and associated machining times, cost and energy consumption.

Principle: if part 1 is assigned into Job Shop 1, all of operations of part 1 need to be processed in Job Shop 1.

Notations in Figure 3-6:

I	Number of part types in the order
F	Number of alternative job shops
o_{ij}	the jth operation of the ith part
m	Machine tool in the job shop
M_1	Total number of machine tools in Job Shop 1
t	Cutting tool in the job shop

L_1 Total number of cutting tools in Job Shop 1

D_1 Total number of TADs in Job Shop 1

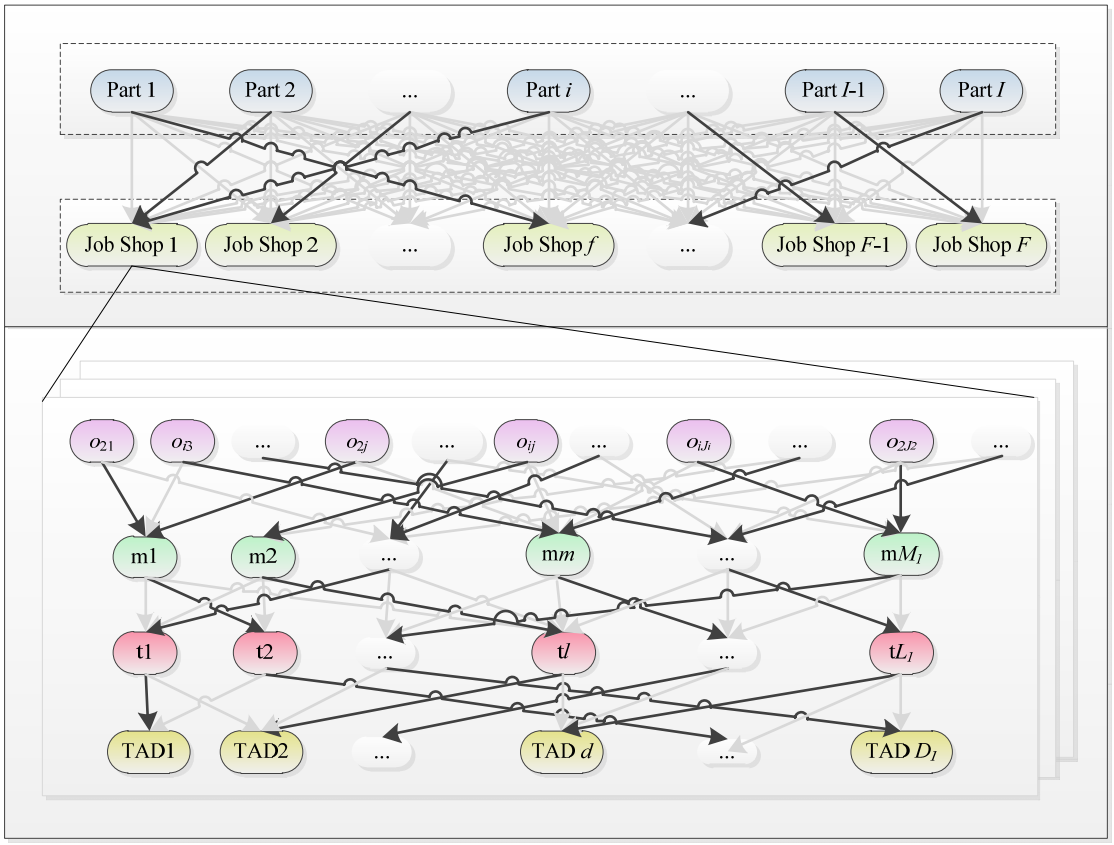


Figure 3-6 Description of IPPS problem in job shop level

The job shop level integration is a matching integration phase. In the selected optimal enterprise, the integration procedures of matching planning phase are as shown in Figure 3-7.

In the matching integration phase, the dual functions of integrated optimization lie in:

- It is a method to optimally utilize the job shop resources.
- It is a mechanism to choose feasible process plans for each job and feasible production plans in the correspondent job shops in terms of current resource status.

In this way, although the process plans finally selected for each job may be not the optimum ones from the point of view of the optimization objectives of process planning, they are undoubtedly the most appropriate ones to optimally utilize job shop resources and reduce conflicts between the optimization objectives of process planning and scheduling in production execution in current job shop environment.

(1) In the matching integration phase, firstly the initial alternative process plan networks of each job will be generated, and *s* (*s* is determined by the user of the system, and it is in the range of 3-8) near optimal candidate process plans for each job will be selected according to the given optimization criteria, such as the minimum machining time, minimum machining

cost and so on. As there may be many alternative process plans for each job, the process plans with poor performances will be filtered out without affecting the necessary flexibility of the model while avoiding combinational-explosive problem effectively in this way.

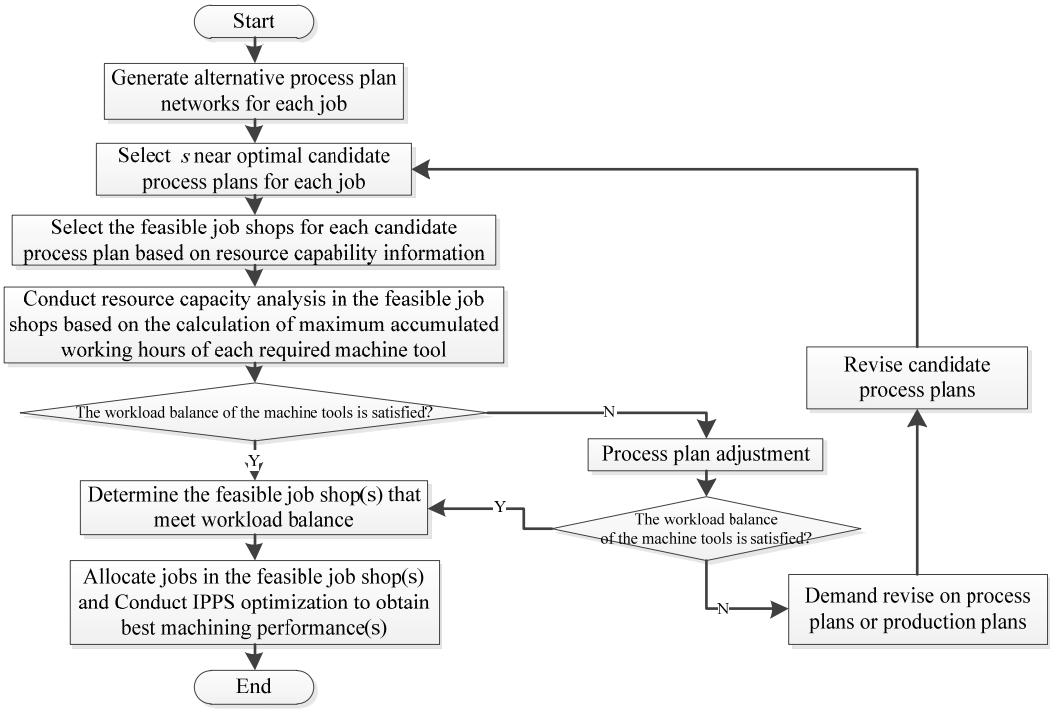


Figure 3-7 The integration procedures in the matching integration phase

(2) Then combining the idea of concurrent and collaborative adopted by DPP with dynamic information on the production resources in the job shops, the scheduling system conducts feasibility analysis for the optimally selected *s* candidate process plans for each job based on resource capacity calculation, ensuring the jobs are executable in the current job shop environment and determining the feasible job shop (set). Including:

- Analyzing and determining if any of the feasible machines for each procedure of the *s* candidate process plans are equipped in the job shops.
- Estimating if the machine tools in the current job shop can satisfy the process plan requirements based on current machine status and the remaining work-capacity in current production planning cycle of the machines, to avoid resource conflicts for multiple jobs and infeasibility in machining the jobs. Firstly, for each machine in each job shop, calculating its cumulative maximum working hours, which is the sum of the already-scheduled-working-hour and the maximum newly-added-working-hour needed to finish all the jobs based on their candidate process plans. The maximum newly-added-working-hour needed to finish all the jobs is an extreme case, and if this extreme case can be satisfied then it is can be affirmed that all the selected *s* near optimal candidate process plans can be processed in the job shop. If not, the Dynamic Key Machine (DKM) going beyond its work capacity in the current production planning cycle should be firstly identified, and then the operation time taken up by each process plan on this machine is listed and the process plan with the longest

working time on the DKM should be altered with another alternative process plan with shorter operation time on the DKM if there are any. The detailed process plan adjustment procedures are shown in Figure 3-8.

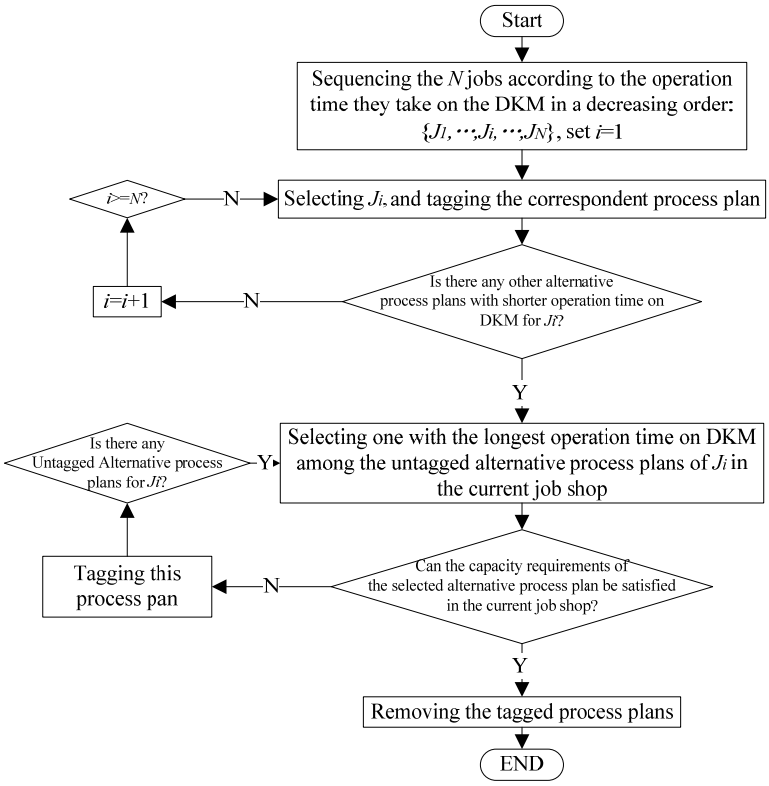


Figure 3-8 The procedures of process plan adjustment

(3) Finally, the jobs will be allocated to the feasible job shop(s) and IPPS optimization will be conducted in the feasible job shop(s) to achieve the most desirable production performances.

In the Matching planning phase, the dual functions of integrated optimization lies in:

- It is a method to optimally utilize the job shop resources.
- It is a mechanism to choose process plans suitable to the resource status and production plans in the correspondent job shops for each job.

In this way, although the process plans finally selected for each job may be not the optimum ones from the point of view of the optimization objectives of process planning, they are undoubtedly the most appropriate ones to optimally utilize job shop resources and reduce conflicts between the optimization objectives of process planning and scheduling in production execution in current job shop environment.

3.3.3 Resource Level Integration

The resource level integration is a final/detailed integration phase, where process planning and scheduling systems conduct detailed planning to obtain the detailed process plan

for each job and the scheduling plan in the selected job shop. The procedures of final/detailed integration phase are shown in Figure 3-9. (where *ss* is determined by user).determined.

As shown in Figure 3-9, in the final/detailed integration phase:

- For process planning system, the final chosen process plan for each job will be designed in detail, including: calculating and determining machining allowances, process dimensions and tolerances, cutting parameters; determining tool path of CNC machining processes and generating NC codes.
- For scheduling system, the resource status in the job shop will be updated and the scheduling plan will be simulated. When dynamic exchanges occur during production execution, rescheduling or scheduling plan adjustment will be conducted.

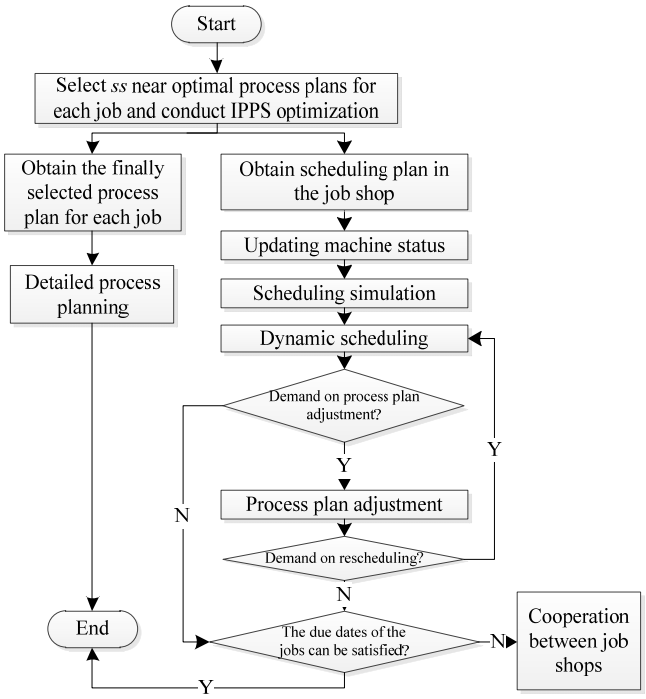


Figure 3-9 The integration procedures in the final integration phase

3.3.4 The overall Integration Process of HMIPPS_DMS

Based on the HMIPPS_DMS framework, as well as the integration procedures and contents in each integration phase, the overall integration process of HMIPPS_DMS can be constructed as shown in Figure 3-10. The overall integration process contains the following main integration modules: generation of alternative processing operation chains for each manufacturing feature, selection of feasible enterprises and determination of the optimal enterprise to process the order in the initial/rough integration phase at enterprise level; generation of alternative process plan networks for each part type, selection of s candidate process plans for each part type, selection of feasible job shops and allocation of the jobs to feasible job shops in the matching integration phase at job shop level; and detailed process planning and scheduling, as well as dynamic scheduling simulation in the final/detailed planning phase at resource level.

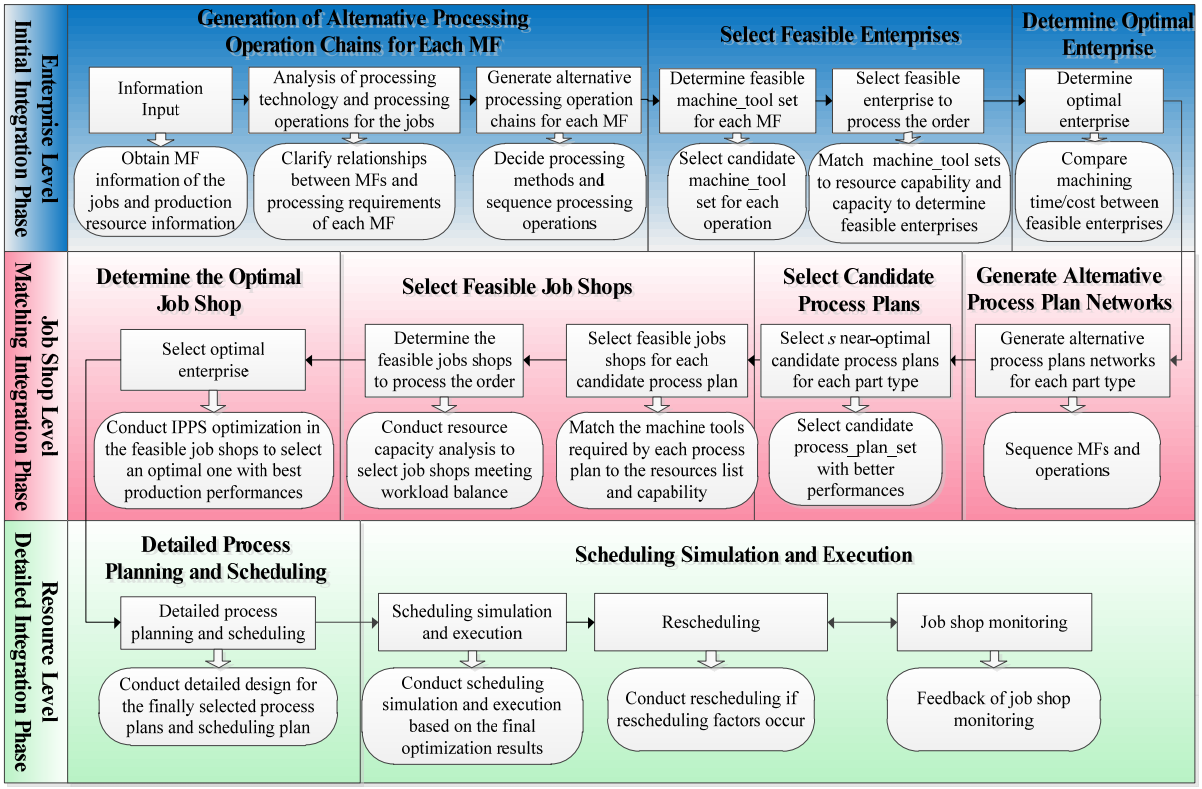


Figure 3-10 Overall integration process of HMIPPS_DMS (Note: MF – Manufacturing Feature)

In the initial/rough integration phase of the overall integration process of HMIPPS_DMS, part feature lists and production resource lists are firstly received as input. Then the alternative processing operation chains will be generated for each manufacturing feature based on processing technology analysis and processing operation analysis. Next the feasible enterprises will be selected through matching resource capability and capacity in the enterprises to resource requirements by each manufacturing feature. Through a rough estimation and comparison of machining cost/time in different feasible enterprises, the optimal one will be determined to process the order. In the matching integration phase, the alternative process plan networks will firstly generated for each part type, from which s near optimal candidate process plans will be selected for each job. Then the feasible job shops meeting both resource requirements of the candidate process pans and workload balance of the demanded resources in the job shops will be selected based on machining capability analysis and capacity calculation of the resources. Through allocating jobs to feasible job shop(s) and conducting IPPS optimization in the feasible job shops, the optimal production performances will be achieved. In the detailed/final integration phase, the detailed process planning for each job and scheduling simulation will be carried out. If rescheduling factors appear, then rescheduling will be activated to respond to dynamic changes.

3.4 Mathematical Description of IPPS Problem in DMS

A typical IPPS problem in DMS environment generally consists of a number of enterprises (and each enterprise normally consists of several job shops) and an order (in an

order that are a number of different jobs). The enterprises in DMS are geographically separated with a travel time and a travel cost from the customers of the order. Each job shop in each enterprise has a different number of machines and can produce various product types with different efficiency and manufacturing cost. Each job has up to G_i alternative process plans, and for each alternative process plan there are P_{il} operations. Each operation can be performed on one or more machines with different processing times. The problem herein is to determine how to allocate these jobs to suitable job shops and then conduct IPPS optimization in the suitable job shops to determine the process plan for each job and the production scheduling of the job shops aiming at minimizing the makespan. Similar to classical scheduling problems, it is generally assumed that each machine can only handle one operation at each time. Each operation will be completed before another operation will be loaded. Note that, once a job is allocated to a job shop, all of its operations will be processed in that job shop. The problem is expressed in the following notation:

F_q Candidate enterpise, $q = 1, 2, \ldots, Q$, Q is the total number of candidate enterprises, $F_q = \{mf_1, mf_2, \ldots\}$ containing a set of machining features that can be machined in the enterprise 's job shop

N Total number of jobs in the order;

M Total number of machines in the job shop;

D_q Travel time between enterprise *q* and the customer of the order;

C_q Travel cost between enterprise *q* and the customer of the order;

G_i Total number of alternative process plans of job *i*;

mf_i Machining features on a job, $i = 1, 2, \ldots, I$, I is the total number of machining features on a part

o_{ijl} The *j*th operation in the *l*th alternative process plan of job *i*;

P_{il} The number of operations in the *l*th alternative process plan of job *i*;

$o_{ijl}.k$ Here *k* is the id of the alternative machine corresponding to o_{ijl} ;

t_{ijlk} The processing time of operation o_{ijl} on machine *k*, t_{ijlk}>0;

c_{ijlk} The earliest completion time of operation o_{ijl} on machine *k*;

v_{ijlk} The processing cost of operation o_{ijl} on machine *k*;

d_i The due date of job *i*;

c_i The completion time of job *i*;

ML_k The initial mean load of machine *k*;

A A very large positive number.

$U_i = \begin{cases} 1 & \text{if } c_i > d_i \\ 0 & \text{otherwise} \end{cases}$ the unit penalty of job *i*;

$X_{il} = \begin{cases} 1 & \text{the } l\text{th alternative process plan of job } i \text{ is selected} \\ 0 & \text{otherwise} \end{cases}$

$Y_{ijlpqsk} = \begin{cases} 1 & \text{if the operation } o_{ijl} \text{ percedes the operation } o_{pqs} \text{ on machine } k \\ 0 & \text{otherwise} \end{cases}$

$Z_{ijlk} = \begin{cases} 1 & \text{if machine } k \text{ is selected for } o_{ijl} \\ 0 & \text{otherwise} \end{cases}$

$W_1 = \begin{cases} 1 & \text{if } X \neq Y \\ 0 & \text{if } X = Y \end{cases}$ $W_2 = \begin{cases} 0 & \text{if } X = Y = 0 \\ 1 & \text{otherwise} \end{cases}$

The Objectives are as following:

(1) Minimizing *makespan* which is the completion time of the last operation of all jobs plus the travel time between enterprise *q* and the customer of the order (assuming enterprise *q* is the final selected enterprise to manufacture the orders);

$$f_1 = Min\ makespan = Min\ Max\{c_{ijlk} \cdot X_{il} \cdot Z_{ijlk}\} + D_q \tag{3-1}$$

$$\forall i \in [1,N], \forall j \in [1,P_{il}], \forall l \in [1,G_i], \forall k \in [1,M]$$

(2) Minimizing the total cost, which is the total manufacturing cost of the order plus the travel cost between enterprise *q* and the customer of the order (assuming enterprise *q* is the final selected enterprise to manufacture the orders);:

$$f_2 = Min\ TMC = Min \sum_{i=1}^{N} \sum_{l=1}^{G_i} \sum_{j=1}^{P_{il}} \sum_{k=1}^{M} (v_{ijlk} \cdot X_{il} \cdot Z_{ijlk}) + C_q \tag{3-2}$$

$$\forall i \in [1,N], \forall j \in [1,P_{il}], \forall l \in [1,G_i], \forall k \in [1,M]$$

Constraints:

(1) For the first operation in the alternative process plan *l* of job *i*:

$$(c_{i1lk} \cdot X_{il} \cdot Z_{i1lk}) + A(1 - X_{il}) \geq t_{i1lk} \cdot Z_{i1lk} \cdot X_{il} + ML_k \cdot Z_{i1lk} \tag{3-3}$$

$$\forall i \in [1,N], \forall l \in [1,G_i], \forall k \in [1,M]$$

(2) For the last operation in the alternative process plan l of job i:

$$(c_{iP_{il}lk} \times X_{il} \times Z_{iP_{il}lk}) - A(1 - X_{il}) \leq makespan \tag{3-4}$$

$$\forall i \in [1,N], \forall l \in [1,G_i], \forall k \in [1,M]$$

(3) The different operations of one job cannot be processed simultaneously:

$$c_{ijlk} \times X_{il} \times Z_{ijlk} - c_{i(j-1)lk_1} \times X_{il} \times Z_{i(j-1)lk_1} + A(1 - X_{il}) \geq t_{ijlk} \times X_{il} \times Z_{ijlk} \tag{3-5}$$

$$\forall i \in [1,N], \forall j \in [1,P_{il}], \forall l \in [1,G_i], \forall k,k_1 \in [1,M]$$

(4) Each machine can handle only one job at a time:

$$\begin{aligned}&(c_{pqsk} \times Z_{pqsk} \times X_{ps}) - (c_{ijlk} \times X_{il} \times Z_{ijlk}) + A(1 - X_{il}) + A(1 - X_{ps}) \\ &+ A(1 - Y_{ijlpqsk} \times Z_{ijlk} \times Z_{pqsk} \times X_{il} \times X_{ps}) \geq (t_{pqsk} \times Z_{pqsk} \times X_{ps})\end{aligned} \tag{3-6}$$

$$\begin{aligned}&(c_{ijlk} \times X_{il} \times Z_{ijlk}) - (c_{pqsk} \times Z_{pqsk} \times X_{ps}) + A(1 - X_{il}) + A(1 - X_{ps}) \\ &+ A(Y_{ijlpqsk} \times Z_{ijlk} \times Z_{pqsk} \times X_{il} \times X_{ps}) \geq (t_{ijlk} \times Z_{ijlk} \times X_{il})\end{aligned} \tag{3-7}$$

$$\forall i,p \in [1,N], \forall j,q \in [1,P_{il}], \forall l,s \in [1,G_i], \forall k \in [1,M]$$

(5) Only one alternative process plan can be selected of job i:

$$\sum_{l} X_{il} = 1 \quad \forall i \in [1,N] \tag{3-8}$$

(6) Only one machine for each operation should be selected:

$$\sum_{k=1}^{M} Z_{ijlk} = 1 \quad \forall i \in [1,N], \forall j \in [1,P_{il}], \forall l \in [1,G_i] \tag{3-9}$$

(7) There is only one precedence relation between two operations in a scheduling plan:

$$Y_{ijlpqsk} \times Z_{ijlk} \times Z_{pqsk} \times X_{il} \times X_{ps} \leq 1 \tag{3-10}$$

$$(Y_{ijlpqsk} \times X_{il}) \leq (Z_{ijlk} \times X_{il}) \tag{3-11}$$

$$(Y_{ijlpqsk} \times X_{ps}) \leq (Z_{pqsk} \times X_{ps}) \tag{3-12}$$

$$\forall i,p \in [1,N], \forall j,q \in [1,P_{il}], \forall l,s \in [1,G_i], \forall k \in [1,M]$$

$$\sum_{i}^{N} \sum_{j}^{P_{il}} \sum_{l}^{G_i} (Y_{ijlpqsk} \times X_{il} \times Z_{ijlk}) = \sum_{o_{k1}}^{o_{pqsk}-1} Z_{o_{km}} \tag{3-13}$$

$$\forall p \in [1,N], \forall q \in [1,P_{il}], \forall s \in [1,G_i], \forall k \in [1,M]$$

Where $\sum_{o_{k1}}^{o_{pqsk}-1} Z_{o_{km}}$ means the total number of operations before o_{pqs} on machine k; o_{k1} means the first operation on machine k; o_{pqsk} means the current operation on machine k.

(8) The completion time of each operation should be either positive or zero.

$$c_{ijlk} - X_{il} \cdot Z_{ijlk} \geq 0 \tag{3-14}$$

$$\forall i \in [1,N], \forall j \in [1,P_{il}], \forall l \in [1,G_i], \forall k \in [1,M]$$

3. 5 A Case Study to Describe HMIPPS_DMS

A case study is designed and conducted to clearly describe the detailed content and the overall integration procedures in HMIPPS_DMS. We set the configuration of the designed DMS as shown in Figure 3-11: this DMS consists of two enterprises (Enterprise A and Enterprise B), and each enterprise consists of two job shops (Job shop A1 and Job shop A2 in Enterprise A; Job shop B1 and Job shop B2 in Enterprise B). The machining tools deployed in each job shop are shown as Figure 3-11 (notice Job shop A2 and Job shop B1 are set to have the same machine tool configuration), and the acronyms stand for (in EL(M1), here 'M1' stands for the code mark of machine EL is 'M1'):

- EL(M1): Engine Lathe;
- BL(M2): Boring Lathe;
- VL(M3): Vertical Lathe;
- VD(M4): Vertical Driller;
- VM(M5): Vertical Lifting Milling Machine;
- HM(M6): Horizontal Knee Type Milling Machine;
- EG(M7): External Grinder;
- SG(M8): Surface Grinders;
- GH(M9): Gear Hobbing Machine.

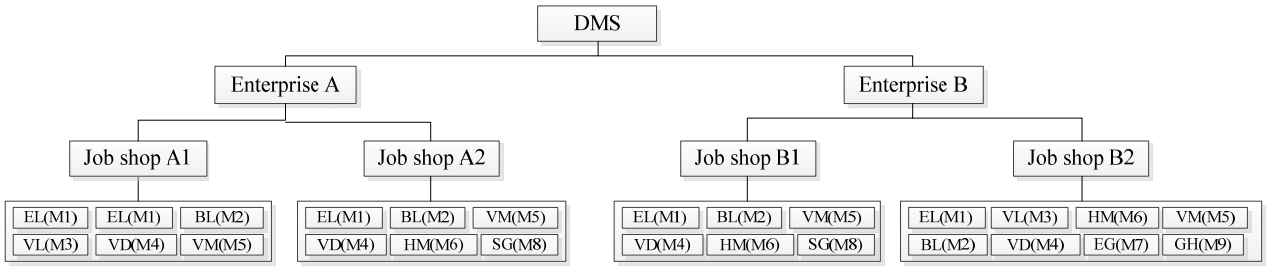


Figure 3-11 DMS structure

Three jobs in an order needed to be processed in this DMS, which are shown as Figure 3-12 – Figure 3-14. And the information on the travel time (D_q) and travel cost (C_q) from the customers to the candidate enterprises is shown in Table 3-1. Here the problem is to select an optimal job shop to process the jobs in the feasible enterprises, based on which IPPS will be conducted in the selected job shop to generate the scheduling plan.

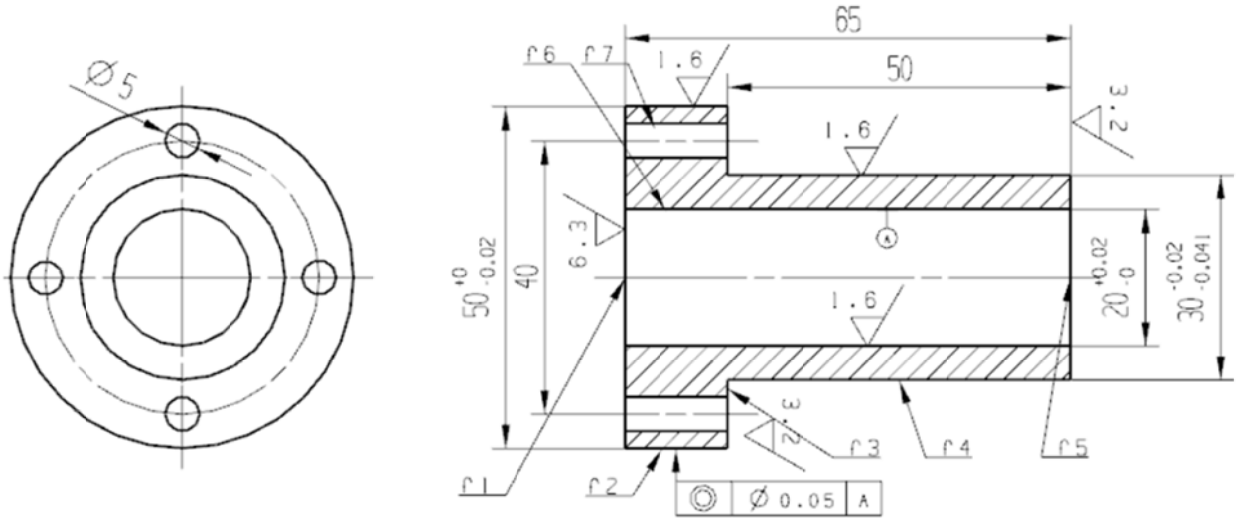


Figure 3-12 Job1 - Sleeve Part

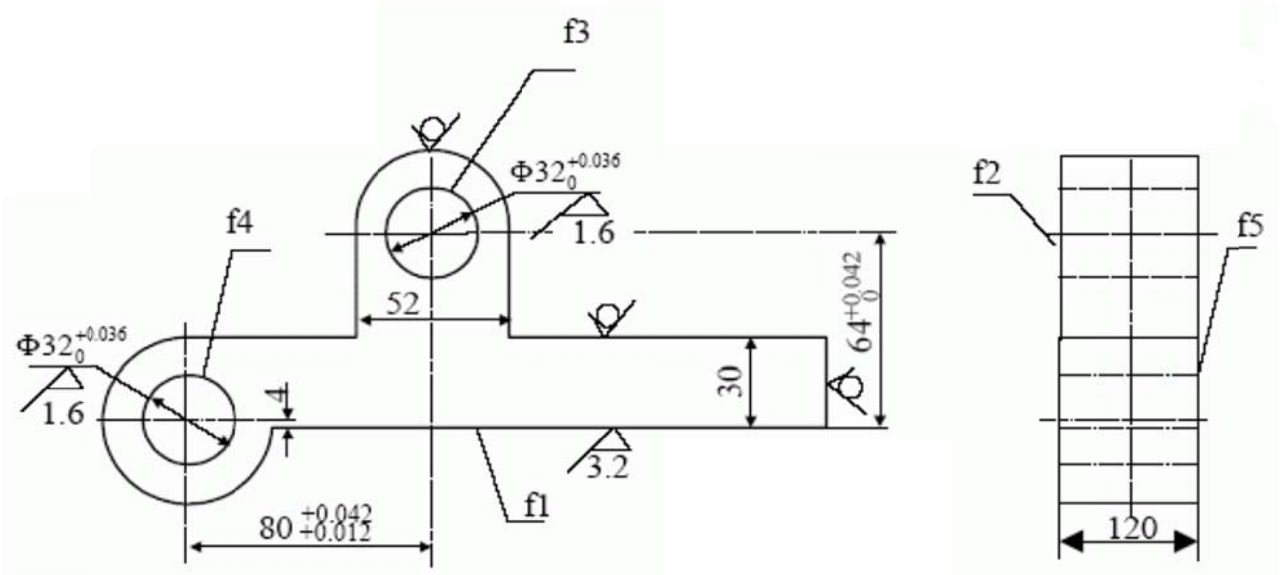


Figure 3-13 Job 2 - Hinge Part

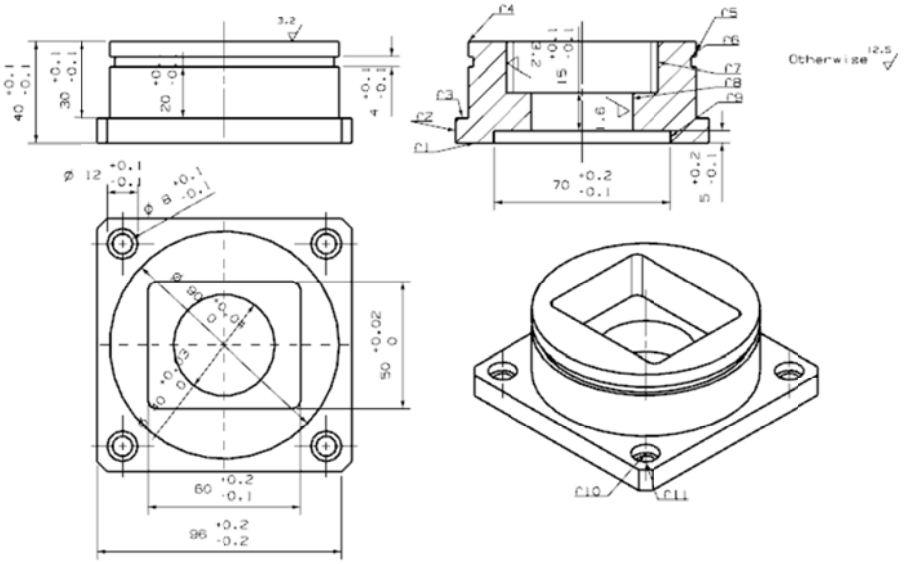


Figure 3-14 Job 3 - Flange Part

Table 3-1 Travel time and travel cost from the customer to the candidate enterprises

	Travel time (D_q)	Travel cost (C_q)
Enterprise A	20 Hours	10 Hours
Enterprise B	50€	25€

3.5.1 Enterprise level integration

(1) Feasibility analysis for the jobs based on resource capability in the job shops

Firstly, on receiving the jobs information, DMS conducts feasibility analysis for the jobs based on part machining tool resource and capability information in each job shop. Table 3-2 shows each part type's manufacturing features (MFs), and each feature's machining precision grade, alternative processing operation steps and machining tools. According to Table 3-2:

Sleeve part: the machining tools required to machine the sleeve part (Figure 3-12) include Lathe (Engine Lathe or Vertical Lathe), Vertical Driller (or Boring Lather) and External Grinder, therefore only Job shop A2, Job shop B1 and JobshopB2 have the capability to machine the sleeve part.

Hinge part: the machining tools required to machine the hinge part (Figure 3-13) include Vertical Lifting Milling Machine (or Horizontal Knee Type Milling Machine) and Vertical Driller (or Boring Lather), therefore all the job shops have the capability to machine the hinge part.

Flange part: the machining tools required to machine the flange part (Figure 3-14) include Lathe (Engine Lathe or Vertical Lathe), Vertical Driller (or Boring Lathe), Vertical

Lifting Milling Machine (or Horizontal Knee Type Milling Machine), therefore all the job shops have the capability to machine the flange part.

(2) Optimal candidate enterprise selection

Through concurrent consideration of the feasibility analysis result as well as the incurred travel time and travel cost, we can get Table 3-3. Although both Enterprise A and Enterprise B are capable to process these part types, the travel time and travel cost from the customer to Enterprise B is lower than Enterprise B, therefore we conclude that Enterprise B is the optimal one to process this order.

Table 3-2 Jobs' manufacturing features, alternative process operation chains and feasible machining tools

Part Type	MF No.	MF Element	Precision Grade/Ra	Alternative Processing Operation Chains	Feasible Machining Tools
Job 1 - Sleeve	f1	Cylinder Head Face	IT8 (6. 3)	Rough turning - Finish turning	Lathe
	f2	Cylinder Excircle Surface	IT7(1. 6)	Rough turning - Finish turning - Grinding	Lathe, Grinder
	f3	Step Face	IT7(3. 2)	Rough turning - Finish turning - Grinding	Lathe, Grinder
	f4	Excircle Surface	IT7(1. 6)	Rough turning - Finish turning - Grinding	Lathe, Grinder
	f5	Cylinder Head Face	IT8(3. 2)	Rough turning - Finish turning	Lathe, Grinder
	f6	Cylindrical Hole	IT9(1. 6)	Drilling hole - Broaching hole - Reaming hole	Vertical Driller or Lathe
	f7	Cylindrical Hole	IT12(6. 3)	Drilling hole - Broaching hole	Vertical Driller or Lathe
Job 2 - Hinge	f1	Bottom Datum Plane	IT7(3. 2)	Rough milling - Semi finish milling - Finish milling	Vertical Lifting Milling Machine or Horizontal Knee Type Milling Machine
	f2	Left Head Face	IT12	Milling	Vertical Lifting Milling Machine or Horizontal Knee Type Milling Machine
	f3	Set PIN holes	IT7(1. 6)	Rough Boring - Semi finish boring - Finish Boring Drilling - Broaching - Rough reaming - Finish reaming	Vertical Driller or Boring lathe
	f4	Connecting Rod Pin Hole	IT7(1. 6)	Rough Boring - Semi finish boring - Finish Boring Drilling - Broaching - Rough reaming - Finish reaming	Vertical Driller or Boring lathe
	f5	Right Head Face	IT12	Milling	Vertical Lifting Milling Machine or Horizontal Knee Type Milling Machine
Job 3 - Flange	f1	Base Undersurface	IT13	Milling	Vertical Lifting Milling Machine or Horizontal Knee Type Milling Machine
	f2	Base Side Face	IT12	Rough milling - Semi finish milling	Vertical Lifting Milling Machine or Horizontal Knee Type Milling Machine
	f3	Base Step Face	IT12	Rough milling - Semi finish milling	Vertical Lifting Milling Machine or Horizontal Knee Type Milling Machine
	f4	Top Surface	IT12(3. 2)	Rough turning - Semi finish turning	Lathe
	f5	Cylinder Excircle Surface	IT7	Rough turning - Semi finish turning - Finish turning	Lathe
	f6	Excircle Groove	IT12	Turning	Lathe
	f7	Rectangular Pocket	IT7(3. 2)	Rough milling - Semi finish milling - Finish milling	Vertical Lifting Milling Machine, Horizontal Knee Type Milling Machine

	f8	Middle Through-hole	IT13(1. 6)	Rough Boring - Semi finish boring - Finish Boring	Boring lathe
	f9	Counterbore	IT13	Rough Boring - Semi finish boring	Boring lathe
	f10	Counterbore(4)	IT13	Drilling hole - Broaching hole	Vertical Driller
	f11	Base Through-hole(4)	IT13	Drilling hole - Broaching hole	Vertical Driller

Table 3-3 Enterprise selection result

	Enterprise A		Enterprise B	
	Job shop A1	Job shop A2	Job shop B1	Job shop B2
Job 1	Unfeasible	Feasible	Feasible	Feasible
Job 2	Feasible	Feasible	Feasible	Feasible
Job 3	Feasible	Feasible	Feasible	Feasible
The order	Unfeasible	Feasible	Feasible	Feasible
Travel time	Unfeasible	20 hours	10 hours	10 hours
Travel cost	Unfeasible	50€	25€	25€
The optimal enterprise	No		Yes	

3.5.2 Job shop level integration

(1) Generation and Optimal Selection of Alternative Process Plans for each Part Type

When generating the alternative process plan networks of the jobs, three types of flexibility are considered in production flexibility (Li et al., 2007)

- Routing flexibility: also called operation flexibility, relates to the possibility of performing one operation on alternative machines, with possibly distinct processing time and cost.
- Sequencing flexibility is decided by the possibility of interchanging the sequence of the required operations.
- Processing flexibility is determined by the possibility of processing the same manufacturing feature with alternative operations or sequences of operations (Shao et al, 2009).

There are many methods used to describe the types of production flexibility explained above such as Petri-net, AND/OR graphs and network. Here we adopt AND/OR graphs to represent the alternative process plans and schedules.

In an AND/OR graph, there are three types of the nodes in the network: starting node, intermediate node and ending node (Ho and Moodie 1996). In Figure 3-15 – Figure 3-17, the alternative process plan networks of the three parts are shown with AND/OR graphs.

- The starting node and the ending node, which are dummy ones, indicate the start and the end of the manufacturing process of a job.
- An intermediate node represents an operation, which contains the alternative machines that can perform the operation and the processing time required for the operation according to the machines.
- The arrows connecting the nodes represent the precedence between them.
- OR relationships are used to describe the processing flexibility that the same manufacturing feature can be performed by different process procedures.
- If the links following a node are connected by an OR connector, it only needs to traverse one of the OR-links (the links connected by the OR-connector are called OR-links), and an OR-link path can of course contain the other OR-link paths.
- OR-link path is an operation path that begins at an OR-link and ends as it merges with the other paths, and its end is denoted by a JOIN-connector.
- For the links that are not connected by OR-connectors, all of them must be visited.
- One path from the starting node to the ending node is one alternative process plan.

The description of the processing operations for each part type in the graphs is shown as Table 3-4. Then the top 8 optimal alternative process plans for each part type are selected in light with the shortest manufacturing time, as shown in Table 3-5.

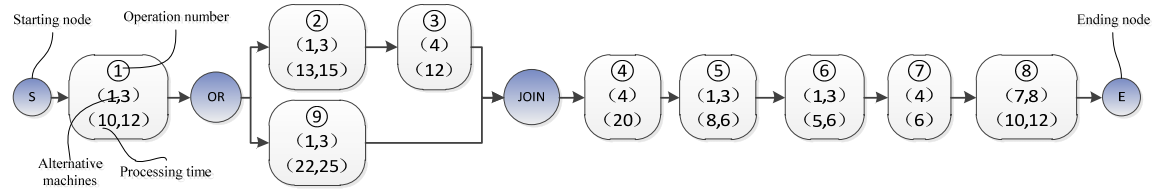


Figure 3-15 Alternative process plans network of part type 1 (Sleeve part)

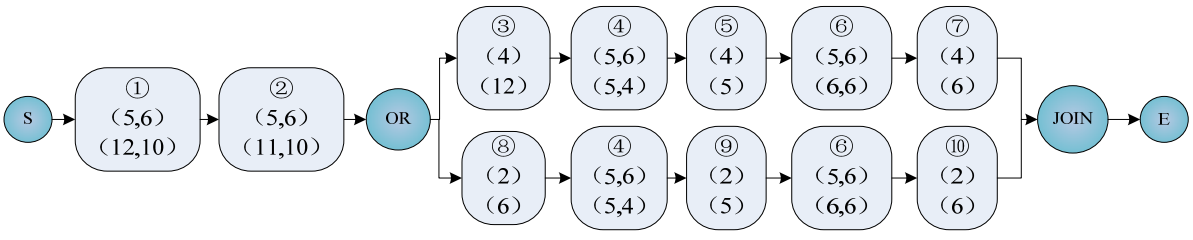


Figure 3-16 Alternative process plans network of part type 2 (Hinge part)

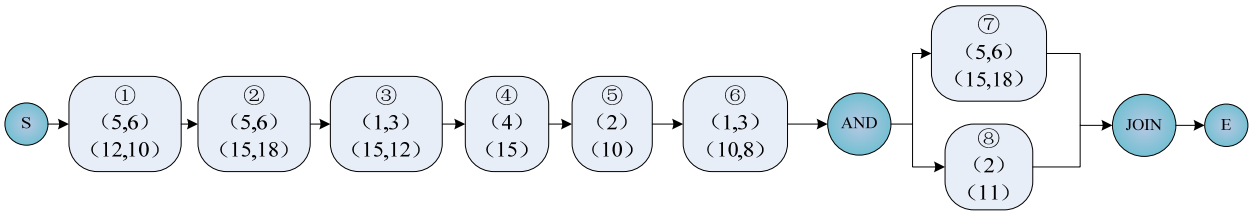


Figure 3-17 Alternative process plans network of part type 3 (Flange part)

Table 3-4 Operation description in AND/OR Graphs of the parts

Sleeve Part (Part Type 1)			**Hinge Part (Part Type 2)**			**Flinge Part (Part Type 3)**		
Operation Number	Operation Content	MF(s)	Operation Number	Operation Content	MF(s)	Operation Number	Operation Content	MF(s)
1	rough turning	f1, f2	1	rough milling	f1	1	rough milling	f1, f2
2	rough turning	f3, f4, f5	2	milling	f5,f2	2	rough turning	f4, f5, f6
3	drilling, broaching	f6	3	drilling, broaching	f3, f4	3	rough milling	f3, f7
4	drilling, broaching	f7	4	Semi-finish milling	f1	4	drilling, broaching	f10, f11
5	finish turning	f1, f2	5	rough reaming	f3, f4	5	rough reaming and semi-finish boring	f8, f9
6	finish turning	f3, f4	6	finish milling	f1	6	Semi-finish turning; semi-finish turning and finish turning	f4; f5
7	reaming	f6	7	finish reaming	f3, f4	7	Semi-finish milling and finish milling	f7
8	grinding	f2, f3, f4	8	semi-finish boring	f3, f4	8	finish boring	f8
9	rough turning; drilling, broaching	f3, f4, f5; f6	9	finish boring	f3, f4			
			10	finish boring	f3, f4			

Table 3-5 The selected 8 near-optimal candidate process plans for each part type (JS: Job Shop; Time unit: minute)

Part Type	**Alternative Process Plans**	**Operation Sequence**	**Machine Tool No. Selected for Each Operation**	**Corresponding Machining Time for Each Operation**	**Total Machining Time/min**	**Feasible Job Shop(s)**
Job 1 - Sleeve Part	1	1-9-4-5-6-7-8	1-1-4-3-1-4-7	10-22-20-6-5-6-10	79	JS B2
	2	**1-9-4-5-6-7-8**	**1-1-4-3-3-4-7**	**10-22-20-6-6-6-10**	**80**	**JS B2**
	3	**1-9-4-5-6-7-8**	**3-1-4-3-1-4-7**	**12-22-20-6-5-6-10**	**81**	**JS B2**
	4	**1-9-4-5-6-7-8**	**1-1-4-1-3-4-7**	**10-22-20-8-6-6-10**	**82**	**JS B2**
	5	1-9-4-5-6-7-8	1-1-4-1-1-4-8	10-22-20-8-5-6-12	83	JS B1
	6	1-2-3-4-5-6-7-8	1-1-4-4-3-1-4-7	10-13-12-20-6-5-6-10	82	JS B2
	7	1-9-4-5-6-7-8	1-3-4-3-1-4-7	10-25-20-6-5-6-10	82	JS B2
	8	1-9-4-5-6-7-8	3-1-4-1-3-4-7	12-22-20-8-6-6-10	84	JS B2
Job 2 - Hinge Part	**1**	**1-2-3-4-5-6-7**	**6-6-4-6-4-5-4**	**10-10-5-4-5-6-6**	**46**	**JS B1 & JS B2**
	2	**1-2-3-4-5-6-7**	**6-6-4-6-4-6-4**	**10-10-5-4-5-6-6**	**46**	**JS B1 & JS B2**
	3	1-2-3-4-5-6-7	6-6-4-5-4-5-4	10-10-5-5-5-6-6	47	JS B1 & JS B2

	4	1-2-3-4-5-6-7	6-6-4-5-4-6-4	10-10-5-5-5-6-6	47	JS B1 & JS B2
	5	1-2-3-4-5-6-7	6-5-4-6-4-5-4	10-11-5-4-5-6-6	47	JS B1 & JS B2
	6	1-2-3-4-5-6-7	6-5-4-6-4-6-4	10-11-5-4-5-6-6	47	JS B1 & JS B2
	7	**1-2-8-4-9-6-10**	**6-6-2-6-2-5-2**	**10-10-6-4-5-6-6**	**47**	**JS B1 & JS B2**
	8	1-2-8-4-9-6-10	6-6-2-6-2-6-2	10-10-6-4-5-6-6	47	JS B1 & JS B2
Job 3 - Flange Part	**1**	**1-2-3-4-5-6-7-8**	**6-5-3-4-2-3-5-2**	**10-15-12-15-10-8-15-11**	**96**	**JS B2**
	2	1-2-3-4-5-6-8-7	6-5-3-4-2-3-2-5	10-15-12-15-10-8-11-15	96	JS B2
	3	**1-2-3-4-5-6-7-8**	**5-5-3-4-2-3-5-2**	**12-15-12-15-10-8-15-11**	**98**	**JS B2**
	4	**1-2-3-4-5-6-8-7**	**5-5-3-4-2-3-2-5**	**12-15-12-15-10-8-11-15**	**98**	**JS B2**
	5	1-2-3-4-5-6-7-8	6-5-3-4-2-1-5-2	10-15-12-15-10-10-15-11	98	JS B2
	6	1-2-3-4-5-6-8-7	6-5-3-4-2-1-2-5	10-15-12-15-10-10-11-15	98	JS B2
	7	1-2-3-4-5-6-7-8	6-6-3-4-2-3-5-2	10-18-12-15-10-8-15-11	99	JS B2
	8	1-2-3-4-5-6-8-7	6-6-3-4-2-3-2-5	10-18-12-15-10-8-11-15	99	JS B2

(2) Feasibility Analysis of the Selected Process Plans based on resource capacity analysis

The current production plan will be established with the above three part types. Assuming the batch size for each part type is 180. The delivery date of part type 1 is the seventh week, the delivery date of part type 2 and 3 is the eighth week, and the current time is the end of the first week. The job shops work 5 days (from Monday to Friday) per week, and 7 hours every day, therefore at the end of the seventh week, the maximum working time is 245h ($245 = 5 \times 7 \times 7$), and at the end of the eighth week is 280h ($280 = 5 \times 7 \times 8$).

According to the feasible job shops determined for the selected top 8 near optimal alternative process plans for each part type (Table 3-5), for part type 1 and part type 2, both Job Shop B1 and Job Shop B2 are feasible in terms of resource capability, while for part type 3, only Job Shop B2 is feasible. The accumulated maximum working hours of each machine tool is calculated based on the selected top 8 candidate process plans for each part type, by which the workload balance analysis for each machine tool is carried out.

For Job Shop B1, from Table 3-5, we can see that only part type 1 and part type 2 can be machined in Job Shop B1. For part type 1, only the fifth candidate process plan is feasible in Job Shop B1, and the machine tools needed by this process plan are M1, M4 and M8, while for part type 2, the machine tools required in the candidate process are M2, M4, M5, M6. Therefore, we need to conduct workload balance analysis for M1, M2, M4, M5, M6 and M8 in Job Shop B1. M1 is only needed the fifth candidate process plan of part type 1, so the maximum working hours of M1 to machine part type 1 is calculated as $(10 + 22 + 8 + 5) \div 60 \times 180 = 135$h. For M2, it is only needed in the seventh and the eighth candidate process plans of part type 2, and the maximum working hours of M2 can be obtained as $(6 + 5 + 6) \div 60 \times 180 = 51$ h. M4 is needed both by part type 1 and part type 2, and its maximum working hours needed by part type 1 is $(20 + 6) \div 60 \times 180 = 78$h while by part type 2 is

$(5 + 5 + 6) \div 60 \times 180$h, so the maximum working hours of M2 is 78+48=136h. Similarly, the maximum working hours demanded for M5, M6 and M8 are 81h, 90h and 36h respectively, as shown in Table 3-6. The total workload for each machine tool is the sum of the already scheduled working hours and the newly added working hours on it, for example, the total workload of M1 is 120+135=255h. We can see that the total workload on the M1 is beyond its allowed capacity in the current production plan period, meanwhile there is no other alternative candidate process plan in Job Shop B1 for part type 1, therefore Job Shop B1 is not feasible to machine the part types as M1 in Job Shop B1 cannot meet workload balance.

In a similar way, the workload balance analysis is conducted for the required machining tools in Job Shop B2, as shown in Table 3-6. Actually, as the current time is the end of the first week, so the 35h in the first week should not be considered (therefore the total workload of M3 in Jobshop3 is calculated to be 121 (35+36+60=121) but not 116 (30+36+60=116), for M4 is the same situation). From Table 3-6, we can see that the accumulated maximum working hours for each machining tool do not surpass its allowed capacity in the current production planning period, therefore Job Shop B2 should be chosen as the feasible job shop of the part types.

Table 3-6 Workload balance analysis

Job Shop No.	Machine Tool	Machining Tool	Scheduled Working hours	Newly Added Working Hours	Total Workload	Overload?
Job Shop B1	M1	EL	120	135	255	>245
	M2	B	120	51	171	No
	M4	VD	100	78+48	226	No
	M5	VM	150	33	183	No
	M6	HM	160	90	250	>245
	M8	SG	90	36	126	No
Job Shop B2	M1	EL	50	111	161	No
	M2	B	80	51+66	197	No
	M3	VL	30	36+60	116(121)	No
	M4	VD	20	78+48+45	191(206)	No
	M5	VM	60	18+90	168	No
	M6	HM	40	90+84	214	No
	M7	EG	50	30	80	No

3.5.3 Resource level integration

Table 3-7 The selected 3 feasible candidate process plans for each part type

Part Type	**Alternative Process Plans**	**Operation Sequence**	**Machine Tool No. Selected for Each Operation**	**Corresponding Machining Time for Each Operation**	**Total Machining Time/min**
Job 1 Sleeve Part	2	1-9-4-5-6-7-8	1-1-4-3-3-4-7	10-22-20-6-6-6-10	80
	3	1-9-4-5-6-7-8	3-1-4-3-1-4-7	12-22-20-6-5-6-10	81
	4	1-9-4-5-6-7-8	1-1-4-1-3-4-7	10-22-20-8-6-6-10	82
Job 2 Hinge Part	1	1-2-3-4-5-6-7	6-6-4-6-4-5-4	10-10-5-4-5-6-6	46
	2	1-2-3-4-5-6-7	6-6-4-6-4-6-4	10-10-5-4-5-6-6	46

	7	1-2-8-4-9-6-10	6-6-2-6-2-5-2	10-10-6-4-5-6-6	47
Job 3 Flange Part	1	1-2-3-4-5-6-7-8	6-5-3-4-2-3-5-2	10-15-12-15-10-8-15-11	96
	3	1-2-3-4-5-6-7-8	5-5-3-4-2-3-5-2	12-15-12-15-10-8-15-11	98
	4	1-2-3-4-5-6-8-7	5-5-3-4-2-3-2-5	12-15-12-15-10-8-11-15	98

As shown in Table 3-7, select 3 feasible candidate process plans from the selected near optimal process plans feasible in Job Shop B2 for each part type, then based on the mathematical description of IPPS problem in DMS, IPPS optimization is conducted using a genetic algorithm to obtain the minimum makespan. The process plan finally selected for each part is shown in Table 3-8. The scheduling result is shown as Figure 3-18.

From the result we can see that the finally selected process plan for each job may not be the optimal one in the light of optimization criterion of process planning, however, they are the most appropriate one to achieve the most desirable production performances from the point of view of IPPS.

Table 3-8 The finally selected process plan for each part type

Part Type	**Operation Sequence**	**Machine Tool No. Selected for Each Operation**	**Corresponding Machining Time for Each Operation**	**Total Machining Time/min**
Job 1 Sleeve Part	1-9-4-5-6-7-8	3-1-4-3-1-4-7	12-22-20-6-5-6-10	81
Job 2 Hinge Part	1-2-8-4-9-6-10	6-6-2-6-2-5-2	10-10-6-4-5-6-6	47
Job 3 Flange Part	1-2-3-4-5-6-7-8	6-5-3-4-2-3-5-2	10-15-12-15-10-8-15-11	96

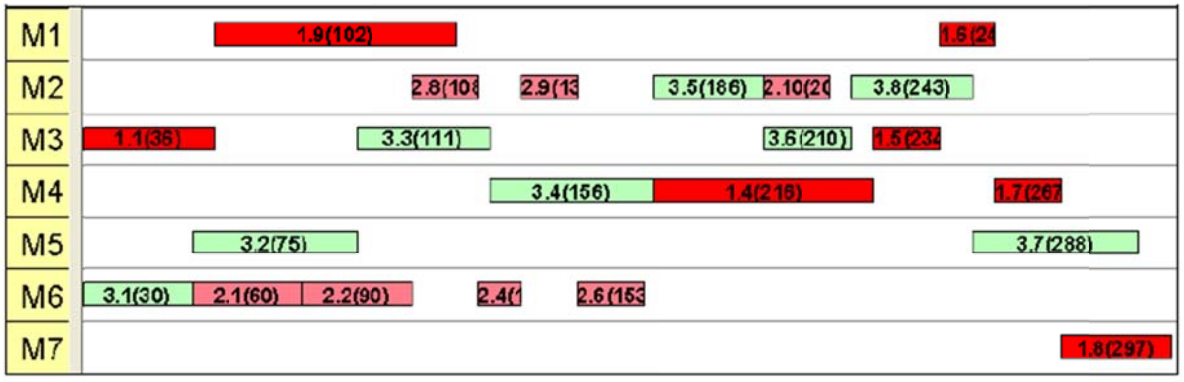


Figure 3-18 Scheduling result

3.6 Conclusion

In this chapter, firstly the information integration model for IPPS problem in DMS was established based on the definition of DMS and its structure. Then to solve the IPPS optimization problems in a DMS environment, a new Hybrid Model of IPPS in DMS

(HMIPPS_DMS) facilitating both information exchange and functional collaboration by combining NLPP and DPP in DMS environment was proposed. In HMIPPS_DMS, the hierarchical integration of process planning and scheduling is realized through three integration hierarchies: initial/rough integration phase in Enterprise Level Integration, matching integration phase in Job Shop Level Integration and final/detailed integration phase in Resource Level Integration. What's more, in job shop level integration, *s* near optimal alternative process plans are selected to be integrated with scheduling, which enhances production performances and offers process plan flexibility at the same time. Concurrent capability planning and capacity planning of the production resources avoids resource conflicts and unbalanced utilization of the resources, assuring production stability and efficiency in the job shops. A case study was designed and conducted based on the mathematical description of IPPS problem in DMS to demonstrate the reliability and describe the detailed procedures of HMIPPS_DMS, showing that the proposed HMIPPS_DMS can be very effective in solving the IPPS optimization problems in DMS environment.

Chapter 4 Multi-objective Optimization Problem in IPPS

Introduction:

So far, most of the current researchers on IPPS optimization have been concentrated on the single objective, which cannot meet the requirements from the real-world production, where different departments have different expectations in order to maximize their own profits, for example, the manufacturing department expects to reduce costs and improve work efficiency; the managers want to maximize the utilization of the existing resources; and the sale department pursues to better meet the delivery requirements of the customers. Besides, shop floor schedules could significantly affect energy consumption as well as other environment impacts of an individual machine. Optimized operation schedules could further reduce energy costs. In this chapter, based on the concept of Multi-Objective Optimization Problem (MOOP), the complete mathematical model to explain and describe the MOOP in IPPS in a single job shop will be constructed, in which some new parameters and objectives relating energy consumption in machining the parts will be studied and adopted. Then NSGA-II (Non-dominated Sorting GA-II) will be improved to effectively solve the multi-objective optimization problems in IPPS so that the decision-makers in the enterprises and job shops can make reasonable choices according to their preferences for the optimization objectives.

4.1 Introduction on Optimization Problems

Optimization is the act of obtaining the best result under given circumstances. In design, construction and maintenance of any engineering systems, engineers have to take many technological and managerial decisions at several stages. The ultimate goal of all such decisions is either to minimize the effort required or to maximize the desired benefit. Since the effort required or the benefit desired in any practical situation can be expressed as a function of certain decision variables, optimization can be defined as the process of finding the conditions that give the maximum or minimum value of a function (Rao, 2009).

A single-objective optimization problem involves a single objective function and usually results in a single solution, called an optimal solution. On the other hand, a multi-objective optimization task considers several conflicting objectives simultaneously. In such a case, there is usually no single optimal solution, but a set of alternatives with different trade-offs, called Pareto optimal solutions, or non-dominated solutions (Branke et al., 2008).

4.2 Basic concepts of Multi-objective Optimization Problem

A Single-Objective Optimization Problem (SOOP) with uncontrollable parameters can be defined as:

Definition 1: A general SOOP with uncontrollable parameters includes an objective/performance function, a set of design variables, a set of design environment parameters, and a set of constraints. Performance functions and constraints are functions of the design variables and the design environment parameters. The optimization goal is to:

Minimize $f(x, p)$

$$\text{Subject to} \quad \begin{aligned} & g_k(x,p) \leq 0, \quad k = 1,...,q \\ & h_e(x,p) = 0, \quad e = 1,...,t \\ & x_l^l \leq x_l \leq x_l^u, \quad l = 1,...,n \end{aligned}$$

$$\text{Where} \quad \begin{aligned} & x = [x_1\ x_2\ ...\ x_n]^T \in D^n \\ & p = [p_1\ p_2\ ...\ p_r]^T \in P^r \end{aligned} \tag{4-1}$$

And $f(\mathbf{x},\mathbf{p})$ is the performance function, $g_k(\mathbf{x},\mathbf{p})$ and $h_e(\mathbf{x},\mathbf{p})$ are the inequality and equality constraints, respectively. $\mathbf{x} = [x_1 x_2 \cdots x_n]^T$ denotes the n-dimensional vector of *Design Variables (DVs)*. $\mathbf{D}^n$ is denoted as the Decision Space (D-Space). Note that the nominal values of DVs are controllable, x_l^l and x_l^u are the lower and upper bound of x_l respectively. $\mathbf{p} = [p_1\ p_2\ ...\ p_r]^T$ denotes the r-dimensional vector of *Design Environment Parameters (DEPs)*, which cannot be adjusted by the designer, and they are uncontrollable parameters. $\mathbf{P}^r$ is denoted as the *Paremeter Space (P-Space)*.

Similarly, the MOOP with uncontrollable parameters can be defined as:

Definition 2: A general MOOP with uncontrollable parameters includes a set of objective/performance functions, a set of design variables, a set of design environment parameters, and a set of constraints. Performance functions and constraints are functions of the design variables and the design environment parameters. The optimization goal is to:

$$\text{Minimize} \quad f(x,p) = [f_1\ f_2\ ...\ f_m]^T$$

$$\text{Subject to} \quad \begin{aligned} & g_k(x,p) \leq 0, \quad k = 1,...,q \\ & h_e(x,p) = 0, \quad e = 1,...,t \\ & x_l^l \leq x_l \leq x_l^u, \quad l = 1,...,n \end{aligned} \tag{4-2}$$

$$\text{Where} \quad \begin{aligned} & x = [x_1\ x_2\ ...\ x_n]^T \in D^n \\ & p = [p_1\ p_2\ ...\ p_r]^T \in P^r \end{aligned}$$

and $f(x,p) = [f_1\ f_2\ ...\ f_m]^T$ denotes the m-dimensional vector of performance function.

Generally speaking, one equality function can be presented by two inequality functions, so in the following work, all the constraints will be presented as inequality functions. Then all the constraints are presented as $g_k(x,p) \leq 0,\ k=1, \ldots, q$.

A design that does not violate any of the constraints is called ‘feasible’. In contrast, the design that violates any constraint is called ‘non-feasible’.

Definition 3: The *Feasible set* **F** is defined as the set of decision vectors **x** that satisfy the constraints:

$$\mathbf{F} = \{x : g_k(x,p) \le 0,\ k = 1, \ldots, q\} \quad (4\text{-}3)$$

Each element **x** of **F** is called as a *feasible solution*. The images of these feasible solutions by the mapping functions from D-space to PF-space form the *feasible region* in the PF-space.

Definition 4: A feasible solution **x*** is said to dominate another feasible solution x if and only if

$$(a)\ \forall i \in \{1, 2, \ldots, m\}: f_i(x^*,p) \le f_i(x,p); \quad (4\text{-}4)$$

$$(b)\ \exists j \in \{1, 2, \ldots, m\}: f_j(x^*,p) < f_j(x,p). \quad (4\text{-}5)$$

Since there are trade-offs among the *m* conflicting objectives, there is no solution which can dominate all the other solutions in the feasible set. The optimization problem (2) generally has more than one optimal solution. Those solutions are defined as *Pareto optimal solutions*, which cannot be dominated by any other feasible solution (Deb, 2001; Li and Wong, 2009; Coello, 2006; Bui et al., 2012).

Definiton 5: A feasible solution **x*** is said to be a Pareto optimal solution if there is no feasible solution **x** such that **x** dominates **x***.

The set of all Pareto optimal solutions is called *Pareto optimal set*: **P**. The Pareto optimal solutions lie on a boundary in the PF-Space, called the *Pareto front*.

Definition 6: The Pareto front of a multi-objective optimization problem is bounded by a so-called *nadir performance vector* and *an ideal performance vector*, if these are finite.

The ideal performance vector and nadir performance vector are defined as:

$$(a)\ f^{ideal} = \left(f_1^{\min}(x,p)\ f_2^{\min}(x,p)\ \ldots f_m^{\min}(x,p)\right)^T;\ subject\ to\ x \in \mathbf{P}; \quad (4\text{-}6)$$

$$(b)\ f^{nadir} = \left(f_1^{\max}(x,p)\ f_2^{\max}(x,p)\ \ldots f_m^{\max}(x,p)\right)^T;\ subject\ to\ x \in \mathbf{P}. \quad (4\text{-}7)$$

In other words, the components of a nadir and an ideal performance vector define upper and lower bounds for the performance function values of Pareto optimal solutions, respectively. In practice, the nadir and ideal performance vector can only be approximated as, typically, the whole Pareto optimal set is unknown.

Figure 4-1 shows a simple example to explain the definitions of dominance and Pareto optimal, assuming that *m*=2. Each feasible solution in the D-space has corresponding values in the PF-Space, and these vectors form the *feasible region* in the PF-Space, which are described as grey area in Figure 4-1. Solution A, solution B and solution C are selected to compare their attributes. The solution A and solution B are Pareto optimal, since there is no feasible solution which can dominate them. Since $f_1(A) < f_1(B)$ and $f_2(A) > f_2(B)$, solution A and solution B cannot dominate each other. Instead, solution C can be dominated by

solution A and solution B, for that $f_1(A) < f_1(C)$ and $f_2(A) < f_2(C)$, $f_1(B) < f_1(C)$ and $f_2(B) < f_2(C)$. The Pareto front is part of the boundary of the feasible region in the PF-Space, as described in Figure 4-1. Solution A and solution B are on the Pareto front while solution C is not. The ideal performance vector ($\mathbf{f}^{ideal}$) and nadir performance vector ($\mathbf{f}^{nadir}$) are also marked in Figure 4-1.

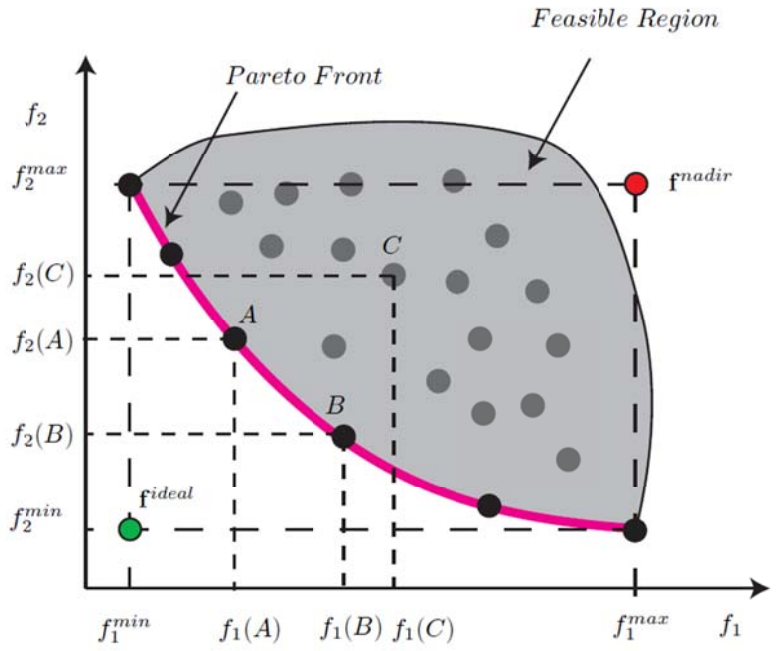


Figure 4-1 The feasible solutions and Pareto optimal solutions in the PF-Space

4.3 Methods of Solving MOOP

4.3.1 Classical Methods

(1) Global criterion method

In the method of global criterion, the distance between some desirable reference point in the PF-Space and the feasible region is minimized. The designer selects the reference point. A natural choice is to set it as the ideal performance vector ($\mathbf{f}^{ideal}$). We can use, for example, the L_p-metric, to measrue the distance to the target performance vector $\mathbf{f}^{target}$ (which can be selected by the designer, eg $\mathbf{f}^{ideal}$) and then we need to solve the problem:

$$\text{minimize } \left\| \mathbf{f}(x,p) - \mathbf{f}^{target} \right\|$$

$$\text{subject to } x \in \mathbf{F} \tag{4-8}$$

In the above problem, $\|\bullet\|$ can be any L_p norm, with common choices including L_1, L_2 and L_∞. Let us point out that if the performance functions have different magnitudes, the method works properly only if we scale the performance functions to a uniform, dimensionless scale (Miettinen, 1999; Branke et al., 2008).

(2) Weighted sum method.

The weighted sum method is the most common approach to solve MOOP. In this approach, the MOOP are converted into a scalar preference function using a linear weighted sum function of the form:

$$\text{minimize } \sum_{i=1}^{m} w_i f(x,p)$$

$$\text{subject to } x \in \mathbf{F} \tag{4-9}$$

$$w_i \geq 0;\ \sum_{i=1}^{m} w_i = 1$$

For this method, the weighting factor for the *i*th objective function ω_i reflect, a priori, the designer's preferences. It is simple, but in practice it is very difficult to select the weights that would accurately represent the designer's preferences.

However, solving the above optimization problem for a certain number of different weight combinations yields a set of solutions. On condition that an exact optimization algorithm used and all weights are positive, this method will only generate Pareto optimal solutions which can be easily shown. The main disadvantage of this technique is that it cannot generate all Pareto optimal solutions with non-convex trade-off surfaces (Zitzler, 1999; Miettinen, 1999; Chinchuluun and Pardalos, 2007).

(3) ε-constraint method

In the ε-constraint method, one of the performance functions is selected to be optimized, the others are converted into constraints and the problem gets the form:

$$\text{Minimize } f_i(x,p)$$

$$\text{Subject to } f_j(x,p) \leq e_j \quad j = 1, 2, ..., m; \forall j \neq i \tag{4-10}$$

$$x \in \mathbf{F}$$

The definition of the limits ε_j requires knowing a priori the designer's preference. This method works for both convex and non-convex problems. A set of Pareto optimal solutions can be obtained with a systematic variation of ε_j. However, improper selection of ε_j can result in a formulation with no feasible solution (OB Augusto, Fouad Bennis, et al., 2012). In another words, in practice, it may be difficult to specify the upper bounds so that the resulting problem has solutions, that is, the feasible region will not become empty. This difficulty is emphasized when the number of objective functions increases (Miettinen, 1999; Branke et al., 2008).

4.3.2 Genetic Algorithm and NSGA-II

With those classic methods, only one Pareto solution can be expected to be found in one simulation run of a classical algorithm and not all Pareto optimal solution can be found by some algorithms in non-convex MOOP. However, other approaches such as some heuristics

inspired in nature process can solve MOOP getting the Pareto set directly (Augusto et al., 2012). For example, genetic algorithm, particle swarm, simulated annealing etc. The genetic algorithm and the NSGA-II (Non-dominated Sorting Genetic Algorithm-II) are briefly introduced here.

Genetic algorithm is a metaheuristic inspired by the Darwin evolutionist theory explaining the origin of species. In nature, weak and unfit species within their environment are faced with extinction by natural selection. The strong ones have greater opportunity to pass their genes to future generations via reproduction. In the long run, species carrying the correct combination in their genes become dominant in their population. Sometimes, during the slow process of evolution, random changes may occur in genes. If these changes provide additional advantages in the challenge for survival, new species evolve from the old ones. Unsuccessful changes are eliminated by natural selection.

The concept of genetic algorithm was generalized to many different areas of engineering and sciences. The specific mechanics of the algorithm involve the language of microbiology and, in developing new potential solutions, mimic genetic operations. A population represents a group of potential solution points. A generation represents an algorithmic iteration. A chromosome is comparable to a design point, and a gene is comparable to a component of the design vector. Given a population of designs, three basic operations are applied: selection, crossover, and mutation. The selection operator involves selecting design vectors, called parents, in the current generation, which are combined together, by crossover, to form new chromosomes, called offspring. By iteratively applying the crossover operator, genes of good chromosomes are expected to appear more frequently in the population, eventually leading to convergence to an overall good solution. The mutation operator introduces random changes into characteristics of chromosomes. Mutation reintroduces genetic diversity back into the population and assists the search escape from local optima (Augusto et al., 2012).

Being a population-based approach, genetic algorithm is well suited to solve MOOPs finding a set of multiple non-dominated solutions in a single run. The NSGA II, proposed by Deb et al. (2002), is a very famous multi-objective optimization algorithm.

In the NSGA II, the population is initialized as usual. Once the population is initialized the population is sorted based on non-domination into each front. The first front being completely non-dominant set in the current population and the second front being dominated by the individuals in the first front only and the front goes so on. Each individual in the each front are assigned rank values (fitness) or based on front in which they belong to. Individuals in first front are given a fitness value of 1 and individuals in second are assigned fitness value as 2 and so on. In addition to fitness value a new parameter called crowding distance is calculated for each individual. The crowding distance is a measure of how close an individual is to its neighbors. Large average crowding distance will result in better diversity in the population. Parents are selected from the population by using binary tournament selection based on the rank and crowding distance. An individual is selected in the rank is lesser than the other or if crowding distance is greater than the other. The selected population generates offspring from crossover and mutation operators (Aravind, 2004).

The step-by-step procedure of the generation of NSGA II is shown as following, which is also shown in Figure 4-2.

- Step 1: Based on the initial population of the *t*-th generation: P_t, the usual binary tournament selection, recombination, and mutation operators are used to create an offspring population Q_t;
- Step 2: Combine parent and offspring population $R_t = P_t \cup Q_t$;
- Step 3: Finding all non-dominated fronts of R_t; B_1 are the best solutions from R_t. B_2 are the second best solutions and so on;
- Step 4: If the size of B_1 is small than the number of individuals, then we definitely choose all members of the set B_1 for the new population P_{t+1}; the remaining members of the population P_{t+1} are chosen from subsequent non dominated fronts in the order of their ranking. This procedure is continued until no more sets can be accommodated. Say that the set B_l is the last non dominated set beyond which no other set can be accommodated;
- Step 5: Calculate the crowding distance in B_l. The solutions in B_l are sorted by the crowded-comparison operator and the best solutions are chosen to fill all population slots;
- Step 6: Based on the new population of the *(t + 1)*-th generation: P_{t+1}, go to Step 1.

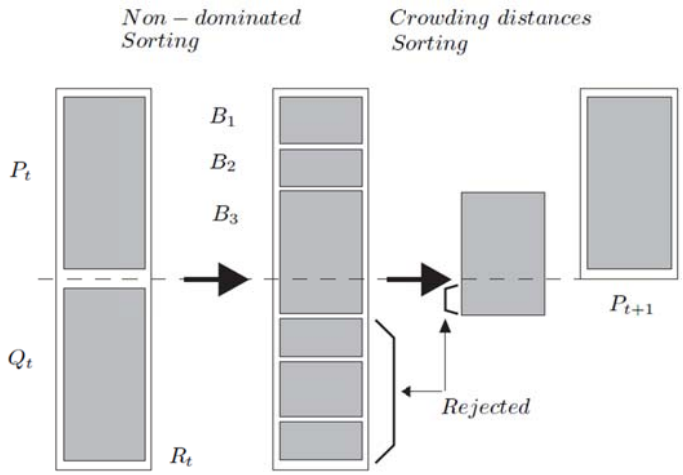


Figure 4-2 NSGA-II procedure

Due to its clever mechanisms, performance of the NSGA-II is so good, that it has become very popular in the last few years, becoming a landmark against which other multi-objective evolutionary algorithms have to be compared (Coello, 2006). Therefore, in the following of this thesis, NSGA-II is widely used as a tool for solving MOOP.

4.4 Mathematical Model of MOOP in IPPS

In the mathematical model considering energy consumption, three quantitative parameters should be determined: the time needed by a specified machine tool to process each operation of the parts, the machining cost per unit time of a specified machine tool and the energy consumption per unit time of a specified machine tool. In the literatures, there are numerous researchers focusing on determining the machining time and cost of the machine tools, however how to determine the energy consumption per unit time of a specified machine tool still remains a field needing further studied. Hence, the energy consumption of the machine tools will be firstly analyzed based on literature study, and then the reasonable mathematical model considering energy consumption can be established.

4.4.1 Energy Consumption Analysis in Manufacturing Industry

4.4.1.1 Status Quota

Over the last 60 years, the consumption of energy by the industrial sector has almost doubled. The industrial sector is the largest energy consumer and currently accounts for about one-half of the world's total energy consumption. In addition, industrial energy consumption, which was at 175 quadrillion Btu in 2006, is projected to increase 40% by 2030 (Fang et al., 2011). In Germany, statistical data shows that industrial sector is responsible for approximately 47% of total national electricity consumption. The corresponding amount of CO_2 emissions generated by this electricity was 18–20% (BMWi, 2007). In the United States, approximately 34% of all the end-use energy consumption was associated with the industrial sector, and the associated energy cost in 2006 was about $100 billion. Since the U.S. energy supply is dominated by fossil fuels (more than 85% of the energy comes from such sources such as coal and natural gas), the industrial sector contributes 27% of the U.S. greenhouse gas (GHG) emissions. This makes the industrial sector second to the transportation sector in terms of GHG emissions (Fang et al., 2011).

A study has suggested that this could be exacerbated by a potential shortfall in energy supply due to declining fossil based energy sources as shown in Figure 4-3 (Seow et al., 2011). Furthermore, it is commonly reported that for the foreseeable future, the main source of power generation will be from fossil fuels and therefore the rationalization of energy consumption still provides the most effective method of CO_2 reduction. Governments have consequently responded by introducing a number of energy related legislation, audits and accreditation. More recently, aiming at reducing annual consumption of primary energy by 20% by 2020, the European Commission (EC) has specifically addressed energy usage with the introduction of directives such as Eco-Design of Energy using Products (EU Directive 2005/32/EC) and Energy End-Use Efficiency and Energy Services (EU directive 2006/32.EC) (Seow et al., 2011).

Therefore, besides facing complex and diverse economic trends of shorter product life cycles, rapidly changing science and technology, increased diversity in customer demand, and the globalization of production activities, manufacturing enterprises also face enormous environmental challenges. These include global climate change (e.g. greenhouse effect), rapid

exhaustion of various non-renewable resources (e.g. gas, oil, coal), and decreasing biodiversity (Dai et al., 2013).

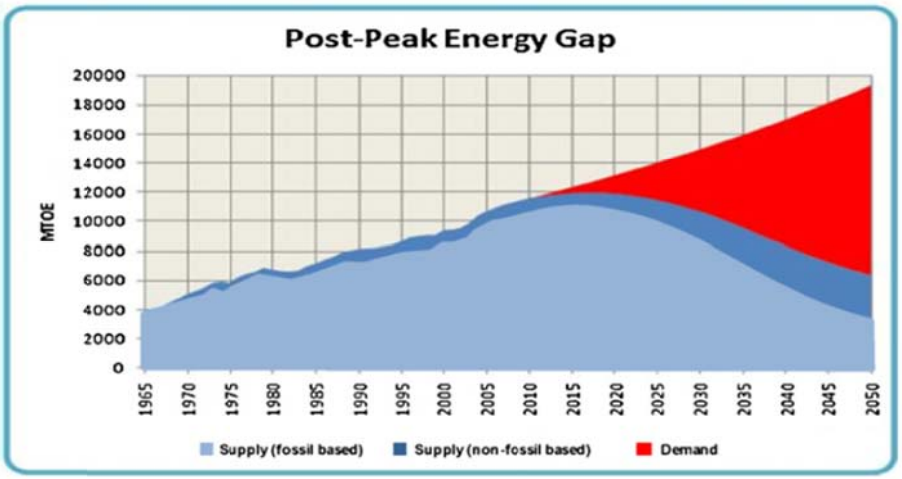


Figure 4-3 Growing gap between energy supply and demand (Seow et al., 2011)

Considering the hierarchical structure of a manufacturing plant and associated planning functions, shop floor schedules have an impact on schedules at the equipment level. As a result, shop floor schedules could significantly affect energy consumption as well as other environment impacts of an individual machine. Optimized operation schedules could further reduce energy costs. Compared to machine or process redesign, implementation of optimized shop floor scheduling and plant operation strategies only requires a modest capital investment (Fang et al., 2011). Unfortunately, although a variety of performance measures have been considered for shop scheduling, these efforts have largely focused on economic, time, or operational considerations. In contrast, research on scheduling with environmentally-oriented objectives is relatively scarce. Seldom of the previous studies addressed energy related objectives in modelling the scheduling problem.

4.4.1.2 Energy Consumption by a Specified Machine Tool

Figure 4-4 shows the power profile of an exemplary turning process (Li et al., 2010), from which we can see that the energy consumption of a machine tool results from the temporal power demand which is not static but rather dynamic throughout a machining process. The variable power includes not only the power required for removing material but also the process-depended operation of components (e.g. spindle rotation and movement of axis). Apart from that, the constant power demand resumes the fixed, machine-related power ensuring a functional mode of operation (ready for operation) (Li et al., 2011).

Machine tools can be characterized as assemblies of components ensuring a specific function (Weck et al., 2006). Each component performs a particular act enabling the entire machine to perform more complex, useful functions. Table 4-1 summarizes briefly the individual functions of electrical components in machine tools which can generally be classified into spindle drives, servo drives, hydraulic system periphery system, cooling and lubrication system, control system and auxiliary system (Li et al., 2011).

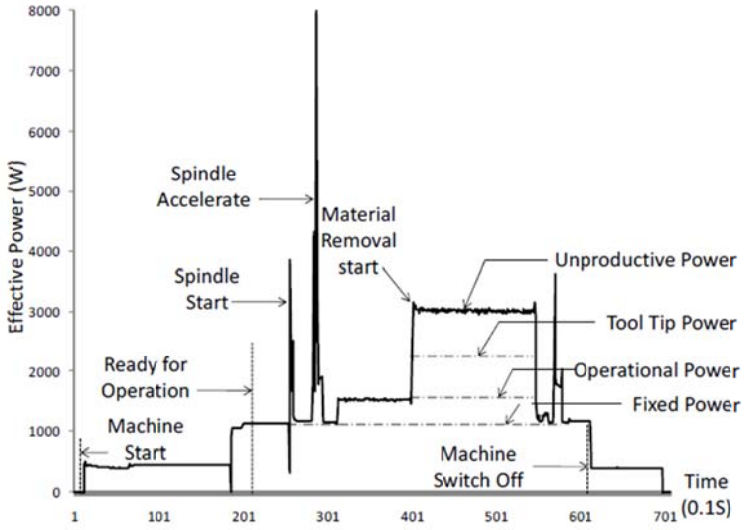


Figure 4-4 Power profile of a turning process (Li et al., 2010)

Table 4-1 The individual functions of electrical components in machine tools

	Component	**Function**
Spindle Drives	Main Spindle Motor	Besides rotary motion, holds as well as centers work piece
	Rotary Tool Spindle Motor	Rotary motion for cutting tool
Servo Drives	i-Axis Motor	Linear motion for cutting tools towards i-axis
	Tailstock Spindle	Besides rotary motion, holds as well as centers work piece at tailstock
	Turret Motor	Rotary motion for cutting tool change
Hydraulic System	Hydraulic Unit Motor	Rotary motion for pump to supply clamping pressure
Cooling Lubrication System	Lubricant Pump Motor	Rotary motion for pump to supply lubricant
	Oil Cooler Pump Motor	Rotary motion for pump to supply oil cooler circuit
Control System	Spindle Amplifier/Frequency Converter	Transfer numerical control signal for spindle rotation speed into adjusted electrical signal
	Servo Amplifier/Frequency Converter	Transfer numerical control signal for servo feed into adjusted electrical signal
Auxiliary System	Computer and Display	Processing and visualization of program
	Lightning	Lightning the working area
	Fan	Air flow generation for cooling electrical components
Periphery System	Coolant Pump Motor	Rotary motion for pump to supply coolant circuit with pressure
	Chip Conveyer Motor	Rotary motion for chip conveyer
	Tool Change Arm Motor	Rotary motion for tool change

According to previous research on manufacturing energy consumption, the energy requirements for the active removal of material can be quite small compared to the background functions needed for manufacturing equipment operation. (Drake et al., 2006) showed that there are significant amounts of energy associated with machine start-up and machine idling. As a result, in a mass production environment, more than 85% of the energy is utilized for functions that are not directly related to the production of parts (Fang et al., 2011). The research in (Gutowski et al., 2005) and (Kordonowy, 2001) also proposed the same conclusion, as shown in Figure 4-5 and Figure 4-6.

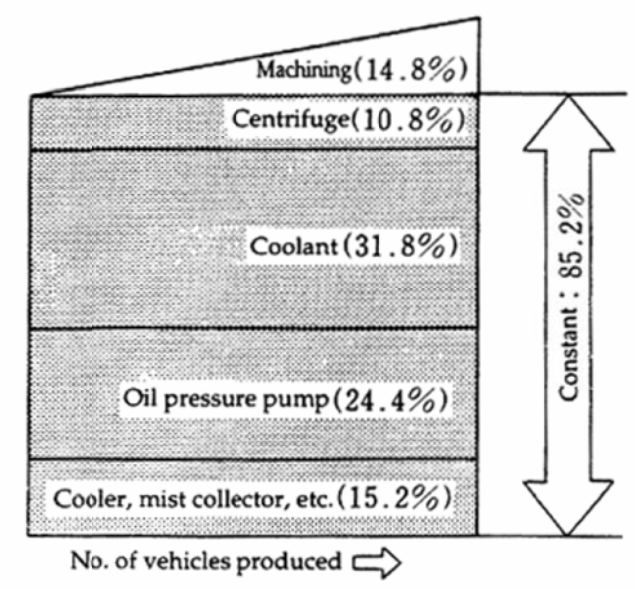


Figure 4-5 Energy used as a function of a production rate for an automobile production machining line (Gutowski et al., 2005)

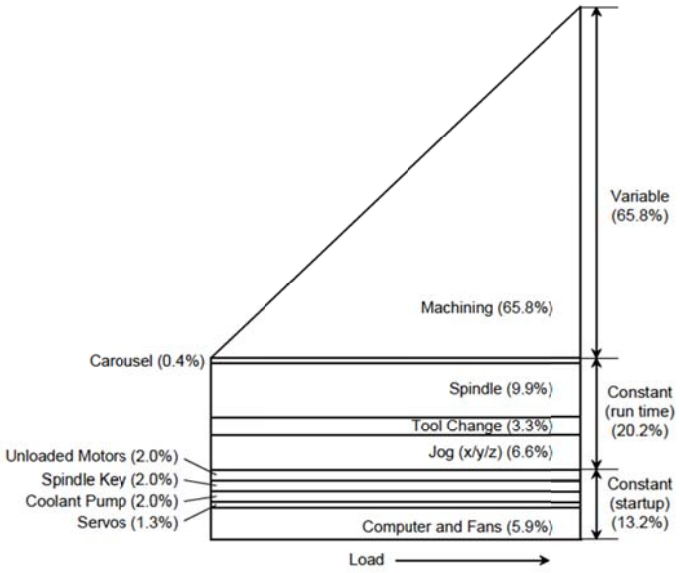


Figure 4-6 Energy used as a function of material removal rate for 3-axis CNC milling machine (Kordonowy, 2001)

Based on the above analysis, the energy consumed by a certain machine tool when it is machining the parts can be divided into three categories:

- **Basic energy:** corresponds to the lowest power level of machine tool operation. For the basic level, machine tool energy is consumed by lighting, the NC controller, chiller system, oil pump, and way lube system. Activities performed while the machine tool is at the basic power level include work piece loading/unloading, positioning, and fixturing.
- **Idle Energy:** corresponds to a power level higher than the basic level. For the idle power level, the main spindle is turned on and power is also provided to the automatic tool changer and cutting fluid pump. Activities performed while the machine tools is at the idle power level include the tool approaching the work piece, the tool retracting from the work piece, too motion between features, adjustments in the machine settings, and tool change operations.
- **Cutting energy:** corresponds to a power level and the period of time when material is actually being cut.

The above literature study and analysis can offer some tips in establishing the mathematical model of IPPS considering energy consumption of the machines, and the following factors should be paid attention to:

(1) As shown in Figure 4-4, machine tool passes different state to achieve operational readiness. During this period, machine tool not only consumes electrical energy but also requires a certain amount of time to achieve operational readiness. The same situation is applied to machine power-off stage. Therefore, in the proposed mathematical model considering energy consumption, we will assume that once a machine tool is turned on for machining the parts, it will not be turned off until it finishes the last operation of the jobs processed on it.

(2) To practice energy saving strategies, it is essential to acknowledge the energy performance of the machine tool during start-up, standby and power-off stages. However, the existing machine documentations do not provide sufficient information for energy consumption estimation. Moreover, energy metering and monitoring of each individual machine is time consuming and costly. In order to avoid further physical measurements at machine level, it is important that the machine documentation should provide sufficient information of energy consumption to improve the transparency of the machine tool (Li et al., 2011). As thus, one of the future trends of machine tool design is to include power demand of the electrical consumer at different stages in the machine manuals, namely the energy consumed by a certain machine with a certain production rate will be clear and transparent, making energy consumption as one of the important parameters of the machine tool.

(3) As the active removal of material can be quite small compared to the background functions needed for manufacturing equipment operation, when designing the parameters of energy consumption for the machine tools, the proportion between the cutting energy consumption and non-cutting energy consumption should be determined properly.

4.4.2 Mathematical Description of MOOP in IPPS

The IPPS problem can be defined as (Kim et al., 2003): Given a set of *N* jobs which are to be performed on *M* machines with routing flexibility, sequence flexibility and process flexibility, find an operations sequence and corresponding machines sequence for each job and a schedule in which operations on the same machines are processed such that it satisfies the precedence constraints and it is optimal with respect to some relevant criteria.

Three types of flexibility in production flexibility (Li et al., 2007):

- Routing flexibility: also called operation flexibility, relates to the possibility of performing one operation on alternative machines, with possibly distinct processing time and cost.
- Sequencing flexibility is decided by the possibility of interchanging the sequence of the required operations.
- Processing flexibility is determined by the possibility of processing the same manufacturing feature with alternative operations or sequences of operations (Shao et al, 2009).

In the manufacturing systems considered in this study, the alternative process plan network and the optimally selected *s* alternative process plans of each part is designed and maintained. The generation of one scheduling plan is determined based on the minimum objectives. The mathematical mode of IPPS is defined here. In this thesis, scheduling is often assumed as job shop scheduling, and the mathematical model of IPPS is based on the mixed integer programming model of the job shop scheduling problem (JSP).

In order to solve this problem, the following assumptions are made (Lv and Qiao, 2013; Jain and Elmaraghy, 1997; Kim et al., 2003; Shao et al., 2009):

(1) Jobs are independent. Job preemption is not allowed and each machine can handle only one job at a time.

(2) The different operations of one job cannot be processed simultaneously.

(3) All jobs and machines are available at time zero simultaneously.

(4) After a job is processed on a machine, it is immediately transported to the next machine on its process, and the transmission time is assumed to be negligible.

(5) Setup time for the operations on the machines is independent of the operation sequence and is included in the processing times.

Based on these assumptions, the mathematical model of IPPS considering energy consumption is proposed and the notations used to explain the model are described below:

N the total number of jobs in the order;

M the total number of machines in the job shop;

G_i the total number of alternative process plans of job *i*;

o_{ijl}	the *j*th operation in the *l*th alternative process plan of job *i*;
P_{il}	the number of operations in the *l*th alternative process plan of job *i*;
$o_{ijl}.k$	here *k* is the id of the alternative machine corresponding to o_{ijl};
Machine_list()	the candidate machine list for executing the operations;
t_{ijlk}	the processing time of operation o_{ijl} on machine *k*, $t_{ijlk}>0$;
s_{ijlk}	the starting machining time of operation o_{ijl} on machine *k*, $s_{ijlk}>0$;
$(c(o_{ijl}-1))_k$	the ending machining time of the precedent operation of o_{ijl} on the same machine *k*
c_{ijlk}	the earliest completion time of operation o_{ijl} on machine *k*; ($c_{ijlk}=s_{ijlk}+t_{ijlk}$)
VM_k	the machining cost per unit time when processing an operation with machine *k*
VI_k	the idle cost per unit time when machine *k* is in idle status (namely when machine is turned on but not processing any operation)
d_i	the due date of job *i*;
c_i	the completion time of job *i*;
L_i	the lateness of job *i*;
E_i	the earliness of job *i*;
IP_k	the non-cutting power per unit time of machine k;
PP_k	the cutting power to process a job per unit time of machine k ;
SE_k	the setup energy (i.e. the energy consumed when turning on/off machine k)
$U_i=\begin{cases}1 & \text{if } c_i>d_i\\ 0 & \text{otherwise}\end{cases}$	the unit penalty of job *i*;
$X_{il}=\begin{cases}1 & \text{the } l\text{th alternative process plan of job } i \text{ is selected}\\ 0 & \text{otherwise}\end{cases}$	

$$Y_{ijlpqsk} = \begin{cases} 1 & \text{if the operation } o_{ijl} \text{ percedes the operation } o_{pqs} \text{ on machine } k \\ 0 & \text{otherwise} \end{cases}$$

$$Z_{ijlk} = \begin{cases} 1 & \text{if machine } k \text{ is selected for } o_{ijl} \\ 0 & \text{otherwise} \end{cases}$$

$$W_1 = \begin{cases} 1 & \text{if } X \neq Y \\ 0 & \text{if } X = Y \end{cases} \qquad W_2 = \begin{cases} 0 & \text{if } X = Y = 0 \\ 1 & \text{otherwise} \end{cases}$$

Objectives:

(1) Minimizing *makespan* which is the completion time of the last operation of all jobs.

$$f_1 = Min\ makespan = Min\ Max\left\{c_{ijlk} \cdot X_{il} \cdot Z_{ijlk}\right\} \tag{4-11}$$

$$\forall i \in [1,N], \forall j \in [1,P_{il}], \forall l \in [1,G_i], \forall k \in [1,M]$$

(2) Balanced level of machine utilization. The standard deviation concept is used here to evaluate the balanced machine utimization.

$$Machine[k].Utilization = \sum_{i=1}^{N} \sum_{i=1}^{G_i} \sum_{j=1}^{P_{il}} (t_{ijlk} \cdot X_{il} \cdot Z_{ijlk}) + ML_k \cdot Z_{ijlk}$$

$$c = \frac{\sum_{k=1}^{M} (Machine[k].Utilization)}{M}$$

$$f_2 = Min\ \text{Utilization\_Level\_Deviation} = \text{Min}\sqrt{\sum_{k=1}^{M} (Machine[k].Utilization - c)^2} \tag{4-12}$$

(3) Minimizing energy consumption(the total energy consumption = the energy consumption in machining the operations + the energy consumption when machines are in idle status)

$$f_3 = Min\ energy\_consumption = \sum_{i=1}^{N} \sum_{l=1}^{G_i} \sum_{j=1}^{P_{il}} \sum_{k=1}^{M} ((t_{ijlk} \cdot X_{il} \cdot Z_{ijlk}) PP_k + (s_{ijlk} - (c(o_{ijl} - 1))_k) IP_k) \tag{4-13}$$

(4) Minimizing the total machining cost: (the total machining cost = the cost when the machines are processing the operations + the cost when machines are in idle status)

$$f_4 = Min\ TMC = \sum_{i=1}^{N} \sum_{l=1}^{G_i} \sum_{j=1}^{P_{il}} \sum_{k=1}^{M} ((t_{ijlk} \cdot X_{il} \cdot Z_{ijlk}) VM_k + (s_{ijlk} - (c(o_{ijl} - 1))_k) VI_k)) \tag{4-14}$$

$$\forall i \in [1,N], \forall j \in [1,P_{il}], \forall l \in [1,G_i], \forall k \in [1,M]$$

Constraints:

(1) For the first operation in the alternative process plan l of job i:

$$(c_{i1lk} \cdot X_{il} \cdot Z_{i1lk}) + A(1 - X_{il}) \cdot t_{i1lk} \cdot Z_{i1lk} \cdot X_{il} + ML_k \cdot Z_{i1lk} \tag{4-15}$$

$$\forall i \in [1,N], \forall l \in [1,G_i], \forall k \in [1,M]$$

(2) For the last operation in the alternative process plan l of job i:

$$(c_{iP_{il}lk} \cdot X_{il} \cdot Z_{iP_{il}lk}) - A(1 - X_{il}) \le makespan \tag{4-16}$$

$$\forall i \in [1,N], \forall l \in [1,G_i], \forall k \in [1,M]$$

(3) The different operations of one job cannot be processed simultaneously:

$$c_{ijlk} \cdot X_{il} \cdot Z_{ijlk} - c_{i(j-1)lk_1} \cdot X_{il} \cdot Z_{i(j-1)lk_1} + A(1 - X_{il}) \cdot (t_{ijlk} + tt(k,k_1)) \cdot X_{il} \cdot Z_{ijlk} \tag{4-17}$$

$$\forall i \in [1,N], \forall j \in [1,P_{il}], \forall l \in [1,G_i], \forall k,k_1 \in [1,M]$$

(4) Each machine can handle only one job at a time:

$$\begin{aligned}&(c_{pqsk} \cdot Z_{pqsk} \cdot X_{ps}) - (c_{ijlk} \cdot X_{il} \cdot Z_{ijlk}) + A(1 - X_{il}) + A(1 - X_{ps}) \\ &+ A(1 - Y_{ijlpqsk} \cdot Z_{ijlk} \cdot Z_{pqsk} \cdot X_{il} \cdot X_{ps}) \cdot (t_{pqsk} \cdot Z_{pqsk} \cdot X_{ps})\end{aligned} \tag{4-18}$$

$$\begin{aligned}&(c_{ijlk} \cdot X_{il} \cdot Z_{ijlk}) - (c_{pqsk} \cdot Z_{pqsk} \cdot X_{ps}) + A(1 - X_{il}) + A(1 - X_{ps}) \\ &+ A(Y_{ijlpqsk} \cdot Z_{ijlk} \cdot Z_{pqsk} \cdot X_{il} \cdot X_{ps}) \cdot (t_{ijlk} \cdot Z_{ijlk} \cdot X_{il})\end{aligned} \tag{4-19}$$

$$\forall i,p \in [1,N], \forall j,q \in [1,P_{il}], \forall l,s \in [1,G_i], \forall k \in [1,M]$$

(5) Only one alternative process plan can be selected of job i:

$$\sum_{l} X_{il} = 1 \quad \forall i \in [1,N] \tag{4-20}$$

(6) Only one machine for each operation should be selected:

$$\sum_{k=1}^{M} Z_{ijlk} = 1 \quad \forall i \in [1,N], \forall j \in [1,P_{il}], \forall l \in [1,G_i] \tag{4-21}$$

(7) There is only one precedence relation between two operations in a scheduling plan:

$$Y_{ijlpqsk} \cdot Z_{ijlk} \cdot Z_{pqsk} \cdot X_{il} \cdot X_{ps} \le 1 \tag{4-22}$$

$$(Y_{ijlpqsk} \cdot X_{il}) \le (Z_{ijlk} \cdot X_{il}) \tag{4-23}$$

$$(Y_{ijlpqsk} \cdot X_{ps}) \le (Z_{pqsk} \cdot X_{ps}) \tag{4-24}$$

$$\forall i,p \in [1,N], \forall j,q \in [1,P_{il}], \forall l,s \in [1,G_i], \forall k \in [1,M]$$

$$\sum_{i}^{N} \sum_{j}^{P_{il}} \sum_{l}^{G_i} (Y_{ijlpqsk} \cdot X_{il} \cdot Z_{ijlk}) = \sum_{o_{k1}}^{o_{pqsk}-1} Z_{o_{km}} \tag{4-25}$$

$$"p\hat{I}[1,N],"q\hat{I}[1,P_{il}],"s\hat{I}[1,G_i],"k\hat{I}[1,M]$$

Where $\sum_{o_{k1}}^{o_{pqsk}-1} Z_{o_{km}}$ means the total number of operations before o_{pqs} on machine k; o_{k1} means the first operation on machine k; o_{pqsk} means the current operation on machine k.

(8) The completion time of each operation should be either positive or zero.

$$c_{ijlk} \cdot X_{il} \cdot Z_{ijlk} \geq 0 \tag{4-26}$$

4.5 Design of the Improved NSGA-II

To describe the design of the improved NSGA-II, we firstly assume there are 3 jobs in an order received by the job shop and each job has 3 alternative process plans. As shown in Table 4-2. (Note: in the table, the number out of the bracket is machine No. and the number in the bracket is the time needed to by this machine to finish the operation)

Table 4-2 The part information: the alternative process plans for 3 jobs

Jobs	Three alternative process plans of each job
Job 1	1(3)-2(4)-2(4)-3(3) 1(5) -1(3)-3(5) 2(2) -1(3)-1(3)-1(4)
Job 2	1(3) -1(4)-2(3)-3(5) 1(3)-2(2)-3(4) 2(4) -1(6)-1(3)-1(2)
Job 3	1(4) -1(5)-2(3)-3(4) 1(4)-2(6)-1(4) 2(2)-1(6)-1(3)-1(4)

4.5.1 Encoding and Decoding

(1) Encoding

Each chromosome in the population consists of two parts with different length as shown in Figure 4-7.

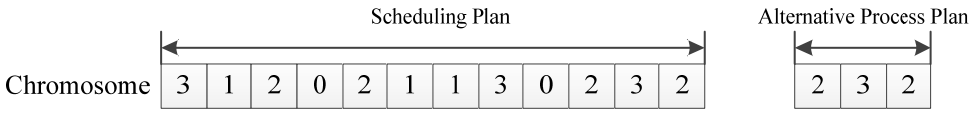


Figure 4-7 The example of the chromosome of a scheduling plan

Scheduling plan string: in this thesis, the operation-based representation with job numbers is adopted in scheduling plan encoding. The scheduling plan chromosome is presented by a permutation of the operations of each job. It is practicable in representing the

operation as a sequence and then the crucial information containing parents can be easily passed on to the offspring. The job numbers are used to represent the operations of the jobs. In this representation, each job number appears P_{il} times in the chromosome. By scanning the chromosome from left to right, the *f*th appearance of a job number refers to the *f*th operation in the selected alternative process plan of this job. The important feature of this representation is that any permutation of the chromosome can be decoded to a feasible solution. It is assumed that there are *N* jobs, and q_i is the number of operations of the process plan that has the most operation numbers among all the alternative process plans of the job *i*. Then the length of the scheduling plan string is equal to $\sum q_i$. The number of appearances of *i* in the scheduling plan string is equal to the number of operations of the selected alternative process plan based on this principle, the composition elements of scheduling plan string are determined. If the number of elements is less than $\sum q_i$, all the other elements are filled with 0. Therefore, the scheduling plan string is made up of jobs' numbers and 0. One scheduling plan string is generated by arraying all the elements randomly.

Alternative process plan string: in the alternative process plan string, the positions from 1 to *N* represent the jobs from Job 1 to Job *N*. The number in the *i*th position represents the selected alternative process plan of the job *i*. The number of appearances of *i* in the scheduling plan string is equal to the number of operations of the alternative process plan which has been chosen. Based on this principle, the composition elements of scheduling plan string are determined. And the process plan string is generated by choosing the alternative process plan randomly for every job. For example, in Figure 4-7, the selected alternative process plan for Job 1 to Job 3 is the 2nd, 3rd and 2nd alternative process plan respectively.

Table 4-2 shows an example of 3 jobs and each job has 3 alternative process plans. Figure 4-7 shows an individual scheduling plan of this example. In this example, *N* is equal to 3, and q_i =4 (*i*=1, 2, 3). Therefore, the scheduling plan string is consisted of 12 elements and the process plan string is consisted of three elements. For Job 1, the second alternative process plan is chosen, with three operations in this process plan. Thus three elements of '1' will appear in the scheduling plan string. For Job 2, the third alternative process plan is chosen, with four operations in this process plan, and four elements of '2' will appear in the scheduling plan string. For Job 3, the second alternative process plan is chose, with three operations in this process plan, therefore three elements of '3' will appear in the scheduling plan string. As such, the scheduling plan string is made up three '1', four '2' and three '3'. The other elements of this string are 0, and the number of 0 is equal to 2=12-3-4-3. And all these elements are arrayed randomly to generate a scheduling plan string.

(2) Decoding

The permutations can be decoded into semi-active, active, non-delay, and hybrid schedules. To obtain minimal makespan, the active schedule is adopted. Recall that at this decoding stage, a particular individual of a scheduling population has been determined, that

is, a fixed alternative process plan for each job is given. The notations used to explain the procedure are described below:

m the total number of machines;

o_{ij} the *j*th operation of the *i*th job;

as_{ij} the allowable starting time of operation o_{ij} ;

s_{ij} the earliest starting time of operation o_{ij} ;

k the machine used by operation o_{ij} ;

t_{ijk} the processing time of operation o_{ij} on machine k;

c_{ij} the completion time of operation o_{ij} , $c_{ij} = s_{ij} + t_{ijk}$.

As shown in Figure 4-8, the transformation from semi-active decoding to active decoding is as following.

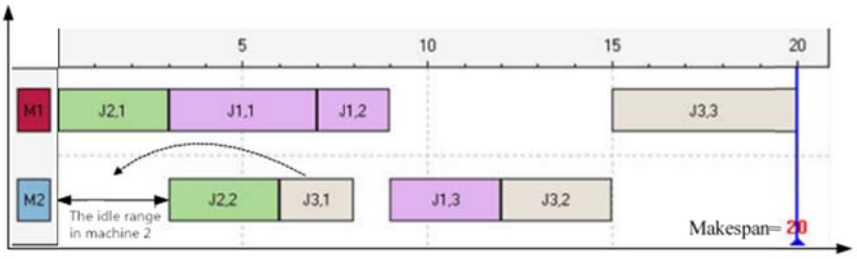


Figure 4-8(a) The semi-active encoding

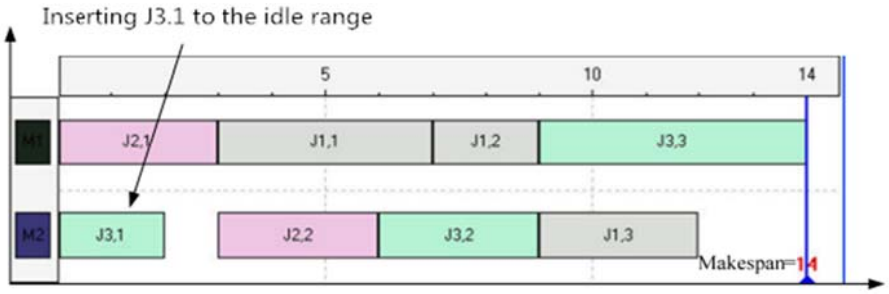


Figure 4-8(b) The active decoding

Figure 4-8 Transformation from semi-active decoding to active decoding

Step1: transforming the chromosome to the corresponding operation list, according which the corresponding machine list and processing time list will be obtained;

Step 2: determining the set of operations for every machine: $M_a = \{o_{ij}\}\ 1 \leq a \leq M$;

Step 3: determining the set of machines for every job: $JM_d = \{machine\}\ 1 \pounds\ d \pounds\ N$;

Step 4: obtaining the allowable starting time for every operation:

$as_{ij} = c_{i(j-1)}\ (o_{ij}\ \hat{I}\ M_a)$, and $c_{i(j-1)}$ is the completion time of the pre-operation of o_{ij} for the same job.

Step 5: check the idle time of the machine of o_{ij}, and get the idle ranges (t_s, t_e), check these ranges in turn:

$if: \max(as_{ij}, t\_s) + t_{ijk} \pounds\ t\_e,\ s_{ij} = t\_s;$

$else$: check the next idle range.

If there is no range satisfying this condition: $s_{ij} = \max(as_{ij}, c(o_{ij}-1))$. $c(o_{ij}-1)$ is the completion time of the pre-operation of o_{ij} for same machine.

Step 6: the completion time of every operation: $c_{ij} = s_{ij} + t_{ijk}$;

Step 7: Generate the sets of starting time and completion time for every operation of each job: $T_d(s_{ij}, c_{ij})\ 1 \pounds\ d \pounds\ N$.

4.5.2 Initial Population

The encoding principle in this thesis is an operation-based representation. It cannot break the constraints on precedence relations of operations. The initial population is generated based on the encoding principle.

4.5.3 Genetic Operators

(1) Selection

In this thesis, the tournament selection scheme has been used for selection operation. In tournament selection, a number of individuals are selected randomly (depending on the tournament size, typically between 2 and 7) from the population and the individual with the best fitness is chosen for reproduction. The tournament selection approach allows a tradeoff to be made between exploration and exploitation of the gene pool (Moon et al., 2008; Shao et al., 2009). This scheme can modify the selection pressure by changing the tournament size.

(2) Crossover

As shown in Figure 4-9, the procedure of crossover is described as follows:

Step 1: Select a pair of parent chromosomes P1 and P2 by the selection scheme and initialize two empty offspring: O1 and O2.

Step 2: Crossover of the alternative process plan strings.

Firstly, crossover the alternative process plan strings of P1 and P2 and get the alternative process plan strings of O1 and O2, as following:

Step 2.1: Compare the two parent alternative process plan strings of P1 and P2, if the element of P1 is the same as P2, record the value and position of this element. This process is repeated until the end of comparing all the elements of the two alternative process plan strings.

Step 2.2: The recorded elements in P1 in Step 2.1 are added to the same positions in O1, while the recorded elements in P2 in Step 2.1 are added to the same positions in O2. The other elements (the different elements between P1 and P2) in P2 are added to the same positions in O1, while the other elements in P1are added to the same positions in O2.

Step 3: Crossover of the scheduling plan strings.

Secondly, in order to match the process plan strings of O1and O2 and avoid getting unreasonable O1 and O2, the scheduling plan strings of P1and P2 are crossovered as follows:

Step 3.1: If the values of elements in scheduling plan string of P1 are the same as the recorded positions in the alternative process plan string, these elements (including 0) are append to the same positions in O1 and they are deleted in P1. If the values of elements in scheduling plan string of P2 are the same as the recorded positions in the alternative process plan string, these elements (including 0) are append to the same positions in O2 and they are deleted in P2.

Step 3.2: Get the numbers of the remaining elements in scheduling plan of P1 and P2, they are n_1 and n_2. If $n_1 \ ^3 \ n_2$, for O1, it implies that the numebr of empty positions in O1 is larger than the number of remaining elements in P2. Therefore, $n_1 - n_2$ empty positions in O1 are selected randomly and be filled with 0. Then, the remaining elements in scheduling plan of P2 are added to the remaining empty positions in O1 seriatim. For O2, $n_1 \ ^3 \ n_2$ means that the number of empty positions in O2 is smaller than the number of remaining elements in P1. So $n_1 - n_2$ 0s are selected randomy in O2 and are set to empty. And then, the remaining elements in scheduling plan of P1 are added to the emtpy position in O2 seriatim. If $n_1 < n_2$, the procedure is reversed.

Step 4: then two valid offspring O1 and O2 are obtained.

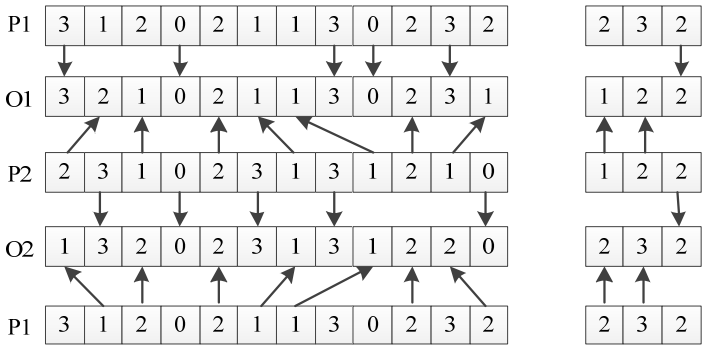


Figure 4-9 The crossover operation of the scheduling plan chromosome

(3) Mutation

As shown in Figure 4-10, two kinds of mutation operators are used in this thesis: one is two-point swapping mutation, and the other one is changing one job's alternative process plan. In the evolution procedure, one operator has been chosen randomly in every generation.

The procedure of two-point swapping mutation for scheduling is described as follows:

Step 1: select one parent chromosome P by the selection scheme.

Step 2: select two points in the scheduling plan string of P randomly.

Step 3: Generate a new offspring chromosome O by interchanging these two elements.

The procedure of the other mutation of changing one job's alternative process plan for scheduling is described as follows:

Step 1: select one chromosome P by the selection scheme.

Step 2: Select one point in the process plan string of P randomly.

Step 3: Change the value of this selected element to another one in the selection range (the number of alternative process plans).

Step 4: Judge the number of the operations of the selected job's alternative process plan which has been changed. If it increases, a new chromosome O is generated by changing the margin 0s which are selected randomly to the job number in the scheduling plan string of P seriatim. If it decreases, a new chromosome O is generated by changing the margin job numbers which are selected randomly in the scheduling plan string of P to 0 seriatim.

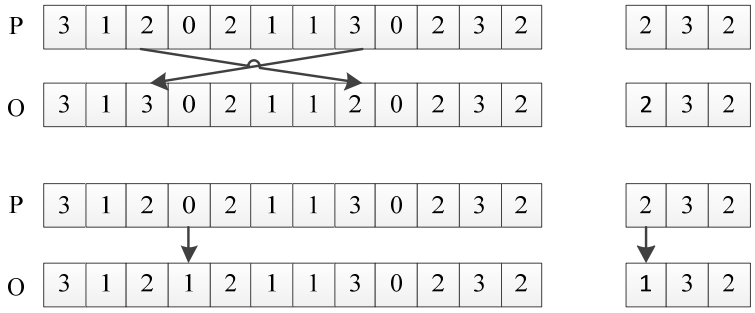


Figure 4-10 Mutation Operations

4.6 Case studies and Discussions

Some case studies have been conducted to measure the adaptability of the improved NSGA-II algorithm and to verify the proposed mathematical model for solving the MOOP problems in IPPS. The improved NSGA-II approach procedures were coded in Matlab Language. To illustrate the effectiveness and performance of the method, two problem instances will be conducted. The GA parameters are set as shown in Table 4-3. The algorithm terminates when the number of generations reaches the maximum value.

Table 4-3 GA parameters

Parameters	Values
The size of the population, *S*	100
Total number of generations, *M*	100
Tournament size, *b*	2
Probability of selection operation, p_r	0.10
Probability of crossover operation, p_c	0.80
Probability of mutation operation, p_m	0.10

4.6.1 Case Study 1

Test problems: three jobs with 3 optimally selected alternative process plans for each job, as shown in Table 4-4. (Note: in the table, the number out of the bracket is machine No. and the number in the bracket is the time needed to by this machine to finish the operation). Five machining tools (M1-M3: lathe; M4: grinder; M5: milling machine) are available in the job shop. The machining cost per unit time of each machine tool is (8 7 10 12 16). Three objectives were considered in this experiment: (Note: M1 stands for Machine 1)

- Minimizing makespan;
- Balance level of machine utilization;
- Minimizing the total machining cost.

Table 4-4 The part information: the alternative process plans for 3 jobs

Jobs	Three alternative process plans of each job
Job 1	1(3)-2(4)-2(4)-3(3) 1(5) -1(3)-3(5) 2(2) -1(3)-1(3)-1(4)
Job 2	1(3) -1(4)-2(3)-3(5) 1(3)-2(2)-3(4) 2(4) -1(6)-1(3)-1(2)

Job 3	1(4) -1(5)-2(3)-3(4) 1(4)-2(6)-**1**(4) 2(2)-1(6)-**1**(3)-1(4)

The Pareto optimal solutions finally generated is shown as Figure 4-11. The Pareto optimal solutions are shown in Table 4-5.

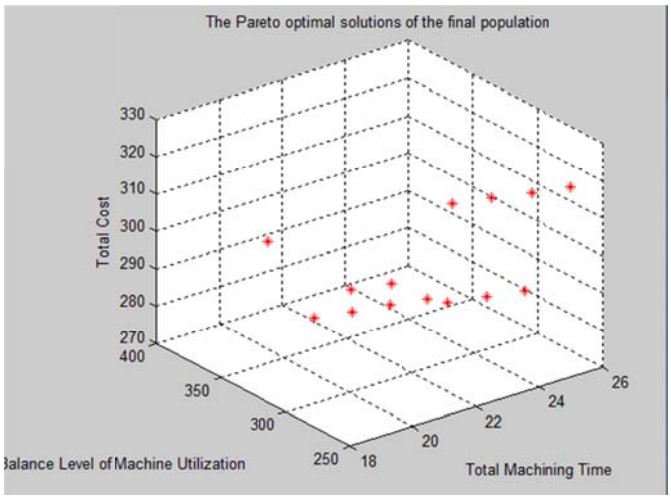


Figure 4-11 The Pareto optimal solutions

Table 4-5 The Pareto optimal results

Pareto Optimal Solutions	***f*1: minimizing makespan**	***f*2: balance level of machine utilization**	***f*3: minimizing machine cost**	**The selected process plan for each part type**
1	**19**	337.4	306	J1: 1(3)-2(4)-2(4)-3(3) J2: 1(3)-2(2)-3(4) J3: 2(2)-1(6)-1(3)-1(4)
2	**19**	337.4	306	J1: 1(3)-2(4)-2(4)-3(3) J2: 1(3)-2(2)-3(4) J3: 2(2)-1(6)-1(3)-1(4)
3	20	298.0	298	J1: 1(5) -1(3)-3(5) J2: 1(3)-2(2)-3(4) J3: 1(4)-2(6)-1(4)
4	21	291.8	298	J1: 1(5) -1(3)-3(5) J2: 1(3)-2(2)-3(4) J3: 1(4)-2(6)-1(4)
5	21	351.2	**278**	J1: 2(2) -1(3)-1(3)-1(4) J2: 1(3)-2(2)-3(4) J3: 1(4)-2(6)-1(4)
6	22	345.8	**278**	J1: 2(2) -1(3)-1(3)-1(4) J2: 1(3)-2(2)-3(4) J3: 1(4)-2(6)-1(4)
7	22	272.2	294	J1: 1(3)-2(4)-2(4)-3(3) J2: 1(3)-2(2)-3(4) J3: 1(4)-2(6)-1(4)
8	22	268.6	321	J1: 1(3)-2(4)-2(4)-3(3) J2: 1(3)-2(2)-3(4) J3: 1(4) -1(5)-2(3)-3(4)
9	23	340.8	**278**	J1: 2(2) -1(3)-1(3)-1(4) J2: 1(3)-2(2)-3(4)

				J3: 1(4)-2(6)-1(4)
10	23	262.0	321	J1: 1(3)-2(4)-2(4)-3(3) J2: 1(3)-2(2)-3(4) J3: 1(4) -1(5)-2(3)-3(4)
11	23	266.4	294	J1: 1(3)-2(4)-2(4)-3(3) J2: 1(3)-2(2)-3(4) J3: 1(4)-2(6)-1(4)
12	24	255.8	321	J1: 1(3)-2(4)-2(4)-3(3) J2: 1(3)-2(2)-3(4) J3: 1(4) -1(5)-2(3)-3(4)
13	24	261.0	294	J1: 1(3)-2(4)-2(4)-3(3) J2: 1(3)-2(2)-3(4) J3: 1(4)-2(6)-1(4)
14	24	336.2	**278**	J1: 2(2) -1(3)-1(3)-1(4) J2: 1(3)-2(2)-3(4) J3: 1(4)-2(6)-1(4)
15	25	**250.0**	321	J1: 1(3)-2(4)-2(4)-3(3) J2: 1(3)-2(2)-3(4) J3: 1(4) -1(5)-2(3)-3(4)

Decision-makers can choose the most suitable scheduling result according to different objective(s) from the final Pareto optimal results shown in Table 4-5. For example, for minimizing makespan, the first and second result are the best; for balance level of machine utilization, the last one is the best; and for minimizing total machining cost, the 5th, 6th, 9th and 14th are the best.

Besides, from the Pareto optimal results, by comparing the values of the different objectives, we can see that the conflicts are existing between the objectives. E.g., while the balance level of machine utilization was minimized, the makespan and the total machining cost reach the maximum; and when makespan is minimized, the other two objectives values are not good.

The Gantt chart of the 1st result is shown in Figure 4-12.

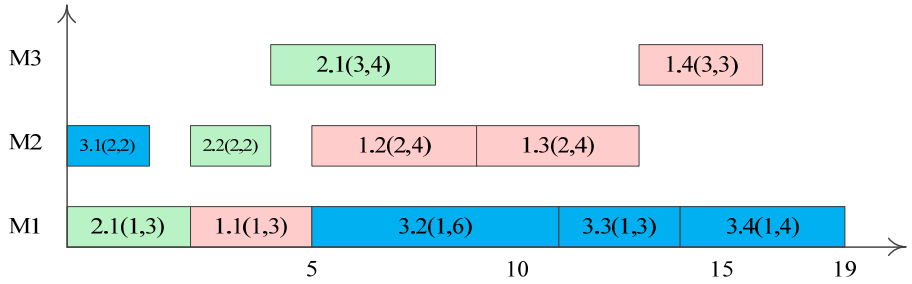


Figure 4-12 Gantt chart of the 1st result

4.6.2 Case Study 2

Case study 2 is designed as following: six jobs with 3 optimally selected alternative process plans for each job are received by the job shop, as shown in Table 4-6. (Note: in the table, the number out of the bracket is machine No. and the number in the bracket is the time needed to by this machine to finish the operation). Five machining tools (M1-M3: lathe; M4: grinder; M5: milling machine) are available in the job shop. (Note: M1 stands for Machine 1)

Machining cost per unit time for each machine:

M1(5) （Namely the machining cost per unit time of machine 1 is 5）, M2(5), M3(4), M4(6), M5(4)

Idle cost per unit time for each machine：

M1(0.5), M2(0.5), M3(0.4), M4(0.6), M5(0.4)

Non-cutting power consumption per unit time for each machine:

M1(1), M2(0.8), M3(0.8), M4(0.5), M5(0.3)

Cutting power consumption per unit time for each machine：

M1(10), M2(8), M3(8), M4(10), M5(6)

Four objectives are taken into consideration:

- f1: Minimizing makespan;
- f2: Balanced level of Machine Utilization;
- f3: Minimizing total power consumption;
- f4: Minimizing total machining cost.

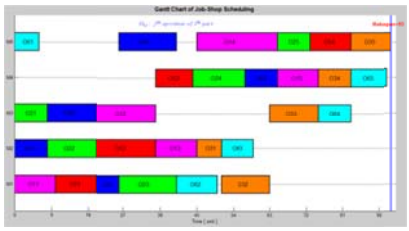
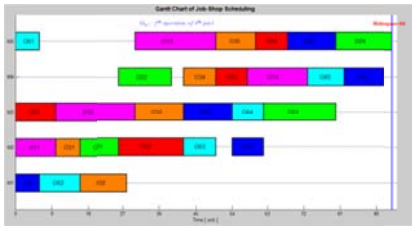
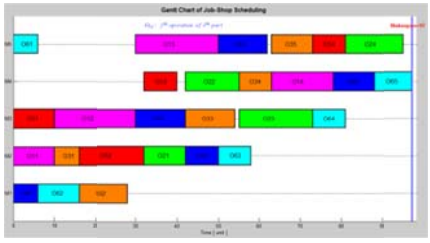
Table 4-6 The alternative process plans for 6 jobs

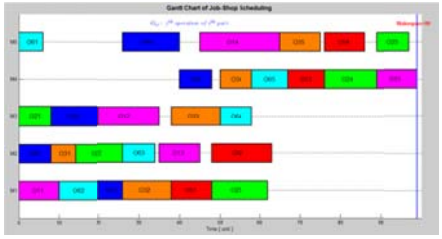
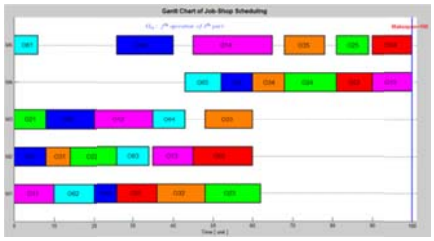
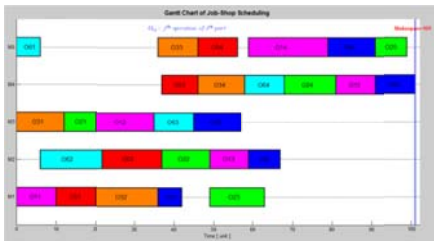
Jobs	Three alternative process plans of each job
Job 1	***P1:*** 1(10)-3(15)-2(10)-5(20)-4(10) ***P2:*** 1(10) -3(22)-4(21)-5(12) ***P3:*** 2(10) -3(20)-5(20)-4(15)
Job 2	***P1:*** 1(10) -3(18)-4(12)-5(15) ***P2:*** 3(8)-2(12)-1(14)-4(13)-5(8) ***P3:*** 2(10) -4(13)-3(18)-5(14)
Job 3	***P1:*** 3(12) -1(16)-5(10)-4(12) ***P2:*** 1(10)-2(8)-3(14)-4(6)-5(10) ***P3:*** 2(6)-1(12)-3(12)-4(8)-5(10)
Job 4	***P1:*** 1(6)-3(12)-2(8)-5(12)-4(10) ***P2:*** 3(10)-1(8)-2(9)-4(12)-5(10) ***P3:*** 2(8)-3(12)-1(6)-5(14)-4(8)
Job 5	***P1:*** 1(10) -2(15)-4(9)-5(10) ***P2:*** 3(10) -2(16)-4(8)-5(8) ***P3:*** 4(6) -3(10)-2(8)-1(10)-5(8)
Job 6	***P1:*** 5(6) -2(16)-3(10)-4(10) ***P2:*** 1(9) -2(7)-4(8)-5(8)-3(9) ***P3:*** 5(6) -1(10)-2(8)-3(8)-4(9)

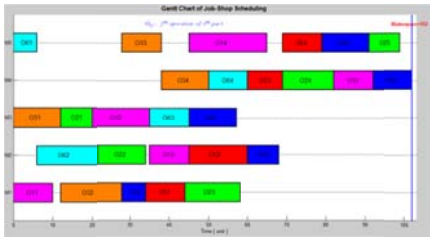
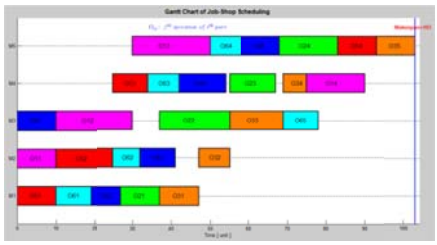
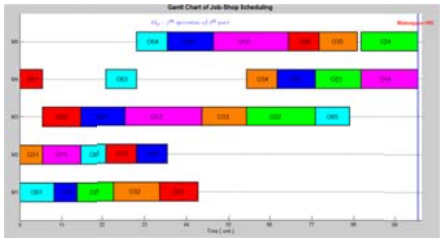
The Pareto optimal results obtained by using the improved NSGA-II are shown in Table 4-7.

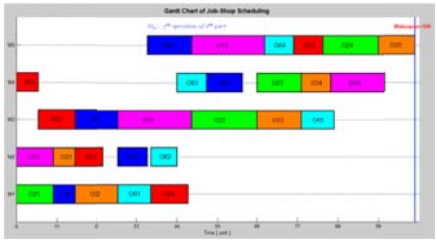
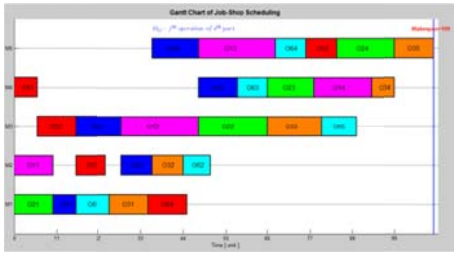
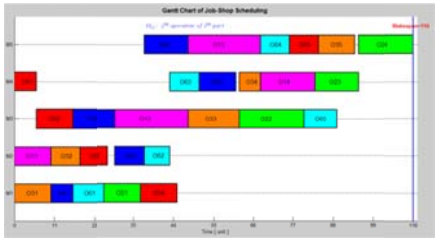
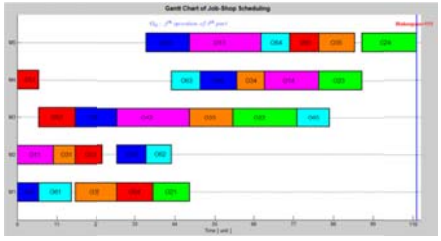
Table 4-7 The Pareto optimal results (the result in the red box is the best result for each objective)

POS	**f1**	**f2**	**f3**	**f4**	**Finally selected Process Plans for each job**	**Gantt chart**

1	90	10.14	1468	2543	J1: 1(10)-3(15)-2(10)-5(20)-4(10) J2: 3(8)-2(12)-1(14)-4(13)-5(8) J3: 2(6)-1(12)-3(12)-4(8)-5(10) J4: 2(8)-3(12)-1(6)-5(14)-4(8) J5: 1(10) -2(15)-4(9)-5(10) J6: 5(6) -1(10)-2(8)-3(8)-4(9)	
2	93	10.14	1460	2430	J1: 1(10)-3(15)-2(10)-5(20)-4(10) J2: 3(8)-2(12)-1(14)-4(13)-5(8) J3: 2(6)-1(12)-3(12)-4(8)-5(10) J4: 2(8)-3(12)-1(6)-5(14)-4(8) J5: 1(10) -2(15)-4(9)-5(10) J6: 5(6) -1(10)-2(8)-3(8)-4(9)	
3	94	10.14	1458	2447	J1: 1(10)-3(15)-2(10)-5(20)-4(10) J2: 3(8)-2(12)-1(14)-4(13)-5(8) J3: 2(6)-1(12)-3(12)-4(8)-5(10) J4: 2(8)-3(12)-1(6)-5(14)-4(8) J5: 1(10) -2(15)-4(9)-5(10) J6: 5(6) -1(10)-2(8)-3(8)-4(9)	
4	94	39.20	1421	2198	J1: 2(10) -3(20)-5(20)-4(15) J2: 2(10) -4(13)-3(18)-5(14) J3: 2(6)-1(12)-3(12)-4(8)-5(10) J4: 1(6)-3(12)-2(8)-5(12)-4(10) J5: 3(10) -2(16)-4(8)-5(8) J6: 5(6) -1(10)-2(8)-3(8)-4(9)	
5	96	39.20	1420	2182	J1: 2(10) -3(20)-5(20)-4(15) J2: 2(10) -4(13)-3(18)-5(14) J3: 2(6)-1(12)-3(12)-4(8)-5(10) J4: 1(6)-3(12)-2(8)-5(12)-4(10) J5: 3(10) -2(16)-4(8)-5(8) J6: 5(6) -1(10)-2(8)-3(8)-4(9)	
6	97	39.20	1419	2172	J1: 2(10) -3(20)-5(20)-4(15) J2: 2(10) -4(13)-3(18)-5(14) J3: 2(6)-1(12)-3(12)-4(8)-5(10) J4: 1(6)-3(12)-2(8)-5(12)-4(10) J5: 3(10) -2(16)-4(8)-5(8) J6: 5(6) -1(10)-2(8)-3(8)-4(9)	

7	98	9.23	1465	2491	J1: 1(10)-3(15)-2(10)-5(20)-4(10) J2: 3(8)-2(12)-1(14)-4(13)-5(8) J3: 3(12) -1(16)-5(10)-4(12) J4: 3(10)-1(8)-2(9)-4(12)-5(10) J5: 3(10) -2(16)-4(8)-5(8) J6: 1(9) -2(7)-4(8)-5(8)-3(9)	
8	98	24.15	1446	2343	J1: 2(10) -3(20)-5(20)-4(15) J2: 1(10) -3(18)-4(12)-5(15) J3: 1(10)-2(8)-3(14)-4(6)-5(10) J4: 3(10)-1(8)-2(9)-4(12)-5(10) J5: 1(10) -2(15)-4(9)-5(10) J6: 1(9) -2(7)-4(8)-5(8)-3(9)	
9	99	10.14	1455	2423	J1: 1(10)-3(15)-2(10)-5(20)-4(10) J2: 3(8)-2(12)-1(14)-4(13)-5(8) J3: 2(6)-1(12)-3(12)-4(8)-5(10) J4: 2(8)-3(12)-1(6)-5(14)-4(8) J5: 1(10) -2(15)-4(9)-5(10) J6: 5(6) -1(10)-2(8)-3(8)-4(9)	
10	99	24.15	1446	2373	J1: 2(10) -3(20)-5(20)-4(15) J2: 1(10) -3(18)-4(12)-5(15) J3: 1(10)-2(8)-3(14)-4(6)-5(10) J4: 3(10)-1(8)-2(9)-4(12)-5(10) J5: 1(10) -2(15)-4(9)-5(10) J6: 1(9) -2(7)-4(8)-5(8)-3(9)	
11	100	10.14	1454	2407	J1: 1(10)-3(15)-2(10)-5(20)-4(10) J2: 3(8)-2(12)-1(14)-4(13)-5(8) J3: 2(6)-1(12)-3(12)-4(8)-5(10) J4: 2(8)-3(12)-1(6)-5(14)-4(8) J5: 1(10) -2(15)-4(9)-5(10) J6: 5(6) -1(10)-2(8)-3(8)-4(9)	
12	101	8.65	1477	2469	J1: 1(10)-3(15)-2(10)-5(20)-4(10) J2: 3(8)-2(12)-1(14)-4(13)-5(8) J3: 3(12) -1(16)-5(10)-4(12) J4: 1(6)-3(12)-2(8)-5(12)-4(10) J5: 1(10) -2(15)-4(9)-5(10) J6: 5(6) -2(16)-3(10)-4(10)	

13	102	8.65	1475	2435	J1: 1(10)-3(15)-2(10)-5(20)-4(10) J2: 3(8)-2(12)-1(14)-4(13)-5(8) J3: 3(12) -1(16)-5(10)-4(12) J4: 1(6)-3(12)-2(8)-5(12)-4(10) J5: 1(10) -2(15)-4(9)-5(10) J6: 5(6) -2(16)-3(10)-4(10)	
14	103	24.15	1435	2212	J1: 2(10) -3(20)-5(20)-4(15) J2: 1(10) -3(18)-4(12)-5(15) J3: 1(10)-2(8)-3(14)-4(6)-5(10) J4: 3(10)-1(8)-2(9)-4(12)-5(10) J5: 1(10) -2(15)-4(9)-5(10) J6: 1(9) -2(7)-4(8)-5(8)-3(9)	
15	104	24.15	1431	2182	J1: 2(10) -3(20)-5(20)-4(15) J2: 1(10) -3(18)-4(12)-5(15) J3: 1(10)-2(8)-3(14)-4(6)-5(10) J4: 3(10)-1(8)-2(9)-4(12)-5(10) J5: 1(10) -2(15)-4(9)-5(10) J6: 1(9) -2(7)-4(8)-5(8)-3(9)	
16	105	9.23	1451	2292	J1: 1(10)-3(15)-2(10)-5(20)-4(10) J2: 3(8)-2(12)-1(14)-4(13)-5(8) J3: 3(12) -1(16)-5(10)-4(12) J4: 3(10)-1(8)-2(9)-4(12)-5(10) J5: 3(10) -2(16)-4(8)-5(8) J6: 1(9) -2(7)-4(8)-5(8)-3(9)	
17	105	34.94	1428	2425	J1: 2(10) -3(20)-5(20)-4(15) J2: 1(10) -3(18)-4(12)-5(15) J3: 1(10)-2(8)-3(14)-4(6)-5(10) J4: 1(6)-3(12)-2(8)-5(12)-4(10) J5: 4(6) -3(10)-2(8)-1(10)-5(8) J6: 1(9) -2(7)-4(8)-5(8)-3(9)	
18	106	24.15	1431	2167	J1: 2(10) -3(20)-5(20)-4(15) J2: 1(10) -3(18)-4(12)-5(15) J3: 1(10)-2(8)-3(14)-4(6)-5(10) J4: 3(10)-1(8)-2(9)-4(12)-5(10) J5: 1(10) -2(15)-4(9)-5(10) J6: 1(9) -2(7)-4(8)-5(8)-3(9)	

19	109	34.94	1427	2421	J1: 2(10) -3(20)-5(20)-4(15) J2: 1(10) -3(18)-4(12)-5(15) J3: 1(10)-2(8)-3(14)-4(6)-5(10) J4: 1(6)-3(12)-2(8)-5(12)-4(10) J5: 4(6) -3(10)-2(8)-1(10)-5(8) J6: 1(9) -2(7)-4(8)-5(8)-3(9)	
20	109	35.96	1426	2435	J1: 2(10) -3(20)-5(20)-4(15) J2: 1(10) -3(18)-4(12)-5(15) J3: 1(10)-2(8)-3(14)-4(6)-5(10) J4: 1(6)-3(12)-2(8)-5(12)-4(10) J5: 4(6) -3(10)-2(8)-1(10)-5(8) J6: 1(9) -2(7)-4(8)-5(8)-3(9)	
21	110	35.96	1420	2356	J1: 2(10) -3(20)-5(20)-4(15) J2: 1(10) -3(18)-4(12)-5(15) J3: 1(10)-2(8)-3(14)-4(6)-5(10) J4: 1(6)-3(12)-2(8)-5(12)-4(10) J5: 4(6) -3(10)-2(8)-1(10)-5(8) J6: 1(9) -2(7)-4(8)-5(8)-3(9)	
22	111	34.94	1425	2392	J1: 2(10) -3(20)-5(20)-4(15) J2: 1(10) -3(18)-4(12)-5(15) J3: 1(10)-2(8)-3(14)-4(6)-5(10) J4: 1(6)-3(12)-2(8)-5(12)-4(10) J5: 4(6) -3(10)-2(8)-1(10)-5(8) J6: 1(9) -2(7)-4(8)-5(8)-3(9)	

Obviously, the conflicts exist between different objectives. When makespan is minimized (the 1st result), the total machining cost reaches the maximum, and the total energy consumption almost reaches the maximum. The reason is that to minimize makespan, the machine tools that take less time to process the operations will be selected with preference, however, these machine tools are usually with higher inherent cost and machining cost, and the energy demand per unit time also will be higher for these machine tools to process the operations in shorter time.

When the balanced level of machine utilization is optimized (the 15th result), the other objectives are not good enough. The reason is that to achieve the optimal balanced level of machine utilization, the total machining time of the machine tools should be balanced. In this case, no priority order exists between the machine tools in light with machining efficiency, cost and energy consumption, resulting in the bad performance in other objectives.

And when the total energy consumption and total machining cost are minimized, the balanced level of machine utilization is not realized. Because the machine tools with lower machining cost and consuming less energy will be selected with high priority in this case, so

the balanced utilization of the machines cannot be guaranteed.

4.7 Conclusion

In this chapter, based on the concept of Multi-Objective Optimization Problem (MOOP), the complete mathematical model to explain and describe the MOOP in IPPS in a single job shop was established, in which some new parameters and objectives relating energy consumption in machining the parts were adopted according to the related study and analysis. Then based on the mathematical model, multi-objective optimization for IPPS problems was realized using the improved NSGA-II so that the decision-makers in the enterprises and job shops can make reasonable choices according to their preferences for the objectives. The encoding, decoding and genetic operators adopted in this improved NSGA-II method were explained in detail. Finally, two case studies have been conducted to measure the adaptability of the improved NSGA-II algorithm and to verify the proposed mathematical model for solving the MOOP problems in IPPS.

Chapter 5 Rescheduling Problem of IPPS in Dynamic Job Shop Simultaneously Considering Production Efficiency and Stability

Introduction:

A rescheduling process will be required in IPPS in Dynamic Job Shops (IPPS_DJS) when the unexpected disturbances occur. In this chapter, a rescheduling model simultaneously considering production efficiency and stability will be proposed. The measurements adopted in light of efficiency optimization will be makespan, machining cost, and energy consumption; while the measurements defined in stability optimization will be the machine-related deviation cost and job-related deviation cost caused in the rescheduling plan. In conducting IPPS_DJS, the three types of production flexibility (routing flexibility, sequence flexibility and process flexibility) will be used in the rescheduling process to maintain rescheduling flexibility. Then the mathematical model of the rescheduling problem in IPPS_DJS will be built, in which a final objective function will be proposed by weighting method considering both the measurements involved in efficiency and stability, which is more practical in decision-making in real manufacturing systems. Case studies will be designed to verify the proposed rescheduling model by using GA.

5.1 Framework of IPPS_DJS

5.1.1 Term Definition

In (GUILHERME et al., 2003), the terms relating to rescheduling are defined in detail, which will be used in this chapter, as following:

Order release controls a manufacturing system's input by determining which orders (jobs) should be moved into production. It may be known as job release, order review/release, input/output control, or just input control.

A ***production schedule*** specified, for each resource required for production, the planned start time and end time of each job assigned toe that resource.

Scheduling is the process of creating a production schedule for a given set of jobs and resources.

Rescheduling is the process of updating an existing production schedule in response to disruptions or other changes (namely rescheduling factors).

The ***rescheduling environment*** identifies the set of jobs that the schedule should include.

A ***rescheduling strategy*** describes whether or not production schedules are generated.

A ***rescheduling policy*** specifies when and how rescheduling is done. The policy specifies the events that trigger rescheduling. These events may be predictable (even regular) or unpredictable. The policy specifies the method used to revise the existing schedule.

Rescheduling methods generate and update production schedules.

Scheduling point *(or* ***rescheduling point****)*: the point in time when a scheduling decision is made (Sabuncuoglu and Karabuk, 1999), namely the point in time when a schedule is created or revised.

Scheduling stability: it measures the number of revisions or changes that a schedule undergoes during execution (Church and Uzsoy, 1992; Wu et al., 1993).

***Scheduling nervousness*:** it was originally mentioned in the context of material requirement planning (MRP) systems, where it was defined as "significant changes in MRP plans" or "instability" (Vollmann et al., 1997). Because nervousness is constant change in the schedule (frequent rescheduling), it is the opposite of schedule stability. A "nervous" system presents little predictability. A rescheduling policy that yields fewer revisions increases schedule stability, and so decreases schedule nervousness.

Schedule robustness: it measures how much disruptions would degrade the performance of the system as it executes the schedules. Stability and nervousness measure the changes to a schedule, but robustness measures the changes to system-level performance.

5.1.2 Rescheduling Model in IPPS_DJS

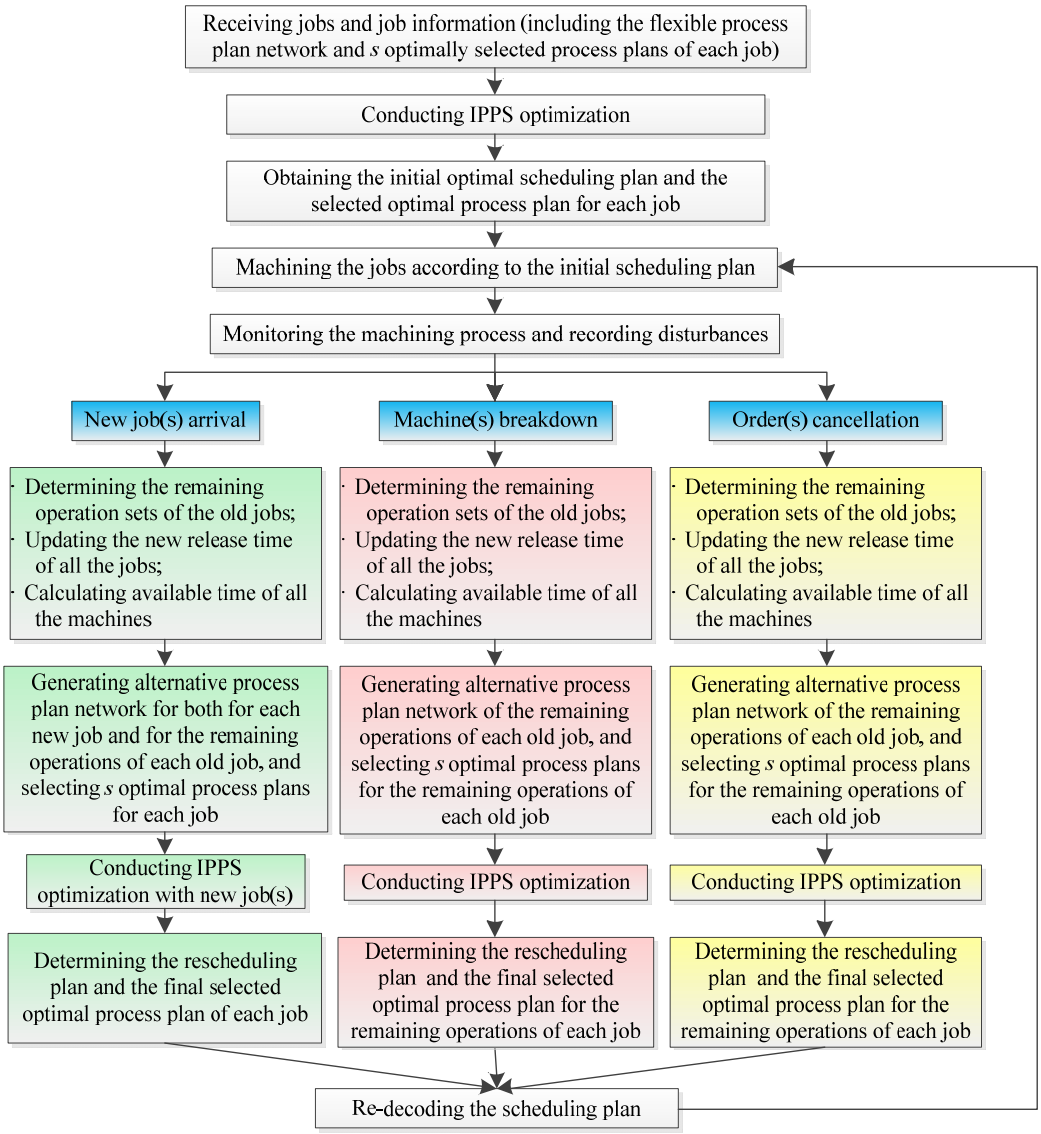


Figure 5-1 Rescheduling model in IPPS_DJS

The IPPS problem can be defined as (Kim et al., 2003): Given a set of *N* jobs which are to be performed on *M* machines with production flexibilities (routing flexibility, sequence flexibility and process flexibility), find an operation sequence and corresponding machine sequence for each job and a schedule in which operations on the same machines are processed such that it satisfies the precedence constraints and it is optimal with respect to some relevant criteria, e.g. minimum makespan and minimum mean flow time. Rescheduling in dynamic job shop for IPPS is an extension of this definition by considering practical uncertainties and conducting dynamic scheduling instead of only static scheduling. Based on this definition, the rescheduling framework is established for dynamic job shop scheduling considering the three types of disturbances such as arrival of new jobs, machine breakdown and order cancellation, as illustrated in Figure 5-1. The main steps and content in the rescheduling framework are as following:

- Receiving the jobs needed to be manufactured by the job shop and job information (including the flexible process plan network generated according to the ideal resource information of the job shop by the process planning system and *s* optimally selected process plans of each job).
- Conducting IPPS optimization and determining the final selected optimal process plan for each job and the initial optimal scheduling plan for all the jobs simultaneously, according to which the jobs will be manufactured in the job shop.
- Monitoring and rescheduling plan under different disturbances:
  - For arrival of new jobs, firstly the remaining operation sets of the old jobs need to be considered in rescheduling process will be determined, meanwhile the new release time of all the jobs and the new available time of all the machines will be updated. Then the alternative process plan network both for each new job and for the remaining operations of each old job will be generated, based on which *s* optimal process plans will be selected for each job. Next, the IPPS optimization will be conducted using the optimally selected *s* process plans for each job (including both new job and old job) to determine the rescheduling plan and the final selected optimal process plan of each job.
  - For machine breakdown, firstly the remaining operation sets of the old jobs need to be considered in rescheduling process will be determined, meanwhile the new release time of all the jobs and the new available time of all the machines will be updated. Then the alternative process plan network for the remaining operations of each old job will be generated, based on which *s* optimal process plans will be selected for the remaining operations of each job. Next, the IPPS optimization will be conducted using the optimally selected *s* process plans for each job to determine the rescheduling plan and the final selected optimal process plan of the remaining operations of each job.
  - For order cancellation, firstly the remaining operation sets of the old jobs (except for the jobs that are cancelled) need to be considered in rescheduling process will be determined, meanwhile the new release time of all the jobs and the new available time of all the machines will be updated. Then the alternative

process plan network for the remaining operations of each old job will be generated, based on which *s* optimal process plans will be selected for the remaining operations of each job. Next, the IPPS optimization will be conducted using the optimally selected *s* process plans for each job to determine the rescheduling plan and the final selected optimal process plan of the remaining operations of each job.

5.2 IPPS_DJS Model Simultaneously Considering Efficiency and Stability in IPPS

5.2.1 Definition of Scheduling Stability

In IPPS_DJS, while rescheduling will optimize production efficiency measures like makespan, tardiness and so on, the strategy re-generates schedules that are often radically different from the previous one. This means that many, if not all, of the previously scheduled jobs that have not begun processing can have their start time accelerated or delayed. This effect is troublesome in practice, especially in the common situation where the process being scheduled uses material that must be delivered from external sources.

Clearly, improving production efficiency is important in IPPS_DJS, but the instability problem induced by unrestricted rescheduling renders the approach useless. The impact of disruptions induced by moving jobs during a rescheduling event is frequently called 'stability'.

In IPPS_DJS, the deviations related to the jobs and machines comparing to the original scheduling plan are the factors that induce instability. Therefore, two types of deviation are adopted here to measure scheduling stability:

(1) Job-related deviation

Once an operation is pre-scheduled on a machine, its related manufacturing resources such as materials, sub-assemblies or human workers are expected to be ready right before its starting time. Any change of its starting time will alter the resource allocation and hence the resources are either expedited or delayed to cope with the new schedule, resulting in job-related deviation cost. For a job *i*, the job-related deviation cost jdc_i is defined as

$$jdc_i = \sum_{k \in i} d_k \left| st_k - st_k^* \right| \tag{5-1}$$

Where d_k denotes the penalty cost of operation *k* due to the change of its starting time per unit time. st_k and st_k^* denote the starting times of the preschedule (original schedule) and the new schedule, respectively. Here d_k has different value for the two situations of accelerating the operations or delaying the operations. As delaying an operation is still worse than accelerating an operation, the penalty cost of delaying operation *k* should be set bigger than that of accelerating operation *k*. Here, d_k is set to be 1 for accelerating operation *k*, while to be 2 for delaying operation *k*.

(2) *Machine-related deviation*

A machine has to prepare tooling and setups for a prescheduled operation. If the operation is re-scheduled to another machine, the preparation of the tooling or setup will be wasted. But the newly selected machine is required to setup again. Therefore, both the original and new machines are suffered from an additional cost. Let y_m be the number of operations added to the original schedule (preschedule) or deleted from the original schedule (preschedule) in machine *m*, the machine-related deviation cost mdc_m of machine *m* is defined as:

$$mdc_m = p_m \times y_m \tag{5-2}$$

Where p_m denotes the machine's penalty per change of operation in the preschedule.

One of the most important features of IPPS is that the following three types of flexibility will be considered in process plans: operation flexibility, sequencing flexibility and processing flexibility:

- Routing flexibility relates to the possibility of performing one operation on alternative machines, with possibly distinct processing time and cost.
- Sequencing flexibility is decided by the possibility of interchanging the sequence of the required operations.
- Processing flexibility is determined by the possibility of processing the same manufacturing feature with alternative operations.

Therefore, conducting IPPS_DJS means that during the generation of a new scheduling plan due to a certain disturbance, the above three types of flexibility will also be taken into consideration, which will accordingly lead to different types of deviation, as follows:

- If routing flexibility is conducted, then the machines used by the remaining operations of the old jobs will be changed, bringing about instability related to 'machine-related deviation'.
- If sequencing flexibility is conducted, the sequence of the remaining operations of the old jobs will be changed, and the starting time to machine these operations will be changed comparing to the original scheduling plan, bringing about instability related to 'job-related deviation'.
- If processing flexibility is conducted, a same manufacturing feature will be processed with alternative operations, which means that new operations will be generated and added to the machines while some old ones will be deleted in the new scheduling plan. This will also bring about instability related to 'machine-related deviation'.

To maintain good stability of the manufacturing process, the deviations from the pre-schedule should be minimized, hereby the objective of keeping the total deviation cost at

minimal is proposed. For the production of N parts with M machines, the total deviation cost tdc of the rescheduling problem is defined as the sum of the job-related deviation cost (jdc) and machine-related deviation cost (mdc), which is:

$$tdc = \sum_{i \in N} jdc_i + \sum_{m \in M} mdc_m = \sum_{i \in N} \sum_{k \in i} d_k \left| st_k - st_k^* \right| + \sum_{m \in M} p_m' \, y_m \tag{5-3}$$

5.2.2 Mathematical model of IPSS_DJS

The following assumptions are firstly made for the designing the mathematical model of rescheduling in IPPS_DJS (Lv and Qiao, 2013; Jain and Elmaraghy, 1997; Kim et al., 2003; Shao et al., 2009):

- Job pre-emption is not allowed and each machine can handle one job at a time.
- The jobs are available at their release time and they are available at time zero for the initial scheduling.
- Different operations of one job cannot be performed simultaneously.
- After a job is finished on a machine, it is immediately transported to the machine chosen to manufacture the next operation in its process plan, and the transportation time is ignored.
- Set-up time for each operation on the machine is independent of operation sequence and is included in the processing time if it is not provided separately.
- The computing time required for rescheduling optimization is assumed to be negligible. All the jobs and machines are immediately resumed to execution once the rescheduling is completed.
- After rescheduling of an interrupted operation, the operation will be restarted in its status at the interruption on the machine assigned in the new scheduling plan. That is, the operation may have to be restarted on a different machine if it is not on the same one as before interruption.

The mathematical model of the rescheduling problem in IPPS_DJS simultaneously considering efficiency and stability in IPSS is as following:

N Total number of jobs in the prescheduling;

M Total number of machines in the job shop;

o_{ijk} The kth operation in the jth alternative process plan of job i;

o_{ijk}^m The kth operation in the jth alternative process plan of job i is performed on machine m;

N_i Total number of alternative process plans of job i;

N_{ij} Total number of operations in the jth alternative process plan of job i;

N_n	Number of newly arrived jobs in rescheduling; initializing $N_n = N$ for the initial scheduling;
N_d	Number of cancelled order in rescheduling;
N'	Total number of jobs in rescheduling; initializing $N' = N$;
J_m	Job set manufactured on machine *m*;
J_s	Job set involved in (re)scheduling;
f	The number of hob has been finished between the pre-scheduling and current rescheduling;
p_{ijk}^m	Processing time of o_{ijk} on machine *m*;
M_{ijk}	Alternative machine set for o_{ijk};
m_{ijk}	The chosen machine of o_{ijk} in a (re)scheduling plan;
es_{ijk}^m	The earliest starting time of o_{ijk}^m;
ec_{ijk}^m	The earliest completion time of o_{ijk}^m, $ec_{ijk}^m = es_{ijk}^m + p_{ijk}^m$;
$ec(o_{ijk}^m - 1)$	The earliest completion time of the precedent operation of o_{ijk}^m on machine *m*
as_{ijk}^m	The allowed starting time of o_{ijk}^m;
O_m	The operation set manufactured on machine *m* (the sequence of different operations is determined), $O_m = \{o_{ijk}^m\}, 1 \le m \le M, i \in J_s, 1 \le j \le N_i$;
r_i	The release time of job *i*, initializing r_i=0;
VM_m	The machining cost per unit time when processing an operation with machine *m*
VI_m	The idle cost per unit time when machine *m* is in idle status (namely when machine is turned on but not processing any operation)
IP_m	the non-cutting power per unit time of machine *m*;
PP_m	the cutting power to process a job per unit time of machine *m* ;
SE_m	the setup energy (i.e. the energy consumed when turning on/off machine *m*)

d_i the due date of job *i*;

c_i the completion time of job *i*;

L_i the lateness of job *i*;

E_i the earliness of job *i*;

$tt(m,m^*)$ the transportation time from machine m to machine m^* ;

ML_m the initial machining load of machine *m* ;

jdc_i job-related deviation cost ;

d_k the penalty cost of operation *k* due to the change of its starting time per unit time

st_k, st_k^* the starting times of the preschedule (original schedule) and the new schedule, respectively

mdc_m machine-related deviation cost

y_m the number of operations added to the original schedule (preschedule) or deleted from the original schedule (preschedule) in machine *m*

p_m the machine's penalty per change of operation in the preschedule

tdc the total deviation cost in the new scheduling plan

A a number with positive infinity

$U_i = \begin{cases} 1 & \text{if } c_i > d_i \\ 0 & \text{otherwise} \end{cases}$ the unit penalty of tardiness job *i*;

$X_{ij} = \begin{cases} 1 & \text{the } j\text{th alternative process plan of job } i \text{ is selected} \\ 0 & \text{otherwise} \end{cases}$

$Y_{ijkpqsm} = \begin{cases} 1 & \text{if the operation } o_{ijk} \text{ percedes the operation } o_{pqs} \text{ on machine } m \\ 0 & \text{otherwise} \end{cases}$

$Z_{ijkm} = \begin{cases} 1 & \text{if machine } m \text{ is selected for } o_{ijk} \\ 0 & \text{otherwise} \end{cases}$

$W_1 = \begin{cases} 1 & \text{if } X \neq Y \\ 0 & \text{if } X = Y \end{cases}$ $W_2 = \begin{cases} 0 & \text{if } X = Y = 0 \\ 1 & \text{otherwise} \end{cases}$

Objectives:

(1) Minimizing *makespan* which is the completion time of the last operation of all jobs

$$f_1 = Min\ makespan = Min\ Max\{c_i\},\ "i \hat{I}\ [1, N] \tag{5-4}$$

(2) Minimizing the total machining cost: (the total machining cost = the cost when the machines are processing the operations + the cost when machines are in idle status)

$$f_2 = \min TMC = \min \sum_{i=1}^{N} \sum_{j=1}^{N_i} \sum_{k=1}^{N_{ij}} \sum_{m=1}^{M} ((p_{ijk}^m \times X_{ij} \times Z_{ijkm}) VM_m + (es_{ijk}^m - ec(o_{ijk}^m - 1)) VI_m)) \tag{5-5}$$

$$"i \hat{I}\ [1,N],\ "k \hat{I}\ [1,N_{ij}],\ "j \hat{I}\ [1,N_i],\ "m \hat{I}\ [1,M]$$

(3) Minimizing energy consumption (the total energy consumption = the energy consumption in machining the operations + the energy consumption when machines are in idle status)

$$f_3 = \min energy\_consumption = \min \sum_{i=1}^{N} \sum_{j=1}^{N_i} \sum_{k=1}^{N_{ij}} \sum_{m=1}^{M} ((p_{ijk}^m \times X_{ij} \times Z_{ijkm}) PP_m + (es_{ijk}^m - ec(o_{ijk}^m - 1)) IP_m) \tag{5-6}$$

$$"i \hat{I}\ [1,N],\ "k \hat{I}\ [1,N_{ij}],\ "j \hat{I}\ [1,N_i],\ "m \hat{I}\ [1,M]$$

(4) Minimizing the total deviation cost *tdc* of the rescheduling problem is the sum of the job-related deviation cost (*jdc*) and machine-related deviation cost (*mdc*)

$$f_4 = \min tdc = \min(\sum_{i \hat{I}\ N} jdc_i + \sum_{m \hat{I}\ M} mdc_m) = \min(\sum_{i \hat{I}\ N} \sum_{k \hat{I}\ i} d_k \left| st_k - st_k^* \right| + \sum_{m \hat{I}\ M} p_m \times y_m) \tag{5-7}$$

In this thesis, the value of p_m is set as 1, and the value of d_k is set to be 1 for accelerating operation *k*, while to be 2 for delaying operation *k*.

(5) Multi-objective function proposed with weighting method (the objective function used in rescheduling)

As different objectives are different in measurement unit, a normalization process will be needed to propose a multi-objective function with weighting method. For objective f_i (i=1, 2, 3, 4), assuming f_i^* is the minimum objective value, then the normalized objective f_i^N can be obtained by $f_i^N = \frac{f_i}{f_i^*}$. Thus the multi-objective functions proposed with weighting method is:

$$f = 0.5 \times efficiency + 0.5 \times stability = 0.5 \times (0.6 \times \frac{f_1}{f_1^*} + 0.3 \times \frac{f_2}{f_2^*} + 0.1 \times \frac{f_3}{f_3^*}) + 0.5 \times \frac{f_4}{f_4^*} \tag{5-8}$$

Constraints:

(5) The different operations of one job cannot be processed simultaneously:

$$ec_{ijk}^{m} \cdot X_{ij} \cdot Z_{ijkm} - ec_{ij(k-1)}^{m^*} \cdot X_{ij} \cdot Z_{ij(k-1)m^*} + A(1 - X_{ij}) \geq (p_{ijk}^{m} + tt(m, m^*)) \cdot X_{ij} \cdot Z_{ijkm} \quad (5\text{-}9)$$

$$\forall i \in [1, N], \forall k \in [1, N_{ij}], , \forall j \in [1, N_i], \forall m, m^* \in [1, M]$$

(6) Each machine can handle only one job at a time:

$$\begin{aligned} &(ec_{pqs}^{m} \cdot Z_{pqsm} \cdot X_{pq}) - (ec_{ijk}^{m} \cdot X_{ij} \cdot Z_{ijlm}) + A(1 - X_{ij}) + A(1 - X_{pq}) \\ &+ A(1 - Y_{ijkpqsm} \cdot Z_{ijkm} \cdot Z_{pqsm} \cdot X_{ij} \cdot X_{pq}) \geq (p_{pqs}^{m} \cdot Z_{pqsm} \cdot X_{pq}) \end{aligned} \quad (5\text{-}10)$$

$$\begin{aligned} &(ec_{ijk}^{m} \cdot X_{ij} \cdot Z_{ijlm}) - (ec_{pqs}^{m} \cdot Z_{pqsm} \cdot X_{pq}) + A(1 - X_{ij}) + A(1 - X_{pq}) \\ &+ A(Y_{ijkpqsm} \cdot Z_{ijkm} \cdot Z_{pqsm} \cdot X_{ij} \cdot X_{pq}) \geq (p_{ijk}^{m} \cdot Z_{ijkm} \cdot X_{ij}) \end{aligned} \quad (5\text{-}11)$$

$$\forall i, p \in [1, N], \forall k, s \in [1, N_{il}], \forall j, q \in [1, N_i], \forall m \in [1, M]$$

(7) Only one alternative process plan can be selected of job *i*:

$$\sum_{l} X_{ij} = 1 \quad \forall i \in [1, N] \quad (5\text{-}12)$$

(8) Only one machine for each operation should be selected:

$$\sum_{m=1}^{M} Z_{ijkm} = 1 \quad \forall i \in [1, N], \forall j \in [1, N_i], \forall k \in [1, N_{il}] \quad (5\text{-}13)$$

(9) There is only one precedence relation between two operations in a scheduling plan:

$$Y_{ijkpqsm} \cdot Z_{ijkm} \cdot Z_{pqsm} \cdot X_{ij} \cdot X_{pq} \leq 1 \quad (5\text{-}14)$$

$$(Y_{ijkpqsm} \cdot X_{ij}) \leq (Z_{ijkm} \cdot X_{ij}) \quad (5\text{-}15)$$

$$(Y_{ijkpqsm} \cdot X_{pq}) \leq (Z_{pqsm} \cdot X_{pq}) \quad (5\text{-}16)$$

$$\forall i, p \in [1, N], \forall k, s \in [1, N_{il}], \forall j, q \in [1, N_i], \forall m \in [1, M]$$

$$\sum_{i}^{N} \sum_{k}^{N_{il}} \sum_{j}^{N_i} (Y_{ijkpqsm} \cdot X_{ij} \cdot Z_{ijkm}) = \sum_{o_{m1}}^{o_{pqsm}-1} Z_{o_m} \quad (5\text{-}17)$$

$$\forall p \in [1, N], \forall q \in [1, N], \forall s \in [1, N_{il}], \forall m \in [1, M]$$

Where $\sum_{o_{m1}}^{o_{pqsm}-1} Z_{o_m}$ means the total number of operations before o_{pqs} on machine *m*; o_{m1} means the first operation on machine *m*; o_{pqsm} means the current operation on machine *m*.

(10) The completion time of each operation should be either positive or zero.

$$ec_{ijk}^{m} \cdot X_{ij} \cdot Z_{ijlm} \geq 0 \quad (5\text{-}18)$$

Here a unique requirement related to scheduling a machine when two jobs arrive at the same time. Specially, it is assumed that the job released to the system earliest in the original schedule of the planning horizon is given a higher priority and released first to the machine. Since jobs are allowed to have unique routings and different processing time on each machine in the simulation, it is easy to visualize two simulated jobs arriving to the same machine at the same time. In these cases, the one that was started first in the original schedule is given priority.

The measurement of stability is directed solely at the remaining operations of the old jobs, but not at the operations of the new jobs.

5. 3 A Case to Explain the Rescheduling Model in IPPS_DJS

Here the following four jobs (Job 1: Gear Shaft; Job 2: Sleeve Part; Job 3: Hinge Part; Job 4: Flange Part) will be taken as an example to explain the IPPS_DJS framework and model, as shown in Figure 5-2 – Figure 5-5. The alternative process plan of the four jobs networks illustrated by the AND/OR network graph are shown in Figure 5-6 – Figure 5-9.

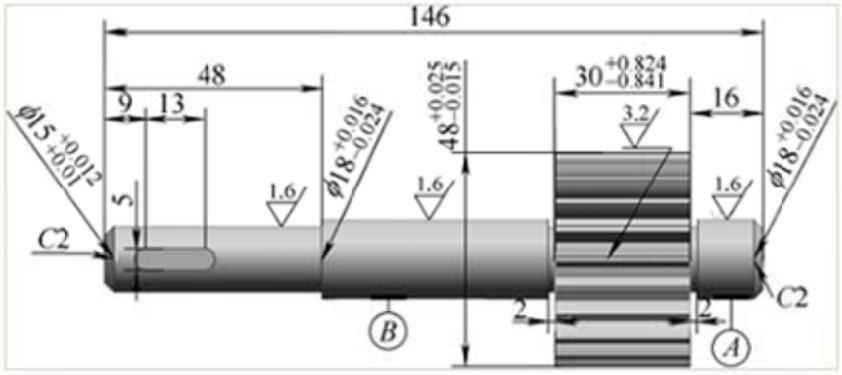


Figure 5-2 Job1 – Gear shaft

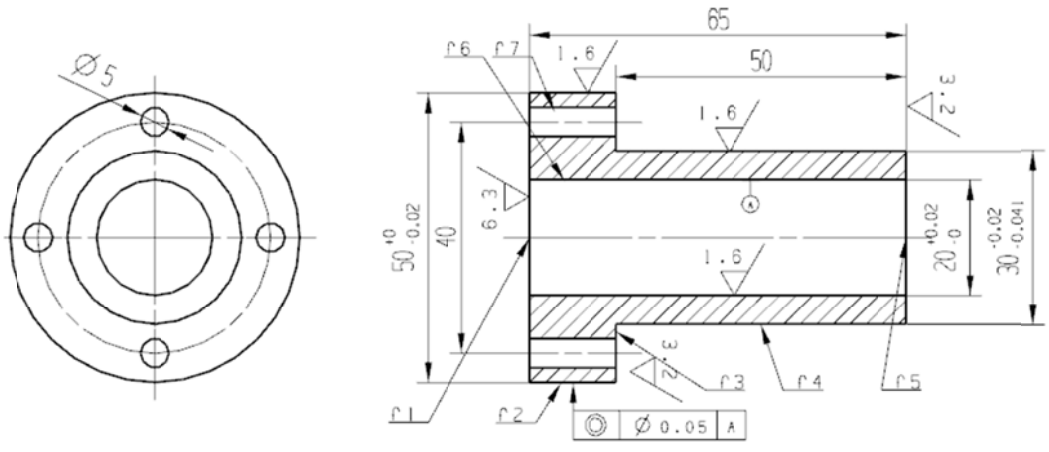


Figure 5-3 Job2 - Sleeve Part

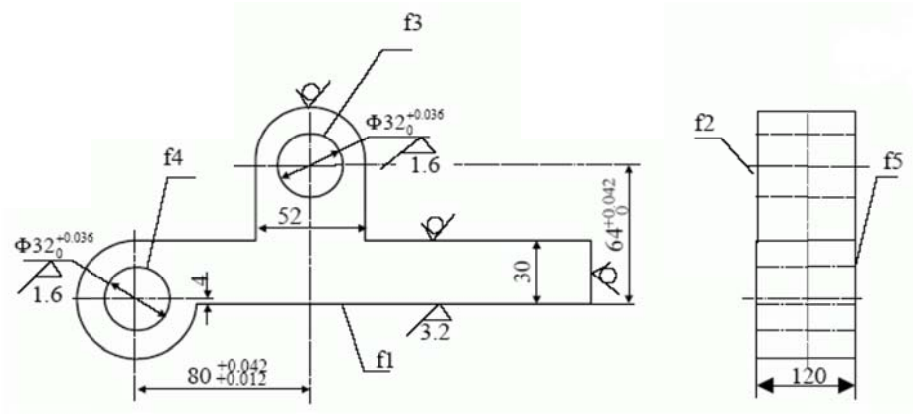


Figure 5-4 Job3 Hinge Part

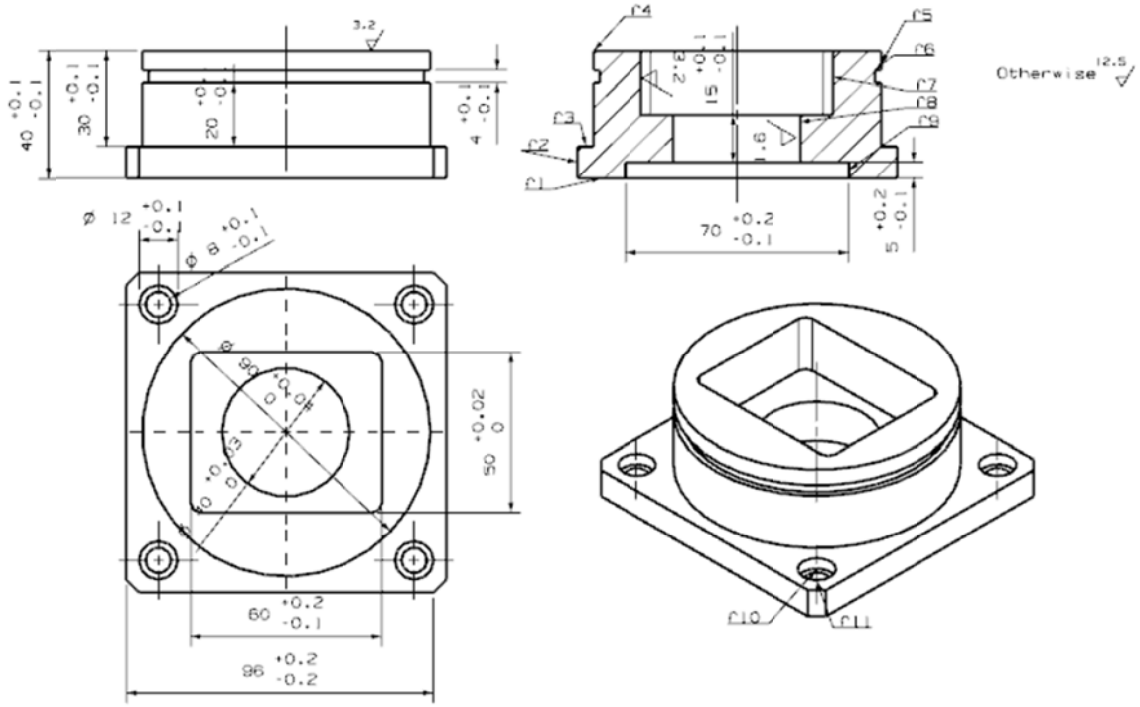


Figure 5-5 Flange Part

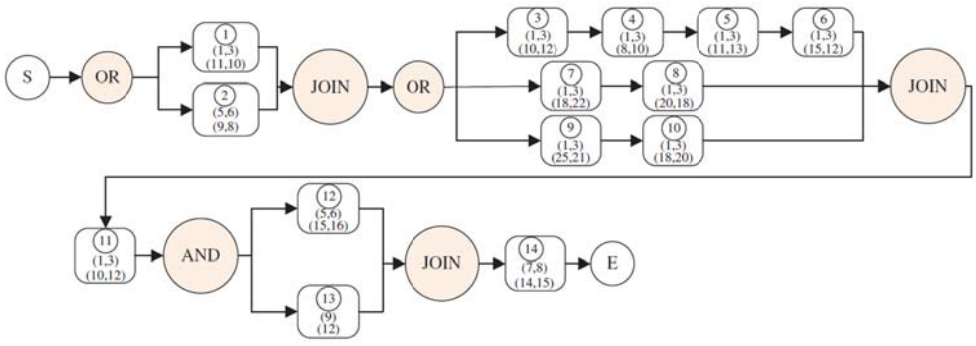


Figure 5-6 Flexible process plan network of Job 1

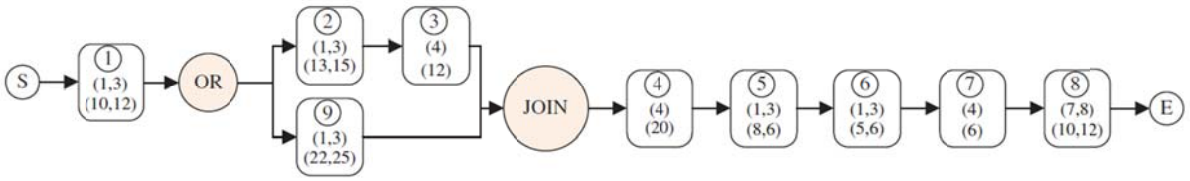


Figure 5-7 Flexible process plan network of Job 2

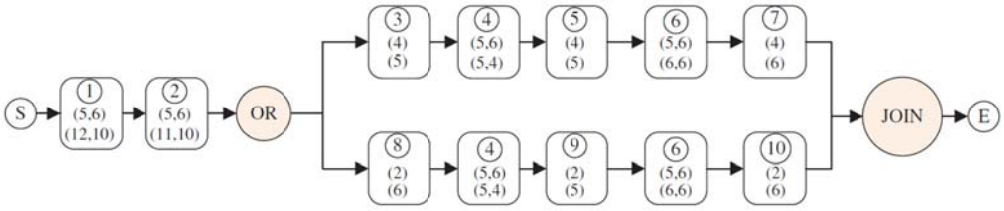


Figure 5-8 Flexible process plan network of Job 3

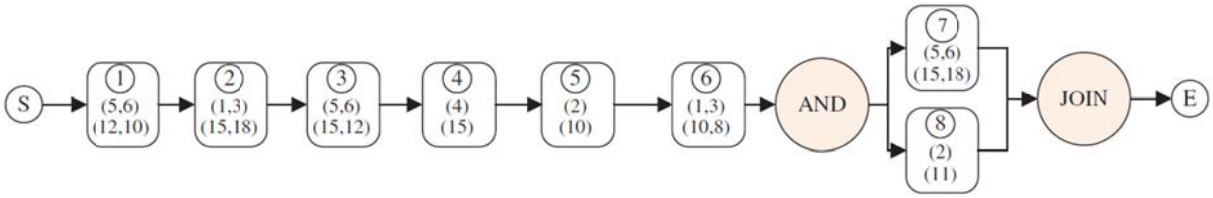


Figure 5-9 Flexible process plan network of Job 4

The initial scheduling plan generated for the order of the four jobs using the GA method designed in Chapter 4 is shown as Figure 5-10.

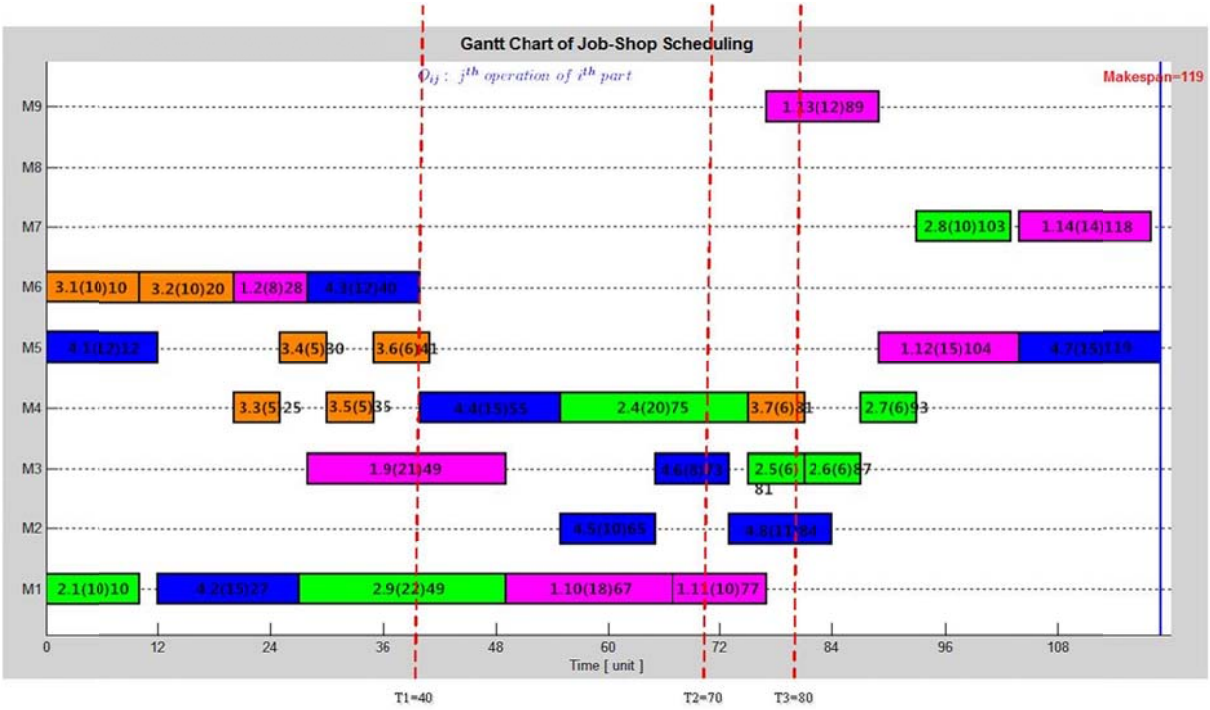


Figure 5-10 Gantt chart of the initial scheduling plan

Note: in the Gantt chart, e.g., 1.9(21)30, for the number of '1.9', it means the operation corresponding to node '9' in the flexible process plan network of the job '1', 21 means the required machining time of operation 1.9, and 30 means the completion time of operation 1.9.

As shown in Figure 5-10, we assume three types of disturbance will occur during the execution of the initial scheduling plan, they are:

- at T1=40, job 4 is canceled;
- at T2=70, machine 3 breaks down for 20 time unites;
- and at T3=80, three new jobs arrive.

When conducting rescheduling, the operations left in initial scheduling plan are called old operations here.

(1) Job 4 is canceled at t_1=40

Step 1: Updating the new release time of all the jobs

As shown in Figure 5-10, when a job order is cancelled at time t_1 (assuming job 4 is cancelled here), thus t_1 is the rescheduling point. The operations o_{ijk} with $ec_{ijk} < t_1$, $es_{ijk} < t_1 < ec_{ijk}$ or the operations have been cancelled are deleted from the problem, such as the operations of 1.2, 1.9, 2.1, 2.9, 3.1, 3.2, 3.3, 3.4, 3.5, 3.6, 4.1, 4.2 and 4.3. The left operations can be calculated as $O_{it_1} = \{o_{ijk} \mid es_{ijk} > t_1, 1 < k < N_{ij}\}$, $"i \hat{I} J_s$, $j \hat{I} [1, N_i]$. If O_{it_1} ¹ Æ, the new release time of old job j can be calculates as $r_i = \max_{1 £ k £ N_{ij}} \{es_{ijk} + p_{ijk} \mid es_{ijk} < t_1\}$, $"i \hat{I} J_s$, $j \hat{I} [1, N_i]$, otherwise, the job i can be deleted. Based on the initial result shown in Figure 5-10, the new release time of jobs 1, 2 and 3 are 49, 49 and 41, respectively.

Step 2: Calculating the available time of all machines

The available time of machine at the rescheduling point can be calculated as $t_m = \max(\max_{i \hat{I} J_m} \{es_{ijk} + p_{ijk} \mid es_{ijk} < t_1\}, t_1)$, $1 < m < M$, $j \hat{I} [1, N_i]$ for the situation of order cancellation, such as the available time of M1, M3 and M5 shown in Figure 5-10 at the rescheduling point is 49, 49 and 41 respectively, and the available time for the other machines is t_1.

Step 3: Calculating the allowed starting time of the first operation manufactured on machine m, $1 < m < M$. Assuming the operation o_{ijk}, $o_{ijk} \hat{I} O_m$, is the first operation manufactured on machine m, then $as_{ijk} = \max(ec_{ijk-1}, t_m)$, ec_{ijk-1} is the completion time of the previous operation of o_{ijk}.

Step 4: After updating the release time of the jobs and the available time of machines, rescheduling of the jobs can be conducted.

(2) Machine 3 breaks down at t_2 =70 for 20 time unites

Step 1: Updating the new release time of all the jobs

When machine breakdown occurs at time t_2 (namely the rescheduling point here is t_2) the new release time of the old job *i* can be calculated as $r_i = \max_{1 \le k \le N_{ij}} \{es_{ijk} + p_{ijk} \mid es_{ijk} < t_2\}$, $\forall i \in J_s,\ j \in [1, N_i]$ except for the one that is manufactured on the breakdown machine at time t_2 which should be set to $r_i = t_2$. In Figure 5-10, the new release time of job 1, 2 and 3 is 77, 75 and 41 respectively, while the new release time of job 4 is t_2 for the operation of 4.6 is being manufactured on M3 (breakdown machine) at time t_2 .

Step 2: Calculating the available time of all machines

For the machines that are not breakdown, the available time of machine at the rescheduling point can be calculated by $t_m = \max(\max_{i \in J_m} \{es_{ijk} + p_{ijk} \mid es_{ijk} < t_2\}, t_2), 1 < m < M$, $1 \le i \le J_m,\ j \in [1, N_i],\ m \neq m'$. While for the breakdown machine, its available time should be calculated as $t_m = t_2 + \Delta t$ (Δt is the time needed to repair the breakdown machine). Therefore, the available time of M3 (breakdown machine) is $t_2 + \Delta t$; the available time of M1 and M4 is 77 and 75 respectively, while for the other machines, the available time is t_2 .

Step 3: Calculating the allowed starting time of the first operation manufactured on machine *m*, $1 < m < M$. Assuming the operation o_{ijk} , $o_{ijk} \in O_m$, is the first operation manufactured on machine *m*, then $as_{ijk} = \max(ec_{ijk-1}, t_m)$, ec_{ijk-1} is the completion time of the previous operation of o_{ijk}.

Step 4: After updating the release time of the jobs and the available time of machines, rescheduling of the jobs can be conducted.

(3) New jobs arrival at t_3=80

Step 1: Calculating the new release time of jobs.

When new jobs arrive at t_3 (rescheduling point), the operations o_{ijk} with $ec_{ijk} < t_3$, $es_{ijk} < t_3 < ec_{ijk}$ are deleted from the problem. The left operations can be calculated as $O_{it_1} = \{o_{ijk} \mid es_{ijk} > t_3, 1 < k < N_{ij}\}$, $\forall i \in J_s,\ j \in [1, N_i]$. If $O_{it_1} \neq \varnothing$, the new release time of old

job j can be calculates as $r_i = \max_{1 \le k \le N_{ij}} \{es_{ijk} + p_{ijk} \mid es_{ijk} < t_3\}$, $\forall i \in J_s$, $j \in [1, N_i]$, otherwise, the job i can be deleted. The release time of newly arrived jobs are set as $r_i = t_3$, $\forall i \in [i, N_n]$. Hence, the new release time for job 1 is 89, for job 2 is 81, for job 3 is 81 and for job 4 is 84 respectively.

Step 2: Calculating the available time of all machines

The available time of machine at the rescheduling point can be calculated as $t_m = \max(\max_{i \in J_m} \{es_{ijk} + p_{ijk} \mid es_{ijk} < t_3\}, t_3)$, $1 < m < M$, $j \in [1, N_i]$ for the situation of arrival of new jobs. Therefore, the available time of M1, M5, M6, M7 and M8 at the rescheduling point is t_3, while of M2, M3, and M4 is 84, 81 and 81 respectively.

Step 3: Calculating the allowed starting time of the first operation manufactured on machine m, $1 < m < M$. Assuming the operation o_{ijk}, $o_{ijk} \in O_m$, is the first operation manufactured on machine m, then $as_{ijk} = \max(ec_{ijk-1}, t_m)$, ec_{ijk-1} is the completion time of the previous operation of o_{ijk}.

Step 4: After updating the release time of the jobs and the available time of machines, rescheduling of the jobs can be conducted.

5.4 Case Studies

The order including 4 jobs in section 5.2 will be used as an example to demonstrate the proposed IPPS_DJS framework and model using the GA method proposed in Chapter 4. Table 5-1 shows the optimally selected 5 process plans for each job based on the alternative process plan networks (Note: in the table the number out of the bracket is machine No. and the number in the bracket is the time needed to by this machine to process the operation).

Table 5-1 The alternative process plans for 4 jobs

Jobs	Five alternative process plans of each job
Job 1	***P1:*** 1.2 - 1.9 - 1.10 - 1.11 - 1.12 - 1.13 - 1.14 6(8)- 3(21)-1(18)-1(10)-5(15)-9(12)-7(14) ***P2:*** 1.2 - 1.9 - 1.10 - 1.11 - 1.12 - 1.13 - 1.14 5(9)- 3(21)-1(18)-1(10)-5(15)-9(12)-7(14) ***P3:*** 1.2 - 1.9 - 1.10 - 1.11 - 1.13 - 1.12 - 1.14 6(8)- 3(21)-1(18)-1(10)- 9(12)- 5(15)-7(14) ***P4:*** 1.1 - 1.3 - 1.4 - 1.5 - 1.6 - 1.11 - 1.12 - 1.13 - 1.14 3(10)- 1(10)-1(8)-1(11)- 3(12)- 1(10)-5(15)-9(12)-7(14) ***P5:*** 1.2 - 1.7 - 1.8 - 1.11 - 1.12 - 1.13 - 1.14 6(8)-1(18)- 3(18)-1(10)-5(15)-9(12)-8(15)

Job 2	***P1:*** 2.1 - 2.9 - 2.4 - 2.5 - 2.6 - 2.7 - 2.8 1(10) -1(22)-4(20)-3(6)-1(5)-4(6)-7(10) ***P2:*** 2.1 - 2.9 - 2.4 - 2.5 - 2.6 - 2.7 - 2.8 1(10) -1(22)-4(20)-3(6)- 3(6)-4(6)-7(10) ***P3:*** 2.1 - 2.9 - 2.4 - 2.5 - 2.6 - 2.7 - 2.8 3(12) -1(22)-4(20)-3(6)-1(5)-4(6)-7(10) ***P4:*** 2.1 - 2.9 - 2.4 - 2.5 - 2.6 - 2.7 - 2.8 1(10) -1(22)-4(20)-1(8)- 3(6)-4(6)-7(10) ***P5:*** 2.1 - 2.2 - 2.3 - 2.4 - 2.5 - 2.6 - 2.7 - 2.8 1(10) -1(13)-4(12)-4(20)-3(6)-1(5)-4(6)-7(10)
Job 3	***P1:*** 3.1 - 3.2 - 3.3 - 3.4 - 3.5 - 3.6 - 3.7 6(10) -6(10)-4(5)-6(4)-4(5)-5(6)-4(6) ***P2:*** 3.1 - 3.2 - 3.3 - 3.4 - 3.5 - 3.6 - 3.7 6(10) -6(10)-4(5)-6(4)-4(5)-6(6)-4(6) ***P3:*** 3.1 - 3.2 - 3.3 - 3.4 - 3.5 - 3.6 - 3.7 6(10) -6(10)-4(5)-5(5)-4(5)-5(6)-4(6) ***P4:*** 3.1 - 3.2 - 3.3 - 3.4 - 3.5 - 3.6 - 3.7 6(10) -6(10)-4(5)-5(5)-4(5)-6(6)-4(6) ***P5:*** 3.1 - 3.2 - 3.8 - 3.4 - 3.9 - 3.6 - 3.10 6(10) -6(10)-2(6)-6(4)-2(5)-5(6)-2(6)
Job 4	***P1:*** 4.1 - 4.2 - 4.3 - 4.4 - 4.5 - 4.6 - 4.7 - 4.8 6(10) -1(15)-6(12)-4(15)-2(10)-3(8)-5(15)-2(11) ***P2:*** 4.1 - 4.2 - 4.3 - 4.4 - 4.5 - 4.6 - 4.8 - 4.7 6(10) -1(15)-6(12)-4(15)-2(10)-3(8) -2(11)-5(15) ***P3:*** 4.1 - 4.2 - 4.3 - 4.4 - 4.5 - 4.6 - 4.8 - 4.7 5(12) -1(15)-6(12)-4(15)-2(10)-3(8) -2(11)-5(15) ***P4:*** 4.1 - 4.2 - 4.3 - 4.4 - 4.5 - 4.6 - 4.7 - 4.8 5(12) -1(15)-6(12)-4(15)-2(10)-3(8) -5(15)-2(11) ***P5:*** 4.1 - 4.2 - 4.3 - 4.4 - 4.5 - 4.6 - 4.7 - 4.8 6(10) -1(15)-6(12)-4(15)-2(10)-1(10)-5(15)-2(11)

In the initial scheduling, the three objectives related to efficiency are optimized using weighting method:

$$f = \min(0.6' \frac{f_1}{f_1^*} + 0.3' \frac{f_2}{f_2^*} + 0.1' \frac{f_3}{f_3^*})$$

The Gantt chart of the initial scheduling plan is shown as Figure 5-11. And the objective function values are f_1=119, f_2=2965 and f_3=3843.

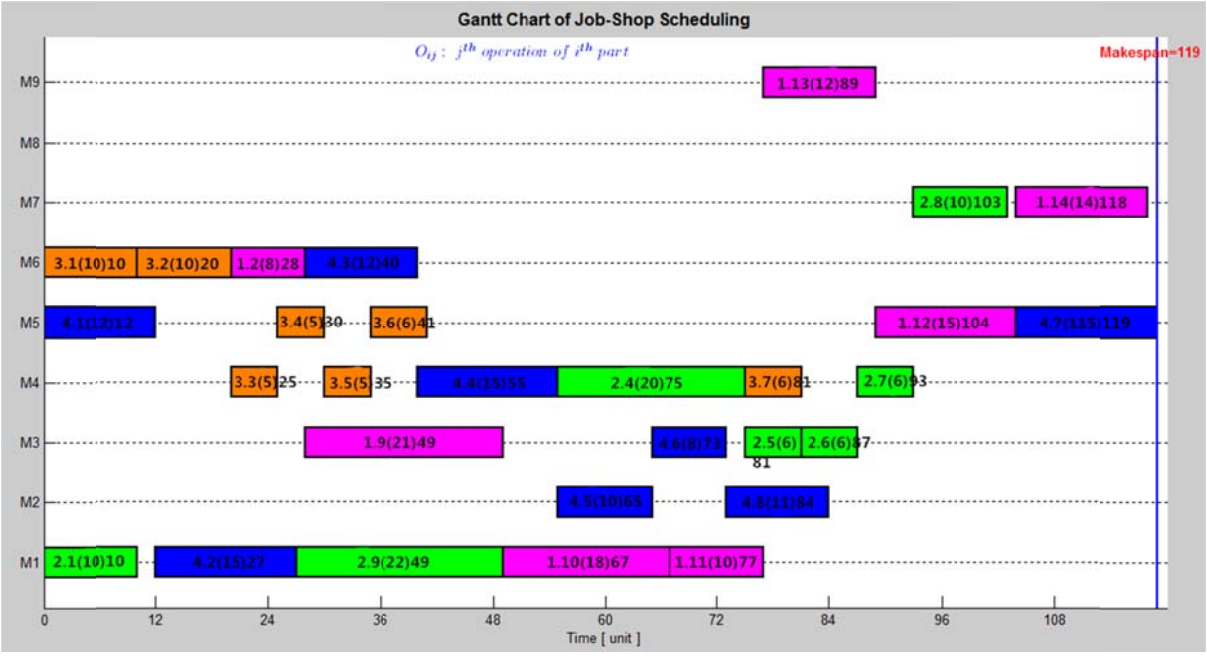


Figure 5-11 Initial scheduling plan

And the finally selected process plan for each job in the initial scheduling plan is shown in Table 5-2.

Table 2-2 The finally selected process plan for each job in the initial scheduling plan

Jobs	The selected process plan of each job in the initial scheduling plan
Job 1	***P3:*** 1.2 - 1.9 - 1.10 - 1.11 - 1.13 - 1.12 - 1.14 6(8)- 3(21)-1(18)-1(10)- 9(12)- 5(15)-7(14)
Job 2	***P2:*** 2.1 - 2.9 - 2.4 - 2.5 - 2.6 - 2.7 - 2.8 1(10) -1(22)-4(20)-3(6)- 3(6)-4(6)-7(10)
Job 3	***P3:*** 3.1 - 3.2 - 3.3 - 3.4 - 3.5 - 3.6 - 3.7 6(10) -6(10)-4(5)-5(5)-4(5)-5(6)-4(6)
Job 4	***P3:*** 4.1 - 4.2 - 4.3 - 4.4 - 4.5 - 4.6 - 4.8 - 4.7 5(12) -1(15)-6(12)-4(15)-2(10)-3(8)-5(15)-2(11)

For IPPS_DJS, the objective function is

$$ficiency + 0.5' \ stability = 0.5' \ (0.6' \ \frac{f_1}{f_1^*} + 0.3' \ \frac{f_2}{f_2^*} + 0.1' \ \frac{f_3}{f_3^*}) + 0.5' \ \frac{f_4}{f_4^*}$$

(1) Job 4 is cancelled at t_1 =40

Step 1: Updating the new release time of all the jobs at the rescheduling point

The updated new release time of all the jobs at the rescheduling point is shown in Table 5-3:

Table 5-3 The new release time of all jobs

Job No.	Job 1	Job 2	Job3
New Release Time	49	49	41

Step 2: Updating the new available time of all the machines at the rescheduling point

The updated new available time of all the machines at the rescheduling point is shown in Table 5-4:

Table 5-4 The new available time of all the machines

Machine No.	M1	M2	M3	M4	M5	M6	M7	M8	M9
New Available Time	49	40	49	40	41	40	40	40	40

Step 3: Generating alternative process plan networks of the remaining operations of the old jobs

The alternative process plan networks of the remaining operations of job 1, 2 and 3 at the rescheduling point are shown as Figure 5-12 – Figure 5-14.

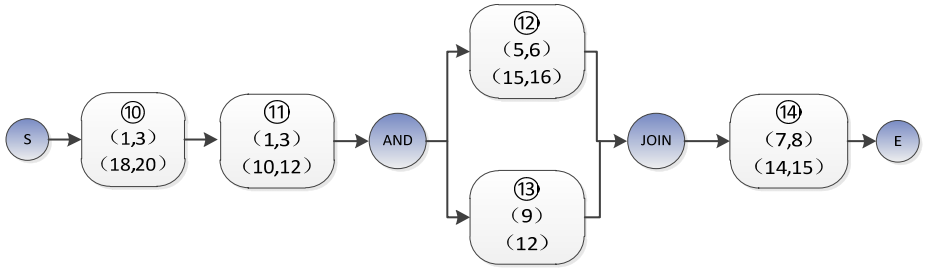


Figure 5-12 The alternative process plan network of the remaining operations of job 1

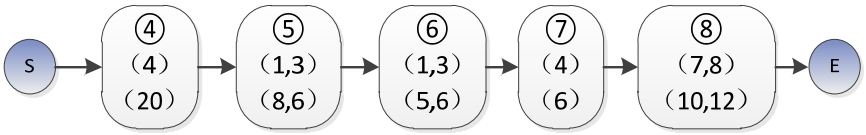


Figure 5-13 The alternative process plan network of the remaining operations of job 2

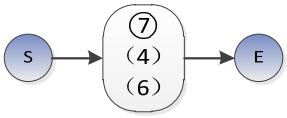


Figure 5-14 The alternative process plan network of the remaining operations of job 3

Step 4: Generating *s* optimal process plans of the remaining operations of the old jobs

Based on the alternative process plan networks of the remaining operations of the old jobs generated in Step 3, the optimal process plans of the remaining operations will be

obtained for each job taking the minimum machining time as objective function, the results is shown is Table 5-5.

Table 5-5 The alternative process plans for the remaining operations of the old jobs

Jobs	Alternative process plans of the remaining operations for each job
Job 1	***P1:***1.10-1.11 - 1.12 - 1.13 - 1.14 1(18)-1(10)- 5(15)-9(12)-7(14) ***P2:***1.10-1.11 - 1.12 - 1.13 - 1.14 1(18)-1(10)- 5(15)-9(12)-8(15) ***P3:***1.10-1.11 - 1.13 - 1.12 - 1.14 1(18)-1(10)- 9(12)-5(15)- 7(14) ***P4:***1.10-1.11 - 1.13 - 1.12 - 1.14 1(18)-1(10)- 9(12)-5(15)-8(15) ***P5:***1.10-1.11 - 1.13 - 1.12 - 1.14 1(18)-1(10)- 9(12)-6(16)- 7(14)
Job 2	***P1:*** 2.4 - 2.5 - 2.6 - 2.7 - 2.8 4(20)-3(6)-1(5)-4(6)-7(10) ***P2:*** 2.4 - 2.5 - 2.6 - 2.7 - 2.8 4(20)-3(6)- 3(6)-4(6)-7(10) ***P3:*** 2.4 - 2.5 - 2.6 - 2.7 - 2.8 4(20)-1(8)- 1(5)-4(6)-7(10) ***P4:*** 2.4 - 2.5 - 2.6 - 2.7 - 2.8 4(20)-3(6)-1(5)-4(6)-8(12) ***P5:*** 2.4 - 2.5 - 2.6 - 2.7 - 2.8 4(20)-1(8)-3(6)-4(6)-7(10)
Job 3	***P1:*** 3.7 4(6)

Step 5: Conducting IPPS optimization and determining the rescheduling plan and the final chosen process plan for each job

The Gantt chart of the rescheduling result is shown in Figure 5-15.

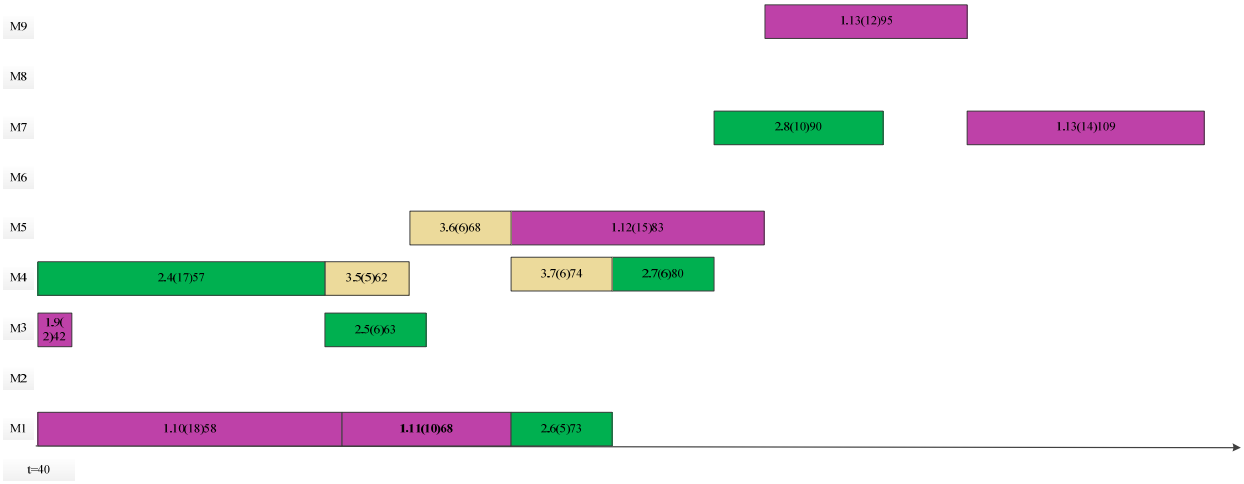


Figure 5-15 Gantt chart of the rescheduling plan with order cancellation (job 4 is cancelled at t_1 =40)

The correspondent objective function values are shown in Table 5-6.

Table 5-6 The objective function values in the rescheduling plan

Objective	Makespan	Cost	Energy Consumption	No.of added or deleted operations	Accelerated Time	Delayed Time
Value	118	1218,2	2710	5	36	0

And the finally selected process plan for the remaining operations of each jobs is shown in Table 5-7.

Table 5-7 The finally selected process plan for the remaining operations of each job

Job No.	The finally selected process plan of each job in the rescheduling plan
Job 1	1.10-1.11 - 1.12 - 1.13 - 1.14 1(18)-1(10)- 5(15)-9(12)-7(14)
Job 2	2.4 - 2.5 - 2.6 - 2.7 - 2.8 4(20)-3(6)-1(5)-4(6)-7(10)
Job 3	3.7 4(6)

(2) Machine breakdown: M5 is breakdown at t_2 =70

Step 1: Updating the new release time of all the jobs

The updated new release time of all the jobs at the rescheduling point is shown in Table 5-8:

Table 5-8 The new release time of all jobs

Job No.	Job 1	Job 2	Job3	Job 4
New Release Time	77	75	41	70

Step 2: Updating the new available time of all the machines

The updated new available time of all the machines at the rescheduling point is shown in Table 5-9:

Table 5-9 The new available time of all the machines

Machine No.	M1	M2	M3	M4	M5	M6	M7	M8	M9
New Available Time	77	70	90	75	70	70	70	70	70

Step 3: Generating alternative process plan networks of the remaining operations of the old jobs

The alternative process plan networks of the remaining operations of job 1, 2, 3 and 4 at the rescheduling point are shown as Figure 5-16 – Figure 5-19.

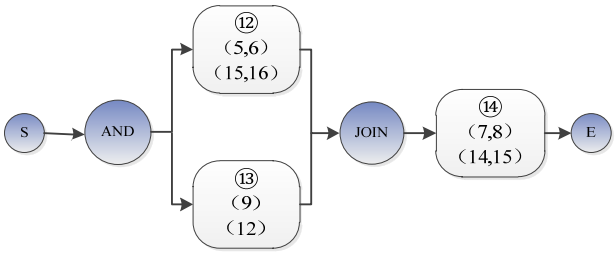


Figure 5-16 The alternative process plan network of the remaining operations of job 1

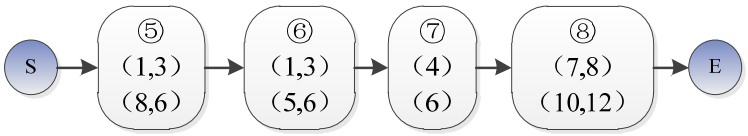


Figure 5-17 The alternative process plan network of the remaining operations of job 2

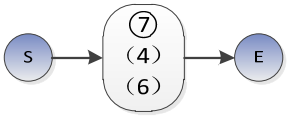


Figure 5-18 The alternative process plan network of the remaining operations of job 3

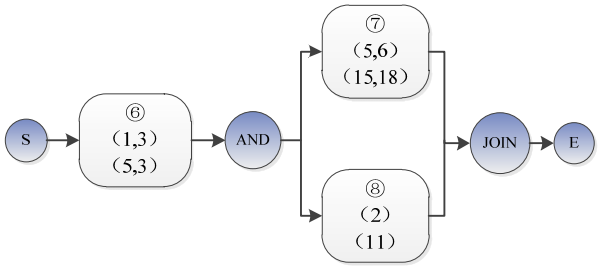


Figure 5-19 The alternative process plan network of the remaining operations of job 4

Step 4: Generating *s* optimal process plans of the remaining operations of the old jobs

Based on the alternative process plan networks of the remaining operations of the old jobs generated in Step 3, five optimal process plans of the remaining operations will be obtained for each job taking the minimum machining time as objective function, the results is shown is Table 5-10.

Table 5-10 The alternative process plans for the remaining operations of the old jobs

Jobs	Alternative process plans of the remaining operations for each job
Job 1	***P1:*** 1.12 - 1.13 - 1.14 5(15)-9(12)-7(14) ***P2:*** 1.12 - 1.13 - 1.14 6(16)-9(12)-7(14) ***P3:*** 1.12 - 1.13 - 1.14 5(15)-9(12)-8(15) ***P4:*** 1.13 - 1.12 - 1.14 9(12)-5(15)- 8(15) ***P5:*** 1.13 - 1.12 - 1.14 9(12)-6(16)- 7(14)
Job 2	***P1:*** 2.5 - 2.6 - 2.7 - 2.8 3(6)-1(5)-4(6)-7(10) ***P2:*** 2.5 - 2.6 - 2.7 - 2.8 3(6)- 3(6)-4(6)-7(10) ***P3:*** 2.5 - 2.6 - 2.7 - 2.8 1(8)- 1(5)-4(6)-7(10) ***P4:*** 2.5 - 2.6 - 2.7 - 2.8 3(6)-1(5)-4(6)-8(12) ***P5:*** 2.5 - 2.6 - 2.7 - 2.8 1(8)-3(6)-4(6)-7(10)
Job 3	***P1:*** 3.7 4(6)
Job 4	***P1:*** 4.6 – 4.7 – 4.8 3(3)-5(15)-2(11) ***P2:*** 4.6 – 4.8 – 4.7 3(3)-2(11)-5(15)

	P3: 4.6 – 4.7 – 4.8 3(3)-6(18)-2(11) ***P4:*** 4.6 – 4.8 – 4.7 3(3)- 2(11) -6(18) ***P5:*** 4.6 – 4.8 – 4.7 1(5)- 2(11)-5(15)

Step 5: Conducting IPPS optimization and determining the rescheduling plan and the final chosen process plan for each job

The Gantt chart of the rescheduling result is shown in Figure 5-20.

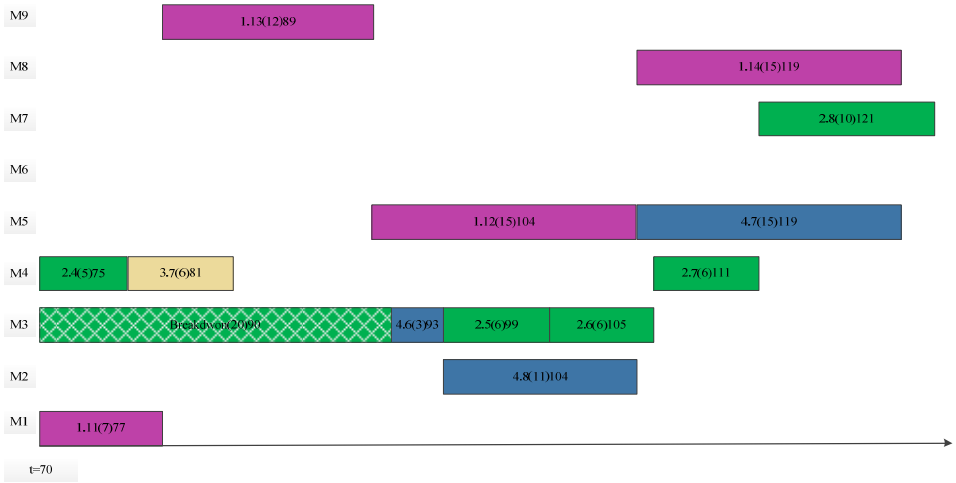


Figure 5-20 Gantt chart of rescheduling with machine breakdown (machine 5 is breakdown at t2=71)

The correspondent objective functions values are shown in Table 5-11.

Table 5-11 The objective function values

Objective	Makespan	Cost	Energy Consumption	No.of added or deleted operations	Accelerated Time	Delayed Time
Value	121	1192,2	2398,4	2	0	113

And the finally selected process plan for the remaining operations of each job is shown in Table 5-12.

Table 5-12 The finally selected process plan for the remaining operations of each job

Job No.	The selected process plan of each job in the rescheduling plan
Job 1	1.13 - 1.12 - 1.14 9(12)-5(15)- 8(15)
Job 2	2.5 - 2.6 - 2.7 - 2.8 3(6)- 3(6)-4(6)-7(10)

Job 3	3.7 4(6)
Job 4	4.6 – 4.8 – 4.7 3(3)-2(11)-5(15)

(3) Arrival of new jobs at t_3=80

Three new jobs (jobs 5, 6 and 7) arrive at t_3=80, and here assuming jobs 5, 6 and 7 are the same as jobs 1, 2 and 3.

Step 1: Updating the new release time of all the jobs

The updated new release time of all the jobs at the rescheduling point is shown in Table 5-13:

Table 5-13 The new release time of all jobs at the rescheduling point

Job No.	Job 1	Job 2	Job3	Job 4	Job 5	Job 6	Job 7
New Release Time	89	81	81	84	80	80	80

Step 2: Updating the new available time of all the machines

The updated new available time of all the machines at the rescheduling point is shown in Table 5-14:

Table 0-14 The new available time of all the machines at the rescheduling point

Machine No.	M1	M2	M3	M4	M5	M6	M7	M8	M9
New Available Time	80	84	81	81	80	80	80	80	89

Step 3: Generating alternative process plan networks of the remaining operations of the old jobs

The alternative process plan networks of the remaining operations of job 1, 2 and 4 (Job 3 is finished at the rescheduling point) are shown as Figure 5-21 – Figure 5-23 and the alternative process plan networks of the newly arrived jobs 5, 6 and 7 are shown as Figure 5-24 – Figure 5-26.

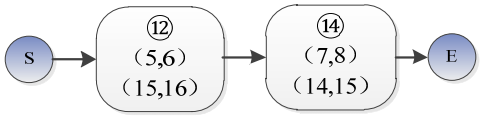


Figure 5-21 The alternative process plan network of the remaining operations of job 1

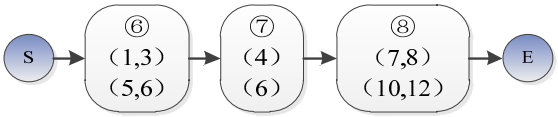


Figure 5-22 The alternative process plan network of the remaining operations of job 2

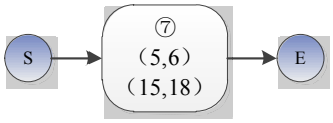


Figure 5-23 The alternative process plan network of the remaining operations of job 4

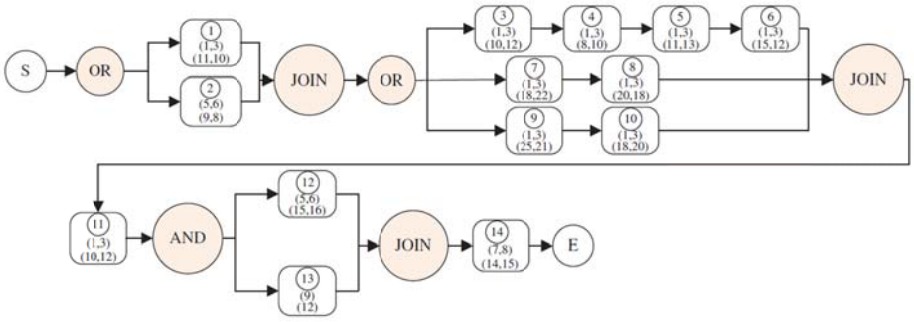


Figure 5-24 Flexible process plan network of Job 5

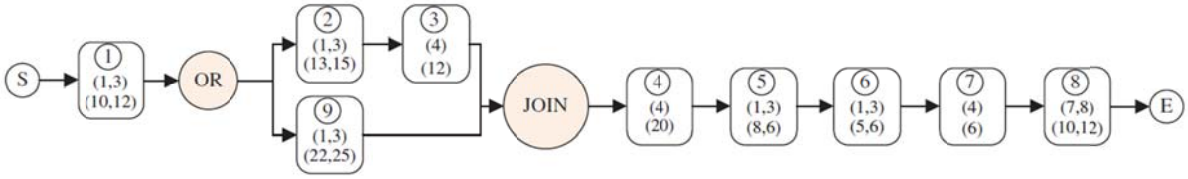


Figure 5-25 Flexible process plan network of Job 6

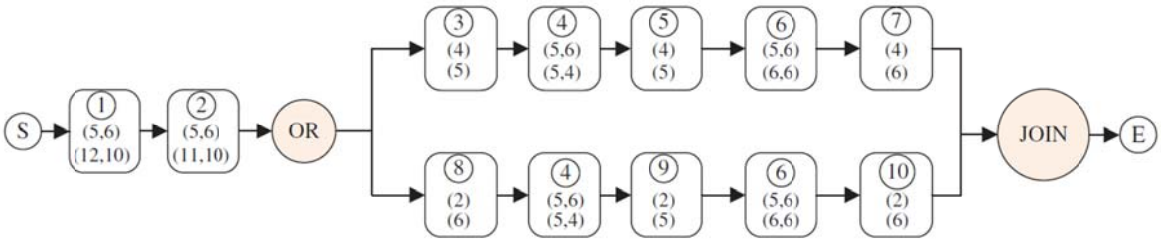


Figure 5-26 Flexible process plan network of Job 7

Step 4: Generating *s* optimal process plans of the remaining operations of the old jobs

Based on the alternative process plan networks of the remaining operations of the old jobs generated in Step 3, five optimal process plans of the remaining operations will be obtained for each job taking the minimum machining time as objective function, the results is shown is Table 5-15.

Table 5-15 The alternative process plans for the remaining operations of the old jobs

Jobs	The alternative process plans of each job
Job 1	***P1:*** 1.12 – 1.14 5(15)-7(14) ***P2:*** 5(15)-8(15) ***P3:*** 6(16)-7(14)

	P4: 6(16)- 8(15)
Job 2	***P1:*** 2.6 – 2.7 – 2.8 1(5)-4(6)-7(10) ***P2:*** 3(6)-4(6)-7(10) ***P3:*** 1(5)-4(6)-8(12) ***P4:*** 3(6)-4(6)- 8(12)
Job 4	***P1:*** 4.7 5(15) ***P2:*** 6(18)
Job 5	***P1:*** 5.2 - 5.9 - 5.10 - 5.11 - 5.12 - 5.13 - 5.14 6(8)- 3(21)-1(18)-1(10)-5(15)-9(12)-7(14) ***P2:*** 5.2 - 5.9 - 5.10 - 5.11 - 5.12 - 5.13 - 5.14 5(9)- 3(21)-1(18)-1(10)-5(15)-9(12)-7(14) ***P3:*** 5.2 - 5.9 - 5.10 - 5.11 - 5.13 - 5.12 - 5.14 6(8)- 3(21)-1(18)-1(10)- 9(12)- 5(15)-7(14) ***P4:*** 5.1 - 5.3 - 5.4 - 5.5 - 5.6 - 5.11 - 5.12 - 5.13 - 5.14 3(10)- 1(10)-1(8)-1(11)- 3(12)- 1(10)-5(15)-9(12)-7(14) ***P5:*** 5.2 - 5.7 - 5.8 - 5.11 - 5.12 - 5.13 - 5.14 6(8)-1(18)- 3(18)-1(10)-5(15)-9(12)-8(15)
Job 6	***P1:*** 6.1 - 6.9 - 6.4 - 6.5 - 6.6 - 6.7 - 6.8 1(10) -1(22)-4(20)-3(6)-1(5)-4(6)-7(10) ***P2:*** 6.1 - 6.9 - 6.4 - 6.5 - 6.6 - 6.7 - 6.8 1(10) -1(22)-4(20)-3(6)- 3(6)-4(6)-7(10) ***P3:*** 6.1 - 6.9 - 6.4 - 6.5 - 6.6 - 6.7 - 6.8 3(12) -1(22)-4(20)-3(6)-1(5)-4(6)-7(10) ***P4:*** 6.1 - 6.9 - 6.4 - 6.5 - 6.6 - 6.7 - 6.8 1(10) -1(22)-4(20)-1(8)- 3(6)-4(6)-7(10) ***P5:*** 6.1 - 6.2 - 6.3 - 6.4 - 6.5 - 6.6 - 6.7 - 6.8 1(10) -1(13)-4(12)-4(20)-3(6)-1(5)-4(6)-7(10)
Job 7	***P1:*** 7.1 - 7.2 - 7.3 - 7.4 - 7.5 - 7.6 - 7.7 6(10) -6(10)-4(5)-6(4)-4(5)-5(6)-4(6) ***P2:*** 7.1 - 7.2 - 7.3 - 7.4 - 7.5 - 7.6 - 7.7 6(10) -6(10)-4(5)-6(4)-4(5)-6(6)-4(6) ***P3:*** 7.1 - 7.2 - 7.3 - 7.4 - 7.5 - 7.6 - 7.7

	6(10) -6(10)-4(5)-5(5)-4(5)-5(6)-4(6) ***P4:*** 7.1 - 7.2 - 7.3 - 7.4 - 7.5 - 7.6 - 7.7 6(10) -6(10)-4(5)-5(5)-4(5)-6(6)-4(6) ***P5:*** 7.1 - 7.2 - 7.8 - 7.4 - 7.9 - 7.6 - 7.10 6(10) -6(10)-2(6)-6(4)-2(5)-5(6)-2(6)

Step 5: Conducting IPPS optimization and determining the rescheduling plan and the final chosen process plan for each job

The Gantt chart of the rescheduling result is shown in Figure 5-27. The correspondent objective functions values are shown in Table 5-16. And the finally selected process plan for each job is shown in Table 5-17.

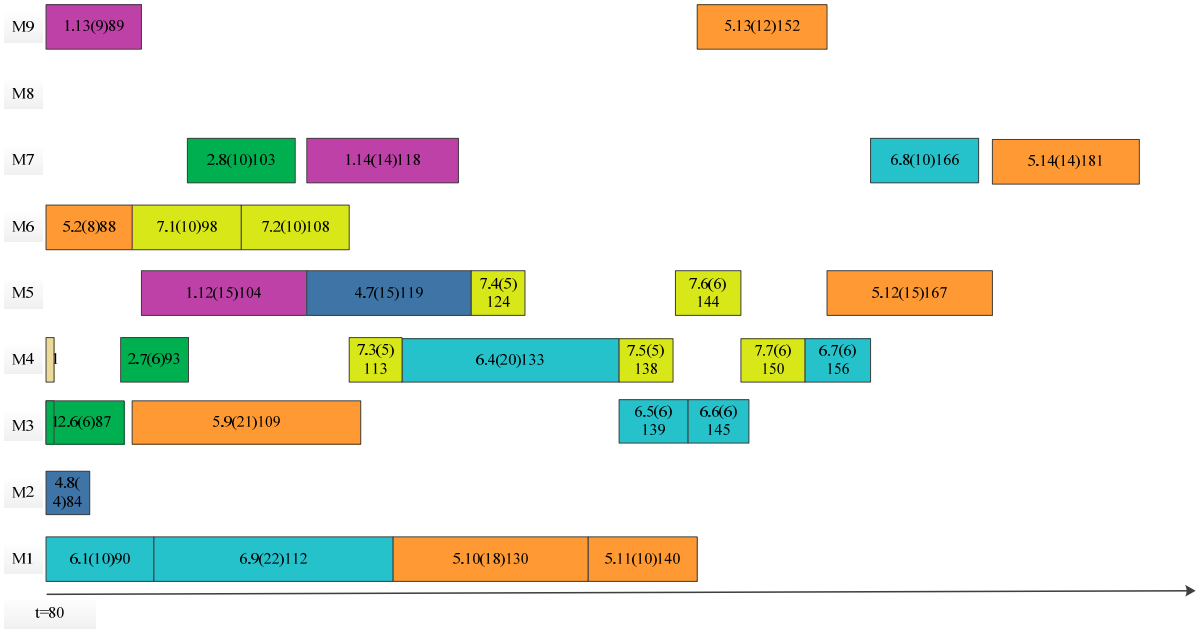


Figure 5-27 Gantt chart of rescheduling plan with arrival of new jobs (jobs 5, 6 and 7 at time t_3=80)

Table 5-16 The objective function values

Objective	Makespan	Cost	Energy Consumption	No.of added or deleted operations	Accelerated Time	Delayed Time
Value	181	2853,3	4648,2	0	0	0

Table 0-17 The selected process plan for the remaining operations of each job

Job No.	The selected process plan of each job in the rescheduling plan
Job 1	1.12 – 1.14

	5(15)-7(14)
Job 2	2.6 – 2.7 – 2.8 3(6)-4(6)-7(10)
Job 4	4.7 5(15)
Job 5	5.2 - 5.9 - 5.10 - 5.11 - 5.13 - 5.12 - 5.14 6(8)- 3(21)-1(18)-1(10)- 9(12)- 5(15)-7(14)
Job 6	6.1 - 6.9 - 6.4 - 6.5 - 6.6 - 6.7 - 6.8 1(10) -1(22)-4(20)-3(6)- 3(6)-4(6)-7(10)
Job 7	7.1 - 7.2 - 7.3 - 7.4 - 7.5 - 7.6 - 7.7 6(10) -6(10)-4(5)-5(5)-4(5)-5(6)-4(6)

5.5 Conclusion

In this chapter, for the purpose of facilitating rescheduling in the integration of process planning and scheduling in dynamic job shop environment, the rescheduling model in IPPS_DJS was firstly proposed to illustrate the rescheduling process when the disturbances of job cancellation, machine breakdown and new order arrival occur during the execution of the initial scheduling plan. Meanwhile, a mathematical model to describe the IPPS_DJS problem simultaneously considering efficiency and stability was established. The measurements adopted in light of efficiency optimization are makespan, machining cost, and energy consumption; while the measurements considered in stability optimization are the machine-related deviation cost and job-related deviation cost caused in the rescheduling plan. A multi-objective function is proposed by weighting method considering both the measurements involved in efficiency and stability, which is more practical in decision-making in real manufacturing systems. Finally, case studies have been done to verify the efficiency and effectiveness of the proposed IPPS_DJS framework and model.

Conclusion of Research

Contributions:

Global market competition and diversified, personalized customer demands have brought about the prevalence of single-piece & small batch production to more quickly respond to the variable market demands and further meet user requirements on product variety, quality, price and personalized service. Under such environment, product design and process planning should be more closely cooperated with practical production to enable the administrators in the enterprises and job shops to grasp the changes in the production site in the shortest time so that they can make accurate judgment and give rapid response to reasonably adjust the production plans.

Process planning and job shop scheduling are highly interrelated as both of them are related with resource assignment. Process planning is the act of preparing detailed operation instructions to transform an engineering design to a final part. A process plan specifies the manufacturing resources and the technical operations/routes that are needed to produce a product. Typically, a job may have one or more alternative process plans as a result of production flexibility. Scheduling receives process plans as their input and its task is to allocate the operations of all the jobs in an order to limited resources in time aspect to satisfy or optimize several criteria while respecting the precedence relations given in the process plans. Scheduling is not only the sequencing, but also the determining of the starting and completing time of each operation based on the sequence. Obviously process planning and job shop scheduling are two very important modules that interrelated and mutually interact with each other and integrating the two functions can improve production performances in the manufacturing systems. Besides, IPPS is very important to the development of CIMS.

In the past three decades, numerous researchers have carried out extensive and in-depth study on IPPS problems and achieved good. Based on the full analysis the results and deficiencies of existing research, this thesis conducted detailed and deeper research in the following aspects.

(1) State of Art Study

A state of the art on the problems related to IPPS was given based on the current published works, as well as a literature review of closely related problems. The related concepts and definitions of process planning, job scheduling and IPPS were introduced. Based on the analysis of the relationship between process planning and scheduling, the necessity to integrate the two was illustrated. The three traditional integration mechanisms of IPPS were studied and the comparison between these three mechasims was conducted to clearly describe the advantages and disadvantages of each traditioanl integration mechanism, based on which the improved integration mechanism of IPPS was researched to facilitate the proposition a new one in this thesis. The implementation approaches of IPPS optimization in the literatures were studies and summerized. The two major extended problems in IPPS were studied, which are multi-objective optimization problem and rescheduling problems. The key techniques involved in these two major extended problems were grasped based on the literature study, analysis and summary.

(2) A new Hybrid Model of Integrated Process Planning and Scheduling in Distributed Manufacturing Systems (HMIPPS_DMS**) was established**

The information integration model for IPPS problem in DMS was established based on the definition of DMS and its structure. Then to solve the IPPS optimization problems in a DMS environment, a new Hybrid Model of IPPS in DMS (HMIPPS_DMS) facilitating both information exchange and functional collaboration by combining NLPP and DPP in DMS environment was proposed. In HMIPPS_DMS, the hierarchical integration of process planning and scheduling is realized through three integration hierarchies: initial/rough integration phase in Enterprise Level Integration, matching integration phase in Job Shop Level Integration and final/detailed integration phase in Resource Level Integration. What's more, in job shop level integration, *s* near optimal alternative process plans are selected to be integrated with scheduling, which enhances production performances and offers process plan flexibility at the same time. Concurrent capability planning and capacity planning of the production resources avoids resource conflicts and unbalanced utilization of the resources, assuring production stability and efficiency in the job shops. A case study was designed and conducted based on the mathematical description of IPPS problem in DMS to demonstrate the reliability and describe the detailed procedures of HMIPPS_DMS, showing that the proposed HMIPPS_DMS can be very effective in solving the IPPS optimization problems in DMS environment.

Note that the integration mechanism in the job shop level and resource level is adaptive to IPPS in single enterprise and single job shop environment. Therefore, in the following research on the extended problems in IPPS in single job shop, this integration mechanism was adopted.

(3) Multi-Objective Optimization in IPPS is realized considering new energy consumption-related parameters and objectives

Based on the concept of Multi-Objective Optimization Problem (MOOP), the complete mathematical model to explain and describe the MOOP in IPPS in a single job shop was established, in which some new parameters and objectives relating energy consumption in machining the parts were adopted according to the related study and analysis. Then based on the mathematical model, multi-objective optimization for IPPS problems was realized using the improved NSGA-II so that the decision-makers in the enterprises and job shops can make reasonable choices according to their preferences for the objectives. The encoding, decoding and genetic operators adopted in this improved NSGA-II method were explained in detail. Finally, two case studies have been conducted to measure the adaptability of the improved NSGA-II algorithm and to verify the proposed mathematical model for solving the MOOP problems in IPPS.

(4) IPPS optimization in dynamic job shop is realized

For the purpose of facilitating rescheduling in the integration of process planning and scheduling in dynamic job shop environment, the rescheduling model in IPPS_DJS was firstly proposed to illustrate the rescheduling process when the disturbances of job cancellation,

machine breakdown and new order arrival occur during the execution of the initial scheduling plan. Meanwhile, a mathematical model to describe the IPPS_DJS problem simultaneously considering efficiency and stability was established. The measurements adopted in light of efficiency optimization are makespan, machining cost, and energy consumption; while the measurements considered in stability optimization are the machine-related deviation cost and job-related deviation cost caused in the rescheduling plan. A multi-objective function is proposed by weighting method considering both the measurements involved in efficiency and stability, which is more practical in decision-making in real manufacturing systems. Finally, case studies have been done to verify the efficiency and effectiveness of the proposed IPPS_DJS framework and model.

Limitations:

Based on the research in this thesis, the author has deepened the understanding and widened the knowledge of IPPS problems. The future work concerning this research should be further carried out in the following aspects.

(1) Besides integrating process planning and scheduling, process planning should also be integrated with the upper stream of product design while job shop scheduling should be integrated with Enterprise Resource Planning (ERP) and job shop control system, based on which CIMS can be realized.

(2) As the problems of energy shortage and environment pollution are becoming increasingly severe all over the world, and considering that the industrial sector is the largest energy consumer and currently accounts for about one-half of the world's total energy consumption, energy consumption mechanism and related parameters in IPPS should be more practically studied and quantified to optimize the energy consumption and environment effects in the job shops.

(3) The mathematical models established are based on the abstraction and simplification of practical environments, therefore these models cannot perfectly reflect the real situation in the job shops. Constructing more practical embedding the complicate and dynamic parameters relating to on site production is of significance in improving production efficiency and flexibility, shortening manufacturing time and lowering manufacturing cost.

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Appendix

Appendix 1: Summary of Recent Research on Multi-Objective Optimization of Production Scheduling Problem

Multi-Objective Optimization					
Authors	Research Domain	Optimization Algorithm	Objectives	MOO Approach	Notes
1. Li et al., 2004. Optimization of process plans using a constraint-based tabu search approach.	Single Part	TS	Six criteria are evaluated: ①cost of machines utilization; ②cost of cutting tools utilization; ③number of machine changes;④number of tool changes;⑤number of set-ups;⑥number of violated constraints (a penalty function)	Weighting method	
2. Xia and Wu 2005. An effective hybrid optimization approach for multi-objective flexible job-shop scheduling problems.	Flexible job-shop scheduling problem (FJSP). The FJS problem consists of two sub-problems of routing and scheduling.	Hierarchical approach: o Particle Swarm Optimization (PSO) to assign operations on machines; o Simulated Annealing (SA) algorithm to schedule operations on each machine.	F1: makespan or maximal completion time of machines; F2: total workload of the machines, which represents the total working time of all machines; F3: critical machine workload, that is the machine with the biggest workload.	Weighted sum of the objective values	Approaches to solve multi-objective optimization: (1) The transformation towards a mono-objective problem consists of combining the different objectives into a weighed sum. (2) The non-Pareto approach utilizes operators for processing the different objectives in a separated way. (3) The Pareto approach is directly based on the Pareto optimization concept. It aims at satisfying two goals: first, converge to the Pareto front and also obtain diversified solutions scattered all over the Pareto front.

3. Sugimura et al., 2007. A study on integrated process planning and scheduling system for holonic manufacturing.	Job-shop in holonic manufacturing systems	GA and DP (Dynamic Programming)	Process planning: F1: minimizing shop time; F2: minimizing machining cost; Scheduling: F1: Minimizing makespan; F2: Minimizing total machining cost; F3: Minimizing weighted tardiness cost	Weighting method	
4. Li-Ning Xing, Ying-Wu Chen, Ke-Wei Yang. Multi-objective flexible job shop schedule: design and evaluation by simulation modeling. 2009	Flexible job shop	Simulation-based	F1: Makespan or maximal completion time of machines; F2: Total workload of machines, which represents the total working time of all machines; F3: Critical machine workload, which is the machine with the biggest workload	Weighting method	
5. M.A. Adibi, M. Zandieh, M. Amiri. Multi-objective scheduling of dynamic job shop using variable neighborhood search. 2010	Dynamic job shop scheduling considering random job arrivals and machine breakdown.	Trained Artificial Neural network (ANN); Variable Neighborhood Search (VNS). VNS is selected as a scheduling method at any rescheduling point. To enhance the efficiency and effectiveness of VNS, its parameters are updated at any rescheduling point by ANN.	Makespan; Tardiness	Weighted sum of the objective values	The fundamental unit of ANN is the neurons which are arranged in layers and are categorized as input (I), hidden (H) and output (O) neurons depending on in which layer they are located. Neurons in each layer are linked to each of those in the layers immediately next to it through connections known as synapses. Each of synapses is characterized by a weight factor which can be adjusted to target

					the desired output signal. A back propagation neural network is adopted in this study in which signals are passed from the input layer to the output layer through a hidden layer and learning is done by adjusting the connection weights by an algorithm that involves back propagating the error to previous layers.
6. Xiaojuan Wang, Liang Goa, Chaoyong Zhang and Xinyu Shao. A multi-objective genetice algorithm based on immune and entropy principle for flexible job-shop scheduling problem. 2010	Flexible job shop	GA	F1: Makespan or maximal completion time of machines; F2: Total workload of machines, which represents the total working time of all machines; F3: Critical machine workload, which is the machine with the biggest workload	Pareto approach	
7. Ghasem Moslehi, Mehdi Mahnam. A pareto approach to multi-objective flexible job-shop scheduling problem using particle swarm optimization and local search. 2011	Flexible job-shop problem (FJSP). The flexible job-shop problem is an extension of the job-shop problem that allows an operation to be processed by any machine from a given set along different routes.	Integrated multi-objective approach based on hybridization of particle swarm optimization and local search algorithm to. PSO allows an extensive search of solution space while the local search algorithm is employed to reassign the machines to operations and to reschedule the results obtained from the PSO, which will enhance convergence speed.	F1: Minimizing makespan or maximal completion time by machine; F2: Total workload of the machines, which represents the total working time of all machines; F3: Critical machine workload.	Weighted sum of the objective values; Pareto approach.	The FJS problem consists of two sub-problems of routing and scheduling. o The routing sub-problem assigns each operation to a machine among a set of machines authorized for each job. o The scheduling sub-problem involves sequencing the operations assigned to the machines in order to obtain a feasible schedule that minimizes a predefined objective
8. E. Moradi, S.M.T. Fatemi Ghomi, M. Zandieh. Bi-objective optimization research	Flexible job shop	NSGA-II	F1: the minimization of makespan;	Pareto approach	

on integrated fixed time interval preventive maintenance and production for scheduling flexible job-shop problem. 2011			F2: the minimization of the system unavailability for the maintenance part		
9. Norhashimah Morad, Ams Zalzala. Genetic algorithms in integrated process planning and scheduling. 1999	Job shop (only routing flexibility was considered)	GA	F1: minimizing makespan; F2: minimizing total rejects; F3: minimizing the total cost of production	Weighting method	
10. Chiung Moon, Yoon ho Seo. Advanced planning for minimizing makespan with load balancing in multi-plant chain. (2005b)	Multi-plant, batch-MFG	aGA	F1: Minimizing makespan F2: Minimizing workload variations	Pareto optimal	
11. Wong T. N., Leung C. W., et al. An agent-based negotiation approach to integrate process planning and scheduling. 2006(a)	Job shop	Agent-based Autonomous architectures Java-based simulation model MAN (Multi-agent Negotiation)	F1: Minimizing makespan F2: Minimizing mean flowtime	Weighting method	
12. W.D. Li, C.A. McMahon. A simulated annealing-based optimization approach for integrated process planning and scheduling. 2007	Single part in variant orders, job shop, IPPS	SA	①Manufacturing cost, including the six criteria mentioned above; ②makespan; ③the balanced level of machine utilization;④part tardiness	Weighting method	
13. Xinyu Li. Research on integrated process planning and scheduling(D). 2009	Single part in variant orders, job shop, IPPS	NSGA-II	o Minimizing the makespan; o Minimizing the total processing cost; o Minimizing the lateness; o Minimizing the weighted number of tardy jobs; o Minimizing the total	Pareto approach	

			earliness plus the total tardiness		
14. Li WD, Gao L, Li XY, Guo Y. Game theory-based cooperation of process planning and scheduling. 2008	Single part in variant orders, job shop, IPPS	PSO, GA, SA	Makespan and manufacturing cost; balanced utilization of machines and manufacturing cost	(Pareto strategy, Nash strategy and Stackelberg strategy have been used to provide a flexible scheme to prioritize objectives in IPPS)	
15. Li WD, Gao L. Intelligent and cooperative manufacturing planning. 2010	Single part in variant orders, job shop, IPPS	PSO, GA, SA	Makespan and manufacturing cost; balanced utilization of machines and manufacturing cost	(Pareto strategy, Nash strategy and Stackelberg strategy have been used to provide a flexible scheme to prioritize objectives in IPPS)	Compared to above, the new content in this paper is fuzzy logic-based Analytical Hierarchical Process (AHP) technique was applied to handle the complex constraints effectively
16. Wang Y F, Zhang Y F, Fuh J Y H. A PSO-based multi-objective optimization approach to the integration of process planning and scheduling. 2010	Job shop, batch-mfg, IPPS	PSO	F1: Minimizing the machining cost; F2: Minimizing the total tardiness	Pareto approach	
17. Baykasoğlu A, Özbakır L. A grammatical optimization approach for integrated process planning and scheduling. 2009	Single part in variant orders, job shop, IPPS	TS	F1: Total flow time; F2: total cost of process plans	Pareto approach	
18. Wenqiang Zhang, Mitsuo Gen. Process planning and scheduling in distributed manufacturing system using multiobjective genetic algorithm. 2010	Distributed manufacturing system environment, where factories with various machines and tools at different geographical locations are often combined to produce various parts with different resource constraints.	Fast MultiObjecitve Genetic Algorithm with Archive Mechanism (fmoGA-A)	F1: minimizing the maximum total processing time; F2: minimizing the maximum variation of workload of machine	Pareto approach	IMPORTANT REFERENCE
19. Xinyu Li, Liang Gao, Weidong Li. Application of game theory based hybrid algorithm for multi-objective integrated process planning and scheduling. 2012	Single part in variant orders, job shop, IPPS	Game theory based hybrid algorithm (GA and TS)	① in order to improve the work efficiency, selecting the maximal completion time of machines, namely the makespan, as one objective; ② in order to improve the	Nash equilibrium, non-cooperative game th eory	

			utilization of the existing resources, especially for the machines, selecting the maximal machine workload, namely, the maximum working time spent on any machine, and the total workload of machines, namely the total working time of all machines, as the other two objectives.		
20. Wen Xiaoyu, Li Xinyu, Gao Liang; Wang Wenwen, Wan Liang. Improved genetic-algorithm with external archive maintenance for multi-objective integrated process planning and scheduling. 2013	Single part in variant orders, job shop, IPPS	Improved GA with external archive to store and maintain the generated non-dominated solutions during the optimization procedure	F1: Minimizing makespan F2: Minimizing the maximal machine workload F3: Minimizing the total workload of machines	Pareto optimal solution	
21. Manupati V. K., Thakkar J. J., Wong K. Y., Tiwari M. K. Near optimal process plan selection for multiple jobs in networked based manufacturing using multi-objective evolutionary algorithms. 2013	Networked Manufacturing Environment, IPPS	Territory Defining Evolutionary Algorithm (TDEA), Non-dominated Sorting Genetic Algorithm (NSGA-Ⅱ), Controlled Elitist- NSGA-Ⅱ (CE- NSGA-Ⅱ)	F1: Minimizing makespan; F2: Maximizing machine utilization	Pareto approach	
22. Mohapatra P., Benyoucef Lyes, Tiwari M. K. Integration of process planning and scheduling through adaptive setup planning: a multi-objective approach. 2013a	Job shop with reconfigurable manufacturing settings	NSGA-Ⅱ	F1: minimizing the machining cost of the part; F2: minimizing the makespan of the parts' F3: maximizing the machine utilization	Pareto approach	

Appendix 2: Summary of Recent Research on Rescheduling Problems

The table contains four main sections: Shop floor, Environment dynamism, Production flexibility, and Approach.

- The Environment dynamism section specifies uncertainty and disturbance sources in the manufacturing systems.
- The Production flexibility section specifies the types of flexibility considered in the manufacturing systems (W. D. Li, C. A. McMahon, 2007)
  - Routing flexibility: also called operation flexibility, relates to the possibility of performing one operation on alternative machines, with possibly distinct processing time and cost.
  - Sequencing flexibility is decided by the possibility of interchanging the sequence of the required operations.
  - Processing flexibility is determined by the possibility of processing the same manufacturing feature with alternative operations or sequences of operations (Xinyu Shao, Xinyu Li et al, 2009).
- The Approach section specifies the attributes of approaches that are used in each work.
- Type represents on-line or offline attribute of each approach.
  - Offline scheduling: in the classical scheduling research, it is assumed that information relating to the jobs and machines availability is completed prior to scheduling generation (Zhang G, Ye D, 2002). Such an approach is called offline scheduling (Amir Rajabinasab, Saeed Mansour, 2011).
  - Online scheduling: machine breakdowns and new job arrivals are online events. Approaches that consider such online events are called online scheduling.

So, any dynamic disturbances can easily be handled in online approaches, but in offline approaches, scheduling generated first must be revised periodically to stay feasible (Sabuncuoglu I, Bayiz M, 2000).

Authors	**Shop Floor Type**	**Environmental dynamism**				**Prodcution flexibility**			**Approach**				
		Order arrival	**Order cancellation**	**Machine breakdown**	**Processing time**	**RF**	**SF**	**PF**	**Objective function**	**Methodology**	**Method**	**Type**	**Policy**
Amir Rajabinasab, Saeed Mnsour (2011)	Job Shop	✓	×	✓	✓	✓	×	✓	F1: minimizing mean flow time; F2: minimizing mean job tardiness	MAS, simulation experiments to statistical analysis	pheromone-based	Online	Event-dirven

Pierpaolo Caricato, Antonio Grieco (2008)	generic hybrid flow shop	✓	×	×	×	✓	×	×	Inserting an incoming job into the current schedule pursuing the double objective of keeping as much as possible of the current schedule and delaying as little as possible the incoming job completion	Neigborhood serching	Constraint programming	Hybrid of online scheduling and rescheduling	Event-dirven
Yang Honghong, Wu Zhiming (2003)	FMS job shop	✓	✓	✓	×	✓	×	×	minimum weighted quadratic tardiness	AI	AGA (Adapative Genetic Alogorithm)	regeneration of new scheduling	Event-dirven
Ruedee Rangsaritratsamee, William G. Ferrell Jr., Mary Beth Kurz (2004)	Job Shop	✓	×	×	×	×	×	×	maximizing efficiency (makespan+job tardiness) and stability (starting time deviation+a penalty proportional to the total deviation)	AI, simulation-based	Genetic local search algorithm	regeneration of new scheduling	Periodic
WONG T. N., LEUNG C. W. et al. (2006c)	Job Shop, IPPS	✓	×	✓	×	✓	×	✓	F1: minimizing parts' flowtime; F2: maximizing machines' utilization F3: minimizing the deviations from the preschedule	Online Hybrid Agent-based Negotiation (Mediator architecture)	Online hybrid contract-net negotiation protocol (oHCNP)	Affected operations rescheduling approach	Event-dirven
Li W. D., C. A. McMahon (2007)	Job Shop, IPPS	✓	×	✓	×	✓	✓	×	Makespan; Balanced level of machine utilization; Part tardiness; Manufacturing cost	AI	Simulated annealing	regeneration of new scheduling	Event-dirven
Li W. D., Gao L., Li X. Y., Guo, 2008	Job Shop, IPPS	✓	×	✓	×	✓	✓	×	Makespan and manufacturing cost; balanced utilization of machines and manufacturing cost	AI (Pareto strategy, Nash strategy and Stackelberg strategy have been used to provide a flexible scheme to prioritize objectives in IPPS)	PSO, SA and GA	regeneration of new scheduling	Event-dirven
Wang Y F, Zhang Y F, Fuh J Y H, et al, 2008(b)	Job Shop, IPPS	×	×	✓	×	✓	✓	✓	Machining cost ; Total job tardiness;	AI	SA for process planning and heuristic rules	Affected operations rescheduling	Event-dirven

									Sequence deviation		for scheduling)	approach	
Guo Yanwu, Li Weidong et al. (2009b)	Job Shop, IPPS	✓	×	✓	×	✓	✓	×	Makespan; Balanced level of machine utilization;Part tardiness	AI	Particle swarm	regeneration of new scheduling	Event-dirven
Li Xinyu (2009)	Job Shop, IPPS	✓	×	✓	✓	✓	✓	✓	Makespan	AI	GA	regeneration of new scheduling	Hybrid of periodic and event-driven
Zhang Luping, Wong T. N., Fung Y. K., (2012)	Job Shop, IPPS	✓	×	✓	×	✓	✓	✓	Makespan	MAS architecture with embedded heuristic algorithms	ACO was taken for example in the paper	regeneration of new scheduling	Event-dirven
Lv Shengping, Qiao Lihong (2013)	Job Shop, IPPS	✓	✓	✓	×	✓	✓	✓	Makespan	AI	GA	regeneration of new scheduling	Event-dirven

Appendix 3: Literature Summary of IPPS

Authors	Shop	Integration	Optimization	Mathematical model	Objective Functions	SOO or	DS?

	Floor Type	Scheme	Approaches	RF	SF	PF	Tool	TAD	Setup	TT	MC		TC		Setup C		Initial machine loading	Energy		MOO	
											T	C	T	C	T	C					
Morad N, Zalzala A M S, 1999	Manufacturing cells	Simultaneous approach	GA	✓	×	×	×	×	×	×	×	×	×	×	×	×	×		F1: Minimizing makespan; F2: Minimizing total rejects produced; F3: Minimizing the total cost of production	MOO Weigthing method	N
Lee H., Kim S. S., 2001	Job shop	NLPP	GA	✓	✓	✓	×	×	×	×	×	×	×	×	×	×	×	×	F1: Minimizing makespan; F2: Minimizing tardiness	SOO	N
Kim Y K, Park K, Ko J, 2003	Job shop	Simultaneous approach	Symbiotic evolutionary algorithm	✓	✓	✓	×	×	×	×	×	×	×	×	×	×	×	×	F1: Minimizing makespan F2: Minimizing mean flow time	SOO	N
Baykasoğlu A, Özbakır L, 2009	Job shop	NLPP	TS	✓	✓	×	×	×	×	×	×	×	×	×	×	×	×	×	F1: Minimizing total flow time; F2: Minimizing total costs of process plan	MOO (Pareto optimal)	N
Jain Ajai, Jain PK, Singh IP, 2006	FMS	Hybrid of NLPP and NLPP, iteration	GA	✓	✓	✓	×	×	×	×	×	×	×	×	×	×	×	×	F1: Minimizing makespan F2: Minimizing mean flow time	SOO	N
Phanden R K, Jain A, Verma R, 2013	Job shop	Hybrid of NLPP and CLPP, iteration	GA	✓	✓	✓	×	×	×	×	×	×	×	×	×	×	×	×	F1: Minimizing mean tardiness; F2: Minimizing makespan	SOO	N
Zattar I. C., Ferreira J. C. E., Rodrigues J. G. G. G., et al, 2010	Job shop	Agent-based	Operation-based time-extended negotation protocol	✓	✓	✓	×	×	✓	✓	×	×	×	×	✓	×	✓	×	F1: Minimizing makespan; F2: Minimizing flow time	SOO	N
Zhao Fuqing, Hong Yi et al, 2010	Job Shop	Agent-based	Fuzzy logic and Hybrid particle swarm optimization	✓	✓	✓	×	×	×	×	×	×	×	×	×	×	✓	×	F1: Minimizing makespan; F2: Minimizing total number of rejects; F3: Minimizing total processing cost	SOO	Y
Amir Rajabinasab, Saeed Mnsour, 2011	Job Shop	Agent-based	Pheromone-based approach	✓	×	✓	×	×	×	×	×	×	×	×	×	×	×	×	F1: minimizing mean flow time; F2: minimizing mean job tardiness	SOO	Y
Chan F. T. S., Kumar V., Tiwari M. K., 2006	Job shop with outsourcing	Simultaneous approach	Artificial Immune System based AIS-FLC (Fuzzy Logic Control)	✓	✓	✓	×	×	×	✓	×	×	×	×	×	×	×	×	F1: Minimizing the makespan	SOO	N

			algorithm																	
Chan F. T. S., Kumar V., Mishra Nishikant, 2008	Multi Plant Supply chain	Simultaneous approach	Cooperative Multiple Particle Swarm Optimization (CMPSO) algorithm	✓	✓	✓	×	×	✓	✓	×	×	×	×	✓	×	×	×	F1: Minimizing the total tardiness	SOO	N
Shukla S. K., Tiwari M. K., Son Y. J., 2008	Job Shop	Agent-based	Contract net protocol, Hybrid SA algorithm	✓	✓	✓	✓	✓	✓	✓	×	✓	×	✓	×	✓	×	×	F1: Minimizing total machining cost F2: Minimizing makespan	MOO Weigthing method	Y
Chan F. T. S., Kumar V., Tiwari M. K., 2009	Job shop with outsourcing	Simultaneous approach	Enhanced Swift Converging Simulated Annealing algorithm	✓	✓	✓	×	×	×	✓	×	×	×	×	×	×	×	×	F1: Minimizing the makespan	SOO	N
Cai Ningxu, Wang Lihui, Feng His-Yung, 2009	Job shop with reconfigurable manufacturing settings	Simultaneous approach	GA	✓	✓	✓	✓	✓	✓	×	✓	×	✓	×	✓	×	×	×	F1: Locating a part as stably and accurately as possible; F2: Grouping as many 3-axis-based setups as possible into a merged final setup; F3: minimizing the total number of final setups; F4: minimizing the machining cost of the part; F5: minimizing the makespan of the parts' F6: maximizing the machine utilization	MOO (Weighted Method)	N
Mohapatra P., Benyoucef Lyes, Tiwari M. K., 2013a	Job shop with reconfigurable manufacturing settings	Simultaneous approach	NSGA-II	✓	✓	✓	✓	✓	✓	×	✓	×	✓	×	✓	×	×	×	F1: minimizing the machining cost of the part; F2: minimizing the makespan of the parts' F3: maximizing the machine utilization	MOO (Pareto optimal)	N
Mohapatra P., Benyoucef Lyes, Tiwari M. K., 2013b	Job shop with reconfigurable manufacturing settings	Simultaneous approach	Artificial Immune System (AIS)	✓	✓	✓	✓	✓	✓	×	✓	×	✓	×	✓	×	×	×	F1: minimizing the machining cost of the part; F2: minimizing the makespan of the parts' F3: maximizing the machine utilization	MOO (Weighted Method)	N
Manupati V. K., Deo Sujay, Cheikhrouhou	Networked manufac	Simultaneous approach	Game theoretic approach	✓	✓	✓	×	×	×	✓	×	×	×	×	×	×	×	×	;	SOO	N

and Tiwari M. K., 2012	turing		with a hybrid dynamic-DNA algorithm																	
Manupati V. K., Thakkar J. J., Wong K. Y., Tiwari M. K., 2013	Networked manufacturing	Simultaneous approach	Territory Defining Evolutionary Algorithm (TDEA), Non-dominated Sorting Genetic Algorithm (NSGA-Ⅱ), Controlled Elitist-NSGA-Ⅱ (CE- NSGA-Ⅱ)	✓	✓	✓	×	×	×	✓	×	×	×	×	×	×	×	×	F1: Minimizing makespan; F2: Maximizing machine utilization	MOO	N
Sugimura N., Hino R., Moriwaki T., 2001	Holonic manufacturing systems	Simultaneous approach	GA and DP (Dynamic Programming)	✓	✓	×	✓	✓	✓	×	✓	×	✓	×	✓	×	✓	×	F1: Minimizing manufacturing time (machining time and set-up time)	SOO	N
Sugimura N, Shrestha R, Inoue J, 2003	Job-shop in holonic manufacturing systems	Simultaneous approach	GA and DP (Dynamic Programming)	✓	✓	×	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	×	F1: minimizing shop time; F2: minimizing machining cost	MOO (Weighted Method	N
Sugimura N, Shrestha R, Tanimizu Y, et al, 2007	Job-shop in holonic manufacturing systems	Iteration approach	GA and DP (Dynamic Programming)	✓	✓	×	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	×	Process planning: F1: minimizing shop time; F2: minimizing machining cost; Scheduling: F1: Minimizing makespan; F2: Minimizing total machining cost; F3: Minimizing weighted tardiness cost	MOO (Weighted Method)	N
Hossein Tehrani, Nobuhiro Sugimura, 2007	FMS (Flexible Manufacturing Systems)	Generating alternative process plans	An incomplete search algorithm	✓	✓	✓	✓	×	✓	×	×	×	×	×	×	×	×	×	F1: Minimizing manufacturing time	SOO	N

Hossein Tehrani Nik Nejad, Nobuhiro Sugimura et al, 2008	FMS (Flexible Manufacturing Systems)	Agent-based Mediator architecture	Contract Net Protocols	✓	✓	×	✓	✓	✓	✓	✓	×	✓	×	✓	×	✓	×	F1: Minimizing manufacturing time F2: Minimizing completion time	SOO	Y
Hossein Tehrani Nik Nejad, Nobuhiro Sugimura et al, 2010	FMS	Agent-based Mediator architecture	Contract Net Protocols	✓	✓	×	✓	✓	✓	✓	✓	×	✓	×	✓	×	✓	×	F1: Minimizing manufacturing time F2: Minimizing completion time	SOO	Y
Hossein Tehrani Nik Nejad, Nobuhiro Sugimura et al, 2011	FMS	Agent-based Mediator architecture	Contract Net Protocols	✓	✓	×	✓	✓	✓	✓	✓	×	✓	×	✓	×	✓	×	F1: Minimizing manufacturing time F2: Minimizing completion time	SOO	Y
Fujiii N., Inoue R and Ueda K, 2008	Job shop	Agent-based Simultaneous approach	Evolutionary artificial neural networks	✓	✓	×	×	×	×	×	×	×	×	×	×	×	×	×	F1: Minimizing makespan	SOO	Y
Chiung Moon, Moonhwan Lee, Yoonho Seo, Young Hae Lee, 2002(a)	Dynamic batch production	Simultaneous approach	GA based on topological sort technique	✓	✓	×	×	×	×	✓	×	×	×	×	×	×	×	×	F1: Minimizing production time F2: Minimizing machine workloads	SOO	N
Chiung Moon, Jongsoo Kim, Sun Hur, 2002(b)	Multi-plant supply chain, batch-MFG	Simultaneous approach	GA	✓	✓	×	×	×	✓	✓	×	×	×	×	✓	×	✓	×	F1: Minimizing total tardiness	SOO	N
Young Hae Lee, Chan Seok Jeong, Chiung Moon, 2002	Multi-plant supply chain, batch-MFG	Simultaneous approach	GA	✓	✓	×	×	×	×	✓	×	×	×	×	×	×	×	×	F1: Minimizing makespan	SOO	N
Chiung Moon, Yoonho Seo, 2005(a)	Multi-plant, batch-MFG	Simultaneous approach	EA	✓	✓	×	×	×	✓	✓	×	×	×	×	✓	×	×	×	F1: Minimizing makespan	SOO	N
Chiung Moon, Yoonho Seo, 2005(b)	Multi-plant, batch-MFG	Simultaneous approach	aGA	✓	✓	×	×	×	✓	✓	×	×	×	×	✓	×	✓	×	F1: Minimizing makespan F2: Minimizing workload variations	MOO (Pareto optimal)	N

Chiung Moon, Yoonho Seo, Youngsu Yun, Mitsuo Gen, 2006	MFG supply chain	Simultaneous approach	aGA	✓	✓	×	×	×	✓	✓	×	×	×	×	✓	×	✓	×	F1: Minimizing makespan	SOO	N
Chiung Moon, Young Hae Lee, Chan Seok Jeong, YoungSu Yun, 2008	MFG supply chain	Simultaneous approach	Evolutionary search approach	✓	✓	×	×	×	✓	✓	×	×	×	×	✓	×	×	×	F1: Minimizing makespan	SOO	N
Saravanan A N, Zhang Y F, Fuh J Y H.	Job shop, batch-MFG	NLPP Iterative approach	SA or GA for process planning; heuristic algorithms for IPPS	✓	✓	✓	✓	✓	✓	×	×	✓	×	✓	×	✓	×	×	F1: Minimizing machining cost (machine cost, tool cost, machine change cost, setup change cost and tool change cost); F2: Machine Utilization; F3: Minimizing job tardiness	SOO	N
Wu S. H., FUH J.Y.H., NEE A. Y.C., 2002	Distributed Virtual Manufacturing (DVM) – Job shop	Hierarchical integration in levels of Enterprise and shop floor. Agent-based	KQML (Knowledge Query and Manipulation Language) protocols	✓	✓	✓	×	×	✓	✓	×	×	×	×	✓	✓	✓	×	F1: Minimizing machining cost	SOO	N
Zhang Y. F., Saravanan A. N., Fuh JYH, 2003	Job shop, batch-MFG	NLPP Iterative approach	SA for process planning; heuristic algorithms for IPPS	✓	✓	✓	✓	✓	✓	×	×	✓	×	✓	×	✓	×	×	F1: Minimizing machining cost (machine cost, tool cost, machine change cost, setup change cost and tool change cost); F2: Machine Utilization; F3: Minimizing job tardiness	SOO	N
Wang Y F, Zhang Y F, Fuh J Y H, et al, 2008(a)	Job shop, batch-MFG	NLPP Iterative approach	SA for process planning; heuristic algorithms for IPPS	✓	✓	✓	✓	✓	✓	×	×	✓	×	✓	×	✓	×	×	F1: Minimizing machining cost (machine cost, tool cost, machine change cost, setup change cost and tool change cost); F2: Minimizing job tardiness	SOO	N
Wang Y F, Zhang Y F, Fuh J Y H, et al, 2008(b)	Job shop, batch-MFG	NLPP Iterative approach	SA for process planning; heuristic algorithms for IPPS	✓	✓	✓	✓	✓	✓	×	×	✓	×	✓	×	✓	×	×	F1: Minimizing machining cost (machine cost, tool cost, machine change cost, setup change cost and tool change cost); F2: Minimizing job tardiness	SOO	Y
Wang J., Zhang Y. F., et al, 2009	Job shop, batch-MFG	NLPP Iterative approach	SA for process planning; heuristic	✓	✓	✓	✓	✓	✓	×	×	✓	×	✓	×	✓	×	×	F1: Minimizing machining cost (machine cost, tool cost, machine change cost, setup change cost and tool change cost); F2: Minimizing job tardiness	SOO	N

			algorithms for IPPS																	
Wang Y F, Zhang Y F, Fuh J Y H, 2010	Job shop, batch-MFG	Simultaneous approach	PSO with local search	✓	✓	✓	✓	✓	✓	×	×	✓	×	✓	×	✓	×	×	F1: Minimizing machining cost (machine cost, tool cost, machine change cost, setup change cost and tool change cost); F2: Minimizing job tardiness	MOO Non-dominated	N
Li W. D., McMahon C. A., 2007	Job shop	Simultaneous approach	SA	✓	✓	×	✓	✓	✓	×	✓	✓	✓	✓	✓	✓	×	×	F1: Minimizing machining cost (machine cost, tool cost, machine change cost, setup change cost and tool change cost); F2: Minimizing makespan; F3: The balanced level of machine utilization; F4: Minimizing part tardiness	MOO, Weighted method	Y
Li W. D., Gao L., Li X. Y., Guo, 2008	Job shop	Simultaneous approach	PSO, GA, SA	✓	✓	×	✓	✓	✓	×	×	✓	×	✓	×	✓	×	×	F1: Minimizing makespan; F2: The balanced level of machine utilization; F3: Minimizing part tardiness F4: Minimizing manufacturing cost	MOO (F1+F4; F2+F4)	Y
Li W. D., Gao L., 2010	Job shop	Simultaneous approach	PSO, GA, SA	✓	✓	×	✓	✓	✓	×	×	✓	×	✓	×	✓	×	×	F1: Minimizing makespan; F2: The balanced level of machine utilization; F3: Minimizing manufacturing cost	MOO (F1+F3; F2+F3)	N
Guo Y. W., Li W. D., et al., 2009(a)	Job shop	Simultaneous approach	PSO	✓	✓	✓	✓	✓	✓	×	✓	×	✓	×	✓	×	×	×	F1: Minimizing makespan; F2: The balanced level of machine utilization; F3: Minimizing part tardiness F4: a fixed penalty time (PT)	SOO	N
Guo Y. W., Li W. D., et al., 2009(b)	Job shop	Simultaneous approach	PSO	✓	✓	✓	✓	✓	✓	×	✓	×	✓	×	✓	×	×	×	F1: Minimizing makespan; F2: The balanced level of machine utilization; F3: Minimizing part tardiness	SOO	Y
Li XY, Zgabg GH, Zhang CY, Shao XY, 2008	Job shop	Simultaneous approach	GA	✓	✓	✓	×	×	×	×	✓	×	×	×	×	×	×	×	F1: Minimizing makespan	SOO	N

Shao Xinyu, Li Xinyu, Gao Liang, Zhang Chaoyong, 2009	Job shop	Hybrid of NLPP and DPP	Modified GA	✓	✓	✓	×	×	×	✓	×	×	×	×	×	×	×	×	F1: Minimizing the production time F2: Minimizing makespan F3: Synthetic consideration of makespan and balanced level of mahine utiliztion	SOO	N
Li Xinyu, Shao Xinyu, Zhang Chaoyong, Wang Cuiyu, 2010(c)	Job shop	Hybrid of NLPP and DPP	EA	✓	✓	✓		×	×	×	×	×	×	×	×	×	×	×	F1: Minimizing makespan; (verified) The following objective functions are defined but not verified: F2: minimizing the total processing cost F3: minimizing the lateness F4: minimizing the total weighted tardiness F5: minimizing the weighted number of tardy jobs; F6: minimizing the total earliness plus the total tardiness	SOO	N
Li Xinyu, Shao Xinyu, Gao Liang, Qian Weirong, 2010(b)	Job shop	Hybrid of NLPP and DPP	HA of GA and TS	✓	✓	✓	×	×	×	×	×	×	×	×	×	×	×	×	As above	SOO	N
Li Xinyu, Zhang Chaoyong, Gao Liang, Liweidong, Shao Xinyu, 2010(d)	Job shop	Simultaneous approach	Multi-agent (Mediator architecture), MGA	✓	✓	✓	×	×	×	✓	×	×	×	×	×	×	×	×	F1: Minimizing makespan	SOO	N
Li Xinyu, Gao Liang, Li Weidong, 2012(a)	Job shop	Simultaneous approach	HA of GA and TS	✓	✓	✓	×	×	×	×	×	×	×	×	×	×	×	×	F1: Minimizing makespan; F2: Minimizing the maximal machine workload; F3: Minimizing the total workload of machines	MOO (Nash equilibrium in Game Theory)	N
Li Xinyu, Gao Liang, Shao Xinyu, 2012(b)	Job shop	Hybrid of NLPP and DPP	ALGA (active learning genetic algorithm)	✓	✓	✓	×	×	×	×	×	×	×	×	×	×	×	×	F1: Minimizing makespan	SOO	N
Wen Xiaoyu, Li Xinyu, Gao Liang; Wang Wenwen, Wan Liang, 2013	Job shop	Simultaneous approach	IGA	✓	✓	✓	×	×	×	×	×	×	×	×	×	×	×	×	F1: Minimizing makespan F2: Minimizing the maximal machine workload F3: Minimizing the total workload of machines	MOO (Pareto optimal solution)	N
Qiao Lihong, Lv Shengping, 2012	Job shop	Hybrid of NLPP and DPP	IGA	✓	✓	✓	×	×	×	×	×	×	×	×	×	×	×	×	F1: Minimizing makespan F2: Minimizing mean flow time F3: Minimizing the maximum of lead time F4: Minimizing the maximum tardiness time	SOO	N

																		F5: Minimizing the mean tardiness F6: Maximizing resource utilization F7: Minimizing the total load of machines F8: Maximizing the balance of machine		
Lv Shengping, Qiao Lihong, 2013.	Job shop	Hybrid of NLPP and DPP	IGA	✓	✓	✓	×	×	×	×	×	×	×	×	×	×	×	As above	SOO	Y
Lv Shengping, Qiao Lihong, 2014	Job shop	Hybrid of NLPP and DPP	IGA	✓	✓	✓	×	×	×	×	×	×	×	×	×	×	✓	F1: Minimizing makespan	SOO	N
Wong T. N., Leung C. W., Mak K. L., Fung Y. K., 2006(a)	Job shop	Agent-based Autonomous architecture	Java-based simulation model MAN (Multi-agent Negotiation)	✓	✓	✓	×	×	×	×	×	×	×	×	×	×	×	F1: Minimizing makespan F2: Minimizing mean flowtime	MOO Weighting method	N
Wong T. N., Leung C. W., et al., 2006(b)	Job shop	Agent-based; Both autonomous architecture and mediator architecture	Simulation-based (hybrid contract net protocol)	✓	✓	✓	×	×	×	×	×	×	×	×	×	×	×	F1: Minimizing the mean parts' flowtime ; F2: Minimizing makespan; F3: maximizing the mean machines' utilization; F4: Minimizing the sum of machines' loading deviation	SOO	N
Wong T. N., Leung C. W., Mak K. L., Fung Y. K., 2006(c)	Job shop	Agent-based Mediator architecture	Simulation-based	✓	✓	✓	×	×	×	×	×	×	×	×	×	×	×	F1: minimizing parts' flowtime; F2: maximizing machines' utilization F3: minimizing the deviations from the preschedule	SOO	Y
Leung C. W., Wong T. N., et al., 2010	Job shop	Simultaneous approach	ACO-MAS (ant colony optimization algorithm in an multi-agent system)	✓	✓	✓	×	×	×	×	×	×	×	×	×	×	×	F1: Minimizing makespan	SOO	N
Wong T. N., Zhang Sicheng, Wang Gong and Zhang Luping, 2012	Job shop	Two stages of process selection and process sequencing	ACO-MAS (ant colony optimization algorithm in an multi-agent system)	✓	✓	✓	×	×	×	×	×	×	×	×	×	×	×	F1: Minimizing makespan	SOO	N
Zhang Luping, Wong T. N. and Fung Y. K., 2012 (a)	Job shop	Simultaneous approach	MAS architecture with embedded	✓	✓	✓	×	×	×	×	×	×	×	×	×	×	×	F1: Minimizing makespan	SOO	Y

			heuristic algorithms																	
Zhang Luping, Wong T. N., 2012(b)	Job shop	Simultaneous approach	Constraint programming	✓	✓	✓	×	×	×	×	×	×	×	×	×	×	×	×	F1: Minimizing makespan	SOO	Y
Zhang Sicheng, Wong T. N., et al., 2013(a)	Job shop	Two stages of process selection and process sequencing	ACO-MAS (ant colony optimization algorithm in an multi-agent system)	✓	✓	✓	×	×	×	×	×	×	×	×	×	×	×	×	F1: Minimizing makespan	SOO	N
Wan S. Y., Wong T. N., et al., 2013	Job shop	Simultaneous approach	Ant Colony Optimization (ACO)	✓	✓	✓	✓	×	✓	×	✓	×	✓	×	✓	×	×	×	F1: Minimizing makespan	SOO	N
Zhang Sicheng, Wong T. N., 2013(b)	Job shop	Simultaneous approach	Enhanced ACO	✓	✓	✓	×	×	×	×	×	×	×	×	×	×	×	×	F1: Minimizing makespan	SOO	N

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PÔLE DE RECHERCHE ET D'ENSEIGNEMENT SUPÉRIEUR

Centrale Nantes

Thèse de Doctorat

Fang LIU

Contributions aux Technologies Clés de l'Intégration de la Planification des Processus et l'Ordonnancement dans les Ateliers d'Usinage

Contribution to Key Techologies of Integrated Process Planning and Scheduling in Job Shops

Résumé

Cette thèse présente une recherche sur les technologies clés de l'Intégration de la Planification des Processus et l'Ordonnancement (IPPS) dans les ateliers d'usinage. Le cadre du Modèle Hybride de l'Intégration de la Planification des Processus et l'Ordonnancement dans les Systèmes de Fabrication Distribués (HMIPPS_DMS) est établi pour illustrer le problème de l'optimisation de l'IPPS dans un DMS. Ce cadre de HMIPPS_DMS, qui adopte à la fois l'idée interface-orientée de NLPP (Non-linear Process Planning) et l'idée fonction-orientée de DPP (Distributed Process Planning, est hiérarchiquement constitué par trois niveaux d'intégration: Niveau d'Intégration aux Entreprises pour sélectionner de façon optimale une entreprise capable de réaliser les pièces attribuées, Niveau d'Intégration aux Ateliers d'Usinage pour sélectionner les ateliers d'usinage capables de fabriquer des pièces, et Niveau d'Intégration aux Ressources pour obtenir l'ordonnancement finalement optimisé et le plan de processus sélectionné pour chaque pièce. Pour répondre aux exigences de la production dans le monde réel, le modèle mathématique pour décrire le Problème de l'Optimisation Multi-Objectif (MOOP) concernant l'IPPO dans les ateliers d'usinage est établi. L'algorithme de NSGA-II (Non-dominated Sorting GA-II) est amélioré pour résoudre efficacement ce MOOP. En pensant que les perturbations inattendues se produisent de temps en temps au cours du processus d'exécution de la production dans les ateliers d'usinage, un modèle de ré-ordonnancement considérant simultanément l'efficacité et la stabilité est mis en place pour traiter le problème de l'optimisation de l'IPPO dans les Ateliers d'Usinage dynamiques (IPPO_DAU). Trois types de perturbations les plus courants sont pris en compte dans ce modèle, que sont une nouvelle arrivée de commande, bris de machine et l'annulation d'une commande.

Mots clés

Planification des Processus, Ordonnancement, Intégration de la Planification des Processus et l'Ordonnancement (IPPS), Système Fabrication Distribué (DMS), NSGA-II (Non-dominated Sorting GA-II), Problème de l'Optimisation Multi-Objectif (MOOP), Ré-ordonnance ment, Ateliers d'Usinage Dynamiques (DJS)

Abstract

This dissertation presents a research on the key technologies of integrated process planning and scheduling (IPPS) in job shops. The framework of Hybrid Model of Integrated Process Planning and Scheduling in Distributed Manufacturing System (HMIPPS_DMS) is established to solve the IPPS optimization problem in DMS. The HMIPPS_ DMS framework, which adopts both the flexible process plans in NLPP (Non-linear Process Planning) and the function integration idea of DPP (Distributed Process Planning), is hierarchically constituted of three integration levels: Enterprise Integration Level to optimally select a feasible enterprise where the jobs will be allocated, Job Shop Integration Level to optimally select the feasible job shops to machine the jobs, and Resource Integration Level to get the final optimized scheduling plan and the final selected process plan for each job. In such way, the hierarchical integration optimization problems of IPPS in each layer will be realized based on the HMIPPS_DVMS framework. To meet the requirements from the real-world production, the mathematical model to describe the Multi- Objective Optimization Problem (MOOP) in IPPS in the job shops is established. NSGA-II (Non-dominated Sorting GA-II) is improved to effectively and efficiently solve this MOOP. Since unexpected disturbances occur from time to time during the production execution process in job shops, a rescheduling model simultaneously considering efficiency and stability is established to deal with the optimization problem of IPPS in dynamic job shops (IPPS_DJS). Three types of the most common disturbances are considered in this model, which are new order arrival, machine breakdown and order cancellation.

Key Words

Process Planning, Scheduling, Integration of Process Planning and Scheduling, Distributed Virtual Manufacturing System HMIPPS_DVMS), NSGA-II (Non-dominated Sorting GA -II), Multi-Objective Optimization Problem (MOOP) , Rescheduling, Dynamic Job Shops (DJS)