Contribution to system design and management in the production of services and goods

Aida Jebali

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PAR AIDA JEBALI

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Bernard Penz
Professeur, Grenoble-INP, Président du jury

Alexandre Dolgui
Professeur, IMT Atlantique (Nantes), Rapporteur

Nabil Absi
Professeur, Mines Saint-Etienne, Rapporteur

Imed Kacem
Professeur, Université de Lorraine (Metz), Rapporteur

Erwin W. Hans
Professeur, University of Twente, Examinateur

Maria Di Mascolo
Directrice de recherche CNRS, Grenoble-INP, Invitée

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At this point, I would like to thank all my colleagues and all my students to whom I owe all my results and who have always nurtured my passionate interest in research. Special thanks to those who encouraged me and supported me and without whom I would have given up this achievement.

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1 Introduction

J'ai commencé à m'intéresser à la recherche quand j'étais élève à l'École Nationale d'Ingénieurs de Tunis (ENIT). En particulier, mon projet de fin d'année 2 et le dévouement de mon encadrant m'ont vraiment marquée et ont suscité mon intérêt pour ce domaine. Cette première expérience m'a ouvert les yeux sur l'importance et les défis sous-jacents à la compréhension d'un problème et à la recherche de solutions appropriées et originales. En outre, mon intérêt pour la recherche était à l'origine de ma motivation à travailler plus dur et à être parmi les meilleurs de ma promotion. Ainsi, j'ai pu obtenir la bourse du Ministère tunisien de l'Enseignement Supérieur et de la Recherche Scientifique qui m'a permis de poursuivre des études doctorales en Génie Industriel à l'Institut National Polytechnique de Grenoble (aujourd'hui Grenoble INP). Tout en étant doctorante au Laboratoire d'Automatique de Grenoble (présentement nommé Gipsa-Lab) et membre du projet HRP (Hospital Resource Planning) financé par la région Rhône-Alpes (présentement nommée Auvergne-Rhône-Alpes), j'ai clairement vu l'intérêt de collaborer et interagir avec d'autres chercheurs ; en effet cela ne peut qu'enrichir la réflexion, favoriser l'interdisciplinarité et stimuler des résultats de recherche innovants.

Après l'obtention de mon doctorat, j'ai réintégré l'ENIT en tant que maître assistante en génie industriel. Ensuite, j'ai rejoint l'Université Prince Sultan (Riyad, Arabie Saoudite) en tant que maître assistante en management des opérations. J'ai eu également l'occasion de rejoindre l'Institut des Sciences et des Technologie de Masdar (Abou Dhabi, Emirats Arabes Unis) en tant que chercheur et l'Université de Sharjah en tant que maître assistante en génie industriel. J'ai aussi eu l'opportunité de rejoindre l'équipe génie industriel du département d'ingénierie des systèmes (ISYS) à l'ESIEE Paris. Depuis Août 2019, j'ai intégré SKEMA Business School en tant que Professeur Associé en gestion des opérations et de la Supply Chain. Dans les différents départements et laboratoires de recherche auxquels j'ai été affiliée, j'ai eu l'opportunité de participer à des projets de recherche, d'encadrer et de co-encadrer des projets de masters et des thèses de doctorat. Cela m'a permis en particulier d'apprendre comment accompagner des nouveaux diplômés dans le processus de devenir des chercheurs autonomes.

Le présent résumé vise à présenter une synthèse succincte de mes travaux de recherche qui ont principalement porté sur les deux axes suivants : (1) conception et planification des systèmes de santé et (2) logistique et management de la supply chain. Les travaux sur les deux axes ont été menés en parallèle. En effet, après ma thèse de doctorat, ma stratégie était d'élargir l'étendu de mes recherches sur ces deux axes en même temps. L'accent sera mis dans tout le rapport sur les principaux travaux et le cadre dans lequel ils ont été réalisés. Je finirai par présenter mes projets en cours ainsi que mes perspectives de recherche.

2 Travaux de recherche

2.1 Conception et planification des systèmes de santé

Planification et ordonnancement des ressources dans les services de soins

J'ai commencé à m'intéresser à l'étude des systèmes de soins dans mon DEA et ma thèse de doctorat où j'ai abordé le problème de la planification et de l'ordonnancement des ressources. Une nouvelle approche considérant les ressources critiques intervenant dans le processus de soins est proposée. L'objectif est de minimiser le délai de séjour du patient dans l'hôpital ainsi

que les coûts de sa prise en charge, et ce dans le respect de la qualité des soins. Cette approche a été particulièrement illustrée dans le cas de processus de soins passant par un service de chirurgie. Afin de tenir compte des aspects aléatoires, l'une des caractéristiques importantes de l'environnement hospitalier, nous avons proposé de traiter le problème de la planification et de l'ordonnancement des ressources suivant une structure hiérarchique qui porte sur quatre niveaux décisionnels. Le premier niveau porte sur la planification des admissions qui consiste à fixer les dates d'hospitalisation des patients pour une intervention chirurgicale. Cependant, la planification des admissions fournit au patient une date d'hospitalisation qui risque de ne pas être très fiable à cause de la possibilité d'occurrence de différentes perturbations. Nous avons ainsi proposé d'adopter un processus de confirmation des dates d'hospitalisation conformément au programme opératoire construit sur l'horizon de T jours. Le troisième niveau décisionnel consiste dans la construction du programme opératoire journalier. Cette construction est à double objectifs : d'une part, mettre à jour le programme opératoire établi sur l'horizon de T jours en intégrant les différents aléas qui ont pu avoir lieu dans le système de soins tel que le report d'interventions à cause d'admissions de cas urgents, non programmées à l'avance ; d'autre part, préciser l'ordre de réalisation des interventions en considérant les ressources critiques utilisées dans le processus opératoire (Jebali et al., 2004 ; Jebali et al., 2006). Ensuite, nous avons proposé une approche temps-réel pour aider au pilotage du bloc opératoire devant l'occurrence d'aléas nécessitant de repenser le programme opératoire journalier, en cours de réalisation.

Ces travaux ont été réalisés au Laboratoire d'Automatique de Grenoble à l'INP de Grenoble sous la direction de Pierre Ladet. Ceux réalisés dans ma thèse ont été aussi co-encadré par Atidel Hadj Alouane de l'ENIT. Par ailleurs, mes travaux de thèse ont été faits dans le cadre du projet HRP (Hospital Resource Planning) associant plusieurs laboratoires de la région Rhône-Alpes et ont bénéficié de deux cadres applicatifs : Hôpital de la Croix Rousse (Lyon) et Hôpital Charles Nicolle (Tunis).

Approches stochastiques pour la planification des interventions au bloc opératoire

Les approches et modèles proposés pour la planification des interventions, dans mes travaux de thèse, sont déterministes. Ces modèles ont été étendus afin de tenir compte explicitement de l'incertitude inhérente à l'activité du bloc opératoire.

Tout d'abord, dans le cadre du master recherche de Sana Aniba, un premier modèle stochastique (M1) a été proposé pour la planification du bloc opératoire avec prise en compte de l'incertitude liée aux durées des interventions chirurgicales (Jebali et Aniba, 2011). Le modèle permet de déterminer les interventions à réaliser chaque jour de la semaine tout en minimisant les coûts liés au patient et à l'utilisation des salles opératoires. Ce dernier inclut les coûts de sous-utilisation et de surutilisation des salles opératoires. Le modèle stochastique est ensuite approximé par un modèle déterministe (programme linéaire en nombres mixtes) utilisant la méthode *Sample Average Approximation* (SAA). Les programmes opératoires générés par l'approche stochastique sont évalués et comparés à ceux obtenus par une approche déterministe en utilisant la simulation. Les résultats montrent l'intérêt de développer des approches stochastiques pour la planification du bloc opératoire. Ce premier travail a été ensuite étendu pour tenir compte, en plus de l'incertitude liée à la durée des interventions chirurgicales, celle liée à l'arrivée des cas urgents (Aniba et Jebali, 2011). Le problème a été formulé sous forme d'un modèle stochastique (M2). Une méthode heuristique a été proposée pour résoudre le modèle SAA en un temps raisonnable.

Par la suite, dans le cadre d'une collaboration avec Ali Diabat de l'Université de New York (NYU), ce travail a été étendu afin de tenir compte des parcours cliniques des patients au sein de l'hôpital. Les contraintes de capacité de toutes les ressources critiques intervenant dans la prise en charge du patient sont désormais prises en compte. Les incertitudes liées à la consommation de ces ressources sont aussi considérées.

Tout d'abord, un modèle stochastique est proposé pour la planification des interventions dans les services de chirurgie cardio-thoracique et vasculaire, tout en tenant compte des contraintes de capacité des trois ressources suivantes : les salles opératoires, les lits dans l'unité de soins intensifs (USI), et les lits d'hospitalisation (Jebali et Diabat, 2015). Le modèle proposé tient compte de l'incertitude des durées opératoires et des délais de séjour du patient dans l'USI et dans le service d'hospitalisation. Un algorithme SAA est développé pour résoudre ce problème de planification. Les résultats obtenus mettent en évidence, en particulier, la supériorité des programmes opératoires obtenus par une approche stochastique par rapport à ceux générés par une approche déterministe en termes de robustesse, ainsi que l'importance de prendre en compte la capacité des lits de l'USI et d'hospitalisation dans la planification du bloc opératoire. La robustesse d'un programme opératoire a été évaluée en fonction du risque d'annulation de l'admission du patient et/ou de l'intervention à cause de l'indisponibilité de l'une des ressources considérées.

Ce travail a été ensuite étendu afin de considérer l'incertitude liée à l'arrivée de cas urgents (Jebali et Diabat, 2017). Un modèle stochastique avec contraintes de hasard (chance-constrained stochastic model) est proposé afin d'assurer que le risque d'annulation de l'admission du patient et/ou de l'intervention ne dépasse pas un seuil donné. Un algorithme SAA adapté aux modèles stochastiques avec contraintes de hasard a été ensuite proposé pour la construction du programme opératoire. Une étude comparative a permis ensuite d'identifier les avantages et les inconvénients de différentes approches de modélisation et de résolution du problème de planification du bloc opératoire avec prise en compte des incertitudes.

Configuration des services logistiques dans les systèmes hospitaliers

De plus, j'ai élargi mes recherches s'intéressant aux systèmes de santé en étudiant des problèmes liés à la configuration des services logistiques dans les systèmes de soins.

Dans un premier temps, dans le cadre du master recherche de Houda Tlahig que j'ai co-encadré avec Hanen Bouchriha de l'ENIT, nous nous sommes intéressées au choix de la meilleure configuration du service de stérilisation au sein d'un hôpital. Le choix entre centralisation et décentralisation du service de stérilisation est alors abordé. Je souligne ici que cette décision est pertinente pour les hôpitaux ayant une structure pavillonnaire où chaque spécialité de chirurgie a ses propres salles opératoires et service de stérilisation. Dans ce cas, il est, en effet, intéressant de montrer les avantages de passer à un service de stérilisation central, partagé par les différentes spécialités de chirurgie de l'hôpital. Afin de résoudre ce problème, une approche de résolution itérative en deux étapes a été proposée (Tlahig et al., 2009).

Ce travail de master s'est ensuite prolongé en une thèse à Gipsa-Lab de l'INP de Grenoble que j'ai co-encadrée avec Pierre Ladet et Hanen Bouchriha. Tout d'abord, le choix entre internalisation et externalisation du service de stérilisation au sein d'un établissement hospitalier a été examiné. En ce qui concerne l'externalisation, deux types de prestataires ont été considérés : (1) une entreprise industrielle et (2) un établissement hospitalier situé dans la

même région. Ensuite, le problème de configuration du service de stérilisation au sein d'un réseau d'hôpitaux a été abordé. Deux options ont été considérées : (1) chaque hôpital du réseau maintient son service de stérilisation en interne ; (2) mutualisation du service de stérilisation. Dans ce dernier cas, un service central de stérilisation assurera cette activité pour tous les hôpitaux du réseau (Tlahig et al., 2013). Ce problème est formulé sous forme d'un programme linéaire en nombres mixtes. Le modèle vise, entre autres, à déterminer la configuration du service de stérilisation dans le cadre d'un réseau d'hôpitaux qui minimise les coûts de transport, d'exploitation, d'acquisition et de transfert de ressources.

Cette thèse a bénéficié du support financier du projet CMCU 05/S1105 et a contribué aux réalisations effectuées dans le cadre des projets de la région Rhône-Alpes HRP2 et HRP3, extensions successives du projet HRP. L'ensemble de ces travaux ont également bénéficié de deux cadres applicatifs : Centre hospitalier de l'Aigle (Orne) et Hôpital Charles Nicolle (Tunis).

Par ailleurs, dans le cadre d'une collaboration avec le Ministère de la Santé Publique en Tunisie, le choix entre internalisation et externalisation a été abordé pour d'autres activités logistiques de l'hôpital. Avec Hanen Bouchriha de l'ENIT et Sondes Hammami de Ecole Nationale d'Ingénieurs de Carthage (ENIC), nous avons abordé ce problème pour les processus de restauration et de blanchisserie au sein de l'Institut de Nutrition de Tunis et de l'Institut Hédi Raîes d'ophtalmologie (Hammami et al., 2009 ; Jebali et al., 2009).

En outre, dans le cadre du master recherche d'Ahlem Jenzri que j'ai co-encadré avec Hanen Bouchriha, nous avons étudié la question de partage d'équipements d'Imagerie par Résonance Magnétique (IRM) par un groupe d'hôpitaux à Tunis (Jenzri et al., 2010).

Conception et gestion des systèmes d'aide médicale urgente

Dans le cadre du master recherche et de thèse de Rania Boujemaa que j'ai co-encadrés avec Sondes Hammami de l'ENIC, nous avons abordé le problème de conception et gestion des systèmes d'aide médicale urgente. De toute évidence, l'objectif de tout système d'aide médicale urgente est de satisfaire la demande en se rendant le plus rapidement possible sur les lieux de l'incident et prodiguant au patient les premiers soins avant d'assurer son transport à un hôpital approprié. Clairement, le temps de réponse, c'est-à-dire le temps écoulé entre la réception de l'appel et l'arrivée de l'équipe SMUR (Services Mobiles d'Urgence et de Réanimation) sur place doit être minimisé afin d'augmenter les chances de survie du patient en état critique. Dans cette recherche, l'accent est mis sur le cas de systèmes d'aide médicale urgente inclusifs à deux niveaux traitant plusieurs types de demandes en déployant deux types d'ambulances.

Dans son master recherche, Rania Boujemaa a développé un modèle déterministe pour la conception du système d'aide médicale urgente. Ces travaux ont été étendus dans le cadre de sa thèse afin de tenir compte des incertitudes.

Dans un premier temps, un modèle stochastique a été proposé pour la conception d'un système d'aide médicale urgente en tenant compte, d'une façon explicite, de l'incertitudes liée à la demande (Boujemaa et al., 2018). Le modèle permet de trouver les sites où localiser les ambulances et le nombre d'ambulances à affecter à chaque site afin d'assurer une couverture rapide des différentes zones de demande. Le modèle stochastique est résolu en utilisant un algorithme SAA. L'approche proposée est appliquée sur le cas du SAMU01

(Services d'Aide Médicale Urgente) de la région nord-est de la Tunisie. Les résultats obtenus démontrent, en particulier, l'applicabilité de l'approche proposée en pratique.

Dans un deuxième temps, nous avons abordé le problème de relocalisation des ambulances (Boujemaa et al., 2020). L'objectif est d'améliorer les performances du système d'aide médicale urgente à travers un repositionnement des ambulances en fonction des fluctuations de la demande au cours de la journée. Un modèle stochastique multi-périodique est ainsi proposé pour la relocalisation des ambulances en tenant compte de l'incertitude liée à la demande. Afin de surmonter la complexité du modèle SAA, deux heuristiques ont été développées : (1) une heuristique de décomposition temporelle (HDT) et (2) une heuristique basée sur la relaxation lagrangienne (SBG). En outre, un modèle de simulation est proposé pour évaluer le niveau de service du système d'aide médicale urgente et le taux d'utilisation moyen des ambulances. Les résultats montrent la supériorité de HDT, car elle fournit une solution proche de la solution optimale en un temps raisonnable. La simulation montre également que le niveau de service du système d'aide médicale urgente est plus élevé lorsque HDT est utilisée.

Une collaboration avec Angel Ruiz de l'Université Laval a eu lieu dans le cadre de ces travaux de thèse. Ainsi, Rania Boujemaa a pu bénéficier de plusieurs stages recherche au Centre interuniversitaire de recherche sur les reseaux d'entreprise, la logistique et le transport (CIRRELT) sous la direction d'Angel Ruiz.

Par ailleurs, avec Sondes Hammami, nous avons développé un modèle pour la conception d'un système d'aide médicale urgente à deux niveaux en prenant en compte une prédiction de l'hôpital où le patient sera transféré (i.e. sa destination finale). Dans le modèle proposé, la prise en charge du patient doit se faire dans le respect d'un temps de réponse exigé. Dans cette recherche, nous avons pu démontrer la supériorité de ce modèle par rapport à ceux qui n'intègrent pas la destination finale du patient. Dans le cas d'étude considéré, une réduction de 3% des coûts peut être obtenu grâce à l'utilisation du modèle proposé (Hammami et Jebali, 2021).

2.2 Logistique et management de la supply chain

Planification intégrée de la production-distribution dans la supply chain du secteur textile

Dans le cadre de la thèse d'Imen Safra que j'ai co-encadré avec Hanen Bouchriha de l'ENIT et, Zied Jemai et Asma Ghaffari de l'Ecole Centrale de Paris (présentement nommée CentraleSupélec), nous nous sommes intéressés à l'étude de la supply chain dans l'industrie textile. Cette étude a été motivée par les défis rencontrés par les entreprises du secteur textile en Tunisie, qui s'efforcent de satisfaire efficacement leurs clients afin de préserver leurs compétitivités. Pour survivre à la concurrence mondiale acharnée, les entreprises du secteur textile doivent être en mesure de réduire leurs délais, satisfaire une demande imprévisible tout en étant efficaces. En particulier, nous considérons ici la planification intégrée production-distribution où deux types de commande sont prises en compte : (1) des commandes de mise en place des collections à venir, souvent de délais longs et (2) des commandes de réassort, souvent de délais très courts, pour les collections en cours de vente.

Tout d'abord, une méthode de planification tactique-opérationnelle qui vise à optimiser simultanément les décisions de production et de distribution est développée (Safra et al., 2019). Cette méthode se caractérise par une anticipation d'une certaine flexibilité dans le plan

de production tactique pour pouvoir insérer les commandes de réassort dans le plan de production opérationnel. La méthode a été appliquée sur des données réelles d'une supply chain internationale, fournies par un partenaire industriel en Tunisie. Les résultats ont démontré qu'une telle méthode permet une réduction de 10% des coûts pour le cas étudié.

Cette méthode a été ensuite étendue pour examiner l'intérêt de partager des informations sur les ventes actuelles entre le fabricant et le détaillant et d'évaluer l'effet de cette coordination sur les performances de la supply chain (Safra et al., 2021). En se basant sur la même étude de cas, il a été constaté qu'une réduction des coûts de 18% peut être réalisée grâce à ce partage d'informations.

Planification des opérations dans le secteur du transport aérien

Les compagnies aériennes s'efforcent d'optimiser leurs opérations pour survivre à une concurrence de plus en plus féroce. De plus, il a été remarqué que les performances de ces compagnies peuvent être considérablement améliorées si les décisions de planification des opérations, à savoir la planification des vols, l'affectation de flotte, le routage d'avions et la planification et l'établissement d'horaires d'équipages sont intégrées. De toute évidence, l'intégration de certains de ces quatre processus de planification reste très difficile vu la complexité associée à ces problèmes.

Dans le cadre de la thèse de Nabil Kenan que j'ai co-encadrée avec Ali Diabat (NYU), nous nous sommes particulièrement intéressés aux problèmes de planification des vols, d'affectation de flotte et de routage d'avions tout en prenant en compte les incertitudes. Dans un premier temps, nous avons étudié le problème intégré de planification des vols et d'affectation de flotte en prenant en compte les incertitudes liées à la demande et aux tarifs (Kenan et al., 2018a). Ce problème est formulé sous forme d'un modèle stochastique. L'objectif est de maximiser le profit. L'algorithme SAA est utilisé pour résoudre le problème et fournir des informations sur la qualité de la solution trouvée. Nous avons ensuite abordé le problème intégré de planification des vols, d'affectation de flotte et de routage d'avions avec prise en compte de l'incertitude liée à la demande. L'objectif est de maximiser le profit. A travers la prise en compte d'un coût de pénalité dans la fonction objectif, le modèle essaye aussi de minimiser le retard des avions (Kenan et al., 2018b). Une approche basée sur la génération de colonnes a été proposée pour résoudre le problème en un temps raisonnable. Ce travail a été par la suite étendu pour inclure le partage de codes (codeshare). Par conséquent, la décision de poursuivre ou d'abandonner un accord de partage de code est considérée dans le problème intégré de planification de vol, d'affectation de flotte et de routage d'avions (Kenan et al., 2018c). L'incertitude de la demande et les retards sont également pris en compte. Ce problème a été aussi résolu en utilisant une approche basée sur la génération de colonnes.

Logistique maritime

La mondialisation de la supply chain a entraîné une augmentation significative des échanges de biens entre les pays. Cela explique, en effet, la croissance continue du nombre de ports et terminaux à conteneurs dans le monde et l'intérêt porté à l'optimisation des opérations portuaires au cours des deux dernières décennies.

Dans le cadre de la thèse de Noura Al-Dhaheri que j'ai co-encadrée avec Ali Diabat (NYU), nous avons abordé le problème d'ordonnancement des opérations de déchargement et de

chargement des conteneurs dans les ports (*Quay Crane Scheduling Problem*, QCSP). L'objectif dans ce problème d'ordonnancement est de déterminer la séquence d'opérations de déchargement/chargement qui permettra de minimiser le temps passé par le navire sur le quai (ce qui correspond à minimiser le temps d'achèvement de toutes les opérations de déchargement/chargement). Dans ces travaux, nous avons essayé d'étendre la littérature selon les deux dimensions suivantes :

- Nous avons proposé une nouvelle formulation du QCSP qui prend en compte les contraintes de stabilité des navires (Al-Dhaheri et al., 2016a). En outre, le modèle proposé intègre d'autres caractéristiques réalistes du problème, telles que la durée de déplacement de la grue, la possibilité de préemption de tâche, les restrictions de franchissement et marge de sécurité (*non-crossing and safety margin restrictions*). Vu la complexité de ce problème, un algorithme génétique (AG) est développé pour le résoudre ce en un temps raisonnable.

- Nous avons développé un modèle stochastique pour l'ordonnancement des opérations de déchargement/chargement tout en considérant la dynamique et l'incertitude inhérentes au processus de manutention des conteneurs dans le port (Al-Dhaheri et al., 2016b). Le problème est résolu en utilisant une approche hybride de simulation-optimisation.

Ces travaux ont été réalisés dans le cadre du projet « Maritime Logistics » financé par les Ports d'Abou Dhabi (ADPC).

Dans un travail plus récent, réalisé en collaboration avec Ali Diabat et Nabil Kenan, nous avons étendu nos travaux sur l'ordonnancement des opérations dans les ports en prenant en compte les émissions de dioxyde de carbone qui en découlent (Kenan et al., 2022). Nous avons traité le problème intégré d'affectation et d'ordonnancement des grues. En particulier, nous avons étudié l'impact de deux formes de taxe carbone (*carbon tax* vs. *carbon cap-and-trade*) sur les coûts et les émissions de dioxyde de carbone dans les ports.

La plupart des travaux de recherche présentés ci-dessous (et mêmes ceux qui n'ont pas été inclus dans ce rapport mais qui pourraient être retrouvés à travers la liste des publications) ont été réalisés dans le cadre d'encadrements ou de co-encadrements d'étudiants en master recherche et de doctorants. J'ai aussi eu l'opportunité, dans mes travaux de recherche, de collaborer avec des enseignants-chercheurs dans plusieurs universités et structures de recherche en Tunisie, en France, aux Emirats Arabes Unis, au Canada et aux États-Unis (Gipsa-Lab, INP Grenoble ; Laboratoire ACS, ENIT ; Labo. Génie Industriel, CentraleSupélec, NYU ; CIRRELT, etc.). Ainsi, les modèles et résultats présentés tout au long de ce rapport émanent d'un travail collectif impliquant des jeunes chercheurs et des collègues, sans qui, rien n'aurait pu avoir lieu.

3 Quelques travaux en cours et perspectives de recherche

Mes projets de recherche sont guidés par les deux objectifs suivants : (1) approfondir et capitaliser sur les recherches que j'ai effectuées ; (2) élargir mes recherches en s'intéressant à des problèmes préoccupants et d'actualité. Ces projets sont suscités par le besoin d'entreprises industrielles et de services à faire face aux différents changements et défis auxquelles elles sont confrontées dans le contexte actuel particulièrement marqué par une forte tendance vers la digitalisation en vue d'offrir des services et des produits mieux adaptés aux besoins des clients et de moindres coûts et une règlementation de plus en plus stricte en

ce qui concerne le respect de l'environnement. Par ailleurs, la crise sanitaire du COVID-19 a été à l'origine de l'intérêt que j'ai porté à l'étude de la résilience et la viabilité de la supply chain, les deux dernières années.

3.1 Approfondissement de la recherche

Le premier objectif, qui vise l'approfondissement de la recherche, inclut le développement de modèles et d'approches de résolution plus sophistiquées et/ou l'extension des recherches actuelles en considérant/intégrant des problèmes connexes.

Plus spécifiquement, dans mes travaux futurs, je souhaiterai développer des approches de résolution avancées pour les problèmes de planification du bloc opératoire et de relocalisation des ambulances. De plus, il serait intéressant de développer une approche stochastique pour l'ordonnancement journalier du bloc opératoire. Comme on peut le constater, la planification et l'ordonnancement du bloc opératoire sont interdépendants et impactent significativement la performance du bloc. En développant une approche qui intègre ces deux problèmes en tenant compte du parcours clinique des patients et des incertitudes, les hôpitaux disposeront d'un outil d'aide à la décision plus complet pour gérer efficacement non seulement les salles opératoires mais aussi d'autres ressources rares et coûteuses de l'hôpital, telles que les lits de l'USI.

Dans ce cadre, une thèse qui vise le développement d'une approche holistique de planification et d'ordonnancement du bloc opératoire sera lancé en collaboration avec Erik Demeulemeester de Katholieke Universiteit Leuven (KUL, Belgique) à partir d'Octobre 2022.

En plus, j'envisage d'approfondir mes recherches très récentes sur la logistique maritime verte et la conception de la chaîne logistique en boucle fermée (*Closed-Loop Supply Chain*, CLSC) vu que la prise en compte des aspects environnementaux et l'évolution vers une économie circulaire deviennent une priorité socio-économique.

Logistique maritime verte

(Kenan et al, 2022) sera étendu, dans un premier temps, pour intégrer les décisions d'attribution des postes d'amarrage avec celles d'affectation et d'ordonnancement des grues tout en prenant en compte l'incertitude inhérente à l'arrivée des navires. Dans un deuxième temps, nous viserons le développement d'une approche holistique pour la gestion et la synchronisation des opérations dans le port, celles prenant lieu avant l'amarrage du navire, après l'amarrage, d'une part entre le navire et le quai et d'autre part, entre le quai et les zones de stockage. L'objectif de cette recherche est de développer des modèles et algorithmes d'ordonnancement des opérations qui permettent une réduction des émissions de dioxyde de carbone générées dans les ports. En effet, au-delà du développent de modèles et solutions plus sophistiqués à ces problèmes complexes, nous visons évaluer l'impact d'une meilleure synchronisation des opérations sur la performance économique et environnementale du port.

Conception de la chaîne logistique en boucle fermée (Closed-Loop Supply Chain, CLSC)

Dans de nombreux pays développés, la législation environnementale oblige les fabricants à recycler une partie de leurs produits en fin de vie et/ou à assurer leur destruction dans le respect de l'environnement. Par exemple, dans l'Union Européenne, la directive sur les

déchets d'équipements électriques et électroniques (*Waste Electrical and Electronic Equipment*, WEEE) impose la collecte et le recyclage de ce type de produits avec un taux minimum prédéfini par habitant et par an. Ces réglementations ont été mises en place suite à une prise de conscience du public et des gouvernements concernant la nécessité imminente de réduire les effets néfastes sur l'environnement causés par certains produits en fin de vie. En plus de réduire les déchets et la pollution, la récupération des produits en fin de vie à travers le recyclage des matières précieuses qu'ils contiennent ou le reconditionnement/rénovation de certains composants offre des opportunités pour réduire et maîtriser la consommation d'énergie et de ressources et pourrait également offrir de nouvelles sources de revenus.

La CLSC comprend toutes les étapes permettant de fournir le produit au client final mais aussi celles qui vont permettre la récupération des produits en fin de vie y compris la collecte, le recyclage et le reconditionnement/rénovation.

Au cours des deux dernières décennies, une littérature abondante a été consacrée à la conception et l'étude du fonctionnement de la CLSC. De toute évidence, les caractéristiques du problème diffèrent d'un secteur industriel à l'autre. En outre, nous pouvons voir que la qualité des retours, l'éco-efficacité et les opportunités de revenus supplémentaires associés avec chaque type de récupération (recyclage, reconditionnement/rénovation) sont des éléments importants à prendre en compte dans le choix du type de récupération à adopter pour un produit en fin de vie.

Dans un premier temps, en collaboration avec Ali Diabat, nous nous sommes intéressés à la conception de la CLSC des produits durables avec prise en compte du contexte législatif (Diabat et Jebali, 2021). Des modèles déterministes ont été développés et utilisés pour évaluer la performance économique et environnementale de la CLSC pour différents types de législations portant sur la reprise de produits (*take-back legislation*). Ces travaux seront étendus pour tenir compte des incertitudes liées à la demande et aux retours. Une autre perspective intéressante consiste à étudier l'impact d'une conception modulaire (*modular design and part commonality*) sur la configuration et la performance de la CLSC.

3.2 Elargissement de la recherche

Dans le cadre du deuxième objectif, visant l'élargissement de la recherche, la plupart de mes travaux ont porté sur le développement de modèles et d'approches pour la conception et la planification d'une supply chain résiliente et viable.

Conception et planification pour une supply chain résiliente et viable

Une pandémie peut faire des ravages dans les supply chain, comme en témoigne la crise du COVID-19. Il est ainsi important de centrer la réflexion sur comment concevoir et planifier une supply chain tout en renforçant sa résilience, sa capacité d'adaptation, sa durabilité et donc sa viabilité sur le long-terme.

Dans un premier travail, avec Xavier Brusset et Davide La Torre (SKEMA Business School), nous avons étudié comment l'effort investi en termes d'implémentation de mesures protectives (au-delà de celles imposées par le gouvernement) au sein d'un système de production pourrait augmenter la résilience de celui-ci et assurer la continuité de production (Brusset et al., 2022). Ce travail a été étendu afin de prendre en compte le niveau de service des fournisseurs pendant la période de crise (i.e. la fiabilité de livrer la quantité commandée

dans les temps). L'originalité de ces deux travaux est double : (1) ils intègrent un modèle épidémiologique avec un modèle de planification de la production ; (2) ils explorent l'implémentation de mesures protectives comme une stratégie de résilience des systèmes de production et de la supply chain. En particulier, les modèles développés sont recommandés pour les industries à forte intensité de main d'œuvre, telle que l'industrie de la viande.

Par ailleurs, nous sommes en train de développer une approche pour la planification de la supply chain de la viande en situation de crise sanitaire. Dans cette recherche, nous considérons tous les maillons de cette supply chain : fournisseur, producteur et détaillant. Notre objectif est de se baser sur ce qui s'est passé dans la crise du COVID-19 pour fournir des recommandations aux managers de la supply chain de la viande sur les types de modèles de prévision de la demande et de la capacité à utiliser, et l'approche de planification à suivre, dans un contexte de crise sanitaire.

Récemment, avec Xavier Brusset, Davide La Torre, Marco Repetto (SKEMA Business School), et Dmiry Ivanov (Berlin School of Economics and Law), nous avons développé un modèle pour la sélection de fournisseurs en situation de crise sanitaire. Ce dernier se distingue par la prise en compte du risque de perte de niveau de service dû à l'effet d'entrainement (*ripple effect*).

Nous sommes actuellement en train d'étendre ce travail à la conception d'une supply chain à quatre étages. Nous visons l'application du modèle proposé dans l'industrie pharmaceutique. En particulier, nous sommes en train d'étudier l'impact de la digitalisation et du niveau technologique du système de production, de la substituabilité des produits (*product substituatability*) et de la diversification de la base fournisseur, sur la résilience de la supply chain.

Les projets de recherche susmentionnés seront réalisés en collaboration avec des enseignants-chercheurs de SKEMA Business School, du KUL, de l'ENIT, du CIRRELT, et de NYU et feront l'objet de soumissions à des appels à projets (tels que les projets ANR, projets PHC Utique, etc.). Par ailleurs, dans ces projets de recherche, nous envisageons de trouver des partenaires économiques et industriels afin de valoriser leur impact socio-économique. Le montage et la réalisation de projets de recherche appliquée co-financés par des partenaires économiques est l'un de nos objectifs sur le court et moyen terme. Cette démarche est d'ores et déjà entamé avec un groupe de consulting d'envergure.

Presentation of the dissertation

My keen interest and motivation for research started since I was an industrial engineering student at Ecole Nationale d'Ingénieurs de Tunis (ENIT). In particular, my second-year project and my experience with my advisor awakened in me this interest. This first research-oriented project opened my eyes on the importance and challenges to understand problems and search how to solve them; besides it uncovered the feeling of being unsatisfied with the solution I found because aware that a better one exists.

After obtaining my engineering degree, and without any hesitation, I decided to pursue a Master of Science followed by a PhD in Industrial Engineering at Grenoble INP. My master project and PhD work were both dedicated to the study of healthcare systems. My master project aimed at conducting an exploratory study in order to point out the problems and challenges of healthcare systems. The imminent need of healthcare systems to improve their performances contrasted by the paucity of works devoted to support decision making in this field motivated me to continue with the same topic in my PhD. Hence the objective of my PhD work was to find out how to improve healthcare systems' performances by developing appropriate and novel optimization models for efficient and effective decision making. In light of this, while adopting a novel approach based on patients' clinical path, I devised models and solution methods that constitute the basis toward a hospital resource planning and scheduling decision tool.

During this period, my passion for research soared. Beyond being a member of Laboratoire d'Automatique de Grenoble (currently named Gipsa-Lab), I got the opportunity, in my PhD, to participate to the research project HRP (Hospital Resource Planning) funded by the Rhône-Alpes region (currently Auvergne-Rhône-Alpes). This experience unveiled the significance of collaborating and interacting with other researchers; indeed, this can only bring up thinking and favor interdisciplinarity and innovative research outcomes. For that, I am particularly thankful to my PhD supervisor Pierre Ladet who let me benefit of a such excellent and rich research context. I also thank Atidel Hadj-Alouane from ENIT who co-supervised my PhD work for her support and pertinent advice.

After successfully completing my PhD, I was appointed as an assistant professor of Industrial Engineering at ENIT. Afterward, I joined the Department of Business Administration at Prince Sultan University (Riyadh, Saudi Arabia) as an assistant professor of Operations Management. Then I got the opportunity to join the Department of Engineering Systems and Management at Masdar Institute of Science and Technology (currently merged with Khalifa University) as a Research Scientist and the University of Sharjah as an assistant professor of Industrial Engineering. I also got the opportunity to join the Department of Systems Engineering (ISYS) at ESIEE Paris (Gustave Eiffel University). Since 2019, I am associate professor of operations and supply chain management at SKEMA Business School. These different appointments gave me the opportunity to enrich my teaching experiences and research activities through different collaborations and the supervision and co-supervision of master and PhD theses. As a scholar, my strategy is indeed to maintain a good balance between teaching and research.

My research works and contributions pertain to two principal areas: (1) healthcare systems engineering and management and (2) logistics and supply chain management. Different topics related to each of these areas have been addressed. The objective of all my researches

is to address topical decision problems and provide both academicians and practitioners with efficient solution approaches and valuable managerial recommendations and insights.

Based on my experiences and credentials, in teaching as well as research, I truly feel ready to state my case toward the Habilitation à Diriger des Recherches (HDR) qualification. First, this would qualify me to go a step forward in my career by obtaining a professorship in industrial engineering and/or operations and supply chain management. Moreover, it will give me, the opportunity to supervise doctoral students and, access to more ambitious responsibilities and research projects as a senior scholar.

The remainder of this dissertation contains four parts that are structured as follows.

In part I, I present a detailed curriculum vitae stating my education and qualifications, my research and teaching activities and outcomes. In addition, I present my administrative responsibilities and editorial activities.

Part II contains a synthesis of my contributions to the literature related to healthcare systems engineering and management. The focus is placed on the works that develop stochastic approaches in order to account for the uncertainty inherent to healthcare activities. This part is composed of two chapters: Chapter II.1 describes my works on operating room planning and scheduling under uncertainty while Chapter II.2 is dedicated to the design and management of Emergency Medical Service (EMS) system.

Part III will be devoted to my works in the area of logistics and supply chain management. Part III is divided into three chapters that cover the main topics addressed in this area. Chapter III.1 deals with the integrated production-distribution planning problem encountered by global textile and apparel supply chains. Chapter III.2 and III.3 summarize my contributions to the existing literature on airline operations planning and maritime logistics, respectively.

In all these chapters, the focus will be placed on the works and results entailing the most significant contributions. Moreover, as can be noted, the presented chapters do not cover all the addressed research topics. The priority in this report was given to the recent works and in particular those that, I deem, are bearing a good contribution to the literature.

In part IV, I present my ongoing work and my future research projects. The latter are intended either to deepen and capitalize on the research I have dealt with up until now or enlarge the scope of my research in the above-mentioned research areas by addressing trending topics and concerns. Henceforth, the focus will be placed mainly on four research projects which are related to the following topics: operating room planning and scheduling, green port operations, the design of closed-loop supply chains and the design of resilient and viable supply chains.

The research findings presented along this dissertation stem from fruitful collaborations with master students, doctoral students and colleagues in different universities in, Tunisia, France, UAE and Canada and to whom I am very thankful and grateful. Their names will be mentioned throughout the report.

Part I

Presentation of the candidate

1 Personal details

- Aida Jebali Karaoud
- Born on December 14, 1975
- Dual Nationality Tunisian-French
- Maried, 2 children
- Professional Address: SKEMA Business School - Campus Grand Paris - 5, quai Marcel Dassault - CS 90067 - 92156 Suresnes Cedex
- Email: aida.jebali@skema.edu; aida_jebali@yahoo.fr
- Phone: +33 6 17 86 43 14

2 Education

PhD in Industrial Engineering, Grenoble INP

- Defended on April 27, 2004
- Subject of the thesis: Towards a decision tool for resource planning and scheduling in healthcare services
- PhD supervisor: Pierre Ladet
- PhD co-supervisor: Atidel Hadj Alouane
- PhD examination committee:
  - President: Mireille Jacomino, Professor, Grenoble INP
  - Reviewers: Christian Tahon, Professor, Université de Valencienne, and Michel Gourgand, Professor, Université Blaise Pascal, Clermont-Ferrand
  - Examiners: Alain Guinet, Professor, INSA de Lyon & Jean-Paul Viale, Professor and Chair of the anesthesiology department, Hôpital de la Croix Rousse, Lyon

Master of Science in Industrial Engineering, Grenoble INP

- Graduated in July 2000 (obtained with Honors)
- Subject of the thesis: Resource assignment and allocation problem in the healthcare services: a literature review and the basis of an optimization model
- Supervisor: Pierre Ladet

Engineer Diploma in Industrial Engineering, Ecole Nationale d'Ingénieurs de Tunis (ENIT)

- Graduated in July 1999
- Ranking: 5/41

3 Academic positions held

- **2019-present:** Associate Professor of Operations and Supply Chain Management, Digitalization academy, SKEMA Business School – Campus Grand Paris – France

- **2018-2019:** Associate Professor, Department of Systems Engineering (ISYS), ESIEE Paris - France

- **2005–present:** Assistant Professor, Industrial Engineering Department, ENIT - Tunisia

- **2016-2018:** Assistant Professor, Department of Industrial Engineering and Engineering Management, College of Engineering, University of Sharjah – United Arab Emirates (UAE)

- **2014–2016:** Research Scientist, Department of Engineering Systems & Management, Masdar Institute of Science and Technology - UAE

- **2011–2013:** Assistant Professor, Business Administration Department, College for Women, Prince Sultan University - Saudi Arabia

- **2001–2005:** Lecturer, Industrial Engineering Department, ENIT - Tunisia

4 Administrative positions held

- Member of the faculty search committee, Industrial Engineering and Engineering Management Department, College of Engineering, University of Sharjah, UAE (2016-2018)
- Member of the faculty social affairs committee, College of Engineering, University of Sharjah, UAE (2016-2018)
- Research coordinator, Business Administration Department, College for Women, Prince Sultan University, Saudi Arabia (2012-2013)
- Learning Management System coordinator, Business Administration Department, College for Women, Prince Sultan University, Saudi Arabia (2012-2013)
- Member of the faculty search committee, Business Administration Department, College for Women, Prince Sultan University, Saudi Arabia (2012-2013)
- Coordinator for the Master of Business Creation and Innovation Management, Industrial Engineering Department, ENIT, Tunisia (2008-2010)

5 Awards

- High Level Scientific Stay, Research Grant of the French Ministry of Foreign Affairs, July 2009 and December 2007
- PhD Scholarship Award of the French Ministry of Foreign Affairs, 2000-2003
- National scholarship for Doctoral Studies of the Tunisian Ministry of Higher Education and Scientific Research, 1999-2000

6 Research activities

My research interests are tied to system design and management in the production of services and goods. More specifically, my research thrives the development of operations research models and solution approaches to address topical decision problems related to operations planning and supply chain design and management. Overall, the problems that I tackle in my research pertain to the following two main areas: (1) healthcare systems engineering and management and (2) logistics and supply chain management. In order to provide managers with useful recommendations and insights, realistic features of the considered problems are taken into account including uncertainty. Moreover, some of my recent research has incorporated environmental aspects and resilience with an objective to curb climate change and/or foster the continuity of operations and supply chains prone to disruptive risks as those of a pandemic.

6.1 Research supervision

I have been involved in the supervision of 5 PhD students in collaboration with professors from Tunisia, France, UAE and Canada. I also supervised and co-supervised 7 research projects of master's students. More details on the supervised PhDs and Master projects are given in subsections 6.1.1 and 6.1.2, respectively.

6.1.1 Supervision of PhD students

Rania Boujemaa

- PhD in Industrial Engineering (ENIT)
- Defended in September 2018
- Subject of the thesis: Stochastic approach for ambulance location and relocation
- Financial support: Tunisian Ministry of Higher Education and Scientific Research
- Supervision rate 50%. Co-supervised with Sondes Hammami (Assistant professor, Ecole Nationale d'Ingénieurs de Carthage (ENIC)) and Hanen Bouchriha (Professor, ENIT)
- PhD examination committee:
  - President: Najoua Dridi (Professor, ENIT)
  - Reviewers: Anis Gharbi (Professor, Tunis Business School) and Jouhaina Siala (Professor, Institut des Hautes Etudes Commerciales)
  - Examiners: Talel Ladhari (Professor, Ecole Supérieure des Sciences Economiques et Commerciales de Tunis) and Angel Ruiz (Professor, Université Laval)
- Publications
  - 2 papers published in international journals
  - 2 international conference papers

Rania is currently « Professionnelle de Recherche » at Laval University - Canada.

Nabil Kenan

- PhD in Interdisciplinary Engineering (Masdar Institute of Science and Technology)
- Defended in August 2017
- Subject of the thesis: Planning in the airline industry under uncertainty
- Financial support: Masdar Institute of Science and Technology PhD scholarship
- Supervision rate 50%. Co-supervised with Ali Diabat (Professor, New York University Abu Dhabi)
- PhD examination committee: I-Tsung Tsai (Associate professor, Masdar Institute of Science and Technology) and David Simchi-Levi (Professor, Massachussets Institute of Technology)
- Publications
  - 3 papers published in international journals

Nabil is currently Senior Specialist - Operations and Development at Abu Dhabi Ports - UAE.

Noura Al-Dhaheri

- PhD in Interdisciplinary Engineering (Masdar Institute of Science and Technology)
- Defended in March 2016

- Subject of the thesis: The Quay Crane Scheduling Problem with Ship Stability Consideration: Formulations and Solution Approaches
- Financial support: Grant EX2014-000003, Abu Dhabi Ports
- Supervision rate 40%. Co-supervised with Ali Diabat (Professor, New York University Abu Dhabi)
- PhD examination committee: I-Tsung Tsai (Associate professor, Masdar Institute of Science and Technology) and David Simchi-Levi (Professor, Massachussets Institute of Technology)
- Publications
  - 2 papers published in international journals

Noura is currently the CEO of Maqta Gateway, Abu Dhabi Ports - UAE.

Imen Safra

- PhD in Industrial Engineering (Ecole Centrale de Paris (ECP) & ENIT)
- Defended in February 2013
- Subject of the thesis: Towards an integrated production-distribution planning in the textile supply chain
- Financial support: Tunisian Ministry of Higher Education and Scientific Research
- Supervision rate 25%. Co-supervised with Hanen Bouchriha (Professor, ENIT), Zied Jemai (Professor, ENIT-ECP), Asma Ghaffari (Associate Professor, ECP) and Chengbin Chu (Professor, ECP)
- PhD examination committee:
  - Reviewers: Gilles Goncalves (Professor, Université d'Artois) and Samir Lamouri (Professor, Ecole Nationale des Arts et Métiers)
  - Examiner: Vincent Giard (Professor, Université Paris Dauphine)
- Publications
  - 2 papers published in international journals
  - 3 international conference papers

Imen is currently assistant professor at ENIB (Ecole Nationale d'Ingénieurs de Bizerte) - Tunisia

Houda Tlahig

- PhD in Industrial Engineering (Grenoble INP)
- Defended in February 2009
- Subject of the thesis: Towards a decision tool support for the choice between the internalisation, the externalisation or the pooling of the hospital logistics activities: the sterilisation service case
- Financial support: Project CMCU 05/S1105
- Supervision rate 50%. Co-supervised with Hanen Bouchriha (Assistant professor, ENIT) and Pierre Ladet (Professor, INP de Grenoble)
- PhD examination committee:
  - President: Eric Marcon (Professor, IUT Roanne)
  - Reviewers: Christian Tahon (Professor, Université de Valencienne) and Michel Gourgand (Professor, Université Blaise Pascal, Clermont-Ferrand)
  - Examiner: Lamine Dhidah (CHU Sahloul, Tunisia)
- Publications

- 1 paper published in an international journal
- 1 paper published in a specialized journal with reading committee
- 6 international conference papers

Houda is currently researcher-lecturer at Cesi, Ecole d'Ingénieurs - France.

6.1.2 Supervision of Masters' students

Rania Boujemaa

- Master of Science in Automatic Control and Production engineering (Tunis College of Sciences and Techniques (ESSTT))
- Defended in March 2012
- Supervision rate 50%. Co-supervised with Sondes Hammami (Assistant professor, ENIC)
- Subject of the thesis: Ambulance location problem
- Publications
  - 1 international conference paper

Sana Aniba

- Master of Science in Automatic Control and Production engineering (ESSTT)
- Defended in December 2010
- Subject of the thesis: A stochastic approach for operating room planning and scheduling
- Publications
  - 3 international conference papers

Ahlem Jenzri

- Master of Science in Automatic Control and Production engineering (ESSTT)
- Defended in December 2009
- Supervision rate 50%. Co-supervised with Hanen Bouchriha (Professor, ENIT)
- Subject of the thesis: Resource pooling in multi-hospital network: case of the MRI equipment
- Publications
  - 1 international conference paper

Jamel Arfaoui

- Master of Science in Industrial Systems Management (ENIT)
- Defended in April 2009
- Subject of the thesis: Modeling and solution approach for the inventory routing problem: application to the textile and apparel distribution network
- Publications
  - 1 international conference paper

Houda Aloui

- Master of Science in Industrial Systems Management (ENIT)
- Defended in December 2005
- Supervision rate 50%. Co-supervised with Hanen Bouchriha (Professor, ENIT)

- Subject of the thesis: Performance evaluation of two strategies for the operating room planning

Houda Tlahig

- Master of Science in Industrial Systems Management (ENIT)
- Defended in July 2005
- Supervision rate 50%. Co-supervised with Hanen Bouchriha (Professor, ENIT)
- Subject of the thesis: Centralization vs. decentralization of the hospital sterilization service department
- Publications:
  - 1 paper published in an international journal
  - 1 international conference paper

6.2 Participation in funded research projects

- 2018-2021: Participation in the joint French-Tunisian research project PHC-UTIQUE 2018 (18G1410) entitled "Robust planning of home healthcare services"

- 2014-2016: Participation in the Research Project « Maritime logistics » (Grant EX2014-000003, Abu Dhabi Ports)

- 2000-2009: Participation in the research projects HRP (Hospital Resource Planning), HRP2 and HRP3 (HRP2 and HRP3 are extensions of the project HRP)
  - Financial support: Région Rhône-Alpes, France

- 2005-2008: Participation in the research project CMCU 05/S1105 (project of Tunisian French joint committee for university cooperation) – Modeling and management of industrial and service production systems

- 2002-2003: Participation in the research project « Collaborative Management in Healthcare »
  - Financial support: CNRS (French National Center of Scientific Research), France

6.3 Main academic collaborators

- Pierre Ladet, Grenoble INP (presently retired). He is my PhD supervisor. Subsequent to my PhD, we co-supervised 1 PhD student. This research collaboration was related to the area of healthcare engineering and management. In the frame of this collaboration, we co-authored 1 paper published in an international journal and 1 paper in a specialized journal with reading committee.

- Hanen Bouchriha, ENIT. We co-supervised the PhD theses of Houda Tlahig, Imen Safra and Rania Boujemaa. In addition, as noted above, we co-supervised 3 master's theses. Most of our collaboration pertained to the configuration of hospital logistics activities and the integrated production-distribution planning in textile and apparel supply chain. We co-authored 6 papers published in international journals and 1 paper published in a specialized journal with reading committee.

- Ali Diabat, NYU. We conducted joint research on operating room planning under uncertainty, maritime logistics, airline operations planning and the design of closed-loop supply chain network. We co-supervised the PhD theses of Noura Al-Dhaheri and Nabil Kenan. We co-authored 9 papers published in international journals.

- Sondes Hammami, ENIC. We conducted joint research on the design and management of EMS systems. We co-supervised the master's thesis and the PhD thesis of Rania Boujemaa. We co-authored 3 papers published in international journals.

- Zied Jemai, ENIT & ECP and Asma Ghaffari, ECP. We conducted joint research on integrated production-distribution planning in textile and apparel supply chain. We co-supervised the PhD thesis of Imen Safra. We co-authored 2 papers published in international journals.

- Angel Ruiz, Université Laval & CIRRELT. We conducted joint research on the design and management of EMS systems. We co-authored 2 papers published in international journals.

- Xavier Brusset and Davide La Torre, SKEMA Business School. We conducted joint research on production and supply chain optimization. We co-authored 4 papers: 2 of them have been recently published in international journals and 2 are under review.

- Sarra Dahmani, SKEMA Business School, and Oussama Ben-Ammar, IMT Mines Alès. We are conducting joint research on the role of Artificial Intelligence in augmenting project resilience. The focus of this research will be put on project scheduling.

6.4 Publications

Table 1 provides a summary of my research outputs. A detailed list of my publications is then given. In this subsection the focus is placed on publications in journal papers and international peer reviewed conference proceedings.

Table 1. Summary of research outputs

Papers in international peer reviewed journals (ISI Journals)	19
Papers in international peer reviewed journals (Non-ISI Journals)	2
Papers in specialized journals with reading committee	1
Papers in international peer reviewed conference proceedings	35

Papers in international peer reviewed journals (ISI Web of Science)

1. Brusset, X., Jebali, A., La Torre, D., Mazahir, S. (2022). Optimal Pollution Control in a Dynamic Multi-echelon Supply Chain. *Environnemental Modeling & Assessment*, 27, 585–598.

2. Brusset, X., Jebali, A., La Torre, D. (2022). Production optimisation in a pandemic context. *International Journal of Production Research*. https://doi.org/10.1080/00207543.2022.2044535.

3. Kenan, N., Jebali, A., Diabat, A. (2022). The integrated quay crane assignment and scheduling problems with carbon emissions considerations. *Computers & Industrial Engineering*, 165, 107734.

4. Safra, I., Jebali, A., Jemai, Z., Bouchriha, H., Ghaffari, A. (2021). The beneficial effect of information sharing in the integrated production-distribution planning of textile and apparel supply chain. *RAIRO-Operations Research*, 55, 1171-1195.

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7 Teaching activities and project supervision

7.1 Teaching activities

I started teaching in 2001. Overall, I ensured a teaching volume of around 3080 hours. 85% of my teaching activities (corresponding to 2630 teaching hours) have been conducted after my appointment as assistant professor in 2005. I gave courses in several institutions: ENIT, PSU, UoS, ESIEE Paris and SKEMA Business School. Most of the courses I taught are

related to operations management, supply chain management, and operations research. All courses I gave at ENIT and ESIEE Paris are in French while those I gave at PSU and UoS are in English. The courses I am giving in SKEMA Business School are in both languages. A summary of my teaching activities is given in table 2.

Table 2. Summary of my teaching activities

Institution	Course	Program	Hourly volume	Period	Total
ENIT	Recherche opérationnelle	2nd year (Industrial engineering and Civil engineering)	45h	2005-2010	825h
	Simulation des systèmes industriels	3rd year (Industrial engineerin) & Mastère Gestion des Systèmes Industriels	30h	2005-2010	
	Analyse des systèmes de production	2nd year (Industrial engineering)	45h	2005-2010	
PSU	Production & Operations Management	3rd year (Bachelor in Business Administration & Bachelor in Computer Science and Information Systems)	45h	2011-2013	675h
	Management Information Systems	3rd year (Bachelor in Business Administration & Bachelor in Computer Science and Information Systems)	45h	2011-2012	
	Introduction to Business	1st year (Bachelor in Business Administration & Bachelor in Computer Science and Information Systems)	45h	2012-2013	
UoS	Operations Research I	3rd year (Bachelor in Industrial Engineering and Engineering Management)	45h	2016-2018	540h
	Operations Research II	4th year (Bachelor in Industrial Engineering and Engineering Management)	45h	2016-2017	
	Operations Management	Master of science in Engineering Management	45h	2016-2017	
	Supply Chain Management	4th year (Bachelor in Industrial Engineering and Engineering Management) & Master of science in	45h	2016-2018	

		Engineering Management			
ESIEE	Supply Chain Management	5th year (Filière Génie Industriel-classique & apprentissage)	28h	2018-2019	160h
	Gestion de projet	3rd year (Filière Génie Industriel - apprentissage)	26h	2018-2019	
	Ordonnancement de la production	4th year (Filière Génie Industriel - classique)	12h	2018-2019	
	Planification de la production	4th year (Filière Génie Industriel -classique & apprentissage)	18h	2018-2019	
	Introduction à la programmation linéaire	3rd year (Filière Génie Industriel - apprentissage)	10h	2018-2019	
	Prévision de la demande	5th year (Filière Génie Industriel - apprentissage)	12h	2018-2019	
SKEMA Business School	Supply Chain Management	MS MCLA (Manager de la Chaine Logistique et Achat)	24h	2020-2022	430h
	Méthodologie de recherche	MS MCLA	24h	2019-2022	
	Operations Management	M1 PGE (Programme Grande Ecole)	18h	2020-2021	
	Achat	MS MCLA	24h	2020-2021	

Figure 1 portrays the distribution of my teaching hours between the above-mentioned courses. It is worth noting here that in figure 1 “Production planning & scheduling” includes the following courses: “Analyse des systèmes de production”, “Planification de la production”, “Ordonnancement de la production” and “Prévision de la demande” while “Operations research” includes “Recherche opérationnelle”, “Operations research I and II”, “Introduction à la programmation linéaire” and “Simulation”. Similarly, “Operations management” in figure 1 includes both “Production and operations management” and “Operations management” while “Supply chain management” includes “Achat”.

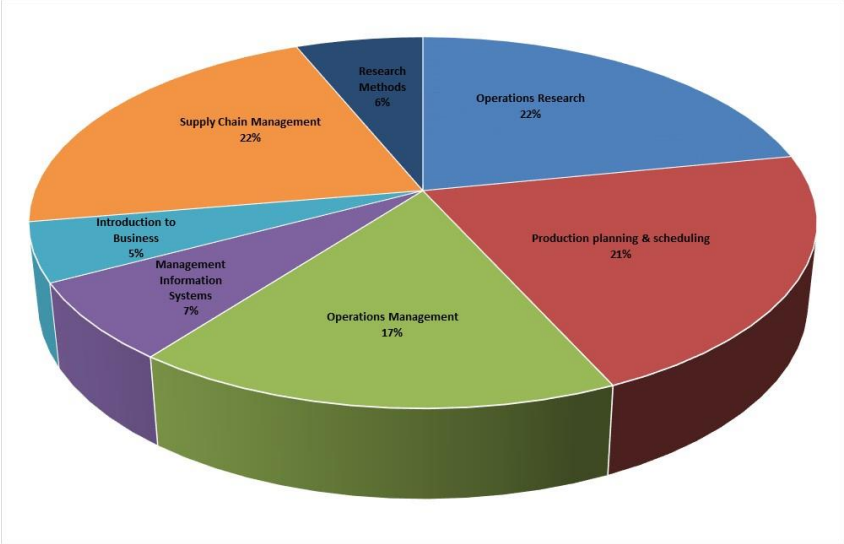

Figure 1 . Distribution of teaching hours

As it can be noticed, 82% of my teaching pertains to Production planning & scheduling, Operations research, Operations management and Supply chain management. The topics covered in these courses are provided in table 3.

Table 3. Main topics covered in the delivered courses

Production planning & scheduling	Introduction to production planning system – Aggregate planning – Master scheduling - Rough-cut capacity planning – Material requirements planning - Capacity requirement planning – Time series and forecasting – Project scheduling – Single machine models – Parallel machine models – Flow shops – Job shops
Operations research	Mathematical modelling – Linear Programming – Graph Theory – Dynamic Programming – Markov chains – Queuing theory - Simulation
Operations management	Introduction to operations management – Operations strategy – Capacity planning - Production planning - Time series and forecasting – Product and service design - Process selection and facility layout – Facility location – Inventory management and control - Quality management and control – Process analysis and improvement – Service Management
Supply chain management	Supply chain strategy – Drivers of supply chain performance – Distribution network design - Supply chain network design – Sales & Operations Planning - Supply chain coordination – Sourcing – Purchasing – Sustainable procurement - Transportation

At this level, it is important to note the consistency between my teaching and research topics. This consistency brings an added value to both activities. First, it permits to enrich the contents of my courses through examples and cases translating my research findings. Second, it forces me to be all the time up to date on the topical problems and applications related to my research areas.

7.2 Project supervision

In addition to teaching, I regularly supervise student projects and internships. Table 4 gives a summary of my supervision activities.

Table 4. Summary of supervision activities

Institution	Type of supervision	Number
SKEMA Business School	MS & MSc Theses	**31** theses (MS MCLA & MSc Supply Chain Management and Purchasing)
ESIEE Paris	Internship	**9** (**4** 5th year students, **2** 4th year students and **3** 3rd year students)
UoS	Senior design project I and II	**4** projects
ENIT	Final year projects	**34** projects
	Second year projects	**18** projects
	Bibliographical research projects	**6** projects

The vast majority of the final year and senior design projects that I supervised were related to production planning and scheduling, supply chain design and management, continuous improvement, cost modelling and information system design. These projects have been always driven by companies' need to improve their performance. Project supervision allowed me to explore the specificities of different industries such as automotive, healthcare, apparel, furniture, etc. Noticeably, some of these projects sparked the interest and motivated some of the addressed topics in my research.

Since 2020, I have supervised at Skema Business School more than 31 MS and MSc theses. In the latter, the students should define a relevant research question and follow a scientific approach to answer it. Therefore, through their thesis, the students are initiated to research. Most of the theses that I supervised are related to the following topics and concepts: supply chain management, procurement, logistics, resiliency, digitalization, sustainability, project management and artificial intelligence.

8 Other activities

8.1 Membership of conference & seminar committees

- Member of the scientific committee of the 10ème Congrès International de Génie Industriel, EIGSI, June 2013, La Rochelle, France.
- Participation in the organization of the special track on « Healthcare Information Systems and Decision Making », IFAC International Conference of Modeling and Simulation (MOSIM), May 2010, Hammamet, Tunisia.
- Member of the organization committee of the project CMCU 05/S1105 seminar "Healthcare system engineering", December 2007, ENIT, Tunisia.
- Organization of the invited session « Health Care Delivery Engineering in Magreb », The 33rd International Conference on Operational Research Applied to Health Services, July 2007, Saint-Etienne, France.
- Member of the organization committee of the project CMCU 05/S1105 seminar "Cost and quality optimization in healthcare systems: reengineering and novel modes of management", December 2006, Cepex, Tunis, Tunisia.

- Member of the organization committee of the seminar "Company change and industrial engineering", Mai 2005, ENIT, Tunisia.
- Member of the organization committee of GISEH 2003 (1ère conférence francophone en Gestion et Ingénierie des SystèmEs Hospitaliers), January 2003, Lyon, France.
- Member of the scientific committee of MAJECSTIC 2003 (Manifestation des jeunes chercheurs STIC), Marseille, France.

8.2 Service as reviewer

I regularly review papers submitted for eventual publication in the following journals:

- International Journal of Production Economics (Elsevier)
- Omega (Elsevier)
- Applied Mathematical Modelling (Elsevier)
- Socio-Economic Planning Sciences (Elsevier)
- Journal of Manufacturing Systems (Elsevier)
- Computers and Industrial Engineering (Elsevier)
- Operations Research for Health Care (Elsevier)
- Annals of Operations Research (Springer)
- European Journal of Industrial Engineering (Inderscience)
- Transportation Research Part E: Logistics and Transportation Review (Elsevier)
- International Journal of Operational research (Inderscience)
- Journal of Logistics Systems and Management (Inderscience)
- Journal of Decision Systems (Taylor & Francis)
- International Journal of Production Research (Taylor & Francis)

I also review papers submitted to the following conferences: MIM, CoDIT, CIGI, MOSIM and APMS.

Overview on My Research Activities

In what follows, I present my research works that have been devoted, on the one hand, to the design and management of healthcare systems, and on the other hand, to the study of some decision problems related to supply chain planning and to airline and maritime logistics. I describe the progress of my research on each of the tackled topics over time, as well as the context in which they have been conducted (Master thesis, PhD thesis, collaboration with colleagues, involved companies, etc.).

Design and management of healthcare systems

- **Master of science and PhD**

- *Resource planning and scheduling in healthcare services*

My research activities officially started when I joined Grenoble Institute of Technology to pursue a Master followed by a PhD in Industrial Engineering. My interest in these research works was focused on studying healthcare systems and finding out how to improve their performance by developing appropriate and novel optimization models for efficient and effective decision making. This interest is spurred by the challenges of healthcare systems to satisfy increasing demand because of aging population and the alarming spread of some chronic diseases and health conditions such as diabetes and overweight while striving to streamline the use of scarce resources and reduce costs.

More specifically, in my PhD Thesis, I investigated resource planning and scheduling problem. A novel approach based on patient clinical path was proposed. This approach intends to take into account all scarce resources needed by the patient during his stay in the hospital. All developed models and solution approaches pertain to clinical paths that include a surgery activity. Resource planning and scheduling aims at maximizing resource utilization, patient satisfaction and safety. One of the major challenges of this research remains in handling uncertainties related to the hospital environment, mainly those stemming from service duration and the arrival of emergency cases. These uncertainties are at the origin of hospital inefficiencies regarding resource utilization. For example, when emergency cases are not properly taken into account, elective cases could be cancelled, and this leads to elongate patient's length of stay. For that, a hierarchical planning approach comprising four decision-making levels was proposed. The first level tackled elective patient admission planning based on a forecast of patient clinical path. A rolling horizon approach is adopted in order to take into account diverse disruptions that can affect the initial planning. Therefore, patient admission date provided to the patient at this level is tentative and should be confirmed further through weekly operating room planning. Thus, the objective of operating room planning, which is the second decision level of this hierarchical planning approach, is to confirm the hospitalization date initially given to the patient, minimize operating room cost and patient length of stay. The third decision level consists in building a daily operating schedule and the objective of this decision level is twofold: (1) update the weekly operating room plan; (2) define a detailed schedule of the operating rooms considering the scarce resources used in the surgery process (Jebali et al., 2004; Jebali et al., 2006). The fourth decision level comprises an approach for real-time operating room rescheduling. This approach is developed to support decision making tied to the admission of emergency cases and their introduction in the operating room schedule. The proposed approach was inspired from real life hospital cases in France and Tunisia.

- **Research conducted after my PhD**

- *Operating room planning and scheduling under uncertainty*

The operating room planning and scheduling problem is very challenging topic. Subsequent to my PhD, I extended my results on OR planning along three foremost dimensions:

- By assessing and comparing the performances of a decentralized versus centralized operating room planning management strategies. The decentralized management strategy arises when each surgery specialty is assigned a specific number of operating rooms. The weekly operating room planning is performed by each surgery specialty independently of the other ones. Contrarily, the centralized management strategy opts for the sharing of operating rooms among the different surgery specialties. Henceforth, the weekly operating room planning considers all surgery specialties and includes the assignment of operating rooms to these specialties over each weekday. The developed models were applied to an operating room suite of a Tunisian hospital and permit to highlight the advantages of a centralized management.

  This research has been initiated within the framework of the Master of Science of Houda Aloui that I co-supervised with Hanen Bouchriha. Thereafter, this research has been refined and deepened and the obtained results have been published in a joint paper with Hanen Bouchriha (Jebali and Bouchriha, 2007).

- By investigating operating room planning and scheduling while explicitly taking into account the uncertainty related to surgery durations and the arrival of emergency cases. First, a stochastic mixed integer programming model (M1) is proposed for operating room planning (Jebali and Aniba, 2011). The proposed model determines the elective cases to perform over each weekday while accounting for operating room capacity and the uncertainty in surgery durations. The objective is to minimize patient-related cost and operating room utilization cost. The latter pertains to operating room underutilization and overutilization cost. The stochastic model is then approximated by a deterministic mixed integer linear program (MIP) using a sampling-based approach. Operating room plans generated by the stochastic vs. the deterministic approach are evaluated and compared using simulation. The obtained results pointed out the interest for developing stochastic approaches for operating room planning. This first work has been then extended to address operating room scheduling while accounting for the uncertainty related to surgery durations and the arrival of emergency cases. In order to construct the operating room schedule and evaluate its performance, a stochastic three-step approach is proposed. The first step consists in: (1) devising a stochastic mixed integer program for operating room planning that accounts for emergency cases and the uncertainty in surgery durations (M2), (2) developing a sampling-based approach to solve the obtained model (Aniba and Jebali, 2011). Clearly, the model (M2) presented in this first step can be seen as an extension of (M1) by including the uncertainty related to the arrival of emergency cases. The second step consists in selecting off-line and on-line sequencing rules. The off-line rules determine the sequence of elective surgeries to perform daily in each operating room. The third step aims at evaluating operating room performance. The operating room schedule obtained in step 2 is evaluated using simulation model. At this level, it is worth noting that the decisions related to the addition of emergency cases are taken based on the on-line sequencing rules selected in step2 (Jebali and Aniba, 2012).

This work has been accomplished through the supervision of the Master of Science of Sana Aniba.

- By studying operating room planning with consideration of patients' clinical paths within the hospital. The capacity constraints of all scarce resources required for patient treatment, including surgery, are accounted for. Uncertainties stemming from the operating room environment and other scarce hospital resources involved in patient treatment are also taken into account. In light of this, first, a two-stage stochastic programming model is proposed for operating room planning in cardiothoracic and vascular surgery departments while taking into account the capacity constraints of three hospital resources: operating rooms, beds in the Intensive Care Unit (ICU), and beds in the ward (or Medium Care Unit, MCU). Elective surgeries to perform over each weekday of the planning horizon are determined while considering uncertainties related to surgery durations as well as patient Length Of Stay (LOS) in the ICU and the ward. Sample Average Approximation (SAA) is then used to solve the planning problem, aiming at minimizing the sum of patient-related costs and expected resource utilization costs. Computational experiments are conducted to evaluate the performance of the proposed solution method. The obtained results highlight the robustness of operating room plans obtained by a stochastic approach, in comparison to those generated by a deterministic approach, and the importance of considering both ICU and ward beds in operating room planning (Jebali and Diabat, 2015). The robustness of the operating room plan has been gauged through the risk of cancellation of patient admission and/or surgery entailed by resource unavailability. This work has been then extended in order to account for the arrival of emergency cases. In addition, the operating room plan is built here while enforcing the risk of cancellation of patient admission and/or surgery to be less than a pre-specified threshold. For that, a two-stage chance-constrained stochastic programming model and a featured SAA algorithm are proposed. A comparison of different modelling and solution approaches of operating room planning under uncertainty highlights the advantages vs. disadvantages of each of them (Jebali and Diabat, 2015).

  This work is the fruit of a collaboration with Ali Diabat.

- *Analysis and design of hospital logistics activities*

Furthermore, I expanded my interests in healthcare systems engineering and management to include the design of hospital logistics activities. First, we addressed the problem of the centralization vs. decentralization of the sterilization activity within hospital's premises. This reflects the case of a Tunisian hospital where many surgical services were located in different wings, with each surgical service having its own sterilization department. A two-stepped iterative approach solution was proposed (Tlahig et al., 2009). The first step consisted of finding the best configuration between the centralization and decentralization of the various sterilization service departments; in the second step, the optimal size of the configuration proposed in the first step is sought. Thereafter, we extended this first work by investigating the choice between outsourcing or keeping in-house the hospital sterilization process. As far as outsourcing is concerned, two types of third-party providers have been considered: (1) an industrial company and (2) a hospital located in the same region. Afterward, we tackled the problem of sterilization service configuration within a hospital network. Two options are considered: (1) each hospital in the network maintains its sterilization service in-house; (2) a central sterilization service ensures this function for all hospitals in the network. A Mixed Integer Program (MIP) is proposed for this location-allocation problem (Tlahig et al., 2013).

The model flags the optimal configuration of the sterilization service (centralized vs. distributed), and determines the optimal location and the optimal capacity of the centralized sterilization service over a multi-period planning horizon. The objective is to minimize costs related to transportation, operation and resource acquisition and transfer.

This research has been done within the framework of the Master of Science and the PhD of Houda Tlahig that I co-supervised with Hanen Bouchriha and Pierre Ladet (from Gipsa-Lab, Grenoble INP). It is worth noting that this research has been supported financially by the joint french-tunisian research project CMCU 05/S1105.

Furthermore, on the one hand, these works have been extended to investigate the outsource vs. insource decision for other hospital logistics activities such as food, laundry and housekeeping within the framework of a collaboration project with the Tunisian Ministry of Health. On the other hand, resource pooling of costly and scarce hospital resources has been addressed in the Master of Science of Ahlem Jenzri that I co-supervised with Hanen Bouchriha. The focus has been placed in this study on the Magnetic Resonance Imaging (MRI) machines that can be shared by different hospitals in order to achieve higher utilization of the equipment and reduce patient waiting time for diagnosis (Jenzri et al., 2010).

- *Design and management of Emergency medical Service (EMS) system*

Obviously, the objective of any EMS system is to satisfy demand requests by providing fast and timely first care medical assistance to the patients at incident scene. In this research, the focus is placed on the case of two-tiered EMS systems where two types of ambulances are considered: (1) Basic Life Support (BLS) ambulances equipped with basic equipment and, (2) Advanced Life Support (ALS) ambulances capable to perform life-saving procedures in addition to all procedures that BLS ambulance can perform. Clearly, ALS ambulance can serve a call requesting a BLS care level. First, a two-stage stochastic programming model is devised in order to design a two-tiered EMS system while accounting for demand uncertainty. The model determines the location of ambulance stations, the number and the type of ambulances to be deployed, and the demand areas served by each station. This design problem is then solved using Sampling Average Approximation (SAA) algorithm. Computational experiments highlight the performance of the proposed solution approach and its applicability in practice (Boujemaa et al., 2018). Second, we investigated ambulance relocation problem that aims at improving the performance of the EMS system through a repositioning of ambulances based on demand fluctuations over the course of the day. Hence a multi-period two-stage stochastic programming model is proposed for ambulance relocation under demand uncertainty. A sampling approach is first used to approximate the stochastic model by a deterministic one. Given the complexity of the obtained model, off-the-shelf solver (more precisely, CPLEX) fails to solve it. In order to overcome this issue, two heuristics are proposed: a Temporal Decomposition Heuristic, and a Lagrangian Relaxation based Heuristic (Boujemaa et al., 2020).

This research has been done within the framework of the Master of Science and the PhD of Rania Boujemaa that I co-supervised with Sondes Hammami and Hanen Bouchriha. Rania defended her PhD in September 2018. Rania's PhD also involves a collaboration with Angel Ruiz (from CIRRELT, Laval University, Canada).

Moreover, in collaboration with Sondes Hammami, we investigate the design of a two-tiered EMS system while considering advanced information on ambulance trip and accounting for

ambulance busy fractions. The proposed approach is compared to the traditional approach that does not consider advanced information on ambulance trip. Results stemming from a real-life case study pointed out the usefulness and superiority of the proposed approach. For the considered case, a cost saving of 3% is achieved, in addition to the reduction in ambulance round-trip time (Hammami et Jebali, 2021).

Figure 2 summarizes the different research works pertaining to the design and management of healthcare systems conducted after the completion of my PhD. In particular, figure 2 provides for each research work its timeframe and the master and PhD theses it has involved.

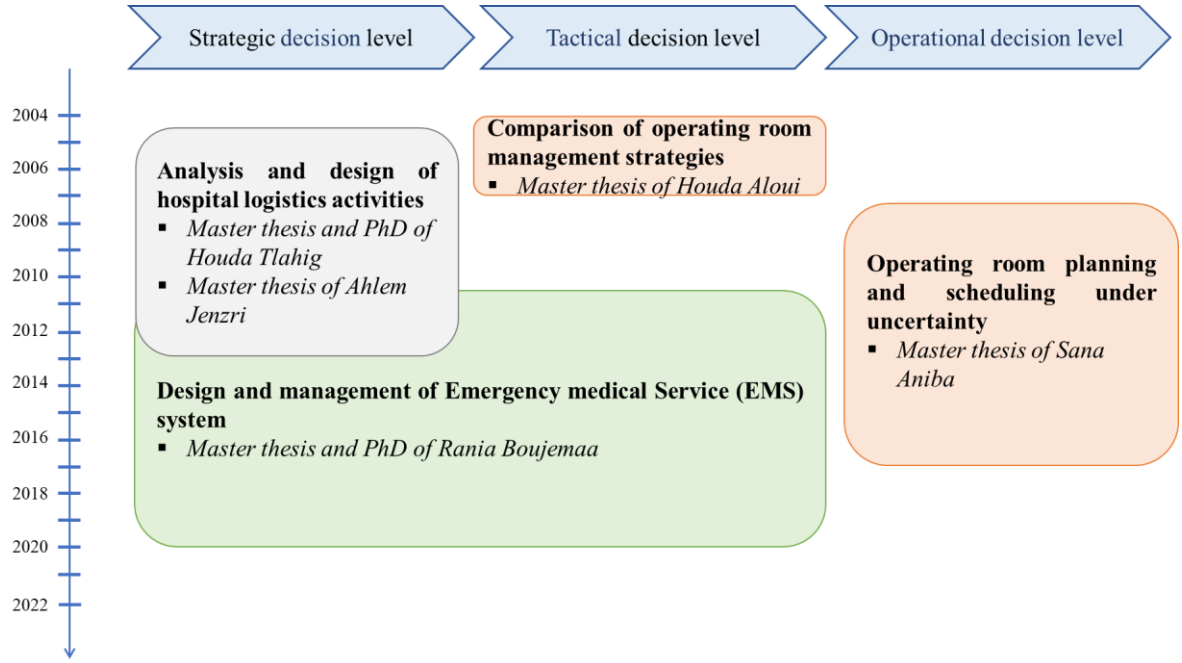

Figure 2. Summary of research works on the design and management of healthcare systems

Logistics and Supply chain management

Production-distribution planning in textile and apparel supply chain

Additionally, we have been interested in studying the textile and apparel supply chain. This interest is driven by the challenges of the Tunisian manufacturers to effectively satisfy their customers and compete on a global scale. In order to survive the fierce global competition, textile and apparel companies should be capable to ensure shorter lead times, responsiveness, adaptability and cost savings. In this perspective, an integrated production-distribution planning approach is proposed while taking into account the features of textile and apparel industry. Tactical and operational decision levels are considered to model the multi-product and multi-period planning problem. At the tactical level, decisions related to production and distribution over a six-month planning horizon are made while considering subcontracting options and reserve production capacity. The operational planning involves available full production capacity in addition to overtime and subcontracting. First, we assessed and demonstrate the importance of considering a monthly variable reserve production capacity at the tactical level. Then, we examined the interest of sharing information on current sales between manufacturer and retailer to adjust short-term production capacity requirements. Using real-life data from a textile and apparel Tunisian firm, we found out that a cost saving

of 18% can be achieved through adequate sizing of the reserve production capacity to consider at the tactical level, and manufacturer-retailer coordination based on information sharing on current sales.

This research has been done within the framework of the PhD of Imen Safra that I co-supervised with Hanen Bouchriha, Zied Jemai and Asma Ghaffari (from Laboratoire de Génie Industriel, CentraleSupelec, France).

Airline operations planning

Airline companies strive to optimize their operations in order to survive the soaring competition. Moreover, it has been noticed that company's performance can be improved significantly if operations planning decisions, namely flight scheduling, aircraft assignment, aircraft routing and crew scheduling are integrated. Obviously, the integration of even some of these four airline planning processes remains very challenging in terms of computational complexity. In this work, we first investigated the integrated flight scheduling and aircraft assignment problem under demand and fare uncertainty (Kenan et al., 2018a). A two-stage stochastic programming model was devised: in the first-stage, a fleet family is assigned to each scheduled flight leg, while at the second-stage, a fleet type is assigned to each flight leg based on demand and fare realization. SAA algorithm is then used to solve the problem and provide information on the quality of the solution. Then, we addressed the integrated flight scheduling, aircraft assignment and aircraft routing under demand uncertainty. This study was also intended to minimize propagated delays in aircraft schedule. A column generation based solution approach has been then proposed to solve the problem within a reasonable computational time (Kenan et al., 2018b). This work has been extended to include codesharing. Hence the decision of continuing or dropping a codeshare agreement is taken while addressing the integrated flight scheduling, aircraft assignment and aircraft routing. Demand uncertainty and delays are also considered. A column generation based solution approach inspired from the one proposed in (kenan et al., 2018b) allows for solving this problem within a reasonable computing time (Kenan et al., 2018c).

This research has been done within the framework of the PhD of Nabil Kenan that I co-supervised with Ali Diabat (at Masdar Institute of Science and Technology, United Arab Emirates).

Maritime logistics

Globalization of the supply chain entails a significant increase in the exchange of goods amongst countries. This explains the continuous growth in worldwide container terminals and the increasing interest for problems pertaining to port operations in research and practice over the last two decades. In particular, we addressed the quay crane scheduling problem (QCSP). The latter consists in scheduling the discharge and load operations of the containers of a vessel by a set of quay cranes; the objective is to minimize the completion time in an attempt to increase container terminal throughput. We tried to extend the literature along three dimensions:

- We devised a novel MIP formulation of the QCSP that takes into account vessel stability constraints. Indeed, despite the importance given by practitioners to vessel stability in scheduling unload and load operations, there is little research that considers this constraint. In addition, the proposed model incorporates many other realistic features of

the QCSP such as crane traveling time, task preemption, non-crossing and safety margin restrictions. A Genetic Algorithm (GA) is developed to heuristically solve the considered QCSP (Al-Dhaheri et al., 2016a).

- We developed a stochastic mixed integer programming model to construct quay crane (QC) schedules while accounting for the dynamics and the uncertainty inherent to container handling process. It is worth noting that this model extends the first one by: (1) including, in addition to seaside operations, container transfer operations, taking place between the quay and the stacking yard; (2) taking into account the uncertainty related to port operations such as container handling time. The problem is solved using a simulation based Genetic Algorithm (GA) solution approach (Al-Dhaheri et al., 2016b).

- We addressed the Quay Crane Assignment and Scheduling Problem (QCASP) while considering carbon mitigation policies, namely the carbon tax and carbon cap-and-trade. Two MIPs are proposed and used to study the impact of these two policies on costs and carbon emissions in ports (Kenan et al., 2022).

The two first works have been done within the framework of the PhD of Noura Al-Dhaheri that I co-supervised with Ali Diabat (at Masdar Institute of Science and Technology, United Arab Emirates) and was supported by grant number EX2014-000003 provided by Abu Dhabi Ports, Abu Dhabi, UAE. The third one was carried out in collaboration with Ali Diabat and Nabil Kenan.

Similarly to figure 2, figure 3 summarizes the different research works pertaining to logistics and supply chain management conducted after the completion of my PhD.

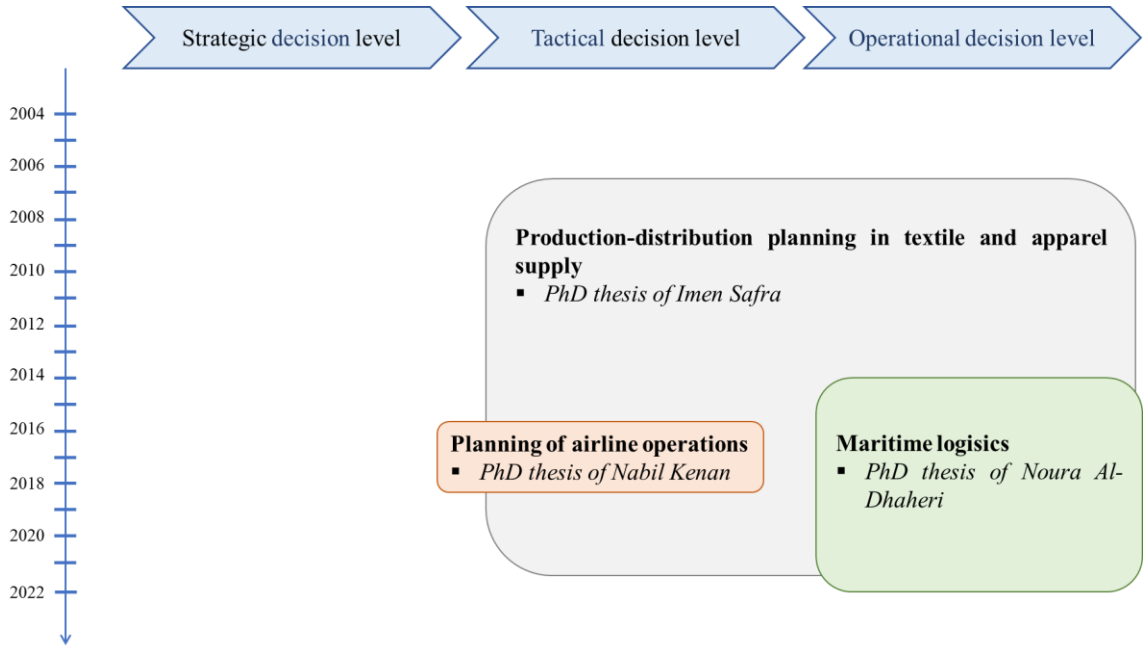

Figure 3. Summary of research works on logistics and supply chain management

As noted above, the chapters of this report do not cover all the addressed research topics. The focus is placed on the recent works which, in my opinion, led to bring a good contribution to the literature.

Part II

Design and management of healthcare systems

Chapter II.1

Operating room planning and scheduling under uncertainty

The chapter is based on (Jebali and Diabat, 2015) and (Jebali and Diabat, 2017)

1 Introduction

Operating rooms generally incur more than 8% of the hospital's cost (Bai and Zare, 2020) and, as such, they are the most costly of hospital facilities. At the same time, they generate a very high revenue for hospitals (Min and Yih, 2010) and hence play a significant role in attaining hospital profit objectives. Optimal use of operating rooms, aiming at containing the cost of surgical service delivery while preserving good quality of care and service, shortening surgical patient waiting times, and increasing patient admission rate, remain one of the major challenges for health care institutions.

Interestingly, operating rooms can be seen as the engine of hospital activity because the use of other scarce hospital resources is also paced by operating room activity. Optimizing operating room activity while considering a hospital's other scarce resources, such as beds in the intensive care unit (ICU) or beds in the suite of regular wards, leads to a better utilization of hospital resources, prevents system congestion (Hsu et al., 2003) and reduces the risk of surgery cancellation due to the unavailability of such resources (Chang et al., 2014). More specifically, this risk is entailed foremost by the different sources of uncertainties inherent to healthcare processes involving a surgery. Evidently, the degree of uncertainty varies among these processes: some processes are indeed more predictable than others. But in all cases, uncertainty often pertains to surgery duration, emergency arrival and the demand for other scarce hospital resources such as the ICU and the beds in the suite of regular wards.

The operating room planning and scheduling problem has become popular in healthcare literature over the last two decades as highlighted in the broad literature reviews provided in (Guerriero and Guido, 2011; Cardoen et al., 2010; Zhu et al., 2019; Wang et al., 2021). Operating room planning consists of specifying the set of elective patients that would be operated on each day-period over a finite planning horizon that can range from one day to one month (Denton et al., 2010; Rizk & Arnaout, 2012; Wang et al., 2014). Nevertheless, it is very common to consider a planning horizon of one week (Molina-Pariente et al., 2015a). This problem is often referred to as surgery case assignment problem (Burni et al., 2014; Denton et al., 2010; Fei et al., 2010; Guinet and Chaabane, 2003; Jebali and Bouchriha, 2007; Lamiri et al., 2009; Lamiri e al., 2008a; Lamiri et al., 2008b; Min and Yih, 2010; Rizk and Arnaout, 2012; Shylo et al., 2012; Wang et al., 2014). It is worth noting at this level that the assignment of a patient to an operating room and day also serves to define patients' admission dates. The set and the sequence of elective surgeries to be performed in each operating room is generally determined on a daily basis in order to account for updated and more detailed data on the list of eligible patients and the availability of scarce resources (Batun et al., 2011; Denton, 2007; Jebali et al., 2006; Mancilla and Storer, 2009; Pulido et al., 2014; Saadouli et al., 2015). This problem is referred to as the daily surgery scheduling problem. Clearly, the above-mentioned operational decisions depend on each other. That is why some authors opt to tackle them jointly while developing multi-step approaches (Addis

et al., 2016; Aringhieri et al., 2015; Fei et al., 2010; Jebali et al., 2006; Molina-Pariente et al., 2015b; Testi et al., 2007).

In this research, we study operating room planning with elective and emergency surgery cases under uncertainty. Daily surgery scheduling and its integration with operating room planning constitutes one of the prominent perspectives of this research as will be detailed later. Note that hereafter surgery case assignment problem and operating room planning problem will be used interchangeably.

In the following, we present the works that tackle the operating room planning problem under uncertainty published before 2017. The vast majority of these works focuses on the operating room only and do not consider other scarce hospital's resources intervening in patient's clinical path. Two main sources of uncertainty have been considered while tackling operating room planning: (1) the uncertainty related to surgery duration and (2) the uncertainty related to the arrival of emergency cases.

Works that consider the uncertainty related to surgery duration

To hedge the uncertainty of surgery durations, Hans et al. (2008) assign capacity slacks to operating room days. Different heuristics are proposed in order to maximize operating room utilization and minimize the risk of overtime. Addis et al. (2014) use robust optimization to build a surgery plan that remains feasible for some variation of surgery durations. Denton et al. (2010) compare two models proposed for daily assignment of surgery cases to operating rooms: (1) a two-stage stochastic programming model that can be used when the distribution of surgery durations is known and (2) a robust optimization model that can be used when only a lower and an upper bound on each surgery duration are available. The objective is to minimize the fixed cost of opening operating rooms and the variable cost of overtime while accounting for the uncertainty of surgery durations. The authors highlight the superiority of the robust optimization model in terms of computing time. This work has been extended by Deng et al. (2016) to include surgery sequencing and the case of ambiguous surgery durations. Jebali and Aniba (2011) develop a two-stage stochastic programming model for weekly operating room planning with random surgery durations. The stochastic model is approximated and solved using a sampling-based approach. Shylo et al. (2012) formulate a chance-constrained stochastic programming model for the assignment of surgery cases to operating rooms. The objective is to maximize the utilization of operating rooms while restricting the probability of an overtime exceeding a given threshold to be less than a pre-specified scalar (ranging between 0 and 1). The model is solved heuristically using an algorithm based on a normal approximation of the sum of surgery durations. Henceforth, the proposed approach is suitable for high-volume surgery specialties.

Works that consider the uncertainty related to the arrival of emergency cases

Obviously, in this stream of research, we consider that operating rooms are shared between elective and emergency cases. Gerchak et al. (1996) develop a stochastic dynamic programming model to determine, at the beginning of each day, how many additional elective surgeries to assign to that operating room day while accounting for emergency cases. In Lamiri et al. (2008a) and Lamiri et al. (2009), and Lamiri et al. (2008b), the authors assume that the surgery durations of elective cases are deterministic while a random slack of operating room capacity is reserved for emergency cases. In Lamiri et al. (2008a), the authors use SAA method to solve the stochastic operating room planning model. In order to

overcome the computational burden of the stochastic model, in Lamiri et al. (2009), the authors solve it using several heuristics and meta-heuristics, namely simulated annealing and tabu search. The obtained results show that SAA outperforms the proposed heuristics and metaheuristics. In these two papers (Lamiri et al., 2008a; Lamiri et al., 2009), the proposed models consider the total operating room capacity and do not specify the assignment of a surgery to a room. A column generation based approach is devised in (Lamiri et al., 2008b) to solve the problem while incorporating the assignment of surgery cases to specific operating rooms. The results demonstrate that near-optimal solutions for problem instances of practical size can be found in a short amount of time.

Works that consider the uncertainty related to both, surgery durations and the arrival of emergency cases

Aniba and Jebali (2011) expand their previous work presented in Jebali and Aniba (2011) by considering emergency cases in weekly operating room planning. Burni et al. (2014) propose a general stochastic programming modelling framework to deal with the weekly operating room planning. The latter encompasses three recourse strategies representative of common practices used in hospitals to handle the uncertainty in surgery durations and emergency arrivals. Based on problem structure, tailored heuristics are developed and allow for solving realistic-sized problem instances within a reasonable computational time. Wang et al. (2014) devise a chance-constrained stochastic programming model for the daily operating room planning. The proposed model determines the operating rooms to open and the surgeries to perform in each operating room. The objective is to minimize the fixed cost of opening operating rooms and the expected overtime cost. In addition, the model incorporates chance constraints in order to enforce an upper bound on the risk of surgery cancellation entailed by exceeding overtime capacity. The SAA method is then used to transform the stochastic model into a deterministic one. The obtained integer program is solved using a column generation based heuristic. The results highlight that accepting higher surgery cancellation risk helps in reducing operating room costs.

Works that consider the scarce resources intervening in the patient's clinical path including a surgery

Min and Yih (2010) develop a two-stage stochastic programming model for weekly operating room planning that accounts for ICU capacity. The model considers the randomness related to elective surgery durations and patients' Lengh Of Stay (LOS) in the ICU. Additionally, a random slack of operating room capacity is reserved for emergency cases. The objective is to minimize the patients' related costs and overtime costs. The proposed model is efficiently solved using SAA algorithm. In (Adan et al., 2008), the authors formulate a MIP to construct a master surgical schedule for a Cardiothoracic Center. The schedule specifies the mix of patients (from different groups) that can be admitted over each day of a four-week planning horizon. The proposed MIP takes into account the capacity of several resources: the operating rooms, the beds in the intensive and medium care units (MCU), and nursing hours in the ICU. This MIP has been extended in (Adan et al., 2011) to account for both elective and emergency patients. In order to deal with the real elective patient flow, operating slots are introduced in the master surgical schedule (also referred to as tactical plan) while considering a higher than average number of patients. These slots are then filled in the operational weekly schedule based on patient group flexibility. An algorithm is proposed to modify the weekly schedule on a daily basis in order to deal with arriving emergency patients. In the algorithm, a

few of the scheduled elective surgeries are cancelled whenever a resource capacity is exceeded.

At this level, first, we can notice that most of the works mentioned above have taken into consideration the capacity of the operating room while only a few have accounted for overtime capacity (Shylo et al., 2012; Wang et al., 2014). Second, although the unavailability of other scarce hospital's resources intervening in the patient's clinical path affect the feasibility of the operating room plan (Blake & Carter, 1997; Bowers, 2013), the models that integrated them are rather scant.

This research seeks to start filling this gap. In the sequel, operating room planning problem under uncertainty is tackled while considering the scarce resources intervening in the patient's clinical path. Specifically, we study two problem variants for which we propose models and solution approaches.

2 Problem description

The objective of the weekly operating room planning is to determine the elective surgery cases to be performed during each day-period so that the overall cost incurred is minimized. We suppose that each elective patient is provided with a tentative admission date as soon as the decision to have surgery (decision-to-treat) is made. An elective patient can undergo the operation on the day of his/her admission or the day after admission depending on the type of surgery he/she shall undergo. However, because of the diverse sources of uncertainty inherent to the demand of scarce resources needed by elective and emergency patients, the tentative admission and surgery date might change. From this angle, operating room planning also serves to confirm elective patients' admission dates. Regarding patient satisfaction, the initial admission date should be respected as much as possible. If the initial date of patient admission cannot be maintained, a penalty cost is incurred based on patient waiting time and the urgency of the case (Testi et al., 2007). This penalty cost is embedded in patient-related costs.

Surgeries can be performed during regular opening hours or overtime. However, in addition to the high cost of overtime, it has been noted that overtime working hours increase nurse dissatisfaction and turnover rate (Nursing Solutions, Inc. 2013). That is why, the use of each operating room beyond its regular opening hours should be avoided. In terms of regulation, the overtime is generally capped to two hours. Undertime is also undesirable as operating rooms and surgical staff incur relatively high fixed costs. Therefore, operating room planning seeks to minimize costs incurred by OR overtime, undertime, as well as patients' waiting time.

As it has been mentioned above, each elective patient can be operated either on the day of admission or one day after admission in the regular ward. It is worth noting that the clinical path of each elective patient can be predicted before admission based on the surgery type and his health status revealed in the pre-operative diagnosis. As can be noticed from figure 4, after undergoing the surgery, some patients are transferred to the ICU where they stay some days for recovery while others are transferred to the regular ward. After recovering in the ICU, the patient is generally transferred to the regular ward. The patient leaves the hospital as soon as his/her health status allows for that.

The scarcity of a resource is tied to its capacity and the demand for it. Indeed, resources whose capacity is sufficiently high and often allows to satisfy the demand are not considered as scarce resources. Apart the operating rooms, in the considered clinical paths, two resources might be considered as scarce resources: (1) the beds in the regular ward and (2) the beds in the ICU. Obviously, the daily capacity of the regular ward and the ICU are measured in terms of number of beds. All other required resources are assumed available.

We consider the uncertainty related to the demand for scarce resources. Note that the demand for operating rooms is gauged by surgery durations while the demand for beds in the ICU and in the regular ward is determined through patient LOS. Therefore, in operating room planning we consider the uncertainty related to surgery duration, to patient's LOS in the ICU and in the suite of regular wards.

The scarce resources are shared between elective patients and emergency patients. The emergency patients may arrive throughout the day (between 8 am and 6 pm) or night (Adan et al., 2011). The surgeries of those arriving during the day are directly incorporated in the operating room schedule. For those arriving during the night, it is assumed that they are operated on during the night shift. Subsequently, a part of the capacity of the operating room over the day shift should be reserved for emergency surgeries. Furthermore, a number of beds in the ICU and in the ward should be also reserved for emergency patients.

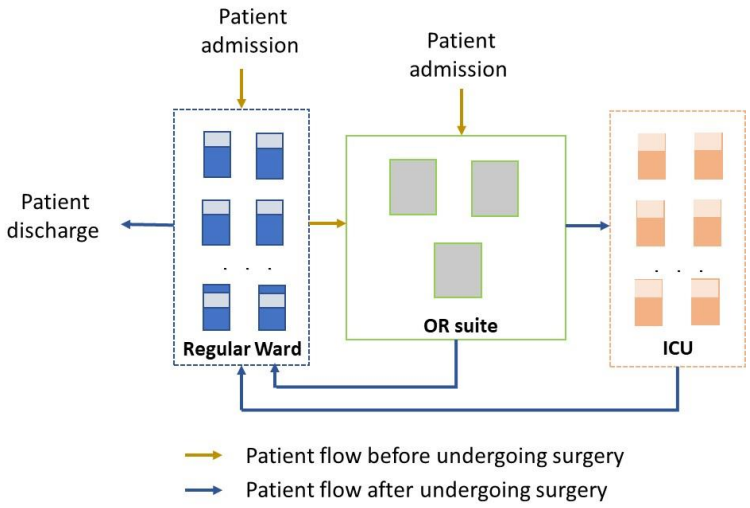

Figure 4. Possible patients' clinical paths including a surgery

3 First problem formulation and solution approach

3.1 Problem formulation

In this first operating room planning problem, we consider the following assumptions:

A1. The operating rooms, the beds in the ward and the beds in the ICU are scarce resources.
A2. A known slack of each scarce resource capacity is reserved for emergency patients, thus allowing for their implicit consideration.
A3. Surgery durations depend on surgery type and are supposed mutually independent.
A4. The duration of each surgery type is assumed to follow a log-normal distribution (May et al., 2000; Strum et al., 2000; Zhou and Dexter 1998) with a known mean and standard deviation.

A5. We know the surgery type of each patient.
A6. The post-operative LOS in the ICU, as well as in the regular ward, are expressed in number of days.
A7. The post-operative LOS in the ICU, as well as in the regular ward, are supposed mutually independent and follow an empirical discrete distribution.
A8. For each patient, we know the empirical discrete distribution that can approximate his/her LOS in the ICU and in the ward.
A9. The remaining LOS in the ICU and/or the regular ward of each hospitalized and operated patient is assumed deterministic (Adan et al. 2011). Based on that, the available capacity of the ICU and the regular ward are determined for each day-period of the planning horizon.
A10. An earliest date is associated with each elective surgery.

The operating room planning problem is first modelled as a two-stage stochastic mixed integer programming model. In the first stage, the model determines the elective surgery cases to be performed on each day of the week. Uncertainty related to operating room planning is represented by the set of possible scenarios. Each scenario is defined through the vector of outcomes of three independent random variables: surgery duration, LOS in ICU and LOS in the ward and has a probability of occurrence. Second-stage variables are scenario-dependent and therefore include overtime and undertime of each operating room on each day-period and the utilization of ICU and ward beds. Moreover, it is worth mentioning that the proposed model can be used regardless of the probability distribution of surgery duration, LOS in the ICU and LOS in the ward.

The proposed model aims at minimizing the sum of the first-stage costs and the expected second-stage costs. The first-stage costs represent patient-related costs, while the second-stage costs include undertime and overtime costs. Each elective surgery can be assigned at most to an operating room over a weekday of the planning horizon. A surgery cannot be performed before its earliest date. Capacity constraints of the three scarce resources (i.e., operating rooms, beds in the ICU, and beds in the regular ward) are accounted for. Operating room can be used only during the permitted opening time, thus ensuring that overtime capacity is respected. Over each day-period, the number of occupied beds in the ward and in the ICU cannot exceed their respective available capacities.

A major concern in stochastic programming models is related to the satisfaction of the condition of relatively complete recourse. Specifically, we seek to determine whether all second-stage problems are feasible when first-stage variables are fixed. For our problem, infeasibility of the second stage can occur from resource capacity constraints. Indeed, for a given realization of surgery durations and LOSs in the ICU and the ward, these constraints might not be satisfied. To overcome this issue, we propose to modify the initial stochastic programming model by including penalty costs to penalize violations of the capacity constraints. For that, three second-stage variables representing the excess of capacity of the operating room, the ICU and the regular ward are introduced in the model. More specifically, these variables are embedded in the objective function to account for the penalty cost for exceeding resource capacity and in the resource capacity constraints.

For the details of the mathematical formulation of the proposed two-stage stochastic programming model we refer the reader to (Jebali and Diabat, 2015).

3.2 Solution approach

A typical problem instance in a real-life case entails thousands of scenarios. Thus, solving the proposed stochastic programming model would be impractical. For that, we propose to use the SAA algorithm, which allows for finding a good solution among a smaller number of scenarios. Random samples including a smaller number of scenarios (or realizations) of the uncertain parameters are generated and integrated in the model. The expected value of the second-stage costs is approximated by the sample average over these scenarios that are assumed equiprobable. As can be noted, the obtained deterministic MIP, hereafter referred to as SAA model, can be seen as an approximation of the stochastic programming model.

In order to reduce the computational burden of the SAA model, we relax the integrality of the second-stage variables that flag if a bed in the ICU or in the ward is occupied by a patient during a day-period of the planning horizon. Indeed, according to (Wolsey 1998), given the characteristics of the coefficients and variables used in the constraints containing these ICU and ward bed utilization variables, the linear relaxation of the latter variables will have integer (0–1) solutions.

The optimal solution of the SAA model converges with probability one to an optimal solution of the stochastic programming model as the sample size L (i.e., number of scenarios integrated in the model) increases (Kleywegt et al., 2001). Choosing the sample size requires making a trade-off between the quality of an optimal solution of the SAA model and the computational effort needed to solve it. Moreover, as presented in (Kleywegt et al., 2001), solving the SAA problem repeatedly by generating M independent samples, each of size L, and solving the associated SAA models, can be more efficient than increasing the sample size L.

The procedure of the implemented SAA algorithm is as follows:

Step 1. For m=1..M do steps 1.1 through 1.4.

Step 1.1. Generate a sample of size L

Step 1.2. Solve the corresponding SAA problem and save its optimal solution $\hat{x}_L^m$ with optimal objective value $\hat{o}_L^m$

Step 1.3. Generate a sample of size L' (L'>L)

Step 1.4. Estimate the "true" objective value $\hat{g}_{L'}(\hat{x}_L^m)$ of the SAA optimal solution $\hat{x}_L^m$ and its variance $\sigma^2_{\hat{g}_{L'}(\hat{x}_L^m)}$

$$\sigma^2_{\hat{g}_{L'}(\hat{x}_L^m)} = \frac{1}{(L'-1)L'}\sum_{l=1}^{L'}\left(\hat{g}_l(\hat{x}_L^m) - \hat{g}_{L'}(\hat{x}_L^m)\right)^2$$

Step 2. Compute $\bar{o}_L^M$ and a corresponding estimate of variance $\sigma^2_{\bar{O}_L^M}$

$$\bar{o}_L^M = \frac{1}{M}\sum_{m=1}^{M}\hat{o}_L^m$$

$$\sigma^2_{\bar{O}_L^M} = \frac{1}{(M-1)M}\sum_{m=1}^{M}(\hat{o}_L^m - \bar{o}_L^M)^2$$

Step 3. For each solution $\hat{x}_L^m$, m=1..M, compute the optimality gap $\hat{g}_{L'}(\hat{x}_L^m) - \bar{o}_L^M$ and a corresponding estimate of variance $\sigma^2_{gap} = \sigma^2_{\bar{O}_L^M} + \sigma^2_{\hat{g}_{L'}(\hat{x}_L^m)}$

Note that samples of size *L'* are generated independently of the samples used in the SAA problems. Because the first-stage solution is fixed, one can choose a value for *L'* larger than for *L* as this step involves only the evaluation of the obtained first-stage solution, using simulation.

The variables $\bar{o}_L^M$ and $\hat{g}_{L'}(\hat{x}_L^m)$ respectively provide a statistical lower bound (LB) and upper bound (UB) on the optimal objective value of the original problem (Mak et al., 1999). If we let o^* denote the optimal objective value of the original problem, then the following inequality holds for the statistical LB: $\bar{o}_L^M \leq o^*$. Now, as the property of relatively complete recourse is valid, $\hat{x}_L^m$ is also a feasible solution of the original stochastic problem. Hence the inequality $\hat{g}_{L'}(\hat{x}_L^m) \geq o^*$ holds. An estimate of the optimality gap of a given SAA solution is thus given by $\hat{g}_{L'}(\hat{x}_L^m) - \bar{o}_L^M$, and the variance of the estimated optimality gap is given by $\sigma_{gap}^2 = \sigma_{\bar{O}_L^M}^2 + \sigma_{\hat{g}_{L'}(\hat{x}_L^m)}^2$.

3.3 Experimentation and main results

Experimentation & Data description

Computational experiments are conducted to evaluate the performance of the proposed solution method and generate some insights. The test problems considered in the experimentation are derived from the real-life case study of the Thorax Centre Rotterdam of the Erasmus University Medical Centre presented in (Adan et al., 2008) and (Adan et al., 2011). The Thorax Centre comprises a MCU (Medium Care Unit), which is the regular ward, four operating rooms and an ICU. For certain patients, it is necessary to spend some days in recovery in the ICU, before being transferred to the MCU, while others do not require an additional stay in the ICU. A known slack of each of these resources' capacity is reserved for emergency cases each day of the week. There are eight elective patient groups that are considered, with patients of the same group requiring a homogeneous use of resources (i.e., for patients belonging to the same group, the surgery duration, LOS in the ICU and LOS in the MCU follow the same probability distribution). The probability distribution of resource demand is known for each patient group. Finally, all patients need hospitalization one day prior to surgery except for patients of group 1 and 2.

Due to the lack of detailed information on the slack capacity reserved in each operating room for emergency cases, the experimentation considers the total available capacity of all operating rooms over each day of the week (i.e., the four operating rooms were aggregated). The regular opening time of operating rooms to be used by elective cases is set to 29 hours (h) for Monday through Thursday and 25 h for Friday. The overtime capacity for each operating room is set to 3 hours. The number of beds in the MCU available for elective cases is 20 out of 27. The number of beds in the ICU available for elective cases is seven during weekdays and two during the weekend. As noted above, to generate surgery case durations, a log-normal distribution is used while to generate LOS in the ICU and in the MCU, an empirical discrete distribution (based upon a sample of 593 patients) is used. At this point, we will provide some details on the model costs. The overtime cost is set to 500 €/h (Lamiri et al., 2008a), while the undertime cost is set to 500/1.75 €/h. As far as penalty costs are concerned, they are given large values in order to prevent as much as possible the violation of resource capacity constraints (Lamiri et al., 2008b). Thus, the penalty for exceeding the OR-day available capacity (regular plus overtime) is set to 4000 €/h. The penalty costs for

exceeding the capacity of MCU and ICU are determined based on the penalty cost for exceeding OR-day available capacity using the relative weight of each resource as defined in (Adan et al., 2011).

Patient-related costs are determined based on the initial date of surgery given to the patient. Obviously, when the waiting time of the patient with reference to that initial date gets higher, patient-related cost increases; the patient is thus given a superior priority to be scheduled.

Main results

Performance of the SAA algorithm

We conducted experiments on a test problem considering 28 elective patients. We first intended to evaluate the SAA algorithm and demonstrate its convergence toward the optimal solution of the initial stochastic programming model. For that, we run the SAA algorithm with L = 10, 50, 100, 400, 700 and 1000; M = 10 and L'= 10,000. Recall that L is the sample size used in the SAA model while L' is the sample size used in the simulation. As can be observed from figure 5, the optimality gap becomes narrower as the sample size L increases, meaning that better solutions are obtained for larger sample sizes. A near-optimal solution of 1.08% optimality gap is obtained with sample size L=1000. Expectedly, the time needed to solve the SAA model increases with the sample size but remains reasonable for a sample size L = 1000 (less than 30 minutes). Overall, these results point out that the SAA algorithm can be used in practical cases.

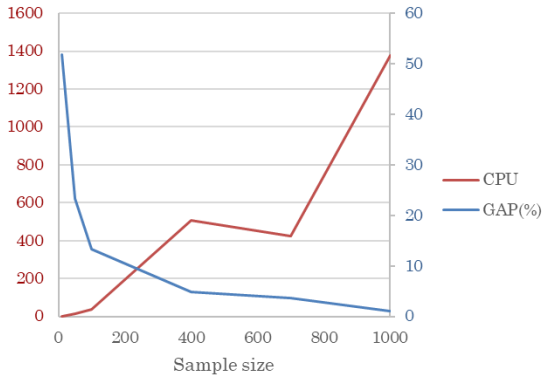

Figure 5. Performance of the SAA algorithm

Robustness of the proposed operating room planning approach

In order to assess the importance of adopting the proposed operating room planning approach, we compared its performance to: (1) the performance of the plan obtained for the expected value problem (EVP) and (2) the performance of a plan obtained without considering overtime capacity and MCU capacity, referred to as, SAA'. In the EVP, random variables are replaced by their means. Therefore, it reflects the solution obtained by a deterministic approach. The SAA' is obtained by solving SAA while omitting the variables and constraints tied to overtime and MCU capacity constraints. SAA' represents indeed the solution obtained for a problem setting similar to the one tackled by Min and Yih (2010). SAA' solutions are also obtained by the SAA algorithm with L = 10, 50, 100, 400, 700 and 1000, L'= 10,000 and M = 10.

The performance of an operating room plan is measured through its 'infeasibility risk', which is simply the probability of 'second-stage problem being infeasible'. Recall that an infeasible second-stage problem is spotted by its solution that encompasses at least a non-zero capacity excess variable. Indeed, building an operating room plan that can be executed, without cancellation of a patient's admission and/or surgery, remains one of the high priority objectives of an operating room manager.

We can observe from figure 6 that the SAA solution outperforms EVP and SAA' solutions in terms of cost and robustness as it induces a lower risk of infeasibility. It has been also noted that this robustness comes at the expense of higher first-stage cost. This higher first-stage cost, resulting from a lesser number of scheduled elective cases, entails a flexibility in the second-stage that mitigates the infeasibility risk. Nevertheless, this flexibility tends to augment undertime.

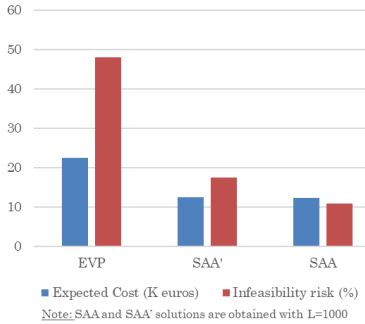

Figure 6. Comparison of the performance of different operating room plans

Furthermore, from figure 7, one can see that for SAA and SAA' the infeasibility risk clearly decreases when the sample size increases. This result points out the increased robustness of the operating room plan when obtained using a larger sample size.

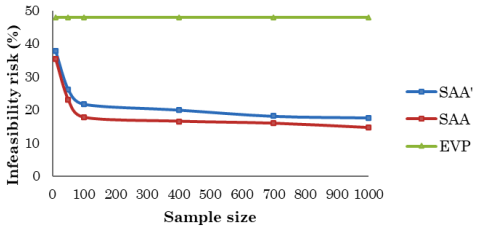

Figure 7. Average infeasibility risk (%) associated with different operating room planning approaches

Effect of ICU and MCU capacity on the operating room performance

In this case, an increase in ICU or MCU capacity has been always followed by an increase in the number of planned patients and the utilization rate of the operating rooms. Therefore, the capacity of any scarce resource intervening in the patient's clinical path can be used as a lever to improve operating room performance and reduce the waiting time for a surgery.

4 Second problem formulation and solution approach

4.1 Problem formulation

Assumptions A3 through A8 are common to the first and second problem. Assumptions A1 and A2 in the first problem are replaced in the second problem by B1 and B2, presented below.

B1. The operating rooms and the beds in the ICU are scarce resources.
B2. Operating room and ICU capacities used by emergency cases are stochastic and therefore a stochastic slack of the capacity of each of these scarce resources should be reserved for emergency patients.

In this problem, each scenario has a probability of occurrence and is defined through the vector of outcomes of four independent random variables: surgery duration, LOS in the ICU, daily capacity of the operating room and the ICU reserved for emergency cases over the planning horizon. Obviously, the randomness of operating room and ICU capacities used by emergency cases is entailed by the randomness of the arrival process of emergency patients and the randomness of their surgery durations and LOS in the ICU. Indeed, the capacity of the operating room used by emergency cases is derived from the sum of a random number of random variables. The number of emergency arrivals over one day is assumed to follow a Poisson distribution (Adan et al., 2011). Therefore, the capacity of the operating room reserved for emergency patients over one weekday is given by the sum of their surgery durations while the capacity of the ICU used by emergency patients is determined through the number of emergency patients admitted over the planning horizon and their respective LOS in the ICU.

This second problem can also be formulated as a two-stage stochastic programming model. However, penalizing the case where the capacity of a scarce resource, such as the ICU, is exceeded reduces the infeasibility risk of the operating room plan, when the per unit penalty cost is relatively high (Jebali and Diabat, 2015), but cannot completely preclude it. More importantly, this type of modelling does not allow to restrict this risk to be lesser than a prespecified threshold, and so control it. In practice, the violation of one capacity constraint entails the cancellation and postponement of the admission and the surgery of planned elective patients. To overcome this issue, we propose to formulate the problem as a two-stage chance-constrained stochastic program (TSCCSP). The chance-constraint tries indeed to guarantee low risk of cancellation of elective patients' admission and surgery over the considered planning horizon.

At this level, it is noteworthy that the proposed formulation considers only the excess of ICU capacity. Indeed, the excess of ICU capacity on a day-period incurs the cancellation of the admission and the surgery of at least one elective patient. However, the excess of operating room capacity can be recovered through overtime. Furthermore, in the considered case, when the ICU capacity is respected, the cancellation of elective surgeries generally does not happen (Jebali and Diabat, 2015). If the cancellation of elective surgeries happens even though the ICU capacity is respected, then the current formulation should be extended to include overtime capacity and the penalty cost for exceeding overtime capacity.

Let us denote by y_t the number of ICU beds used on day-period *t* by elective patients and α ($\alpha \in (0,1)$) the upper bound considered for the risk of cancellation of the admission and the surgery of elective patients because of the excess of ICU capacity. The chance constraint is written as follows: $P(\max_{t=1..T+2}(y_t + WICU_t - Cicu_t) > 0) \leq \alpha$, where y_t and $WICU_t$ are the number of ICU beds occupied by elective and emergency patients on day-period *t*, and $Cicu_t$ is the number of ICU beds available on day-period *t*. The proposed formulation is a TSCCSP with risk level α (also referred to as significance level).

4.2 Solution approach

A featured SAA algorithm is proposed to solve the chance-constrained stochastic problem. This algorithm is based on the theoretical findings of several studies that have been devoted to the use of SAA to solve chance-constrained stochastic problems (namely, Ahmed and Shapiro, 2008; Luedtke et al., 2010; Pagnoncelli et al., 2009) and two-stage stochastic programs (Ahmed and Shapiro, 2002; Kleywegt et al., 2001). To the best of our knowledge, this is the first research that formulates the operating room planning problem as a TSCCSP and develops a featured SAA algorithm to solve it. The proposed algorithm has been inspired from the SAA scheme developed by Wang et al. (2012) to solve a chance-constrained two-stage stochastic program for unit commitment with uncertain wind power output. It starts by writing the SAA model corresponding to the TSCCSP at hand with risk level γ.

In the following, we present three properties that bear the foundation of the proposed algorithm.

Property 1. (Wang et al., 2012): For the same significance levels $\gamma=\alpha$, the optimal objective value $\hat{v}_L$ and solution $\hat{x}_L$ of the SAA problem converge to their counterparts of the true problem TSCCSP, v^* and x^*, with probability one as the sample size L goes to infinity.

From property 1, we can expect that with an increase of the sample size L, an optimal solution of the SAA problem will approach an optimal solution of the true problem TSCCSP with the risk level γ rather than α. Additionally, for L large enough, if $\gamma<\alpha$, then the probability that a feasible solution of the SAA problem is also a feasible solution of the true problem approaches one exponentially fast and; on the other hand, if $\gamma>\alpha$, then the optimal objective value of SAA solution provides a lower bound of the true problem with high probability (Luedtke and Ahmed, 2008). These results are used in the featured SAA algorithm to produce a feasible solution or a lower bound to the true problem with high probability.

If the obtained SAA solution respects the chance constraint, then, as a feasible solution, it can be used to calculate an upper bound for TSCCSP. To verify if a SAA solution is feasible, we employ the Monte Carlo sampling technique to generate a sample of size $L'>L$ and estimate the probability of the chance constraint. Let us denote by $\hat{q}_{L'}(\bar{X})$ the estimate of the probability of the chance constraint ($P(\max_{t=1..T+2}(y_t + WICU_t - Cicu_t) > 0)$ by using the sample of size L'.

According to Ahmed and Shapiro (2008), based on the estimator $\hat{q}_{L'}(\bar{X})$, a (1-β)-confidence upper bound on the probability of the chance constraint is given by:
$U_{L'}(\bar{X}) = \hat{q}_{L'}(\bar{X}) + z_\beta\sqrt{\hat{q}_{L'}(\bar{X})(1-\hat{q}_{L'}(\bar{X}))/L'}$ (1) with $z_\beta = \Phi^{-1}(1-\beta)$ where $\Phi(z)$ is the cumulative distribution function (cdf) of the standard normal distribution. If this upper bound is less than the risk level α, then the obtained SAA solution is a feasible solution to TSCCSP with confidence level (1-β). In this case, the "true" objective value $\hat{g}_{L'}(\bar{X})$ represents an upper bound for TSCCSP with confidence level (1-β). Note that $\hat{q}_{L'}(\bar{X})$ and $\hat{g}_{L'}(\bar{X})$ are determined using Monte Carlo simulation.

Let $\theta_L := B(\lfloor\gamma L\rfloor; \alpha, L)$ and $\bar{V}_L$ the optimal objective value of a SAA solution obtained by considering a sample of size L where B is the cdf of binomial distribution and $\lfloor a \rfloor$ is the integer part of the real number a.

Property 2. (Luedtke and Ahmed, 2008): $P(\bar{V}_L \le v^*) \ge \theta_L$

Property 2 pertains to the probability that the objective value of a solution of the SAA problem with sample of size *L* bears a lower bound of the true problem TSCCSP.

Let us now consider two positive integers *M* and *K* such that *K*≤*M* and *K* is the largest integer such that: $B(K-1;\theta_L,M) \le \beta$ (2)

We generate *M* independent samples of size *L* and denote by $\bar{V}_L^m$ the optimal objective value of the SAA problem *m*, *m*=1..*M*, solved with one of the samples of size *L*. We then sort the obtained optimal objective values $\{\bar{V}_L^m\}_{m=1}^M$ in non-decreasing order such that $\bar{V}_L^{(1)} \le ... \le \bar{V}_L^{(M)}$.

Property 3. (Luedtke and Ahmed, 2008): $P(\bar{V}_L^{(K)} \le v^*) \ge 1-\beta$

According to property 3, the statistical quantity $\bar{V}_L^{(K)}$ is a lower bound of the true problem with probability at least (1-β).

The procedure of the featured SAA algorithm is as follows:

Step 0. Select $\gamma \in [0,1)$, $\beta \in (0,1)$, *L*, *L'*, *S*, *M* and *K* positive integers such that *K*≤*M* and verifying (2)
Step 1. For *s*=1..*S* do steps 1.1. through 1.3.
  Step 1.1. For *m*=1..*M* do steps 1.1.1 through 1.1.6.
    1.1.1. Generate a sample of size *L*
    1.1.2. Solve the corresponding SAA problem and save its optimal solution $\bar{X}_L^m$ and the corresponding objective value $\bar{V}_L^m$
    1.1.3. Generate a sample of size *L'* (*L'*>*L*)
    1.1.4. Estimate $U_{L'}(\bar{X}_L^m)$ using (1)
    1.1.5. If $U_{L'}(\bar{X}_L^m) \le \alpha$ go to step 1.1.6.
    1.1.6. Estimate the "true" objective value of the SAA solution $\hat{g}_{L'}(\bar{X}_L^m)$
  Step1.2. Pick the smallest "true" objective value found in step 1.1. and denote it as $\hat{g}_s$
  Step 1.3. Sort the *M* optimal objective values $\{\bar{V}_L^m\}_{m=1}^M$ in non-decreasing order such that $\bar{V}_L^{(1)} \le ... \le \bar{V}_L^{(M)}$ and pick the K^{th} optimal value $\bar{V}_L^{(K)}$ and denote it as $\bar{V}_s$
Step 2. Compte the statistical lower bound $\bar{V} = \frac{1}{S}\sum_{s=1}^{S} \bar{V}_s$
Step 3. Select the best upper bound $\hat{g} = \min_{1 \le s \le S} \hat{g}_s$ and the corresponding solution
Step 4. Estimate $\frac{(\hat{g}-\bar{V})}{\bar{V}} \times 100\%$, the optimality gap of the best solution

It is expected that the quality of the produced solution increases with an increase of sample size *L*. However, an increase of *L* makes the SAA problem hard to solve. Again, the trade-off between the quality of the SAA solution and the computational time needed to obtain it should be considered when choosing the sample size *L*. Moreover, as increasing *M* and/or *S* entails the exploration of a larger number of SAA solutions, this obviously results in improving the quality of the produced solution.

4.3 Main results

Data description

The conducted experimentation for this second problem also used data pertaining to the real-life case study presented in (Adan et al., 2008) and (Adan et al., 2011). In addition to those presented in subsection 3.2, we generate the necessary data to determine, for each scenario, the capacity of the operating room and the ICU needed by emergency cases. First, the number of emergency patients, of a given group, arriving to the Thorax Center over each day-period of the planning horizon is generated based on a Poisson distribution whose parameters have been extracted from (Adan et al., 2008) and (Adan et al., 2011). The probability that an emergency patient arrives during the day shift is 0.8. A discrete distribution is used to flag the emergency patients that arrive over the day shift. The surgery duration and the LOS in the ICU are generated for emergency patients in the same way they are generated for elective patients of the same group. Therefore, the daily capacity of the operating room reserved for emergency cases is approximated through the sum of surgery durations of emergency patients arriving over the day shift. The number of beds in the ICU used by emergency patients is determined based on the number of emergency arrivals over each day-period of the planning horizon and their LOS in the ICU.

Main results

The results presented in this part are obtained while considering a test problem including 30 elective patients.

Performance of the featured SAA algorithm

The featured SAA algorithm is aimed at solving the proposed TSCCSP at risk level $\alpha = 10\%$. In order to find a larger number of candidate solutions for TSCCSP, the SAA model is solved with $\gamma = 9\%$ (slightly lesser than α). The featured SAA algorithm is tested with $L = 10$, 50, 100, 150 and 200; $M = 10$; $S = 5$ and $L = 2000$. K is chosen for each sample size according to (2) with $\beta = 10\%$. Hence for $L = 10$, 50, 150 and 200, and $K = 2$ for $L = 100$, $K = 3$.

From figure 8, one can see that when the sample size L increases, the optimality gap becomes smaller. A near-optimal solution of 1.87% optimality gap is obtained with sample size $L = 200$. In particular, this result demonstrates the convergence property of the featured SAA algorithm. Although the computing time required to solve SAA problem becomes higher when the sample size increases, it remains relatively reasonable for a sample of size $L = 200$ (less than 40 minutes). Overall, the obtained results demonstrate that the featured SAA algorithm can be used in practice to provide near-optimal solutions with relatively high confidence level.

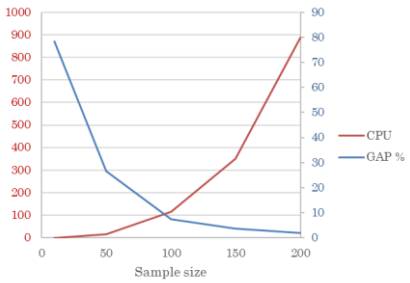

Figure 8. Performance of the featured SAA algorithm

Effect of the risk level α on the operating room performance

The featured SAA algorithm with L = 200, M = 10; S = 5 and L' = 2000 is thereafter used to solve the considered test problem at different risk levels α, ranging from 2% to 20%. The objective is to find a solution with 90% confidence level. The corresponding SAA models are solved while setting $\gamma = 0.9\alpha$.

As it can be seen from table 5, the total cost, the first-stage and second-stage costs decrease as the risk level α increases. This is reasonable because the number of scheduled patients gets smaller when the risk level decreases. Obviously, scheduling a smaller number of patients tends to reduce the risk of cancellation of patient admission and/or surgery entailed by ICU bed shortage. This can also explain why the operating room and the ICU utilization rates decrease when a lower risk level α is considered, as delineated in figure 9. Note that these utilization rates respectively attain a maximum of 89.52% and 74.71% for α= 100% and a minimum of 67.37% and 52.49% for α = 2%. Seeking better patient satisfaction by reducing the risk for admission/surgery cancellation will incur higher costs and reduced operating room and ICU utilization rates. Thus, the choice of the risk level should take into account the targeted levels of resource utilization or hospital cost vs. profit and patient satisfaction.

Table 5. Effect of the risk level on the operating room performance

α (%)	Total cost	First-stage cost	Second-stage cost	Nb. of scheduled patients	Probability_OR overtime (%)
2	19932	2500	17432	26	6.03
5	14630	2200	12430	27	7.44
10	13072	2000	11072	28	11.73
15	12199	1900	10299	29	12.69
20	12039	1600	10439	29	16.53

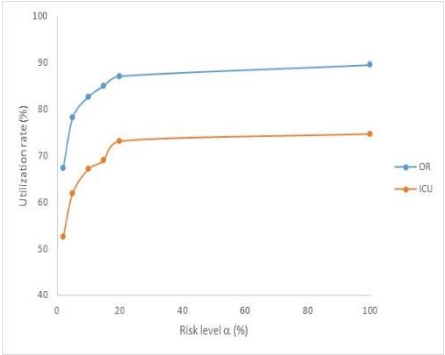

Figure 9. Operating room and ICU utilization rates as a function of the risk level

5 Concluding remarks and future research

This research addressed operating room planning under uncertainty. Apart operating rooms, it considers the capacity of scarce resources intervening in patients' clinical path, namely beds in the ICU and beds in the ward (or medium care unit). First, the problem is formulated as a two-stage stochastic programming model. SAA algorithm is used to solve the planning problem. The obtained results highlight the robustness of the proposed approach and stress the importance of considering, in operating room planning, the availability of hospital's scarce resources. Thereafter, an operating room plan is built while enforcing the risk of

cancellation of patient admission and/or surgery to be less than a pre-specified threshold. For that, a two-stage chance-constrained stochastic programming model and a featured SAA algorithm are proposed.

The current research can be extended to include different types of operating rooms and the assignment of surgery cases to operating rooms. Another interesting extension remains in integrating operating room planning with daily operating room scheduling. These extensions will require the development of sophisticated solution methods such as column generation and simulation-based optimization approaches. The ultimate goal is to develop a holistic approach for operating room management as will be detailed further in part IV.

Chapter II.2

Design and management of Emergency Medical Service (EMS) system

The chapter is based on (Boujemaa et al., 2018) and (Boujemaa et al., 2020)

1 Introduction

Emergency medical services (EMS, for short) are a critical component of any healthcare system. Their first aim is to send ambulances to the emergency scenes in a timely manner to provide medical aid and, in some situations, transport the patient to the hospital. As such, they play a crucial role in reducing human suffering and economic losses resulting from disabilities due to injuries and sudden illnesses by providing the fastest and the highest quality of healthcare services available in a pre-hospital setting. Unfortunately, thousands of patients die because of ambulance delays (O'Keeffe et al., 2010). Each second counts in life-threatening emergencies. Therefore, the emergency vehicle response time is the most used indicator to evaluate the effectiveness of EMS systems. The response time, i.e. the time between the emergency call being received and the ambulance arriving at the incident scene, depends on ambulance deployment and redeployment strategies.

Ambulance deployment pertains to decisions tied to the strategic, tactical and operational levels. Ambulance deployment at the strategic-tactical level, also known as static ambulance location-allocation, is tied to the design of the EMS system where, in addition to deciding on the locations of ambulance stations, the number and the type of ambulances assigned to each station are determined (Bélanger et al., 2019). Ambulance deployment at the operational level includes ambulance redeployment or relocation and dispatching. Ambulance dispatching aims at assigning available ambulances to incoming emergency calls. Ambulance redeployment or relocation is the repositioning of idle ambulances to compensate for coverage loss due to busy ambulances.

In this research, we investigate both decision problems for a two-tiered inclusive EMS system with explicit consideration of demand uncertainty. In such a system, two types of vehicles, namely, Advanced Life Support (ALS) and Basic Life Support (BLS) ambulances, are deployed simultaneously, in order to respond to two types of calls that are distinguished based on case acuity: namely, life-threatening and non-life threatening calls.

2 Design of EMS system

Literature review

Various modelling approaches have been devoted to the design of EMS systems, also called ambulance location-allocation problem. We focus here on those that either tackle ambulance location-allocation problems while accounting for demand uncertainty, or address the design of two-tiered EMS systems.

Three main approaches have been proposed for ambulance location-allocation under demand uncertainty: (1) stochastic programming models (Beraldi et al., 2004; Beraldi and Bruni 2009; Noyan, 2010; Zhang and Li, 2015; Lam et al., 2016; Nickel et al., 2015; van Essen et al., 2013), (2) robust programming models (Zhang and Jiang 2014; Lam et al., 2016) and (3) hypercube queuing models (Iannoni et al., 2011; Geroliminis et al., 2011; McLay, 2009). Obviously, stochastic programming models for ambulance location-allocation are those that are particularly tied to our work. Recall that in this kind of model, contrarily to robust optimization, it is assumed that the probability distributions governing the data are known or can be estimated.

To design a reliable EMS system, Beraldi et al. (2004), Beraldi and Bruni (2009), Noyan (2010), Zhang and Li (2015) and Lam et al. (2016) developed chance-constrained stochastic programming models where the main uncertainty was assumed to be due to the stochastic call arrival process. The reliability is represented by the EMS's capability to guarantee a target service level (also referred to as coverage level), thus ensuring that demand coverage is kept above a specified value of probability for all demand areas. EMS's reliability is enforced in the proposed models through chance constraints. Beraldi et al. (2004), Beraldi and Bruni (2009) and Noyan (2010) restrict the service level, measured by the fraction of calls covered within the required response time, which is a common performance indicator used by EMS managers, to be above a predetermined threshold.

In Beraldi et al. (2004), the authors provided a deterministic equivalent formulation of the chance constraints using the so-called p-efficient points of a joint probability distribution function. This formulation is based on the assumption that the demand is independent which is well justified in normal operating conditions. Indeed, a correlation among demand points can only be established in the case of large-scale emergency situations. Beraldi and Bruni (2009) introduced chance constraints in the traditional two-stage stochastic programming framework. The facilities' location and the definition of the corresponding capacities present the first-stage strategic decisions. Once uncertainty has been resolved, tactical decisions concerning the allocation of demand points to facilities are taken while considering non-splittable demand, i.e., each demand point must be served by exactly one ambulance station under each scenario. In Noyan (2010), the author proposed two models that account for target service level by including risk measures on random unmet demand. The first model incorporates the integrated chance constraints (ICCs) and the second one includes ICCs and a stochastic dominance constraint to account for the largest acceptable expected unmet demand. He modelled the random demands using the scenario approach. With the addition of ICCs constraints, the unmet demand is capped to a predefined nonnegative risk aversion parameter that represents the largest acceptable expected unmet demand value. In order to address the complexity inherent to the two-stage formulation, the author introduced the ICCs in the single-stage formulation, where it is assumed that the assignment of vehicles to demand nodes is scenario-independent. However, this single-stage formulation incurs a significant increase of the total system's cost compared to its counterpart two-stage formulation. Zhang and Li (2015) devised a novel stochastic model with chance constraints to design EMS systems by considering the randomness in the maximum number of simultaneous demands occurring at a demand site over a day. The original model is transformed into a conic quadratic mixed-integer program by approximating the chance constraints as a second-order cone constraints. The obtained model is then solved by a commercial solver for problem instances of practical sizes. Lam et al. (2016) proposed a two-stage stochastic programming model to find an ambulance deployment that minimizes the overall shortfall in demand coverage. They reformulated their problem as a robust

mathematical program by replacing the chance constraints with a set of deterministic constraints based on the Poisson arrival rates and Markov inequality and solved it using a standard solver.

Other works do not include a chance constraint. Nickel et al. (2015) devised a scenario-indexed model to locate and size ambulances based on stochastic demand. In their model, a pre-specified coverage level is enforced by ensuring that the expected number of ambulances allocated to a demand point is greater than or equal to the product of the considered service level factor and the expected demand. The obtained results from small-sized problem instances highlight the relevance of using a stochastic approach to design EMS systems. van Essen et al. (2013) presented a two-stage stochastic program for the joint strategic and tactical ambulance planning. At the first-stage, the model determines the location of ambulance bases and the number of ambulances to assign to each opened ambulance base, while at second-stage, it specifies which ambulance to dispatch to which emergency call for all demand scenarios. The problem is then solved by adopting a two-stepped heuristic approach: the first step solves the strategic level (so determines the location of ambulance bases) and the second step considers the tactical level (so determines the number of ambulances assigned to each base). The authors considered different types of demand (demand from urban vs. rural areas) resulting in different coverage requirements but covered by only one type of vehicle.

It is worth noting that these papers either reformulate the stochastic programming model as a deterministic one or solve it using heuristics. In all cases, limited discussion on the quality and the characteristics of resulting solutions is provided. Moreover, none of them did consider the two types of commonly used ambulances in EMS systems.

The papers that considered different types of ambulances developed deterministic or queuing hypercube models (Schilling et al., 1979; ReVelle and Marianov, 1991; Marianov and ReVelle, 1992; Mandell, 1998; McLay, 2009, to list a few). Hypercube queuing models, such the one proposed in (McLay, 2009), account for the uncertainty in the demand. They include a step where they define the possible combinations of medical units that might be dispatched and solving the problem for each of these combinations. Given that the number of combinations significantly increases in real-life problem instances, these approaches become of little practical use because of their computational intractability. More importantly, these works highlight that ambulance deployment protocols used in two-tiered EMS systems are application specific (the type of vehicles, the skills of the crew assigned to each type of ambulances and their deployment rules are generally country-dependent). Therefore, this research will be devoted to design a two-tiered EMS system in accordance with the ambulance deployment paradigm adopted in Tunisia.

Contribution

In this research, the ambulance location-allocation problem with two types of vehicles is formulated as a cost-based two-stage stochastic programming model with recourse where the demand is assumed to be a random variable with known probability distribution. This model is solved using the SAA algorithm that allows, as indicated in subsection 3.2 of chapter II.1, for computing lower and upper bounds for problem solutions and providing the corresponding optimality gaps. Hence, our solution approach informs on the quality of the generated solutions, which is a valuable contribution in itself.

Problem description and formulation

As noted above, we consider an EMS system that is equipped with ALS and BLS units. Life-threatening calls require an ALS care level while non-life-threatening calls require a BLS care level. An ALS can be used to serve a non-life-threatening call. However, a BLS is under-equipped for a life-threatening call. The target response time for a life-threatening call is obviously shorter than that of a non-life-threatening call.

The number of life-threatening calls and non-life-threatening calls coming from a demand point within a defined time interval is assumed to follow a Poisson distribution (Ingolfsson et al., 2008). An ambulance is busy for a certain amount of time when responding to an emergency call. Similarly to most studies in this area, namely (Beraldi et al., 2004), (Beraldi and Bruni, 2009), (Noyan, 2010), (van Essen et al., 2013) and (Zhang and Jiang, 2014), we assume that one hour is a reasonable time requirement for a service trip. Based on this assumption, the proposed model formulates the ambulance location-allocation problem over a horizon of one hour and does not explicitly consider time. In this formulation, similarly to (van Essen et al., 2013), each ambulance can be assigned to at most one emergency call over one hour.

In the considered EMS system, each demand point can be served by more than one ambulance station and the ambulances housed at a given ambulance station are not dedicated to serve specific demand points.

The problem is formulated as a two-stage stochastic programming model with recourse. The uncertainty related to the number of emergency calls coming from each demand point over one hour is accounted for through the set of possible scenarios. Each scenario is defined by the vector of outcomes of two independent random variables: the number of life-threatening calls and the number of non-life-threatening calls arriving to each demand point over one hour. The ambulance stations to open, the number of vehicles of each type to be housed at each opened station are first-stage decision variables while the allocation of ambulances to demand points, and the unsatisfied demand depend on demand realization, and thus constitute second-stage variables.

The objective is to minimize the location-allocation costs incurred by the system's infrastructure (the fixed cost of setting up ambulance stations and the fixed per-unit capacity cost related to the cost of ambulances), the expected transportation cost, and the expected penalty cost stemming from unsatisfied demand. The reliability of the EMS system to provide adequate demand coverage is therefore reinforced through this penalty cost.

The main constraints of the model are aimed at guaranteeing that the total number of ambulances allocated to demand points under a given scenario is less or equal to the total number of ambulances available in the EMS system. Needless to mention that ambulances are only assigned to opened stations.

Solution approach

Solving the proposed two-stage stochastic programming model with recourse would be computationally intractable given the large number of possible scenarios. To overcome this challenge, we propose to use the SAA algorithm, which allows for finding a near-optimal solution while considering a modest number of scenarios. To start with, a random sample

with *S* scenarios (or realizations) of the uncertain parameters is generated using Monte Carlo simulation technique. The generated scenarios are used to approximate the stochastic programming model with recourse is approximated by a deterministic one, referred to SAA model. The expected value of the recourse costs (travelling and penalty costs) is approximated by the average of these scenarios.

In order to speed up the solution of the SAA model, the integrality constraints on the second-stage variables are relaxed. According to (Wolsey, 1998), given the characteristics of the constraints containing these second-stage variables, the linear relaxation of these second-stage variables will have integer (0–1) solutions.

The used SAA algorithm is an adjusted version of the one presented in section 3 of chapter II.1. The details of the algorithm can be found in (Boujemaa et al., 2018).

Case study

The proposed model and solution approach are applied to a real-life case study arising in the Northern Region of Tunisia (referred to as SAMU 01). In Tunisia, the calls received by the EMS system are classified as follows: (1) calls that do not require an ambulance (code 1); (2) calls that require transportation service without any emergency (code 2); (3) calls associated with a non-life-threatening incident (code 3) and (4) calls involving danger to human life (code 4). The emergency calls requesting an ambulance and a medical team are those of codes 3 and 4. Obviously, the highest priority is given to code 4 calls. To satisfy calls of codes 3 and 4, a team composed of one or two nurses and an emergency physician, and an adequately equipped ambulance are assigned to serve the patient. Two types of ambulances could be used: (1) BLS ambulances and (2) ALS ambulances. Only the crew of the ALS ambulance type includes an emergency physician. This type of ambulance is intended to serve patients of code 4 as it can provide cardiac and medical monitoring and ensure the patient's treatment during transport to the hospital. ALS ambulances can also cover demand of code 3. However, the BLS ambulance type can only cover the demand of code 3. The response time threshold is set to 20 minutes for emergency calls of code 3 and 15 minutes for emergency calls of code 4.

The Northern Region of Tunisia is divided into seven governorates, where each of them is further divided into a number of delegations. Henceforth, the demand points represent the different delegations, while the potential sites for ambulance stations, are proposed by the SAMU 01 manager, and correspond to the region's hospitals. Therefore, 31 potential ambulance stations' sites and 78 demand points are considered. SAMU 01 historical data is used to determine the average hourly demand of codes 3 and 4 associated with each demand point. The number of incoming calls of codes 3 and 4 for each demand point are independently drawn from a Poisson distribution.

The per-unit capacity cost is set to 7.412 (resp. 6.156) Tunisian Dinar (TND) per hour for ALS (resp. BLS). The travelling time between each demand point and potential ambulance site is determined based on the distance between the two locations and the average speed of the ambulance. The ALS ambulance is faster than BLS (the speed of BLS is assumed to be approximately equal to 0.85*the speed of ALS). The transportation cost depends on the distance and is equal to 1.2 TND/Km for ALS and 0.8 TND/Km for BLS (this cost is based on fuel and maintenance costs of each ambulance type). As far as penalty costs are concerned, they are given relatively large values (in comparison to other costs) in order to

prevent as much as possible the violation of demand coverage constraints. Thus, the penalty for an unsatisfied code 3 call (resp. code 4) is set to 300 TND (resp. 500 TND). Moreover, as it can be noticed, penalty cost values are used to enforce a higher priority for demand of code 4 over that of code 3.

Main results

Performance of the SAA algorithm and solution

We begin with verifying the convergence of the SAA algorithm and assessing its performance. We run the SAA algorithm using a number of replications M=10 with sample sizes of S=5, 10, 20, 50, 100 and 200 scenarios. We estimate the "true objective value" of each SAA optimal solution by simulation using a sample of size S'=1000. For each sample size, we estimate the lower bound and select the best-found solution (upper bound).

As it can be seen from figure 10, the optimality gap decreases as the sample size increases, meaning that better solutions are obtained for larger sample sizes. For the problem at hand, a near-optimal solution of 0.5% optimality gap is obtained with sample size S=200 at a reasonable computational time (the CPU is 76 seconds on average). The results for the optimality gap indicate that the solutions produced by the SAA algorithm scheme are good enough to be used in a practical application.

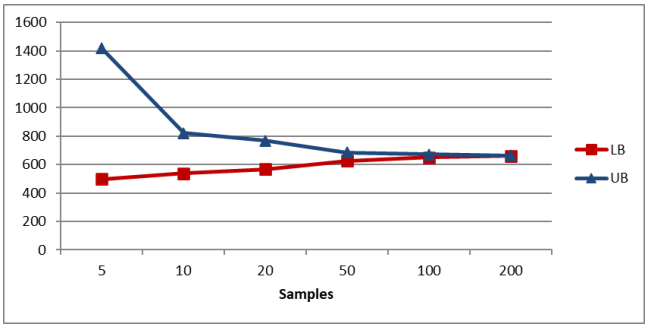

Figure 10. Convergence of the proposed SAA algorithm

Furthermore, as shown by figure 11, when the sample size increases, the first-stage cost increases whereas the expected second-stage cost decreases. Overall, the total cost decreases. This behavior is explained by the nature of the simulation scheme: when larger samples are used, more robust solutions are produced but they require the use of a larger number of facilities and vehicles, thus increasing the first-stage cost. Consequently, the penalty cost is reduced by the higher reliability of the EMS system. This result points out the value of a well-dimensioned infrastructure to achieve better robustness.

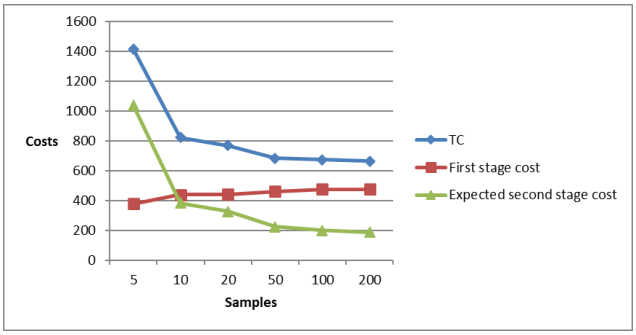

Figure 11. EMS system costs associated with different SAA solutions

Sensitivity analysis

A sensitivity analysis is conducted in order to investigate the effect of a change in the per-unit penalty cost and the demand on EMS system configuration and coverage level. All SAA models are solved with M=10, S=200 and S'=1000.

The per-unit penalty cost used in the base case is multiplied by a factor lying between 0.125 and 2. As it can be noticed from figure 12, when the penalty cost increases, the number of stations and deployed ambulances in the EMS system tend to increase, which entails an increase in the percentage of covered demand. Thus, an increase in the penalty cost favours the design of a more reliable EMS system. When an acceptable coverage level is reached, managers should wonder if additional improvement is worth the incurred cost. It is important to note at this level that an increase in the penalty cost incurs an increase in the average optimality gap of the best-found SAA solution. Henceforth, with an increase in the penalty cost, the quality of the SAA solution can be improved by considering in the SAA algorithm a larger sample size S and/or larger number of replications M.

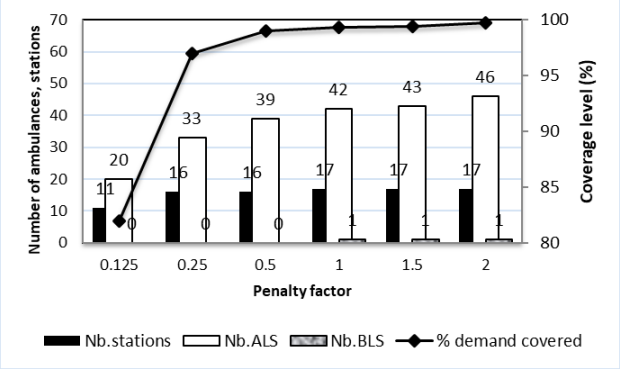

Figure 12. Effect of penalty cost on the configuration of the EMS system and its performance

Figure 13 shows the optimal configuration of the EMS system when the demand is decreased by 20 and 40% and increased by 40 and 80%. It should be noted that an increase in the demand value does not affect the decisions pertaining to the opened ambulance stations. Conversely, with a decrease in the demand, the number of opened ambulance stations is reduced. However, an increase or a decrease in the demand clearly impacts the number of ambulances required by the EMS system. Expectedly, the number of ambulances increases along with the demand. Moreover, an increase of the demand entails an increase in the percentage of covered demand. This means that the increase in the unsatisfied demand is lesser than the increase in the demand.

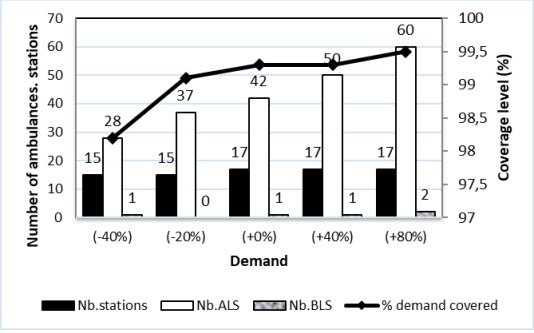

Figure 13. Effect of the demand on the configuration of the EMS system and its performance

3 Ambulance redeployment

Literature review

Ambulance redeployment

In the last two decades, several works have been devoted to the study of ambulance redeployment while accounting for the fluctuations of the demand over time and space. Two alternative approaches are found in the literature: (1) online (Gendreau et al., 2001; Andersson and Värbrand, 2007; Mason, 2013; Naoum-Sawaya and Elhedhli, 2013; Moeini et al., 2014; Jagtenberg et al., 2015; Bélanger et al., 2016; van Barneveld e al., 2016) and (2) offline redeployment approaches (Enayati et al., 2017; van Barnevelda et al., 2018). The online approach seeks on real-time the best ambulance redeployment plan whenever there is a change in the state of the system. In the offline approach, redeployment decisions are precomputed based on an anticipation of the demand or the possible states of the system. Two types of offline approaches can be distinguished according to the manner in which redeployment decisions are made. In the first one, called offline dynamic redeployment approach, the models are solved a priori to generate a set of relocation plans or compliance tables, one for each possible state of the system (Gendreau et al., 2006; Nair and Miller-Hooks, 2009; ; Alanis et al., 2013; Liu et al., 2013; Maleki et al., 2014; Sudtachat et al., 2016; van Barneveld, 2016). This approach is easy to implement in real-life settings; however, the number of states to consider could be significantly large. In the second approach, referred to as multi-period redeployment approach, redeployment decisions are taken at given and fixed time periods over the course of a planning horizon. In the following, we focus on papers that tackle multi-period ambulance redeployment problem and particularly those that are relevant to our research.

Rajagopalan et al. (2008) propose a formulation of the multi-period ambulance redeployment problem called the dynamic available coverage location model (DACL). The latter aims at minimizing the total number of ambulances deployed for each time-period while meeting predetermined ambulance availability requirements. Schmid and Doerner (2010) aim to maximize the demand coverage while considering time-dependent travel times. Contrarily to previous models such as DACL, that do not explicitly account for redeployment costs, in (Schmid and Doerner, 2010), the authors minimize the penalty for relocating vehicles between time-periods. Saydam et al. (2013) build on Rajagopalan et al. (2008) work to introduce the dynamic redeployment coverage location model (DRCL). This model minimizes simultaneously the fleet size and the number of redeployments during a given shift while maintaining overall coverage requirement. Experiments reveal that the DRCL reduces the number of redeployments with respect to DACL and allows for a more stable deployment during the planning horizon. van Berg and Aardal (2015) consider both time-dependent ambulance availability and time-dependent demand. The proposed model aims to maximize the expected coverage throughout the day and minimizes the number of opened locations and the number of relocations between periods. This model provides a higher coverage with lower base locations while taking into account the randomness of vehicle availability. Enayati et al. (2018) propose a two-stage stochastic programming model to redeploy and dispatch ambulances under demand uncertainty while maximizing the expected coverage. The proposed model restricts personnel workload in a shift and considers multiple call priority levels. In order to solve realistic size instances, the authors develop a Lagrangian branch and bound algorithm.

Ambulance dispatching

Ambulance redeployment is highly impacted by dispatching decisions which have a significant effect on response time, service time and thus on the EMS system's performance such as the service level. Various ambulance dispatching policies are proposed in the literature. Nevertheless, the policies that are widely considered are the "nearest idle ambulance'' (Aboueljinane et al., 2012; Buuren et al., 2012; Ingolfsson et al., 2003; Kergosien et al., 2015; Maxwell et al., 2009) and its variants such as the "closest available vehicle with pre-emption'' (Lubicz and Mielczarek, 1987; Savas, 1969), the "closest base'' (Iskander, 1989), the "lower response vehicle'' (Silva and Pinto, 2010), the "nearest available vehicle conditioned by call priorities''(Aringhieri et al., 2007) and the "regionalized response''(Su and Shih, 2003). It has been demonstrated that the "nearest idle" policy may not be the best to adopt (Bandara et al., 2014; Schmid, 2012). Some works devise more sophisticated implementations to jointly address ambulance dispatching and redeployment in a dynamic setting. Gendreau et al. (2001) proposed to dispatch the available ambulance that will minimize subsequent relocation costs. Andersson and Värbrand (2007) suggest dispatching the idle ambulance that will cause the smallest preparedness degradation. Based on a Markov Decision Process (MDP), the models developed by (Bandara et al., 2012; McLay and Mayorga, 2012) determine the dispatching rules that seek to maximize respectively the patient survival and the expected coverage of true high risk calls. Toro-Diaz et al. (2015) propose to dispatch vehicles according to a prefixed preference list for each demand zone so that the first idle ambulance on the list is dispatched upon call arrival. For a more detailed survey on ambulance dispatching rules, we refer the reader to the literature reviews presented in (Aringhieri et al., 2017; Belanger et al., 2019).

The literature review reveals that only a few papers devise a two-stage stochastic programming model for ambulance redeployment (Enayati et al., 2018; Naoum-Sawaya and Elhedhli, 2013). As it has been mentioned earlier, the model proposed by Naoum-Sawaya and Elhedhli (2013) provides real-time decisions on ambulance redeployment given that it considers a very short planning horizon (less than one hour). However, none of the above-mentioned papers investigates the particular redeployment problem that arises in two-tiered EMS systems.

Contribution

The contributions of this research are the following:
(1) unlike most of the works in the literature, this research addresses ambulance redeployment for two-tiered EMS systems that use ALS and BLS ambulances to respond to both, life threatening and non-life threatening calls, according to rules similar to those practiced in Tunisia;
(2) the proposed model tackles time-dependent and stochastic demand in multi-period ambulance redeployment;
(3) to tackle the computational burden of the problem, two heuristic solution approaches are developed and compared.

As can be noted, this work on ambulance redeployment extends the one on EMS system design. Indeed, it complements the strategic-tactical approach devoted to the design of an EMS system by an operational approach aimed at handling ambulances' redeployment. In this vein, it proposes a multi-period framework able to account for demand variability along

the day and anticipate ambulance relocation accordingly. Evidently, ambulance redeployment will rely on the designed EMS system.

Problem formulation

Ambulance redeployment problem is formulated as a multi-period two-stage stochastic programming problem with recourse while considering the following assumptions:
- The base station of each ambulance is known,
- Each ambulance is located at its base station at the beginning of the planning horizon,
- Each emergency call needs only one vehicle,
- The capacity of each ambulance is set to one for each period of the planning horizon,
- Emergency calls arrive according to a non-homogeneous Poisson process,
- The locations of ambulances at the end of one day (length of the planning horizon) are also their location at the start of the next day (cyclic schedule).

At the beginning of each period (namely one hour) of the planning horizon T (namely one day and so T=24), the proposed model: (1) assigns ambulances to demand points based on ambulances' current locations and (2) if it is needed, it relocates ambulances to other stations. The model deals with demand uncertainty during each period of the planning horizon. First-stage decisions pertain to ambulance relocation at the beginning of each period. In the second stage, dispatching decisions are taken through time periods based on demand realization.

The objective is to minimize the overall cost incurred by the relocation cost, the expected ambulance assignment cost and the penalty cost incurred by the unsatisfied demand within the considered horizon. Some constraints enforce the assumptions while others ensure that each ambulance is located at one station at the beginning of each period, and guarantee that at each period the total number of deployed ambulances is less than the number of available ambulances in the EMS system. Some constraints are aimed at ensuring the relation between ambulance location at the beginning of each two consecutive periods and the relocation decision, while others allow for determining the unsatisfied demand. Moreover, some constraints ensure the relation between the assignment of an ambulance to a demand point and its position. As such, they relate some second-stage variables with some first-stage variables.

Solution approach

SAA model

We start by approximating the stochastic model representing the true problem by a deterministic one that integrates a sample of size S, referred to as SAA model. In the latter, the expected value of the recourse costs (assignment and penalty cost) is approximated by the sample average. Recall that the optimal solution of the SAA model converges to an optimal solution of the true problem with probability approaching one exponentially fast as the sample size S tends to infinity (Shapiro and Homem-de-Mello, 2000). However, solving the SAA model with samples of even small sizes could be computationally intractable. For example, in our case, with T=6 an optimal solution of the SAA model can only be obtained within a reasonable time for $S \leq 20$ while with T=24 (which represents the number of periods involved in the considered planning horizon), the solver fails to optimally solve the SAA model even for S=2. In order to overcome this issue, we devise two heuristic approaches able

to solve the SAA model for real-life problem instances within a reasonable computational time.

Time based decomposition heuristic approach

The idea of this heuristic is to decompose the SAA problem including T periods into $\lceil T/\alpha \rceil$ sub-problems containing at most α periods each, while including the prior decisions on ambulance redeployment between periods. The solutions produced to the sub-problems may then be combined to yield a feasible solution to the original problem. In our case, solving subproblems containing more than two periods with an acceptable sample size was very time consuming. Therefore, we decided to set α=2 to obtain $T/2$ sub-problems, referred to as sub_g, g={1,…,$T/2$), where each of them is solved with a generated sample of size S. Notice that the location of the ambulances at the end of the sub-problem (sub_g) is used as the initial location of ambulances when solving the next sub-problem (sub_{g+1}). Moreover, this heuristic determines the ambulances to be relocated and their new location. A detailed version of this algorithm, hereafter referred to as HDT, can be found in (Boujemaa et al., 2020).

A Lagrangian relaxation-based heuristic approach

The main concept of this method is to relax a set of complicating constraints by adding them to the objective function with a penalty attached using Lagrangian multipliers. The new relaxed problem is hence easier to solve optimally; and its optimal objective value represents a lower bound for the original problem.

To better clarify this approach, we consider the following generic model:

$$z = Min\ Cx \qquad (1)$$

Subject to:

$$Ax \geq b \qquad (2)$$

$$Bx \geq d \qquad (3)$$

$$x \geq 0 \qquad (4)$$

Relaxing the complicating constraints (2) into the objective with Lagrangian multipliers $\lambda \in \mathbb{R}^+$, yields the following Lagrangian relaxation problem:

$$zr = Min_{x\geq 0}\{Cx + \lambda(b - Ax)/Bx \geq d\} \qquad (5)$$

As mentioned above, solving the relaxed problem will produce a lower bound of the original problem. However, the best lower bound is provided by the optimal solution of the Lagrangian dual problem (6).

$$zd = Max_{\lambda\geq 0} Min_{x\geq 0}\{Cx + \lambda(b - Ax)/Bx \geq d\} \qquad (6)$$

In the problem at hand, we choose to relax the constraints that link the first-stage decision variables with the second-stage decision variables. Interestingly, in this case the relaxed problem RP can be decomposed into two separable sub-problems, which are hereafter referred to as SP1 and SP2, respectively. The first sub-problem SP1 determines the first-stage variables, namely the number of relocations performed and the location of ambulances in each station at the beginning of each period of the planning horizon. The second sub-

problem, using the solution of SP1 determines the second-stage variables, namely the assignment of each ambulance to the demand points and the unsatisfied demand. Moreover, a set of valid inequalities are added to both sub-problems to speed up their solving and finding a Lagrangian bound.

We propose to solve the Lagrangian dual heuristically using the subgradient method (Fisher, 2004). The concept behind this procedure is to adjust iteratively the Lagrangian multipliers to find values that produce the best lower bound. This process is repeated until a suitable stopping criterion is met (when a tighter gap between the best lower and upper bound is achieved, a negligible change in the solution configuration is detected, or the maximum computing time is reached). The detailed algorithm, hereafter referred to as SBG, is provided in (Boujemaa et al., 2020). Note that the upper bound of the SAA problem is provided by the true objective function value of the first-stage solution found by SP1, estimated by simulation using a sample of size *S'*. We also remark, at this level, that based on (Mak et al., 1999), we can infer that the lower bound of the SAA model determined by SBG allows to determine a lower bound of the true problem (i.e. the multi-period two-stage stochastic programming model with recourse).

Main results

The proposed algorithms were also tested using a set of real-world instances derived from the historical data provided by SAMU 01 in charge of the EMS system within the northern region of Tunisia. In particular, we consider the data pertaining to Tunis region. The design phase, presented above, suggests that SAMU 01 can adequately operate using 1 ambulance of type BLS and 20 ambulances of type ALS located at 7 different EMS stations at Tunis region. The arrival rates of emergency calls are determined for each hour of the day. Obviously, for each demand point, hourly calls of code 3 (non-life threatening) and code 4 (life threatening) were randomly generated accordingly to a Poisson distribution based on the corresponding arrival rate.

Performance of HDT

To assess the performance of the HDT with respect to sample size *S*, the algorithm was tested with *S*=2, 100, 150 and 200 while *M* and *S'* are set to 5 and 1000, respectively. Table 6 reports for each sample size *S*, the total cost (TC) in TND, the relocation cost (RO) in TND, the assignment cost (AS) in TND, the penalty cost (PE) in TND, the percentage of covered demand (CD) and the average computing time (CPU) in seconds. It is worth noting that all costs reported in table 6 are those of the best-found solution estimated via simulation.

Table 6. Performance of HDT with different sample sizes

Sample size S	TC	RO	AS	PE	CD	CPU
2	36434	728	2903	32803	90.18	15
100	15918	978	2863	12077	95.32	147
150	12790	1149	2600	9041	96.81	257
200	12749	1271	2570	8908	97.36	480

As it can be seen in table 6, the first stage cost (composed of the relocation cost), increases with the sample size *S* whereas the expected second stage cost (composed of assignment cost and penalty cost) decreases. Indeed, the consideration of a larger sample size allows for improving the percentage of demand coverage and thus decreasing the total EMS system cost.

Performance of SBG

SBG is tested with *S*=2, 5, 20, 100, 200, *M*=5 and *S'*=1000. In table 7, the first column provides the sample size *S* used in SBG. Column LB corresponds to the average of the sum of the objective values of SP1 and SP2 which represents a lower bound of the true problem. Column UB corresponds to the estimated true objective value of the first-stage solution estimated by simulation. The optimality gap (%) presented in the fourth column is calculated as follows:

$$gap\ (\%) = \frac{UB - LB}{LB} * 100$$

The last column in table 7 reports the average computational times of SBG.

Table 7. Performance of SBG with different sample sizes

S	LB (TND)	UB (TND)	gap (%)	CPU (s)
2	6 228	21 067	>100	83
5	6 410	14 333	>100	111
20	6 465	13 953	>100	1055
50	7 087	13 894	96	1710
100	7 439	13 374	80	3218
200	12 086	13 333	10	5967

As outlined in table 7, when the sample size *S* increases, the lower bound increases while the upper bound decreases, and subsequently the gap between the bounds becomes narrower. In fact, increasing the number of scenarios allows to obtain a better lower bound. For the largest sample (*S*=200), the algorithm reached an acceptable gap of 10% in less than two hours of computational time, which represents a very good trade-off between solution quality and computational effort.

Comparison of HDT and SBG

Table 8 compares the cost term values, the demand coverage and the optimality gap of the best solutions provided by HDT and SBG (with *S*=200, *M*=5 and *S'*=1000).

Table 8. Comparison of different algorithms

Algorithm	TC	RO	AS	PE	CD	gap (%)
HDT	12 749	1 271	2570	8908	97	5
SBG	13 333	1 256	2 523	9 554	96	10

The results reported in table 8 provide further empirical evidence that the quality of the solution obtained by HDT is slightly better than the one incurred by SBG in terms of robustness and costs. HDT exhibits a tighter optimality gap as it can be evidenced by the lower bound of the true problem provided by SBG. Overall, HDT is more computationally efficient than SBG and reveals a notable performance in terms of both demand coverage and total cost. As can be noted, the lower bound produced by SBG allows for estimating the quality of HDT. This sheds light on the complementarity of the two proposed heuristics.

4 Concluding remarks and future research

First, we investigate the design of a two-tiered EMS system with consideration of demand uncertainty. The problem is formulated as a two-stage stochastic programming model. The

objective was to find the configuration of the EMS system that minimizes the total cost composed of the ambulance station opening cost, per-unit capacity cost, transportation cost and penalty cost associated with demand unsatisfaction. A SAA algorithm was then proposed to solve the considered problem. The solution approach has been applied to a real-life case study. The results highlight the usefulness of the proposed approach in practice and stress the importance of calibrating the per-unit penalty cost based on the targeted demand coverage.

Second, for the designed EMS system, we investigate the ambulance redeployment problem. Based on the variability of the hourly demand during the course of a day, the proposed multi-period two-stage stochastic programming model allows to decide on vehicle relocation between periods to offer a better coverage of the demand. The objective is to minimize the total cost composed of relocation cost, dispatching cost and penalty cost incurred by the unsatisfied demand. Two heuristics are proposed to solve the proposed model, namely HDT and SBG. Numerical results show that the solution produced by the HDT outperforms the one generated by SBG, and that in much lower computational times.

Future work will include developing more sophisticated approaches for the design and deployment of two-tiered EMS systems. We intend to devise a chance-constrained two-stage stochastic programming model that aims to restrict the risk of not serving a call within the response time standard to a certain threshold. Furthermore, our future research will include the development of a multi-stage stochastic programming model for ambulance redeployment. Adequate method will be designed to solve it. Another interesting extension of our research remains in developing a simulation-based optimization approach for the design of the EMS system while accounting for other sources of uncertainties such as the travelling and service time. Moreover, such approach will allow to investigate how real-time decisions (ambulance dispatch) are related to strategic and tactical ones and therefore impact the system performance.

Part III

Logistics and supply chain management

Chapter III.1

Production-distribution planning in textile and apparel supply chain

The chapter is based on (Safra et al., 2019) and (Safra et al., 2021)

1 Introduction

To succeed, supply chains compel to keep their goods and services reaching markets quickly, efficiently, and as cost-effectively as possible. This success is challenged by a more complex supply chain structure involving several actors with multiple ownership and different sources of risks and uncertainties. For that, a close coordination across the supply chain actors is necessary. This coordination becomes indeed crucial to business success in sectors, where products have a short lifecycle, a volatile demand and face fierce competition, such as the textile and apparel supply chain (Adhikari et al., 2020). Given that fashion and apparel products are seasonal with short lifespan and uncertain demand, creating an intimate link between production and distribution decisions is essential to achieve a desired on-time delivery performance at a minimum total cost (Chen, 2010).

Demand uncertainty is particularly high in the case of the apparel fashion industry due to customer preferences and tastes that are difficult to predict before the start of the selling season. Achieving a match between demand and supply to minimize unsold quantities and markdowns at the end of the selling season while, at the same time, ensuring the availability of demanded products is very challenging in this case. To better adjust the supply to the demand, textile apparel companies opt for producing a certain quantity of each trendy product before the start of its selling season and the rest during its selling season. Therefore, two types of orders are distinguished: (1) pre-season orders with medium lead time and (2) in-season replenishment orders with short lead time. Pre-season orders are based on demand forecast established before the start of the selling season and target in general to cover a percentage of the whole season's demand while replenishment orders are intended to satisfy the persistent demand for successful trendy items. After observing the sales over the first weeks of the selling season, some companies, such as Zara, can even decide to stop the production and the display of certain items to replace them by others that match better customer preferences (Chopra and Meindl, 2016).

In this research, we address a multi-period production-distribution planning problem arising in global textile and apparel supply chain, involving a manufacturer and retailer stage with multiple actors dispersed all around the world, and offering a wide variety of trendy products with short lifespans and unpredictable demand. Both pre-season orders and in-season replenishment orders are accounted for in production and distribution planning. Because of the difference between the lead time of pre-season and replenishment orders, the considered problem integrates production and distribution decisions pertaining to the tactical and operational planning levels. We investigate two production-distribution planning approaches: (1) with no information sharing on current in-season sales and (2) with information sharing on current in-season sales. In particular, we assess the impact of information sharing on the overall cost of the textile and apparel supply chain.

2 Literature review

Integrated production-distribution planning

The literature on integrated production-distribution planning problem is abundant as shown by Mula et al. (2010), Chen (2010) and Fahimnia et al. (2013). Different variants of this problem have been investigated: some works considered a single manufacturer and/or a single retailer (Armentano et al., 2011; Chen and Vairaktarakis, 2005; Pundoor and chen, 2009) with multiple products, while others took into account a single product (Boudia and Prins, 2009; Liao et al., 2017; Sarkar and Giri, 2018). Some other papers studied the case of multiple manufacturers with multiple products (Kim et al., 2008; Keskin and Üster, 2007), though the latter are limited to a single period. More recently, other works considered the multi-product and multi-period problem (Liu and Papageorgiou, 2013; Ghasemi Bijaghini and SeyedHosseini, 2018; Selim et al., 2008; Kumar et al., 2019).

Noticeably, the vast majority of integrated production-distribution planning models are sector specific and have been especially devoted to time-sensitive and/or perishable products such as medicine (Ghasemi Bijaghini and SeyedHosseini, 2018), food (Li et al., 2019; Chen and Vairaktarakis, 2005; Farahani et al., 2012), dairy products (Ghosh and Mondal, 2018), newspapers (Russell et al., 2008) and fashion apparel (Felfel et al., 2018; Darvishi et al., 2020; Ait-Alla et al., 2014). The works that integrated tactical and operational planning decisions remain scarce (Kanyalkar and Adil, 2005; Rømo et al., 2009; Sousa et al., 2008) though.

More importantly, all the papers mentioned so far do not integrate tactical and operational decision levels in textile and apparel supply chain planning. Nevertheless, this integration is essential to ensure decision process consistency and achieve production-distribution planning objectives. This research is devoted to fill this gap. Two integrated production-distribution planning approaches that account for the most relevant features of apparel supply chain are devised. The proposed approaches are two-level as they incorporate tactical and operational decisions and account for both pre-season and replenishment orders. The first approach pertains to the case where there is no information sharing between the retailer and the manufacturer on current in-season sales. Oppositely, the second approach considers the case where the retailer shares with the manufacturer the information on current in-season sales.

Information sharing

Research streams considering information sharing are emerging given that the latter can be a key factor for a firm's success. Li et al. (2017) evaluated the impact of a disruption arising at the end-customers, and how it can be mitigated through information sharing among different supply chain echelons. Wu et al. (2010) evaluated the benefits of sharing information on suppliers' product quality with the buyer. Yang and Fan (2016) showed that information sharing reduces the bullwhip effect under demand disruptions. Notably, none of these works considers information sharing in the integrated production and distribution planning with consideration of tactical and operational decisions.

Information sharing is aimed at improving the quality of demand forecasts and hence the effectiveness of the resulting planning decisions. This is particularly promising in the textile and apparel supply chain where demand forecasting is highly challenging (Wen et al., 2019).

To the best of our knowledge, integrated production-distribution planning that incorporates tactical and operational decisions with demand forecasting based on information sharing in the textile and apparel supply chain has not been yet investigated. The second planning approach is devoted to fill this gap.

3 Problem description

The considered textile and apparel supply chain planning problem is based on a real-life case study which is representative of the vast majority of current worldwide textile and apparel supply chains. The case study considers the supply chain of a textile and apparel manufacturing company that belongs to one of the largest industrial groups in Tunisia. The group has its own women apparel and fashion brand and operates a large number of retail stores. As illustrated in figure 14, the supply chain network comprises:

- A set of internal manufacturing units located in Tunisia, denoted by *U*
- A set of subcontractors' manufacturing units located either in Tunisia, or overseas (in China), denoted by *V*
- A set of warehouses located in Tunisia, denoted by *J*
- A set of retailers, denoted by *I*, where the majority of them are located in the european market, and a few in the tunisian market

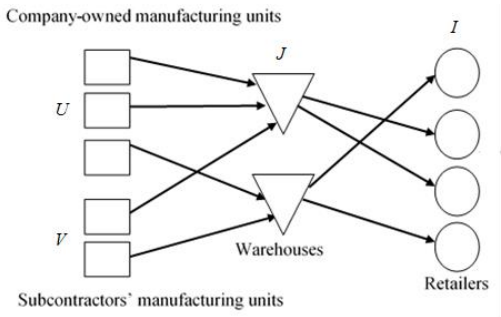

Figure 14. Textile and apparel supply chain network

The considered textile and apparel manufacturing company is adopting a commit-to-delivery business model. After receiving retailers' orders, it validates a delivery due date and assumes for the shipping cost. Finished products are shipped immediately towards the warehouses where they are gathered and stored till their delivery time. More than four million pieces per year are sold to the most well-known clothing brands and retailers (Lacoste, Kookaï, Promod, Camaïeu, Jaqueline Riu, Cache Cache, Bonprix, Morgan, Go Sport, Orsay, Dixit...). A set of transportation modes might be used, namely trucks, ships or aircraft. The received pre-season orders are due within several months (6 months at most) because the ordered products are sold during the next season. Replenishment orders are due within weeks (8 weeks at most) as they are intended to prevent stockouts of products sold over the current selling season. Overseas subcontracting induces higher transportation costs and longer lead times but generally offers lower prices. Local subcontractors are however more flexible, as they are close at hand. Each manufacturing unit is characterized by a production capacity. The production of each item incurs either a variable and a fixed cost, or a subcontracting cost. For more production flexibility, an overtime production capacity in each internal manufacturing unit is considered. The recourse to this capacity induces an overtime production cost. Underutilization cost of internal production capacity at each internal manufacturing unit is also considered to penalize the unused available resources. Each product is characterized by a

production lead time, a unit volume and a unit inventory holding cost tied to the considered time period and facility. Each warehouse has a known storage capacity, and each transportation mode is characterized by a capacity and a lead time. For each product, a variable and a fixed distribution cost are also accounted for. They are associated with the moving of one unit of product, first, from the manufacturing unit to the warehouse, and then, from the warehouse to retailer store.

4 Production-distribution planning approach

4.1 The proposed rolling horizon approach

As portrayed in figure 15, the proposed sequential two-level planning approach uses two models: (1) a tactical model and (2) an operational model.

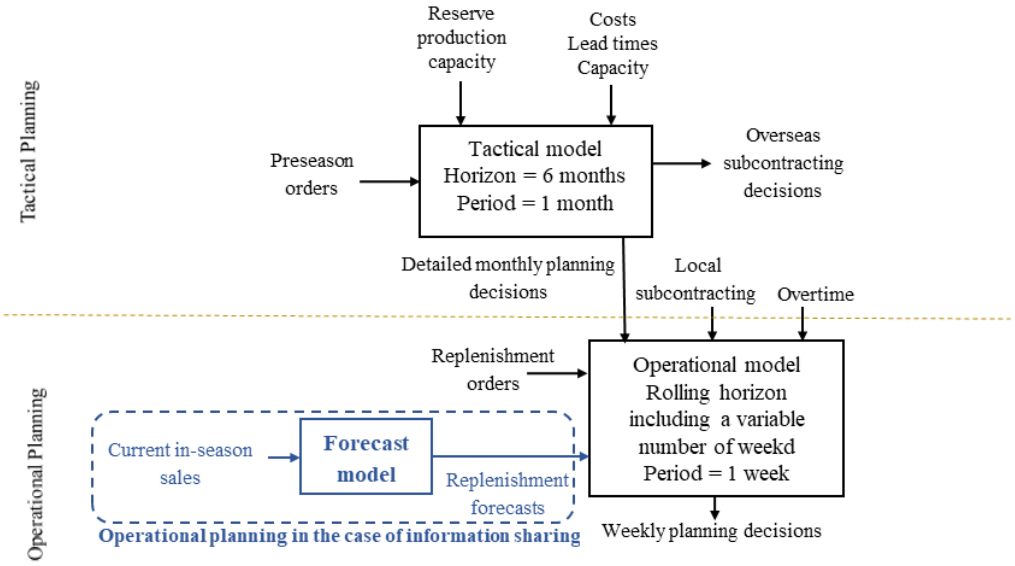

Figure 15. Planning approach

The tactical model (see figure 15) includes six 4-week periods (referred to as a month) planning horizon. The length of the planning horizon is indeed dictated by the lead time of pre-season orders. To face unforeseen and urgent demand that may happen over weeks, a reserve production capacity is considered at the tactical level. The latter provides a lever for incorporating replenishment orders at the operational level. A monthly rolling horizon is considered to integrate newly received preseason orders.

At the operational level, a variable planning horizon including eight to eleven one-week periods is considered (see figure 16). This choice allows to properly detail production decisions taken by the tactical model, and hence strive to guarantee consistency between tactical and operational decisions. A weekly rolling horizon is considered to integrate new replenishment orders received each week. Note that the maximum lead time for a replenishment order (eight weeks) also justifies the chosen length of the operational planning horizon. The objectives of the operational planning model are twofold: (1) split the monthly planned quantities to produce internally, according to the tactical planning, over weeks; and (2) introduce newly arrived replenishment orders over the weekly rolling horizon while respecting their delivery due dates. The reserve production capacity considered at the tactical level is released and the entire internal capacity can be used in addition to overtime. This will give more flexibility to accommodate unforeseen and urgent replenishment orders.

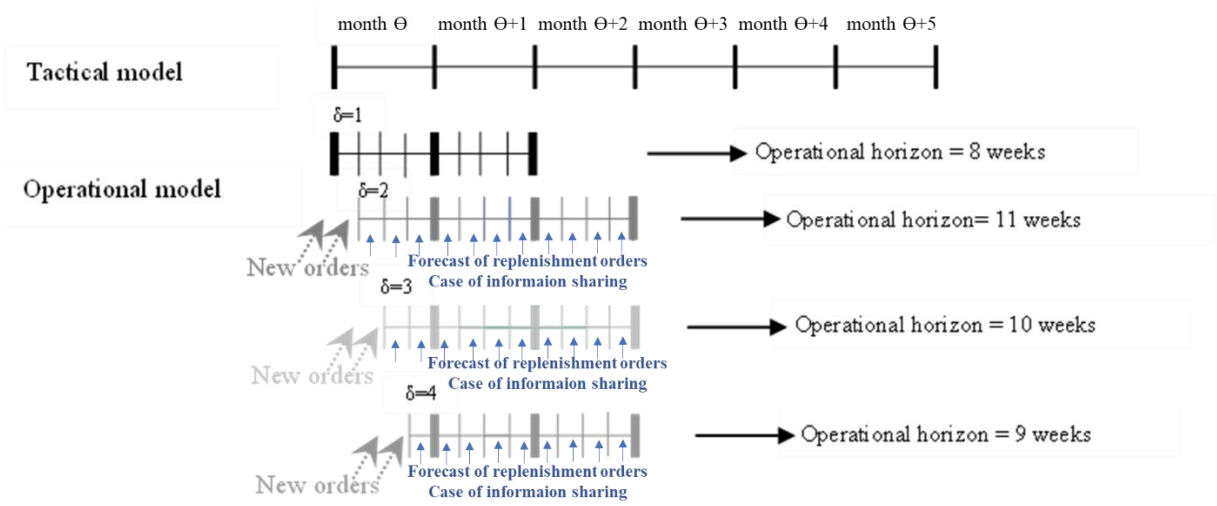

Figure 16. Variable operational planning horizon

When a new pre-season order, with a delivery lead time larger than the number of periods included in the operational planning horizon, arrives, it is introduced to the tactical planning model of the following month to decide on production assignment while taking into consideration subcontractors' capacity. The operational planning model might afterwards incorporate these orders if the tactical model proposes to produce them in internal manufacturing units. This procedure is repeated accordingly to orders' delivery lead times.

Quantities produced, stored and distributed at the first week of each planning horizon are retained and related costs are recorded. However, decisions concerning the other periods (weeks) are released and reconsidered while running the operational planning model, at the beginning of the following week, which allows for incorporating the newly received replenishment orders. Finally, a weekly detailed production, storage and distribution plan is obtained. The latter incorporates the tactical production assignments and new replenishment orders.

In the operational planning with information sharing (see the blue part of figure 15), in addition to received replenishment orders, we integrate the forecast of replenishment orders. The latter is established using an adequately chosen forecast model that considers the observed in-season sales. More details on the used forecast model are provided in subsection 4.4.

4.2 Tactical planning model

The tactical planning model aims at minimizing total production, inventory holding and distribution costs. As such, it minimizes the sum of: variable production cost, set up cost, subcontracting cost, internal capacity underutilization cost, inventory holding cost, variable transportation cost from manufacturing units to warehouses, variable transportation cost from warehouses to retailers, fixed transportation cost from manufacturing units to warehouses and finally the fixed transportation cost from warehouses to retailers. As can be noted, the transportation cost is composed of a variable cost, depending on the transported quantity given the selected transportation mode, and a fixed cost depending on the selected transportation mode. The outcomes of the tactical planning model include the following: monthly production quantities in internal and subcontractors' manufacturing units, monthly stored quantities in warehouses and monthly delivered quantities to retailers. Flow balance

considering the involved lead times, demand satisfaction and capacity constraints represent the main constraints of the addressed tactical production-distribution planning problem. The mathematical formulation of this problem can be retrieved in (Safra et al., 2019).

4.3 Operational planning model in the case of no information sharing

The operational planning model employs the sets, parameters and decision variables of the tactical model but tied to one week given that the latter represents the period considered in this model. It determines the quantities to produce, store and deliver over each week of the planning horizon. Recall that the production plan proposed by the tactical model for any month whose weeks are included in the operational planning horizon becomes input of the operational model and will be detailed per week. In addition to the decision variables used in the tactical planning model, we introduce decision variables that determine overtime.

Similarly to the tactical model, but while considering weekly cost parameters and decisions, the objective function minimizes the total supply chain cost composed of: the variable production cost, the set up cost for producing during regular working hours and during overtime, the subcontracting cost, the overtime cost, the internal capacity underutilization cost, the average inventory holding cost and the transportation costs from manufacturing units to warehouses and then from warehouses to retailers. In addition to flow balance, demand satisfaction and capacity constraints, the operational planning model incorporates constraints that ensure the consistency with decisions made by the tactical planning model.

As can be noted, in this operational planning model, we account only for received replenishment orders and we assume that the retailer does not share information on current in-season sales with the manufacturer. The mathematical formulation of this problem can be found in (Safra et al., 2019).

4.4 Operational planning model in the case of information sharing

This second operational planning model considers information sharing on current sales between the retailer and the manufacturer. Hence, it levels up the first operational planning model as well as the first planning approach, to shed the light on the interest of information sharing and its impact on the total supply chain cost. It extends the first operational planning model by incorporating a forecast of replenishment orders (as highlighted in blue in figure 16) in addition to received replenishment orders. These forecasts are based on shared in-season sales data between the retailers and the manufacturer and are established using a well fitted logistic diffusion model.

Why the logistic diffusion model?

As mentioned above, fashion apparel products are single-period products with short lifespan. The lack of historical demand data in this case constitutes one of the challenges of demand forecasting. To overcome this issue, Şen and Zhang (2009) advocated the use of the sales data observed at the beginning of the season to update the forecast for later in-season demand.

Interestingly, diffusion models, such as Logistic and Gompertz models, are intended to forecast the demand of new products with no or some sales history (Morrison, 1996). For standard life cycle curve products, these models try to determine future sales by quantifying

the long-term saturation level, the period of sales peak over product life cycle and the intensity of the introduction phase (Kurawarwala and Matsuo, 1996). Otherwise, for products whose sales does not follow the standard shape of life cycle curve (one or more phases are absent), Ching-Chin et al. (2010) proposed a model based on the average sales of similar product families.

That is why, we propose to use the logistic diffusion model to predict replenishment orders that may arrive to the manufacturer over the current selling season. First, it is fit to textile and apparel products as it can be used even if there is no or limited historical data on the demand. Moreover, this choice can be justified by the adequacy of fashion apparel products to the standard life cycle curve where sales volumes follow the four phases of introduction, growth, maturity and decline. More importantly, the logistic diffusion model is easy to implement while repeatedly adjusting its parameters based on in-season sales information shared between the retailer and the manufacturer.

Forecast of replenishment orders

Replenishment orders are forecasted according to the following four steps:

- The first step consists in developing the logistic diffusion forecasting model by defining its parameters: (1) the long-term saturation level, (2) the period of inflection, and (3) the intensity of the introduction phase. The latter is based on in-season sales data shared by the retailer and the orders received from and/or delivered to the retailer during the weeks of the selling season.
- The second step involves the construction of the cumulative sales curve. This step also includes forecasting sales of the next periods using the logistic diffusion model.
- The third step consists in defining order points and the quantities to deliver to retailers.
- Finally, forecasts of replenishment orders are used as inputs in the operational planning model.

Once confirmed information regarding cumulative sales is received, this four-step scheme is used to update the forecasts.

An illustration of these steps and the mathematical formulation of the operational planning problem in the case of information sharing can be found in (Safra et al., 2021).

5 Computational experiments & main results

5.1 Case study

Our experimentation focuses on knitting products. This business, with almost 200 different references produced and delivered per year, is amongst the most important activities of the company. Production is performed in three knitting company-owned manufacturing plants. Eleven subcontractors are involved in the company's network: Ten local and one overseas, located China. Local subcontractors offer prices generally 20% higher than the unit costs of internal production. The Chinese subcontractor, oppositely, offers relatively lower prices. However, in this case, subcontracting needs to be planned sufficiently in advance because it involves a 6-week transportation lead time. Produced items are shipped to one of the two

local warehouses and then to retailers. International deliveries are performed using a combination of the transportation modes mentioned above. The inventory holding cost per unit is about 5% of its production cost. Pre-season orders are received well in advance, often six to four months before the start of the selling season, whereas for the replenishment orders, the delivery lead time is in general of three weeks. An underutilization cost corresponding to fixed expenses incurred by idle production, is supposed to be the third of the internal production cost. Overtime production costs 40% higher than production during regular hours.

5.2 Comparison of proposed production-distribution planning approaches

In order to shed the light on the benefits and the value of information sharing, we compare the results obtained by the production-distribution planning approach with no information sharing (hereafter referred to as A1) to those obtained by a production-distribution planning approach with information sharing (hereafter referred to as A2). For that, we simulate each tactical-operational production-distribution planning approach over six months and determine the corresponding total supply chain cost.

To stress the importance of introducing a reserve production capacity at the tactical planning level, the supply chain cost is calculated for three types of production–distribution plans: (1) plans constructed without considering a reserve production capacity, (2) plans constructed while considering a fixed reserve production capacity of 20%, and (3) plans constructed while considering a monthly variable reserve production capacity. These three scenarios will be referred to as WIRP, WFRP-20% and WMVRP, respectively. The monthly variable reserve production capacity is estimated using available two-year historical data on production and incorporated in the tactical planning model. More precisely, it is obtained by computing, for each month, the ratio: replenishment production / total internal production during regular hours. At this level, it is worth noting that A1 under WIRP represents the planning approach currently used by the company.

Table 9 provides supply chain costs obtained by A1 and A2 for the three scenarios WIRP, WFRP-20% and WMVRP. Expectedly, the highest cost is the one tied to A1 without consideration of a reserve production capacity at the tactical planning. Recall that the latter reflects the current practice in the considered company. Moreover, table 9 gives the cost saving that can be achieved for each approach over the current practice.

Table 9. Comparison of total supply chain cost

	WIRP		WFRP-20%		WMVRP	
	C	**CS**	**C**	**CS**	**C**	**CS**
A1	2 864	0%	2 746	4%	2 575	10%
A2	2 429	15%	2 411	16%	2 332	18%

A1: Approach without information sharing
A2: Approach considering information sharing
C: Total cost *(K€)*
CS: Cost saving (%)

The results in table 9 demonstrate that the adoption of a production-distribution planning approach with information sharing and a monthly-varying reserve production capacity allows the company to achieve a cost saving of 18% over the current practice. Let us note, that the cost saving can reach 20% in the case of perfect forecasts. This obviously highlights the interest to develop a reliable and efficient forecast system. Indeed, such a system will

accurately estimate the monthly-varying reserve production capacity and predict the replenishment orders.

Table 10 compares production assignments obtained by A1 and A2 for the three scenarios WIRP, WFRP-20% and WMVRP.

Table 10. Comparison of production assignments

	WIRP		WFRP-20%		WMVRP	
	A1	A2	A1	A2	A1	A2
Regular hour production	259359	259832	259654	261641	259727	268690
Overtime production	1833	1746	1401	1281	2303	154
Subcontracted production	25507	26590	35373	25482	16793	14785
Total quantities	286699	288168	296428	288404	278823	283629

We notice that when the retailer shares in-season sales information with the manufacturer, a better use of the internal production capacity is accomplished whether considering or not a reserve production capacity at the tactical level. This sharing of information enables the company to anticipate the arrival of replenishment orders and hence to produce the ordered quantities internally at a lower cost. However, the best internal production capacity utilization is observed when a monthly-varying reserve production capacity is considered at the tactical level given that this reserve, which in this case is better estimated, allows to adjust internal capacity to accommodate orders. It is also worth noting that the increase in produced quantities at internal production sites is accompanied by a decrease in overtime and a decrease in subcontracted quantities except for the case where the full production capacity is used at the tactical level since no flexibility is provided to accommodate orders at the operational level. In this case, subcontractors' production has increased in A2 with comparison to A1. This increase is explained by advanced production of some quantities using internal capacities or subcontracting. Such a planning decision is made due to: (1) the high cost of overtime production in comparison to competitive prices offered by subcontractors, (2) the use of full internal production capacity available at the tactical planning level and (3) the unavailability of internal capacity when planning newly arrived orders at the operational level. Moreover, as it can be noted, the total produced quantities are not similar for the three scenarios (i.e. WIRP, WFRP-20% and WMVRP). This can be explained by the fact that some orders have to be delivered to customers at a due date beyond the six-month planning horizon. These orders might be processed in advance when the available production capacity is able to accommodate them. Otherwise, the related production will be delayed for the next months, beyond the six-month planning horizon, as their due date is not yet reached.

5.3 Sensitivity analysis

A sensitivity analysis is carried out in order to investigate the impact of some parameters on planning decisions and the performance of the considered supply chain. Three parameters are considered in this analysis: demand, transportation cost and subcontracting cost. Indeed, these parameters may be subject to fluctuations because of different factors such as competition, economic conditions, or diverse disruptions such as the COVID-19 pandemic.

In our experimentation, we constructed production-distribution plans while considering information sharing and a monthly-varying reserve production capacity (A2 – WMVRP) while varying the value of the above-mentioned parameters from -50 to +50%, around their current values. Moreover, we compared the total supply chain cost obtained by this outperforming planning approach to the supply chain cost obtained by the current practice (A1-WIRP).

Sensitivity analysis of demand

The results reported in table 11 show the superiority of A2-WMVRP over A1-WIRP. As can be noted, even when the demand is reduced by half, the cost remains lower for A2-WMVRP. However, the gap between costs gets smaller when demand decreases. Indeed, in this case, internal production sites can satisfy lower demand without considering a reserve production capacity at the tactical level and without sharing information. Nevertheless, the adoption of A2-WMVRP has a significant effect on supply chain cost reduction in the case of a surge in the demand as it yields a 19% reduction in the supply chain cost when the demand increases by 20% and 50%.

Table 11. Effect of demand variation on total supply chain cost

	D-50%	D-20%	D	D+20%	D+50%
A1 – WIRP *(K€)*	1658	2152	2864	3285	3794
A2 – WMVRP *(K€)*	1601	1898	2332	2653	3055
Gap (%)	3	12	18.6	19	19

Sensitivity analysis of transportation cost

Once again, as shown in table 12, A2 – WMVRP outperforms A1 – WIRP when overseas transportation cost fluctuates.

Table 12. Effect of overseas transportation cost variation on supply chain cost

	T-50%	T-20%	T	T+20%	T+50%
A1 – WIRP *(K€)*	2424	2678	2864	2891	2894
A2 – WMVRP *(K€)*	2260	2301	2332	2356	2358
Gap (%)	6	14.1	18.6	18.5	18.5

When the overseas transportation cost decreases, the supply chain cost also decreases. More importantly, we notice a migration of some productions from internal production sites to the manufacturing units of overseas subcontractors. As such, a reduction in overseas transportation costs favors the recourse to overseas subcontracting as the latter offers lower unit production costs compared to those of local production. We also note a small increase of the supply chain cost when the overseas transportation cost increases. In this case, overseas subcontracting becomes an expensive option. That is why an increase of overseas transportation cost fosters production in local manufacturing units.

Sensitivity analysis of subcontracting cost

Let us first note that when the cost of local subcontracting is reduced by half, it becomes more cost competitive than internal production. A large part of the internal production is therefore assigned to local subcontractors. As shown in table 13, the gap between the two approaches is smaller when local subcontracting cost decreases. Hence the value of information sharing is lessened in this case as local subcontracting becomes a lever to

efficiently handle demand unpredictability. Oppositely, the increase of local subcontracting cost can only encourage the manufacturer to plan its internal capacity as well as possible to meet urgent demand that may occur at the operational level without using costly subcontracting, and this is ensured through information sharing with the retailer. The value of information sharing is highlighted by the significant gap estimated at 19% between the supply chain cost of A2 – WMVRP and A1 – WIRP.

Table 13. Effect of subcontracting cost variation on supply chain cost

	S-50%	S-20%	S	S+20%	S+50%
A1 – WIRP *(K€)*	2509	2798	2864	2925	2964
A2 – WMVRP *(K€)*	2305	2321	2332	2382	2408
Gap (%)	8%	17%	18.6%	18.6%	19%

At this level, one can conclude that the interest in adopting A2 – WMVRP significantly increases when demand, overseas transportation cost and subcontracting cost increase. But even if there is a decrease in the value of these parameters, A2 – WMVRP persistently remains superior to A1 – WIRP, i.e. the current practice. Therefore, adopting a planning approach with information sharing and considering a variable reserve production capacity allows to the supply chain to better face disruptions such as those caused by the COVID-19 pandemic.

6 Concluding remarks and future research

In this paper, we propose a sequential two-level approach for the planning of global textile and apparel supply chains including a manufacturer and a retailer stage. The objective is to achieve cost minimization while offering products that fit customer's taste. Both pre-season orders and in-season replenishment orders are accounted for in production and distribution planning. Because of the difference between the lead time of pre-season and replenishment orders, the considered problem integrates production and distribution decisions pertaining to the tactical and operational planning levels. We investigate two planning approaches: (1) with no information sharing on current in-season sales and (2) with information sharing on current in-season sales. To handle demand unpredictability, the proposed approaches recourse to flexibility by considering a reserve production capacity at the tactical level, and overtime and local subcontracting at the operational level.

The proposed approaches are tested over a six-month planning horizon using data stemming from a real-life case study. For each approach, three types of production–distribution plans are constructed: (1) without considering a reserve production capacity, (2) while considering a fixed reserve production capacity of 20%, and (3) while considering a monthly variable reserve production capacity. The lowest supply chain cost is entailed when information sharing is coupled with a variable reserve production capacity at the tactical level; the cost cutting attains 18% with respect to current practice. Moreover, a sensitivity analysis study, reveals that this approach remains superior to the current practice under different changes of market conditions.

The complexity of the devised models will soar if we consider lager sized problem instances. They cannot be solved using off-the-shelf solvers. Therefore, one possible extension of the current research remains in developing more sophisticated solution methods such as decomposition-based methods or meta-heuristics to obtain near-optimal solutions. Another important perspective of this research lies in developing a stochastic approach to account for the uncertainties tied to the demand and the supply.

Chapter III.2

Contribution to airline operations planning

The chapter is based on (Kenan et al., 2018a), (Kenan et al., 2018b) and (Kenan et al., 2018c)

1 Introduction

The airline industry is a highly competitive one and the demand for airline tickets, mainly the last years, is showing important steep swings triggered by different type of crises. Seeking for higher cost-effectiveness and higher value to offer to their customers, airline companies have often opted to reduce operations on non-profitable routes, diversify their business, retire old and fuel-inefficient aircraft. Some choose to create alliances, including codesharing agreements, with other airline companies, which has proven profitable at times. Conversely, some companies enact poor decisions by decreasing their service quality and capital investments or by using aircraft with smaller capacity while increasing fares (Sherali et al., 2013). Each flight that takes off with an empty seat represents a revenue opportunity lost forever. Henceforth, now more than ever, airline companies need to implement a proper operations planning process to accommodate passenger traffic in a profitable manner.

Airline operations planning process involve the following four main steps:

Flight scheduling: It consists of designing a timetable of flights that specifies the covered origins and destinations along with departure and arrival times. It is the component of airline planning that has the most prominent impact on airline profits (Bazargan, 2016). The factors to be considered during flight scheduling include market demand, available aircraft, crew availability, and country and airport rules and regulations.

Fleet assignment: It consists of assigning different aircraft types of different capacities to the scheduled flights. This means it has a direct effect on the revenue and operating costs and thus is considered to have the second most significant impact on airline profits after flight scheduling. These assignments are based on aircraft type characteristics and capabilities, fleet type and size, operational costs, and potential revenues given the demand.

Aircraft routing: It consists of determining the set of flight legs that each aircraft will cover within a rotation given that it ends at the same location from where it started. To ensure safety, each aircraft may spend time in some airports to undergo routine maintenance checks.

Crew scheduling: It consists of assigning different crews to suitable aircraft. In addition, the crew scheduling should account for the large number of restrictive rules mandated both by the airline governing agencies and the labor unions. Given the relatively high salaries of the airline crews, the improvement of the airline crew schedule through the reduction of crew connections would translate into significant savings.

Although these four decision problems are closely interdependent, they are generally solved sequentially because of their size and complexity. The development of airline planning models and solution approaches that integrate some of these decisions has been receiving the greatest level of attention from the research community. In this perspective, we intend, first,

to develop a formulation that solves the integrated flight scheduling and fleet assignment problem as these two steps allow for the selection of the most profitable paths. Moreover, to address some important concerns of the planning process, namely delays and related costs, this first work has been extended to include aircraft routing. Indeed, delays result in huge costs since they translate into increased working hours for the crew, higher fuel consumption, loss of passengers, and thus loss of goodwill. Markedly, cutting delays, and more specifically, the propagated delays, i.e. those caused by delays that happen upstream in the route of an aircraft, and related burden, becomes of great concern to many airline companies.

At this level, it is worth noting that an aircraft type refers to a certain model of aircraft with the same cockpit configuration, crew rating, and a given seating capacity. The set of aircraft types with the same cockpit configuration and crew rating is referred to as an aircraft family. Crew members are usually trained to fly all the aircraft types belonging to a single family. Henceforth, crew scheduling decisions cannot be made independently of fleet assignment decisions. In addition, crew scheduling should be made 10–12 weeks prior to the flight date in order to fulfill the scheduling requirements of the cabin crews as it is mandated by the labor union regulations. The addressed decisions are therefore subject to the same timeframe. However, 10–12 weeks prior to the flight date, the demand is highly uncertain and so are the fares. These sources of uncertainties are henceforth accounted for in the proposed formulations.

2 Literature review

Integrated flight scheduling and fleet assignment

Most of the works found in the literature on airline operations planning are in the field of airline fleet assignment. These works formulate the problem and solve it based on a flight schedule that specifies the covered flight legs and their respective departure times. The underlying frameworks for the fleet assignment problem are time-space networks and/or connection-based networks. Most of the works aimed at maximizing the airline company profit. Some works, mainly the earliest ones, addressed the fleet assignment problem while assuming that the demand is deterministic (Abara, 1989; Hane et al., 1995; Clarke et al., 1996; Rushmeier and Kontogiorgis, 1997; Barnhart et al., 2002; Bélanger et al., 2006). To deal with demand uncertainty, some papers opt for a dynamic reassignment of aircraft within the same family (also called refleeting) in order to account for a more detailed and reliable demand information as departure dates get closer (Berge and Hopperstad, 1993; Fry, 2015; Sherali et al., 2005; Jiang and Barnhart, 2009). The main difficulty in refleeting remains in how to assign aircraft types belonging to the same family to flights such that the swapping respects the practical constraints of the airline network. Indeed, two aircraft can only be swapped if they depart from the same airport and have similar departure times. A more comprehensive and detailed survey on deterministic fleet assignment and refleeting can be found in Sherali et al. (2006). Furthermore, in some other works, the authors have rather opted for incorporating the uncertainty in the demand by using stochastic programming (Pilla et al., 2008; Sherali and Zhu, 2008; Listes and Dekker, 2005; Cadarso and de Celis, 2017). Naumann et al. (2012) also present a two-stage stochastic program to solve the fleet assignment problem while accounting for both, the uncertainty in the demand and in fuel prices. The work of Yan et al. (2008) devises a stochastic flight scheduling model with uncertain demand. These works show that the results obtained by the stochastic approach are an improvement over the ones obtained by the deterministic one.

In an attempt to increase the revenues through improved flight connection opportunities, some works address the integrated flight scheduling and fleet assignment problem (Desaulniers et al., 1997; Lohatepanont and Barnhart, 2004; Sherali et al., 2010; Sherali et al., 2013; Cadarso and Marín, 2013). Although there is common consent on the significance of accounting for demand uncertainty in fleet assignment, all the papers that tackle the integrated flight scheduling and fleet assignment ignore this realistic problem feature. This research attempts to start filling this gap.

Integrated flight scheduling, fleet assignment and aircraft routing

Many works investigate the integration of fleet assignment and aircraft routing with extensions in some recent works to include flight scheduling and crew scheduling considerations (Desaulniers et al., 1997; Barnhart et al., 1998; Haouari et al., 2009; Haouari et al., 2011; Zeghal et al., 2011; Liang and Chaovalitwongse, 2012). Two types of models are distinguished: (1) leg-based models; and (2) itinerary-based models. Leg-based models are well justified for small- to medium-sized airline companies or also low-cost companies operating point-to-point networks as most of the itineraries served in this case include a single flight leg. Oppositely, operations planning of large airline companies should rather resort to itinerary-based models because they use a hub-and-spoke network and commonly serve itineraries that include several flight legs.

Some works integrate flight schedule design, fleet assignment and aircraft routing (Sherali et al., 2013; Gürkan et al., 2016; Jamili, 2017). All these works consider that the demand is deterministic. Jamili (2017) formulates a robust mixed integer mathematical model to account for traveling time uncertainty caused by disturbances. The robustness is achieved through the adequate addition of buffer times while defining the departure times of aircraft. The proposed model in (Gürkan et al., 2016) aims at minimizing costs including passengers spill (lost demand), delay costs, fuel and carbon emission costs while considering the cruise times of each flight and ensuring a pre-specified passengers' connection service level. Nevertheless, to the extent of our knowledge, no work has considered uncertainty in the demand while solving the integrated flight scheduling, fleet assignment and aircraft routing problem. Moreover, even though flight disruptions are a major concern for the airline industry, none of the previously cited works incorporating aircraft routing decisions has tackled this issue, with the exception of Jamili (2017) and Gürkan et al. (2016).

Some works attempt to minimize flight delays through robust aircraft routing and and/or flight retiming. Lan et al. (2006) formulate a stochastic discrete model to minimize the total propagated delay in the flight schedule. They consider that flight total arrival delay is the sum of its independent and propagated delay, and that the latter can be approximated using log-normal distribution. In (Ahmadbeygi et al., 2010), the authors propose a model that minimizes the total propagated delay by retiming flight departure times and hence redistributing the existing slack in the airline schedule. Yan and Kung (2016) propose a robust optimization model that minimizes the maximal possible total propagated delay while assuming that flight leg delays lie in a pre-specified uncertainty set. Marla et al. (2018) compare three classes of models for aircraft routing, namely chance-constrained programming, robust optimization, and stochastic optimization. The authors conclude that three approaches can be used to mitigate the propagated delay and enhance the airline on-time performance.

As can be noted, the amount of work in the literature that integrates aircraft routing with flight scheduling and fleet assignment is sparse, and even rarer are those that consider propagated delay. Although Jamili (2017) and Gürkan et al. (2016) address the integrated flight scheduling, fleet assignment and aircraft routing with delay considerations, they do not consider the maximization of airline profit with explicit consideration of delay costs. Moreover, they do not consider the uncertainty in the demand.

The objective of airline operations planning is to maximize the profit which is substantially impacted by demand variability and disruptions. To achieve this objective, it is required to account for demand uncertainty and also flight delays in the integrated flight scheduling, fleet assignment and aircraft routing. Given that no work addresses this problem, this research is designed to start filling this gap. In addition, some features pertaining to small and medium sized airline companies, such as the need to resort to deadhead flights in order to operate profitable flights, are considered.

3 Integrated flight scheduling and fleet assignment under uncertainty

3.1 Problem description and formulation

The main challenge of the integrated flight scheduling and fleet assignment pertains to the high uncertainty of the demand 10–12 weeks prior to the flight date. On the one hand, assigning an aircraft with a smaller seating capacity than the realized demand will result in lost customers and a missed opportunity. On the other hand, assigning an aircraft with a larger seating capacity than the realized demand will result in empty seats and higher operational costs. Moreover, this uncertainty in the demand incurs uncertainty in fare prices. To overcome this issue, a two-stage stochastic programming model was devised where the randomness in demand and fares are accounted for through the consideration of the set of plausible scenarios and their probabilities. The first-stage variables, are scenario-independent, and pertain to the assignment of a fleet family (for instance, Boeing B737 family) to each scheduled flight leg, while the second-stage variables, are scenario-dependent, and include the refinement of this decision by selecting a fleet type (for instance, Boeing B737-300 type belonging to the Boeing B737 family) for the flight leg based on demand and fare realizations. Given that aircraft belonging to the same family have the same cockpit configuration and crew qualification requirements, the assignment of a fleet family to each scheduled flight leg 10–12 weeks prior to the flight departure date will allow for crew scheduling. The decision on fleet type assignment can be later revised based on more accurate forecasts of the demand. This greater flexibility will foster a more effective decision-making plan that allows for achieving higher profits.

In the first stage, exactly one fleet family is assigned to each of the mandatory flight legs and at most one fleet family is assigned to each of the optional flight legs. In the second stage, each scheduled flight leg is assigned to exactly one fleet type from the fleet family to which it has been assigned. In addition, each fleet type is considered to have up to two different fare classes each with its own capacity and demand. Each airport is characterized by a maximum available number of arrival and departure slots per hour per day. It is particularly important to consider this airport capacity constraint for arrivals and departures in busy airports during rush hours. The demand and fares follow a normal distribution (Listes and Dekker, 2005; Zhu, 2006).

The objective function aims at maximizing the expected profit. Some constraints ensure that exactly one fleet family should be assigned to each of the mandatory flight legs while others specify that at most one fleet family is assigned to each of the optional flight legs. If a flight leg is assigned to a given fleet family, some constraints enforce that this flight leg is assigned to a fleet type of the same family. Other model's constraints are aimed at accounting for the violation of fleet size. The model also includes aircraft and airport capacity constraints and domain constraints.

For the details of the mathematical formulation of the proposed two-stage stochastic programming model we refer the reader to (Kenan et al., 2018a).

3.2 Solution methodology

Real-life situations involve a large number of plausible scenarios which make it extremely difficult to solve this two-stage stochastic programming model. To overcome this challenge, the SAA algorithm was used. As noted, the main advantage of the SAA algorithm is its ability to find near-optimal solutions while considering samples comprising a smaller number of scenarios. Needless to detail the different steps of this algorithm that starts by the approximation of the true stochastic model by the SAA model. Indeed, the used SAA algorithm is an adjusted version of the one presented in section 3 of chapter II.1. The details of the algorithm can be found in (Kenan et al., 2018a).

3.3 Main Results

Data description

The base case is derived from an international airline's flight network. The airline company may cover up to 228 flight legs involving more than 45 destinations. To cover these flights, a fleet of 59 aircraft is deployed. The latter is divided into 4 fleet families and 5 fleet types: A320-200, A319-100, A300-600, B737-500, and B737-600. Each fleet type has two cabin classes, namely the business class and the economy class. Each aircraft type offers a fixed number of available seats for each cabin class. The itinerary-level demand and the fare associated with each cabin class are generated using normal distribution truncated at zero (Ahuja et al., 2007). The average of the itinerary-level demand was randomly generated using a discrete uniform distribution on the interval [0, 118] for the economy class and on the interval [0, 14] for the business class. Note that 118 and 14 represent around 50% of the A300-600 seating capacity for the economy and the business class, respectively. The latter is the aircraft type having the largest seating capacity for both cabin classes. The standard deviation of each itinerary-level demand is set to 200% of its average value. The average fare prices are collected from the airlines website by simply proceeding with a booking and noting down the price of the flight ticket. The standard deviation of the fare is set to 50% of its average value. The cost of assigning an aircraft type to a given flight leg is set to 15% of the maximum average revenue that can be generated by economy fare class of the considered aircraft type. In the base case, 30% of the flight legs are optional. Monte Carlo simulation is used to generate the scenarios based on the probability distribution of the demand and the fare associated with each cabin class.

Convergence of the SAA algorithm

We begin with verifying the convergence of the proposed SAA. For that, the SAA algorithm is run while progressively increasing the number of scenarios from 5 to 200. Moreover, the algorithm is run for 10 replications and considers a sample of 10000 scenarios to obtain a better estimate of the objective function value (lower bound). For each sample size, the best lower bound (objective function value of the best-found solution) and upper bound, and the computational time to obtain them were noted. Figure 17 shows how the upper bound and best lower bound change as sample size increases. Both converge toward an optimal solution of the true stochastic problem as the number of scenarios increases. Figure 17 clearly indicates that the optimality gap becomes tight enough starting from a sample size of 100 scenarios.

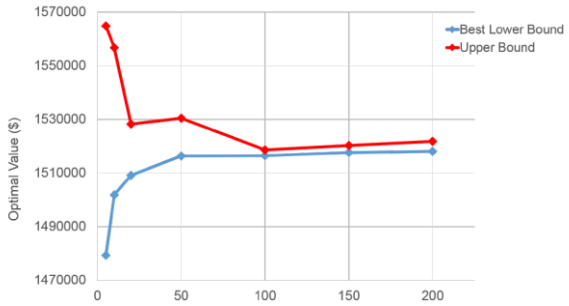

Figure 17. Convergence of the SAA algorithm

A good trade-off between the quality of the solution and the computational effort needed to obtain it can be achieved for a sample size of 100 scenarios. Indeed, with this sample size, a near-optimal solution with an optimality gap less than 1% is obtained within an acceptable computational time (less than 1 h). Additionally, the quality of the solutions obtained while considering samples of size 150 and 200 scenarios are slightly better than the one obtained with a sample size of 100 scenarios whereas the computational time needed to obtain them is much higher than the one required to solve the SAA problem with 100 scenarios. More importantly, these results point out that the SAA algorithm can be used in practical cases pertaining to medium- and small-sized airline companies such as the airline considered in this work.

Sensitivity analysis

An important aspect of the planning process of any airline company is checking whether existing flight legs or potentially new flight legs are profitable or not. This can be done by introducing these flight legs into the optimization model as optional flight legs and determining whether aircraft will be assigned to them or not. This experiment was divided into two parts. Part one consisted of varying the percentage of optional flight legs from 10 to 30% whereas part two consisted of elevating this percentage from 30 to 50%. Another difference between part one and part two remains in the considered upper bounds on the number of arrivals and departures at the capital's airport, respectively. The experiments in part two consider the upper bounds used in the base case. Given that with these values the problem becomes infeasible when only 10% of the flight legs are set optional, higher upper bounds on the number of arrivals and departures are accommodated while carrying out the experiments in part one. As expected, the total number of flight legs between part one and part two drops as it can be seen from table 14. This is mainly due to two reasons: (1) the total number of mandatory flight legs decreases as the percentage of optional flight legs increases,

and (2) the consideration of more optional flight legs gives the possibility of not including in the schedule those that are non-profitable.

Table 14. Effect of the percentage of optional legs on the number of scheduled flights and profit

Optional flight legs (%)	True objective value ($)	Total flight legs	Selected optional flight legs (%)
10	1614391	222	75
20	1614765	223	89
30	1627068	224	94
30*	1517391	201	60
40	1540889	200	70
50	1539566	208	83

*Base case

Demand on specific flight legs is highly variable. As the seasons of the year change, the demand varies significantly. Moreover, demand variation can be influenced by other external factors such as the COVID-19 crisis. Therefore, it is very important to model these changes by varying the standard deviation of the demand. Table 15 shows that even though the total number of scheduled flight legs is almost the same in all cases, the profit increases when the standard deviation of the demand increases. This can be explained by a higher passenger load factor that arises when the standard deviation of the demand increases. This means that the aircraft are on average better filled when the standard deviation of the demand increases. This can be explained by the fact that, in most of the cases, the probability that the demand is greater than a given aircraft capacity increases with the standard deviation.

Table 15. Effect of the standard deviation of the demand on the number of scheduled flights and profit

Std. Dev. of Demand (%)	True Objective Value ($)	Total Flight Legs	Optional Legs (%)
50	571674	199	57
100	860871	206	68
150	1199508	198	56
200	1516472	198	56
250	1789213	198	56

4 Integrated aircraft routing with consideration of propagated delay

4.1 Problem description and formulation

The integrated flight scheduling and fleet assignment determines which aircraft will serve which scheduled flight leg in order to achieve the match between aircraft seating capacity and demand that maximizes the profit. However, the obtained schedule and assignment can later result in aircraft routes with high delays given the scheduled flight departure times, turnaround times and independent delays. Evidently, these delays propagate and result in many disruptions and in some extreme cases might cause flight cancellation. In order to contain the delay, and resulting disruptions and burden, we extend here the previous research by integrating aircraft routing with flight scheduling and fleet assignment. The objective is to determine based on the demand, the available fleet and the independent delay, the flight legs to include in the schedule, the aircraft to perform each served flight leg and the route of each aircraft that maximize the profit while trying to reduce the delay. Without this integration, it is possible to observe excessive delays because, for example, the flight schedule includes a large number of optional flight legs.

A two-stage stochastic mixed-integer programming model for the integrated flight scheduling, fleet assignment and aircraft routing problem under demand uncertainty (hereafter referred to as OFAR) is formulated. The model aims at maximizing the airline's profit that is determined by the difference between the expected revenue and the sum of the different costs including the delay cost. Flight scheduling, fleet assignment and aircraft routing decisions should be made ahead of time, and hence, they constitute the first-stage decisions. The number of passengers accepted on each flight leg represent the second-stage decisions given that they are determined based on demand realization. At this level, it is worth noting that the proposed model and solution approaches will be applied to a medium-sized airline company where most of the served itineraries involve a single flight leg. In addition, the proposed model considers deadhead flights in order to operate profitable flights, which is a practice mainly used by small and medium-sized airline companies. Under this practice, an airline company let some aircraft take passive flights (i.e. fly empty) from one airport to another to serve profitable flights.

The objective function aims at maximizing the profit for the airline company which is the difference between the expected revenue from serving all the scheduled flights and the sum of: expected costs incurred from delay over all the flight legs, the costs incurred from assigning a specific aircraft to a flight leg, and the cost of deadhead flights. With respect to the stochastic programming model, introduced in subsection 3.1, OFAR includes constraints that allow for determining the actual departure time of each flight leg and the corresponding delay cost. These constraints consider the independent delay, the scheduled departure and arrival time of each flight leg, the turn-time and the flight duration associated with the aircraft assigned to the flight leg. The delay cost associated with a given flight leg is weighted by its revenue, which is scenario-dependent, as it depends on the number of accepted passengers, and so the realized demand and aircraft capacity.

4.2 Solution methodology

It was not possible to solve the SAA model approximating OFAR while incorporating medium-sized samples including 100 demand scenarios using commercial software. This complexity is mainly entailed by the large number of constraints it includes. To overcome this complexity issue, we reformulate OFAR using a column-based formulation called the master problem and hereinafter referred to as CGAR. Each column of CGAR represents a feasible route r served by an aircraft type a. Indeed, aircraft of the same type are identical as they have the same capacity for each fare class. Hence instead of assigning a route to a specific aircraft, we assign it to an aircraft type while enforcing the respect of the initial aircraft stations. CGAR aims at selecting a set of feasible aircraft routes, i.e. a set of columns, that optimizes the objective function.

For each column involved in the CGAR, the flight legs included in a feasible route and the aircraft type serving that route are known. While assuming that the demand for each fare class on each flight leg follows a truncated normal distribution (Listes and Dekker, 2005; Zhu, 2006), the closed form of the expected number of passengers accepted in each fare class can be calculated by numerical integration over the truncated normal distribution function. It follows that the expected revenue for each flight leg included in each route can be determined beforehand and input in CGAR as a parameter. Similarly, knowing the order in which the flight legs belonging to a route are performed and the expected revenue, the delay cost associated with each column is determined and input as parameter in the CGAR.

Remarkably, the number of columns of CGAR is extremely large (because the number of feasible routes is huge) and similarly to OFAR, CGAR cannot be solved directly using a commercial solver. Hence, we start by solving the linear relaxation of the CGAR (hereinafter denoted by LCGAR) using column generation. Henceforth, only a subset of LCGAR columns (i.e. a subset of feasible routes) is considered. The solved problem is called the restricted master problem (RMP) associated with LCGAR.

First, a starting set of columns is determined to initiate the column generation-based solution procedure. Afterwards, additional new columns are generated by repeatedly solving the pricing problem called the subproblem. The objective of the subproblem is to construct a column with minimum reduced cost. If the minimum reduced cost is negative this means that the obtained column is added to the RMP because its addition can increase the airline profit. Oppositely, if the reduced cost is positive then the obtained column when added to the RMP cannot increase the airline profit. This means that the optimal solution of the RMP which is also an optimal solution of LCGAR has been reached.

Interestingly, the subproblem can be solved separately for each aircraft type. Therefore, three column generation-based approaches are proposed. The main difference between all three approaches is when to move from one subproblem to the next. This will greatly affect the number of columns generated and, hence, the computational time.

Approach one solves each subproblem until it completely prices out (i.e. produces a positive objective value) and then moves on to the next subproblem. The algorithm terminates when all subproblems price out.

Approach two solves each subproblem one time, updates the dual variables from the RMP, and then moves on to the next subproblem. The algorithm terminates when all subproblems price out.

Approach three starts by solving the RMP and then inserts the dual variables into all subproblems. When all subproblems are solved, the newly generated columns will be inserted into the RMP and solved once again. This process is repeated until all five subproblem price out.

Obviously, the optimal expected profit obtained for LCGAR represents an upper bound for both CGAR and OFAR. Additionally, if the optimal solution of LCGAR is integer then it is also an optimal solution of CGAR and OFAR. However, if the solution of LCGAR is fractional, then it is not a feasible solution of CGAR and OFAR. In this case, a near-optimal solution of CGAR and OFAR will be constructed by directly solving CGAR while incorporating the generated columns associated with the optimal solution of LCGAR. Given that only a subset of the columns (feasible routes) is involved in solving CGAR, the computational complexity and size of the problem are significantly reduced.

The mathematical formulation of OFAR, CGAR and the pricing problem, as well as the algorithms tied to the column generation based solution scheme can be found in (Kenan et al., 2018b).

4.3 Main results

The conducted experimentation relies on the data of the base case introduced in subsection 3.3. Four problem instances with 50, 100, 150 and 228 flight legs are tested. Note that the base case is the one with 228 flight legs.

Table 16 compares the three proposed approaches. Given the number of aircraft types, five subproblems are considered. For the two instances with the largest data set sizes, Approach two outperforms Approach three. This happens for two main reasons, (1) Approach three produces additional unnecessary columns since the dual variables do not update regularly and (2) the nature of the algorithm of Approach three which execution involves many loops. However, it is worth noting that on a cluster computer the subproblems of Approach three may be solved in parallel. In this case, the computing time of Approach three will be significantly reduced and hence it would outperform Approach two.

Table 16. Comparison between the three column generation based approaches

	Number of flight legs	Number of variables	Number of discrete variables	Number of equations	Number of columns	Number of iterations	Optimality gap (%)	CPU (s)
Approach one	50	5645	5594	1021	39	57	0	60
	100	12298	12197	2934	252	272	0	572
	150	20166	20015	6060	656	707	0	2270
	228	35805	35576	14294	1692	1738	0.008	13108
Approach two	50	5645	5594	1021	34	61	0	73
	100	12298	12197	2934	192	238	0	485
	150	20166	20015	6060	491	543	0	1897
	228	35805	35576	14294	771	842	0.07	6854
Approach three	50	5645	5594	1021	39	12	0	49
	100	12298	12197	2934	237	58	0	463
	150	20166	20015	6060	530	120	0	1917
	228	35805	35576	14294	917	203	0.07	7361

A sensitivity analysis is conducted in order to study the effect, of the fleet size and the independent delay, on the profit and other performances. For that, first, the number of aircraft was increased from 20 in increments of 10 until the actual fleet size of 59 is reached. The results are presented in Table 17. The increase in the number of aircraft results in an increase in the number of routes that can be served. This leads to more flight legs (out of the 228) being served if they tend to be profitable. The results show that for a fleet size of 20 aircraft the airline company is only able to serve 85 out of the 228 flight legs. When the fleet size is increased to thirty, 39 additional flight legs that are profitable will be served by the additional 10 aircraft. Certainly, these additional aircraft also incur additional operating costs. It is, however, worth noting that this sensitivity analysis is not intended to determine the fleet size, as the latter relates to the strategic level decision which is beyond the scope of this research.

The most important results in table 17 are the variations of the cost associated with the delay. As can be noted, when the number of aircraft increases, the average cost associated with delay decreases. The indirect effect of these delays is the company's image is tarnished and some customers might be lost to other competitors.

Table 17. The effect of increasing the number of aircraft on profit and propagated delay

No. Of Aircraft	Profit ($)	No. Of Served Flight Legs	Propagated Delay Cost per Route ($)	Propagated Delay Cost per Flight Leg ($)
20	1577268	85	8027	1795
30	2096781	124	7327	1713
40	2449907	170	6622	1519
50	2852135	185	6526	1658
59	3085040	215	6050	1548

Second, we investigate the effect of an increase in the independent delays on the results. As mentioned in Section 3.2, independent delay is caused by conditions that affect a specific flight leg such as crew delay, weather conditions, and congestion on airport runways and terminals. For these reasons, the value of the independent delay for each flight leg is based on historical data. In this experiment, the values of the independent delays used to produce the results shown in table 18 were randomly generated. The obtained results show that independent delays have a huge impact on profits. Recall that independent delays might propagate and cause delays in flight legs downstream of the aircraft route. Therefore, the bigger the independent delay early in the route, the higher the chances are that one flight leg down the route will have to be cancelled, thus canceling the entire route. This is clearly seen in the steep drop in profit with every increment of one hour to the independent delay. The profits of the airline company drop to a third of its original value as the independent delay varies from (0–2) h up until (0–8) h.

Table 18. Effect of increasing the independent delay on the profit and other performance measures

Independent Delay (hours)	Profit ($)	Number of Served Flight Legs	Routes with Deadhead Flights
0-2	2682515	216	9
0-3	2320182	215	7
0-4	1970525	216	7
0-5	1747836	207	5
0-6	1276607	185	7
0-7	1217862	161	10
0-8	988099	136	9

4.4 Integrated aircraft routing with consideration of codesharing

A codeshare agreement permits one or several airlines to market a flight that is operated by another carrier. The former airlines accommodate their own number for the codeshared flight and are called marketing carriers while the latter are called operating carriers. Under such agreement, airline companies can offer their customers a wider range of itineraries and regional connections at minimal cost. In addition, such agreements might contribute to reduce schedule delay. Codeshare agreements are generally signed between airline companies for a specified period of time. Although many types of codeshare agreements exist (Adler and Hanany, 2016), the used one by the considered legacy airline company is the hard block agreement. Under this type of agreement, the marketing carriers swap or purchase a pre-agreed set of seats on the operating airline's flight, normally per season. Therefore, it is common to see that sometimes a route or a flight is added and dropped several times during the agreement period whereas others are codeshared for one quarter and then dropped forever (Du and Starr, 2015).

Even though there is abundant literature on codesharing from a strategic perspective, the works investigating codesharing related decisions at the tactical-operational level are scant. To start filling this gap, our previous research on integrated flight scheduling, fleet assignment and aircraft routing is extended in order to explore the possibilities this type of alliance, and more specifically the hard block agreement, holds. In particular, this extension allows for deciding whether to continue/start or drop a flight codesharing for the next quarter and the number of seats to be taken under block agreement with the involved operating carrier.

More details on this extension can be retrieved in (Kenan et al., 2018c).

6 Concluding remarks and future research

First, a two-stage stochastic programming model for the integrated flight scheduling and fleet assignment under demand and fare price uncertainty was developed. A near-optimal solution of the problem arising at a medium-sized legacy airline company was found using SAA algorithm within a reasonable time. This research has been then extended to include aircraft routing and so account for propagated delay, which remains a major concern of several legacy airline companies. This extended model proves to be of high complexity and hence a commercial solver fails to solve the corresponding SAA model for medium-sized instances. Three column generation-based approaches were developed and were able to solve the problem optimally or near-optimally within a reasonable time. Furthermore, sensitivity analysis reveals that increasing the number of aircraft will have a huge impact on the profit of the company. It also shows that larger independent delays have the biggest impact on the profit of the company.

This research has been further extended by considering codeshare agreements in the integrated flight scheduling, fleet assignment, and aircraft routing in an optimization context. Integrating codeshare agreements with these three processes helped in deciding which flight legs are best to be codeshared and how many seats should be purchased by the marketing carrier.

Many possibilities exist for extending this work. First, it can be extended by considering flexible departure windows which may result in a schedule with even further decreased delay costs. Second, in addition to the current consideration of delays, aircraft routing can also consider maintenance requirements. By knowing the exact path of an aircraft, it is possible to decide on the ending station of each day along the route to make sure the corresponding airport has a maintenance station. Also, integrating crew scheduling as the fourth and final process in airline planning is essential in achieving a fully integrated model and avoiding sub-optimal solutions. This full integration comes along with increased profits and customer satisfaction but at the expense of increased model complexity and the need for more sophisticated solution methods. Furthermore, one of the shortfalls of the extension that incorporates codesharing agreements remains in the fact that the demand of the operating carrier and the demand of the marketing carrier were assumed independent. An interesting prospective of this research consists in integrating a new demand model based on the customers' demand for both the operating and marketing carrier with consideration of competition.

Chapter III.3

Contribution to maritime logistics

The chapter is based on (Al-Dhaheri et al., 2016a), (Al-Dhaheri et al., 2016b) and (Kenan et al., 2022)

1 Introduction

Globalization has driven a steep increase in the exchange of goods amongst countries. This has driven a significant growth in the volume of transshipped containers worldwide as approximately 90% of the incurred international transport is ensured through maritime shipping (UNCTAD, 2018). Therefore, container terminals play a crucial role in the efficiency of the global logistics network and, more widely, in the success of the global supply chain. Container terminals owe operate in the most efficient way, by delivering timely and rapid service to vessels, at the least possible cost. Providing container terminals with models and methods that support them in shortening vessel handling time and increasing terminals' throughput is essential to respond to the incrementing container streams through the universal supply chain system and even achieve a competitive advantage. This explains the great interest given by researchers, the last two decades, to the optimization of seaport operations as demonstrated by the literature review presented by Bierwirth and Meisel (2010), Carlo et al. (2015) and Bierwirth and Meisel (2015).

Container terminals can be divided into four main areas: the berth, the quay, the yard and the gate. The berth and the quay areas are considered seaside, while the yard and the gate are considered landside (Carlo et al., 2015). Once a vessel is berthed, three main operations are processed: loading/unloading containers between vessels and landside trucks, transporting containers between berths and the storage yard and, loading/unloading containers between landside trucks and storage yard. The vessel is divided into several bays and each container is unloaded from or loaded onto a given bay according to the stowage plan; at any time, at most one QC can perform operations on a bay. Containers are temporarily stored in the container stacking yard. Import containers, after being discharged from the vessel, are transported from the quay to the stacking yard where they stay till being delivered to customers through the gate. Transshipment and export containers are stored in the stacking yard until the vessel that ships them to their next destination arrive. They are subsequently transported to the quay and loaded onto the vessel. Container transport from the quay to the stacking yard and vice versa is ensured by shuttle vehicles such as internal trucks, automated guided vehicles and straddle carriers. For a more comprehensive overview on the layout of container terminals and, the handling and transport equipment, the reader can refer to (Steeken et al., 2004) and (Brinkmann, 2011).

Minimizing the handling time of a vessel relies on a variety of interrelated seaside and landside operational decisions. Seaside decisions include the allocation of berths to arriving vessels (known as the Berth Allocation Problem and referred to as BAP), the assignment of QCs to vessels (known as the Quay Crane Assignment Problem and referred to as QCAP) and the scheduling of QC loading/unloading operations (known as the Quay Crane Scheduling Problem and referred to as QCSP). Landside decisions bear on the scheduling of

shuttle vehicles, the allocation of a position in the stack to containers and, the scheduling of yard cranes.

Over the last decade, a major emphasis of the literature in maritime logistics has been placed on the optimization of seaside operations because they involve the utilization of the most expensive and critical resources of a container terminal: the berths and the QCs. In our research, the focus was placed on two problems, the QCSP and the integrated QCAP and QCSP, hereafter referred to as QCASP.

The QCSP considers a set of containers to be discharged and/or loaded from and/or onto a single berthed vessel, according to a stowage plan, by a set of assigned QCs. A solution to this problem consists in defining the containers to be handled by each QC and the start time of each QC operation. The objective is to minimize the handling time of the vessel which is given by the latest completion time of all discharging and loading operations (the so-called vessel makespan). QC scheduling is subject to various practical constraints. For example, to convey containers, QCs move along the quay on a single rail track and are not allowed to cross one another, referred to as non-crossing constraint. Moreover, in order to ensure safe operation, a minimum distance (in number of bays) must be kept between any adjacent QCs, referred to as safety margin constraint. The QCASP extends the QCSP by considering several berthed vessels and the decision on the QC to assign to each of them.

Although there is an abundant literature on the QCSP and the QCASP (Bierwirth and Meisel, 2010; Carlo et al., 2015; Bierwirth and Meisel, 2015; Al-Dhaheri et al., 2016a; Al-Dhaheri et al., 2016b; Kenan et al., 2022), one can note that:

- Some realistic features of the QCSP have been seldom incorporated in the proposed models. For example, despite the importance given by practitioners to vessel stability in crane scheduling, there is little research that considers this constraint. Similarly, safety margin constraints and QC traveling time have not been considered in most of the works.
- Most of the papers that address the QCSP focus on deterministic optimization models and do not consider the dynamics and stochasticity inherent to container terminal operations.
- The extant works do not integrate environmental considerations. A recent stream of research has been devoted to carbon emission and energy consumption at ports though (Bjerkan and Seter, 2019).

At this level, it is worth stressing the importance of integrating environmental aspects in port operations. Indeed, container terminals are presently facing a pressure, like never before, to reduce their carbon emissions. This pressure is entailed by the commitment of the International Maritime Organization (IMO) to reduce international shipping emissions by at least 50% by 2050 compared to 2008 (International Maritime Organization, 2018). It can be followed by the enforcement, in the medium- or long-term, of carbon mitigation policies such as carbon tax and carbon cap-and-trade (Parry et al., 2018; Kachi et al., 2019).

This work is aimed at contributing to fill the above-mentioned three research gaps.

For a more thorough literature review on seaport operations, we refer the reader to (Bierwirth and Meisel, 2010; Carlo et al., 2015; Bierwirth and Meisel, 2015; Al-Dhaheri et al., 2016a; Al-Dhaheri et al., 2016b; Kenan et al., 2022).

2 The quay crane scheduling with consideration of stability constraints

2.1 Problem description and formulation

The considered QCSP tackles a single vessel divided into a set of bays. The workload is expressed in number of work units, where a work unit is a considered fixed number of containers. The workload on the vessel can be processed by a set of identical QCs. Each task refers to container unloading or loading operations to be handled on a bay. Preemption is allowed since a single bay can be assigned to multiple QCs. Nevertheless, at any time, at most one QC can operate on a bay. Each QC has an initial bay position and is ready to commence service at time 0. All QCs are mounted on the same track and can move from one bay to another without crossing. The traveling time between two consecutive bays is constant. A safety margin of ν bays is maintained between each two adjacent QCs. In order to enforce non-crossing and safety margin constraints, a temporal distance should be incorporated in the schedule to separate the processing of containers located in two different bays when processed by two different QCs. The latter is adapted from (Bierwirth and Meisel, 2009).

One of the main contributions of this research remains in incorporating vessel stability constraints in the QCSP. Indeed, the stability of the vessel is violated if the vessel's center of gravity (CG) shifts too much toward one side during the loading or unloading process. This shift results from workload distribution along the vessel and the sequence of operations. Henceforth the incorporation of vessel stability constraints allows for obtaining QC schedules that can be used in practice. In particular, the proposed model ensures the longitudinal stability of the vessel throughout the whole service process. While assuming that initially the vessel's CG is located at its middle point, the shift of the vessel's CG is determined for each time unit based on the distribution of the finished work along the vessel, the average weight of a work unit and the weight of the vessel before starting operations. Nevertheless, the model can be easily accommodated to consider other possible initial positions of the vessel's CG. Vessel stability constraints allow to respect the permitted shift of the CG of the vessel.

Adopting a time-based formulation, the QCSP at hand is modelled as a MIP. The objective is to minimize the makespan of the schedule in order to provide the fastest possible service to the vessel and increase container terminal throughput. Beyond the constraints allowing for the respect of the above-mentioned problem features, some constraints are added in order to identify the completion of a task based on the processed workload on each bay and determine the makespan, i.e. the latest completion time among all bays involved in the service.

Since it considers non-crossing constraints, the considered QCSP is NP-hard (Guan et al., 2013).

First, in order to strengthen the MIP formulation and speed up the solving time, valid cuts related to the safety margin condition are added. The latter imply that at any time, at most one QC can operate on any $\nu+1$ consecutive bays.

Second, unidirectional QC scheduling, in which the QCs do not change the moving direction after the initial repositioning and have identical directions of movement either from upper to lower bays (referred to as right-to-left QC movement) or vice versa (referred to as left-to-right QC movement), is the preferred policy in practice (Legato et al., 2012). Reducing the search space to unidirectional schedules might allow for finding a good solution to the

original problem within reasonable computational time (Bierwirth and Meisel, 2009). Therefore, it might represent a good strategy for solving the considered QCSP heuristically. This can be achieved by solving, for example, the proposed MIP while adding the constraints that restrict the direction of QCs' movement. Evidently, amongst the two unidirectional QC schedules, we retain the one with the lowest makespan. However, even when we reduce the search to unidirectional schedules, an optimal solution (using off-the-shelf solver) can only be reached, within a reasonable computational time, for small-sized instances. That is why we propose a Genetic Algorithm (GA) based heuristic to solve this problem.

2.2 Solution approach

The general structure of the GA is illustrated by figure 18. It starts by randomly generating an initial population of chromosomes. Each chromosome encodes a solution of the problem and entails a fitness value derived from the value of the objective function for that solution. In the proposed GA, a chromosome is a matrix whose columns represent the bays of the vessel while rows represent the QCs. Each element of this matrix specifies a bay's work units assigned to a QC.

As the proposed GA embraces the strategy of searching a good solution to the considered QCSP within the space of unidirectional schedules, the sequence of bays to be processed by each QC is thus determined based on a unidirectional operating mode. First, the left-to-right and the right-to-left unidirectional schedules that account for the travel time and the non-interference constraints, are represented through a properly defined disjunctive graph model. Let us denote, hereafter, these schedules by S^L and S^R, respectively. The makespan of each schedule is determined by the longest path of the corresponding disjunctive graph. Hence, the Critical Path Method (CPM) is then used to determine the longest path and so the makespan of each schedule. We consider that in S^L and S^R the QCs perform their operations on bays at their earliest start time (i.e. QCs do not stay idle while they can start processing a bay). If S^L and S^R violate vessel stability constraints, the chromosome is discarded by setting its fitness value to 0. If vessel stability constraint is respected by S^L and S^R, then the schedule that minimizes the makespan is retained. Otherwise, the feasible schedule among S^L and S^R is retained. Let us denote by S the retained schedule for the chromosome. The fitness of the chromosome is set as follows: $F = \frac{1}{Cmax(S)}$

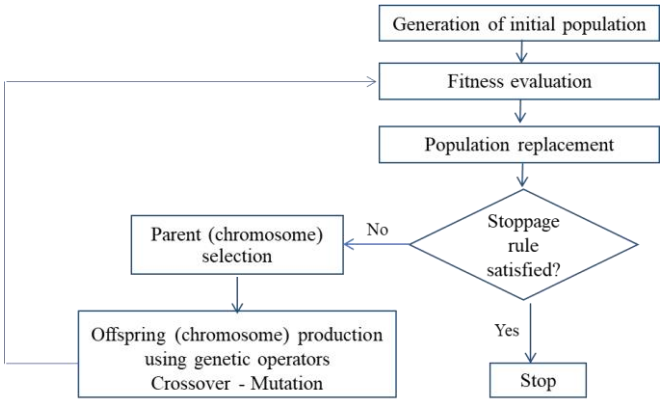

Figure 18. Procedure of the proposed GA

Then, during each iteration step (referred to as "generation"), crossover and mutation are employed to breed offspring (new chromosomes) from two parent chromosomes, that are

selected based on their level of fitness. The quality of the population should keep improving along with generations through the selection process of better fitted genes as occurs in the natural evolution of individuals (Goldberg, 1989). The GA is run until a suitable solution is found or a certain number of iterations (generations) is reached.

2.3 Lower bound for the assessment of solution quality

A combined lower bound, $LB=\max\{LB1, LB2\}$, where *LB1* and *LB2* represent two lower bounds of the considered QCSP (without including any restriction on the search space) is determined. This is particularly needed to assess the quality of the GA solution for problem instances that cannot be optimally solved within reasonable computational time, and for which linear programming relaxation cannot provide a good lower bound.

LB1 is determined by a dynamic programming algorithm (LBA), adapted from the dynamic programming algorithm ALB, proposed in (Guan et al., 2013). The foundation of ALB stems from the observation that when preemption is allowed and safety margin and vessel stability constraints are not considered, in an optimal solution, each QC will serve consecutive bays (Guan et al., 2013). Under this scenario, ALB provides a lower bound for the preemptive QCSP and therefore a lower bound for the preemptive QCSP that considers safety margin and vessel stability constraints. In LBA, we improve ALB by incorporating the range of bays that can be served by each QC. Indeed, this allows to exclude some of the schedules that do not respect the safety margin from the search space. Nevertheless, this will not guarantee finding a solution that satisfies all safety margin constraints.

As highlighted by Lu et al. (2012), in a feasible schedule at any time there can be at most one QC processing any $\nu+1$ consecutive bays. Building on this finding, the maximum time to process the work units of any $\nu+1$ consecutive bays (referred to as *LB2*), represents another lower bound of the makespan.

More details on the proposed MIP, GA and LBA can be found in (Al-Dhaheri et al., 2016a).

2.4 Main results

The performance of the proposed MIP formulation when solved with GAMS and the effectiveness of the developed GA are evaluated by solving small, medium, and large-sized problem instances.

In all instances, QCs are assumed to be equally located on the vessel at time 0. The traveling time of a QC between adjacent bays is set to one time unit and the safety margin is set to one bay. For each QC, the service rate is set to one work unit per time unit. The permitted shift of the vessel's CG is assumed to be of one bay length. The average weight of a work unit is set to 1 and the weight of the vessel before starting operations is assumed to be around 4 times the total number of work units on the vessel.

Small-sized problem instances

Thirty small-sized instances are considered. The number of QCs ranges from 2 to 5 and the number of bays ranges from 8 to 12. For each number of QCs and bays, five problem instances, with different workload at each bay, are generated. The workload of each bay in number of work units is randomly generated from a uniform distribution of $U(0,20)$.

GAMS is used to find the optimal objective value of the unidirectional schedule and wherever possible, the optimal objective value of the bidirectional one, within a time limit of four hours. The same instances are also solved by the proposed GA. Based on the preliminary tests, the population size, the probability of crossover, the probability of mutation, and the maximum number of generations are set to 50, 0.8, 0.2, and 50, respectively. Each problem instance is solved 10 times. If the optimal objective solution of an instance is not provided by GAMS within the computational time limit, the corresponding best lower bound is determined. This best lower bound is the largest value amongst *LB* and the lower bound provided by GAMS.

An optimal unidirectional schedule is obtained for all the considered small-sized instances. Moreover, for 90% of the considered small-sized instances, GAMS returned the optimal unidirectional schedule in less than 30 minutes. Nonetheless, an optimal schedule (bidirectional) has been found only for 19 instances and with an excessive computational burden. An optimal unidirectional schedule bears an optimal solution of the problem on 21 out of the 30 small-sized instances. Overall, the average optimality gap between the optimal unidirectional schedule and the optimal one, is 0.85%. This confirms that the search for a unidirectional schedule is a good strategy to find an optimal or a near-optimal solution to the considered QCSP. Moreover, it is worth mentioning that for 18 out of the 30 instances, the proposed lower bound *LB* either equals the optimal objective value or outperforms the lower bound provided by GAMS. Based only on *LB*, the average optimality gap between the optimal unidirectional schedule and the optimal one, amounts to 2.61%, with a maximum value of 13.79%.

In addition, GA returns the optimal unidirectional schedule for all small-sized instances. The computational time to obtain the GA solution (the average computational time to obtain a GA solution is 6.28 seconds) is markedly lower than the one spent to obtain the GAMS solution (the average computational time to obtain the optimal unidirectional schedule using GAMS is 591.30 seconds). This indeed highlights the major advantage of the proposed GA.

Medium and large-sized problem instances

The GA is used to solve thirty medium and large -sized instances. In these problem instances, the number of QCs ranges from 2 to 6 while the number of bays ranges from 15 to 25. For each number of QCs and bays, five problem instances, with a different workload at each bay, are generated. The workload of each bay in number of work units is randomly generated from a uniform distribution of $U(0,100)$. In these experiments, the parameters of the GA are maintained similar to those used for small-sized problem instances, except for the number of generations. The latter is tuned based on problem complexity as revealed by preliminary tests conducted on instances characterized by the same number of QCs and bays. Accordingly, the number of generations is set to 50, 100, 150 or 200.

For the considered medium and large -sized problem instances, GAMS is not able to reach a solution within the time limit. However, the GA delivers solutions for these problem instances within reasonable computational time (the average computational time is less than 30 minutes for 22 out of the 30 problem instances). *LB* is used to estimate the optimality gap. Interestingly, for all instances, *LB* is obtained in a very short time (less than 1 second). As it can be seen from figure 19, on average, both the computational time and the optimality gap increase when the number of bays increases and/or the number of QCs increases. More

computational effort is indeed needed for instances of larger sizes to better explore the unidirectional search space. For the most intractable instances, the computational time of the GA does not exceed 50 minutes and the quality of the obtained solutions is acceptable. These results can only favor the recommendation of the proposed GA for use, particularly, in medium and large size problems.

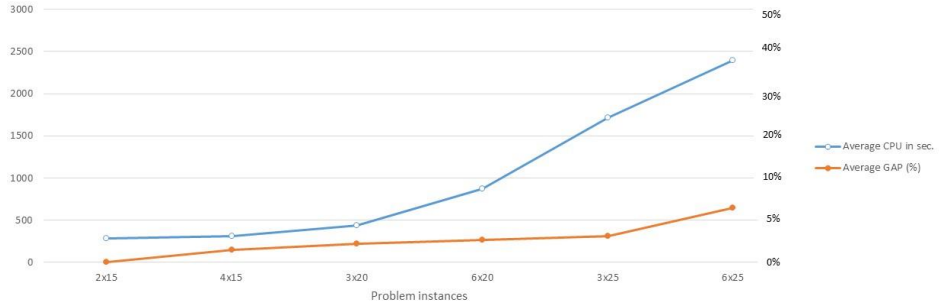

Figure 19. GA performance – Medium and large-sized instances

3 The QC scheduling with consideration of uncertainty

3.1 Problem description and formulation

As noted above, most papers in the QCSP literature do not consider the dynamics and uncertainty inherent to container terminal operations. For example, they assume that QCs are characterized by a constant handling rate and so do not consider the randomness in container processing time. Additionally, they ignore the QC idleness that may be incurred by landside operations and related randomness. The handling time of a vessel is indeed the output of the entire discharging/loading process that certainly involves seaside operations but also, transfer operations taking place between the quay and the stacking yard. Here we investigate QCSP while taking into account the dynamics and uncertainty related to QC and straddle carriers' (SC) operations. The consideration of this type of shuttle vehicles is motivated by their common deployment in medium and large size deep-water terminals such as Khalifa port in Abu Dhabi. After discharging an import container from the vessel, the QC places it on one of the lanes, located on the quay underneath it, and which serve as a buffer area. As soon as one SC becomes available, it picks it up from the lane and transports it to the stack where it is stored at the designated position. If the buffer area is full, the import container remains held by the QC until a lane becomes available. This incurs an idle time for the QC. Similarly, a SC might wait for a container to be placed on the lane before starting pick up operation. This situation rather incurs an idle time for the SC. For loading operations, first the SC picks up an export container from the stack and drops it down at one of the lanes. Then, the QC loads it on the vessel. If the buffer is empty, the QC waits until the SC brings a container and places it at one of the lanes. This situation incurs an idle time for the QC. On the other hand, the SC can arrive to the QC and waits for a lane to become available.

We start by devising a mathematical formulation of the considered stochastic QCSP. The objective is to minimize the expected makespan. Both QCs and SCs operations, the uncertainty tied to their durations and resulting idleness, are considered. More precisely, in the considered problem, three parameters are assumed mutually independent random variables with known probability distribution: (1) the handling time of a container by a QC, (2) the time for a SC to pick up a container and (3) the time for a SC to transport the container to the stack, store it and come back to the quay (referred to as SC round-trip time).

The model accounts for all the constraints introduced in 2.1, at the exception of the stability constraints. In addition, it takes into account constraints related to SCs' operations and their interaction with QCs' operations.

For problems of practical size including the discharge of a large number of containers, the proposed model cannot be solved using off-the-shelf solver within reasonable time even when stochastic parameters are replaced by their expected values (Tang et al., 2014). Therefore, we propose a simulation based GA to solve the tackled stochastic QCSP.

3.2 Solution approach

The GA proposed in subsection 2.2 is extended by: (1) embedding a simulation Monte Carlo model to evaluate the fitness of each chromosome (or solution) and (2) adding a local search in an attempt to improve the solution.

Recall that the fitness is determined based on the expected vessel makespan. The latter is estimated while considering QC idleness entailed by the dynamics and the duration of QCs and SCs' operations under each scenario of the generated sample of size *L*, used in the simulation.

The local search is used whenever an improvement of the so-far-best solution occurs during GA process. The idea is to reduce the expected vessel makespan through the elimination of a part of the expected QC idleness. Therefore, the expected idleness of each QC while serving each bay is determined by simulation. The QC *i* having the highest expected idleness is selected. The highest and lowest index of bays served by QC *i* are determined. QC *i'* that can process these two bays and having the lowest expected idleness is determined. The containers assigned to QC *i* are reassigned to QC *i'*. The newly generated chromosome is evaluated by simulation and replaces the best-so-far solution in case it achieves a lower expected vessel makespan (i.e. a higher fitness).

The simulation based GA terminates when the maximum number of generations is reached. The flowchart of the proposed solution procedure is given by figure 20. The formulation and simulation based GA are detailed in (Al-Dhaheri et al., 2016b).

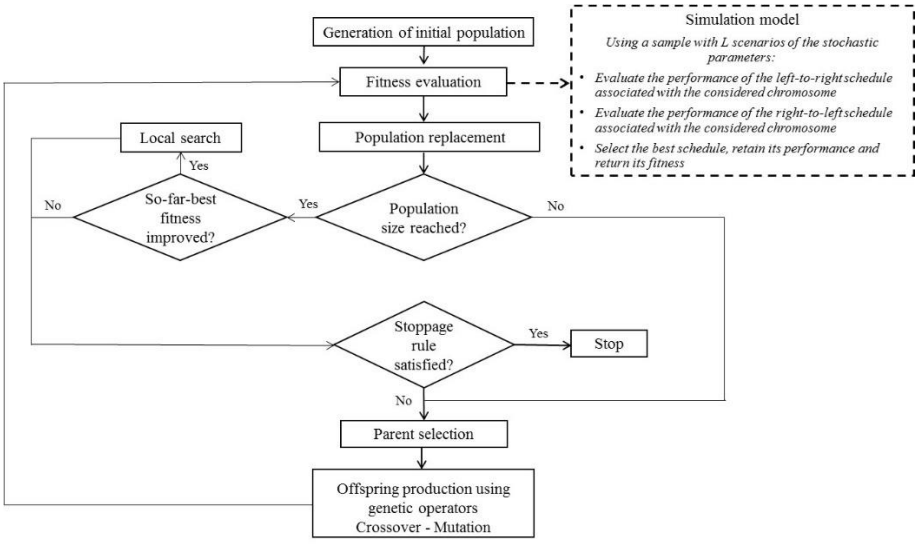

Figure 20. Procedure of the proposed simulation based GA

3.3 Main results

Fist, experimentation is conducted in order to tune the parameters of the simulation based GA. The results showed that a reasonable trade-off between computational time and the quality of the best solution found can be attained for a population size, a crossover rate, a mutation rate, a number of generations and a sample size of 50, 0.8, 0.2, 100 and 200, respectively. It is worth noting that all presented results hereafter are based on those parameters' values and 10 runs of the proposed algorithm.

In order to evaluate the performance of the proposed simulation based GA, 9 problem instances are generated while varying the number of employed QCs from 2 to 4 and the number of SCs assigned to each QC from 2 to 4. In all instances, we consider a vessel with 20 bays, and that in the buffer area, 6 lanes are available beside each bay to drop down containers before transporting them to the yard stack. The traveling time of a QC between adjacent bays is set to 1 minute and the safety margin is set to 1 bay. For each QC, the handling time of a container follows 32-Erlang distribution with an expected value of 2.45 minutes. The time requested to lift a container from the lane follows 16-Erlang distribution with an expected value of 1.67 minutes. The SC round-trip time follows a Weibull distribution with a mean value of 10.2 minutes and a shape parameter equal to 1.28. It is worth noting here that these service times and the number of containers to be discharged from each bay of the vessel have been extracted from the real-life case study presented in (Legato et al., 2010).

The simulation based GA is used under both stochastic and deterministic environment. Under deterministic environment, the simulation based GA employs only one scenario in which the stochastic parameters are substituted to their mean values when evaluating the fitness of each chromosome. Let us denote by S1 the QC schedules obtained under stochastic environment and, by S2 those obtained under deterministic environment. The simulation model is furthermore used to evaluate the solutions S1 and S2; the sample size is set to 1000 in order to obtain more accurate estimates of solutions' performances.

Table 19 reports the obtained results. For each solution S1 and S2, we provide the expected vessel makespan (E.Cmax) and vessel makespan (Cmax) obtained by the simulation based GA (in minutes), respectively. Moreover, table 19 gives for each solution S1 and S2, the average computational time (Avg. CPU) to obtain it (in seconds), the expected vessel makespan obtained by the simulation model (S_Cmax) and its standard deviation (S_Sd).

Table 19. Results – Simulation based GA

N. QCs	N. SCs per QC	E.Cmax S1	Avg. CPU S1	Cmax S2	Avg. CPU S2	S_Cmax S1	S_SdS1	S_Cmax S2	S_Sd S2
4	4	1778.00	3160.24	1751.65	16.28	1779.73	32.87	1800.39	34.3
	3	2366.98	3365.74	2324.77	14.94	2364.04	45.88	2378.28	47.22
	2	3523.86	2979.93	3485.41	12.45	3527.53	67.17	3577.11	72.32
3	4	2350.29	3531.99	2303.46	16.44	2355.29	41.9	2356.17	42.43
	3	3126.47	3286.35	3066.64	15.55	3126.61	54.42	3133.09	56.85
	2	4676.83	2842.20	4595.38	13.06	4684.8	84.86	4689.22	86.62
2	4	3500.91	3861.84	3461.28	18.01	3507.95	53.18	3509.11	54.67
	3	4650.73	3133.34	4607.45	17.05	4658.42	74.07	4659.86	76.36
	2	6973.01	2693.98	6907.99	11.72	6976.02	109.69	6987.86	116.4

Table 19 shows that the expected makespan increases when the number of SCs assigned to each QC decreases. Similarly, with a same number of SCs assigned to each QC, the expected

makespan increases when the number of QCs decreases (also meaning that the total number of deployed SCs decreases). Moreover, it can be observed that the variance of vessel makespan increases when the number of SCs assigned to each QC decreases.

The average computational time to obtain S1, even though it can be considered acceptable, it is much larger than the one needed to obtain S2. The comparison between S1 and S2 based on simulation shows that S1 slightly outperforms S2. However, the comparison between the value of vessel makespan obtained by the solution procedure under deterministic circumstance (Cmax S2) and its estimate obtained by simulation (S_Cmax S2), stresses the importance of considering the randomness related to QCs and SCs operations. Based on these results, one can opt for embedding a deterministic simulation model inside the GA framework in order to significantly reduce the computational time. Nevertheless, the final solution must be evaluated through the stochastic simulation model in order to obtain more realistic and reliable performance of the proposed QC schedule. It is worthwhile to note that if the standard deviation of vessel makespan obtained by the stochastic simulation takes high values, it becomes more appropriate to use the simulation based GA under stochastic environment.

4 The Integrated QCASP with consideration of carbon emissions

Several studies have concluded that vessels at berth and cargo handling equipment are the two major sources of carbon emissions in ports (Yun et al., 2018; Styhre et al., 2017; Corbett et al., 2009). Moreover, carbon emissions resulting from container terminal operations are often correlated to the efficiency of vessel handling. The latter is indeed aimed at reducing vessel turnaround time at port which results in less energy consumption from berthed vessels and QCs. Furthermore, as mentioned above, enacting carbon mitigation policies in ports, such as carbon tax and carbon cap-and-trade, might happen in the next few years.

Our previous research on QCSP is extended here in order to investigate the QCASP with consideration of these two carbon mitigation policies. Indeed, although there is an abundant literature that tackles QCASP, to the best of our knowledge, there are no works that study it while assessing the impact of such policies on emissions and costs.

Two MIPs have been devised. The first formulates the QCASP with consideration of carbon taxation. The main principle of this policy is that carbon emissions from the QCs and vessels involved in the considered processes are taxed. The objective function minimizes the sum of the penalty/rewards due to vessel departure delay/earliness, the operating cost of QCs including the labor cost and the cost due to energy consumption by QCs, and carbon taxation costs. The model accounts for all the constraints introduced in 2.1, at the exception of the stability constraints. In addition, it takes into account constraints related to the assignment of QCs to vessels, and to the determination of the earliness or tardiness of a vessel based on departure time as per the agreement between the port and the vessel. In addition, some constraints allow to determine the waiting and the operating time of each QC. This first model is then adjusted in order to consider cap-and-trade policy. The principle of this policy is that each entity is allocated a cap on the amount of its emissions. In the events of exceeding the allocated cap or having an abundance of unused units, the entity is allowed to buy or sell additional units, respectively. In this second formulation, we introduce the price of purchasing and selling carbon units as well as the cap on carbon emissions. Decisions include the amount of carbon units purchased and the amount of carbon units sold. The objective function is similar to its counterpart in the first formulation, only the taxation cost is replaced

by the purchasing/selling carbon emissions allowance. Constraints that determine the amount of carbon units purchased and sold based on carbon cap are also added.

Results showed that neither policy provides a clear-cut edge over the other in terms of reducing emissions but with the used data, extracted from the industry and literature, carbon cap-and-trade yields slightly lower carbon emissions and costs. Noticeably, the costs associated with the vessels, whether from emissions or delay penalties, have a high weight and hence influence the decisions most. Whether carbon taxation or carbon cap-and-trade policy is implemented, in ports, the focus should be therefore on the vessels staying less and departing as early as possible. This is because even with the implementation of optimal QC operations, the reduction in emissions remains insignificant, especially in comparison to those of the vessel. For example, berthing the vessel when it arrives to the port, with no wait, can substantially reduce carbon emissions. Increasing the number of operating QCs is the most decisive factor in reducing emissions for berthed vessels, as it contributes to reducing vessel handling time, but comes at the expense of acquiring these QCs.

5 Concluding remarks and future research

In this research, we start by investigating the QCSP. First, we propose a novel MIP model for the QCSP that takes into account several practical features of the problem, such as preemption, non-crossing, safety margin, QC traveling time, QC initial position and vessel stability. A Genetic Algorithm (GA), embracing the unidirectional search strategy, is then designed to solve the problem. The results demonstrate that the proposed GA can optimally or near-optimally solve the problem within a reasonable computational time. As such, they foster its use as a solution approach, especially for medium and large sized problem instances that off-the-shelf solver fails to solve.

This first work has been thereafter extended by considering the dynamics and randomness related to QCs and SCs' operations taking place between the vessel, the quay and the stacking yard. First a stochastic mixed integer programming model is proposed. A simulation based GA approach is then developed to generate the QC schedules. The proposed algorithm is tested under both stochastic and deterministic environments. Furthermore, the obtained solutions are evaluated more accurately using simulation with a larger sample size. Results show that the algorithm provides better QC schedules when it is used under stochastic environment but at the expense of higher computational burden. It has also been noted that the intended QC performance in terms of utilization rate cannot be reached without employing a sufficient number of SCs. Given that the QCs represent one of the major valuable resources at container terminals, it is worth to further investigate the SCs to assign to each QC while taking into account more details regarding yard congestion and containers' stack location. Also, it is noteworthy to investigate other SCs deployment strategies such as pooling, where SCs are assigned to vessels rather than to QCs.

More recently, we addressed the QCASP with consideration of carbon mitigation policies, namely carbon tax and carbon cap-and-trade. Results indicate that future work should study the impact of these regulatory policies while integrating berth allocation with QC assignment and scheduling. In particular, uncertainties related to vessels' arrivals will be considered. Thereafter, transfer operations taking place between the quay and the yard using shuttle vehicles such as trucks, AGVs and SCs will be integrated in the work to provide a more accurate estimation of the expected emissions in port premises.

Part IV

Ongoing Work and Research Perspectives

Our research aimed at developing models and solution approaches that support managers in making effective and efficient decisions. For that, it always starts from a decision problem encountered in real-life with an important impact on the concerned industry, and more broadly on the economy and the society. Evidently, the considered problems are characterized by a high complexity and that is why they are attractive for research. As such, they require the development of novel modelling and solution approaches that allow for integrating, incrementally, some of problem's realistic features.

Several problems related to the domains of healthcare management, supply chain design and planning, and maritime and airline logistics have been addressed. As mentioned above, most of the contributions consisted in accounting for more realistic features of these problems. The interest for some of the tackled research topics has been sparked by new problem features stemming from latest technology advances, changes in the regulatory context, or have emerged in the sequel of a crisis such as the COVID-19. Novel models and/or solution approaches are devised in order to incorporate the new problem's feature. My goal in research is henceforth to contribute in creating scientific value that aids practitioners to sustainably create value in the production of services and goods. What nurtures my motivation is the soaring need of practitioners for relevant research findings, accounting for real-life features of the decision problems they encounter, that allow to derive useful managerial recommendations and insights and create value.

The above-mentioned goal and motivation guided my previous and ongoing research; and they will continue guiding my future research. To achieve that, two objectives are sought in my future research: (1) deepen and capitalize on the research I have dealt with; (2) direct my research toward novel and topical research subjects.

The first objective pertains to the development of more sophisticated solution approaches and/or the extension of some of the current research by investigating them jointly with other related problems. More specifically, future work will include the development of advanced solution approaches for operating room planning and scheduling, and ambulance relocation. In addition, I intend to extend the study of operating room planning by including daily operating room scheduling under uncertainty. As can be noticed, operating room planning and daily scheduling are interrelated and both are determinant of operating room performance. Henceforth, developing an approach that integrates them with consideration of patients' clinical path will devise hospitals with a more holistic decision-making approach. The latter will support hospitals in managing efficiently not only operating rooms but also other hospital scarce and costly resources such as the beds in the ICU, etc.

Furthermore, I intend to deepen my very recent research on green maritime logistics and the design of closed-loop supply chain (CLSC) for durable products since the consideration of environmental aspects and the evolution toward a circular economy are becoming a socio-economic priority.

In addition, the COVID-19 health crisis reveals that supply chain resiliency is not sill comprehensively understood. Some recent works foster to target supply chain viability, in order to avoid supply chain market collapse and secure the provision of goods and services in cases of extraordinary event such as pandemic (Ivanov, 2020); a new concept in supply chain management literature, that needs to be dug more in-depth. The need of companies for further understanding of resiliency and viability, how they can be achieved and their impact on

supply chain performance, sparked my interest. One of my projects is henceforth devoted to this topic.

Finally, I would like to point out that in my future research, I will try to validate the proposed models and solution approaches using data stemming from real-life cases. This, undoubtedly, will lead to add value to the research outcomes and result in high impact studies. For that, I intend to involve in my future research projects socio-economic partners.

More details on my ongoing and my main future research projects are described below.

Toward a holistic approach for operating room planning and scheduling

Operating room planning and scheduling involves four different hierarchical decision levels: strategic, tactical, offline operational, and online operational (Hans and Vanberkel, 2012). The strategic level addresses the dimensioning of OR time among different patient surgical groups (often referred to as case mix planning), typically with a long-term planning horizon (e.g., a year or more). The tactical planning level assigns the OR time surgery specialties or surgeons over a medium term (e.g., several weeks). This level usually provides the so-called Master Surgery Schedule (MSS) which defines the number, type, and opening hours of available ORs, as well as the allocation of OR time among surgical specialties or surgeons. The offline operational level usually includes the selection of elective patients to operate each day of the planning horizon (generally of one week) and scheduling decisions and daily surgery sequencing. The online operational level handles the monitoring and control of the process during OR schedule execution. When operating rooms are shared between elective and emergency patients, this fourth decision level encompasses the insertion of emergency cases.

Given the complexity of each of the above-mentioned decisions (Wang et al., 2021; Aringhieri et al., 2022) and the data available when they are needed (Jebali, 2004), they are generally treated separately, although this leads to sub-optimal decisions and performance of the operating rooms. From another perspective, the improvement of the extant modelling and solution approaches proposed for these decision problems, even without integration, remains one of the research objectives in this field.

As far as operating room management is concerned, it is worthwhile to distinguish two common practices in hospitals, namely block and open scheduling. In block scheduling, surgeons are guaranteed blocks of specific OR times on specific days of the week, whereas in open scheduling there are no guaranteed allocations and cases are booked on a first-come, first-served basis. Some operating rooms use flexible block scheduling that combines open and block scheduling. Under flexible scheduling, some OR blocks are either not allocated, or released if they are unused till a few days (in general one week) before each surgery day. These OR blocks can therefore be used by the surgical specialties/surgeons that face the highest need for OR time (in general during that week). Most of the literature is devoted to block and open scheduling. The works on flexible scheduling are scant even though flexible scheduling can capture the advantages of block scheduling while avoiding the operating room being unused because of lack of demand or the unavailability of a surgeon[1]. Among these advantages, one can cite the elimination of time wastage incurred by the moving time of surgeons amongst operating rooms, restricted delay propagation and less complexity in the

[1] https://hospitalmedicaldirector.com/operating-room-block-scheduling-versus-open-scheduling/

decision problems posed at the offline operational level. Although surgeons in many hospitals would rather prefer block scheduling over flexible scheduling, but it is worth investigating the latter and assessing the improvement it could bring to operating room performance.

As mentioned above, most of the hospitals are using either open scheduling or block scheduling. What is the best practice, including flexible scheduling, to use and what are the determinants of such choice? For example, which practice fits better large operating room suits, or operating room suits where a few operating rooms contain special equipment (such as robotic surgery equipment)? These are important questions that have not sufficiently tackled in operating room planning and scheduling literature.

The aim of this research project is to develop a holistic approach for operating room planning and scheduling that integrates tactical, offline and online operational decisions. This approach will be based on several models and solution algorithms designed for block scheduling, open scheduling and flexible scheduling that should be used according to a specified decision process. Building on my previous work on operating room planning and scheduling (Jebali, 2004; Jebali et al., 2006; Jebali and Diabat, 2015; Jebali and Diabat, 2017), we propose to account for all scarce resources intervening in patient's clinical path.

This project will include the following steps:

- Design a hierarchical decision process for each scheduling practice (namely, block scheduling, open scheduling, and flexible scheduling) integrating the three decision levels (namely, tactical, offline and online operational levels).

In this step, the deployed decision processes under open, block and flexible scheduling will be explored and compared. The objective is to understand in which operating room suits they are used, and what are the determinants of this choice. Improvement of the current processes will be proposed based on this exploration phase. The improved decision process should consider for each involved decision the available data and when those data become available.

- Develop more sophisticated models to deploy in the designed decision processes.

In particular, this step will involve the development of novel models and solutions to build the MSS, the operating room plan (assigning elective cases to operating rooms over a planning horizon of on week) and the daily operating room schedule. The proposed models should consider the uncertainty related to hospital environment, as this constitutes the biggest challenge in the considered decisions. Contribution can be brought in two ways: (1) jointly investigating some of the above-mentioned problems and/or (2) adopting a new methodology in modelling and solving the posed problems. Models integrating some of these problems will be designed in order, for instance, to improve the quality of the taken decisions, mainly at the upper decision level. More concretely, I will investigate the integrated operating room planning and scheduling problem with consideration of uncertainty in the case of open scheduling. Different sources of uncertainty (namely, availability of critical resources intervening in patient's clinical path, resource demand, and the arrival of emergency cases) will be accounted for. A first idea, for example, is to extend the work presented in (Naderi et al., 2021) while accounting for the above-mentioned sources of uncertainty. From methodological perspective, I will use distributionally robust optimization as the uncertain input data is generally not precisely known. Another interesting avenue for future research, will foster the use of machine learning techniques in order to (1) obtain more accurate

predictions of model parameters and (2) better overcome the complexity issue of the tackled problems. More specifically, I intend to embed scenario clustering in solving stochastic programming models. Another perspective will consist in devising simulation optimization approaches, in which multi-level decisions can be addressed while taking into account uncertainty within a reasonable computational burden.

In the frame of this project, Gabriela Pinto Espinosa has been recently recruited to pursue a PhD in which she will develop a holistic approach for operating room planning and scheduling. The focus will be put on studying large to medium sized hospitals in Belgium and France, deploying block scheduling. This PhD is launched in collaboration with Erik Demeulemeester from Katholieke Universiteit Leuven (KUL, Belgium) and will start in October 2022.

At the same time, I am planning to extend this project into a research proposal that I will submit for ANR. The project will be conducted in collaboration with other researchers in France and involve hospitals as partners

Green port operations

Although there is a soaring pressure to reduce carbon emissions entailed by maritime transportation, the literature on the optimization of port operations with environmental consideration remains relatively scant. In (Kenan et al., 2022), we investigated the QCASP with consideration of carbon mitigation policies, namely carbon tax and carbon cap-and-trade. This first work shed the light on several interesting future research avenues toward greener port operations. Thereafter, we provide some details on those that can contribute to the current literature and at the same time represent some of the most important topics to be presently tackled by terminal ports.

First, the integrated berth allocation and QCASP (referred to as BACASP) under uncertainty will be addressed with considerations of environmental aspects. Several carbon mitigation policies and sources of uncertainties will be investigated. Maritime transportation is indeed frequently affected by several uncertainty factors such as weather conditions and equipment failures (Rodrigues and Agra, 2021), that are at the origin of the uncertainty inherent to vessel arrival and handling time. As revealed by many works (Murty et al., 2005; Han et al., 2010; Rodrigues and Agra, 2021), this uncertainty may affect the efficiency of port operations if not proactively accounted for. As such, this research can be viewed as an extension of the recent works of Wang et al. (2018), Wang et al. (2020) and Rodrigues and Agra (2021). Sophisticated modelling and approaches should be developed to overcome the complexity issue of this problem, which will bring a methodological contribution to the literature.

Second, I will develop a holistic approach for the management and synchronization of operations in the port, those taking place before the mooring of the ship, after the mooring, on the one hand, between the ship and the quay, and on the other hand, between the quay and the storage areas. Therefore, my first work will be extended in order to include transfer operations taking place between the quay and the yard using shuttle vehicles such as trucks, SCs or AGVs (electric or alternatively powered vehicles). The objective of this research is to develop models and algorithms for scheduling operations that allow to find the best trade-off between port efficiency, service and carbon emissions. Beyond the development of more sophisticated models and solutions to these complex problems, we aim to assess the impact of deploying more energy-efficient equipment and better synchronization of operations on the

economic and environmental performance of the port. Another research outcome consists in providing management insights that help policy makers finding how ports can reduce their carbon footprint without compromising their operation efficiency.

The first part of this research project constitutes one of the projects I am going to work on this year.

Design of closed-loop supply chain

In many countries, environmental legislation mandates manufacturers to take-back a part of their end-of-life products and/or to ensure their eco-friendly disposal and landfilling. This legislation aims at curbing the harmful environmental impact caused by some end-of-life products and/or recovering their remaining value through the recycling of their valuable materials and whenever possible the remanufacturing of their components. As such, the take-back of end-of-life products yields lower resource and energy usage and could also offer new sources of raw material and revenue.

Environmental legislation primarily emphasizes environment and resource efficiency. However, in terms of regulations and implementation details, one can distinguish a diversity around the world. For example, in the European Union, the Waste Electrical and Electronic Equipment (WEEE) directive enforces the collection, recycling, and recovery of all types of electrical goods, with a minimum rate of 4 kilograms per head of population per annum (Georgiadis and Besiou, 2010). Thereafter, a recast of the WEEEs directive in the European Union introduces recovery targets of WEEEs. Henceforth, manufacturers are required to process a pre-specified fraction of returns or products sold in the market (Jeihoonian et al., 2016; Wang et al., 2018). In some provinces of China, the local governments enacted environmental legislation based on reward-penalty (RP) mechanisms to stimulate the take-back of used products. Under this scheme, the manufacturer receives a reward if the actual recovery rate, hereafter referred to as reverse service level, exceeds a pre-specified recovery target, and, in the opposite condition, the manufacturer should pay a penalty (Wang et al., 2017; Wang et al., 2018).

The collection, recycling, and recovery including remanufacturing is called the reverse supply chain (RSC) as the flows of products are moving from customers to producers, which is opposite to the forward supply chain. Closed-loop supply chains (CLSC) are those where forward and RSCs are considered simultaneously. Obviously, environmental legislation should be accounted for while designing the CLSC as it impacts the take-back decision, the RSC structure, and the CLSC performance in terms of economic and environmental efficiency.

Markedly, although abundant literature has been devoted to study the design of CLSC, scant research explicitly accounts for take-back regulations. Many works assumed a 100% recovery of the return stream in the design of the CLSC network which does not necessarily reflect the take-back regulations with which most comply. A few works (Krikke et al., 2003; Jeihoonian et al., 2016; Jeihoonian et al., 2017) incorporated recovery target in the design of the CLSC network, while others penalized unrecovered returns (Qin and Ji, 2010; Jerbia et al., 2018). To the best of our knowledge, take-back regulations based on RP mechanism have not been considered yet in the design of CLSC network.

In order to start filling the above-mentioned research gap, in collaboration with Ali Diabat, we investigated the design of a multi-product and multi-period CLSC network for durable products with consideration of take-back legislation (Diabat and Jebali, 2021). In particular, this work was motivated by the CLSC for durable products that can be disassembled into different components when they reach their end-of-life, such as washing machines and tumble dryers. At this point, it is worth noting the particular features of the considered design problem pertaining to a company, an original equipment manufacturer (OEM), that is the liable for the take-back of returns. The company produces different products with common components. Various types of facilities are involved in both the forward and reverse chains, namely manufacturing, distribution, inspection/disassembly, and remanufacturing facilities. Some components are remanufactured or recycled while others are properly disposed of. First, mixed integer programming (MIP) model is proposed while assuming a 100% recovery target. The latter is then extended in order to incorporate other take-back legislations, namely regulation based on other recovery targets and regulation based on reward-penalty (RP) mechanisms. Sensitivity analysis is then carried out in order to capture how some model parameters influence the take-back decision, the integration of the reverse supply chain, and its structure when there are no regulatory restrictions on the take-back of returns. In addition, the CLSC performance, in terms of environment and economic efficiency, is investigated under different take-back legislations. The results unveiled that, for the considered case study, a higher reverse service level and CLSC profit can be achieved when a regulation based on RP mechanism is implemented.

The models proposed so far are deterministic. This work will be extended, first, to take into account uncertainties related to the demand and the returns. Another interesting perspective is to study the impact of modular design and component commonality on the configuration and performance of the CLSC. In the first work, even though we consider that there are common components used in the two manufactured products (washing machine and tumble dryer), we do not assess the impact of such product-design strategy on the configuration and performance of the CLSC. Moreover, we intend to incorporate the option of outsourcing inspection/disassembly and remanufacturing in the design of the CLSC. Let us note at this level that the impact of product-design strategy, including commonality, on the CLSC and its operations have been investigated using game theoretic models (Subramanian et al., 2013; Liu et al., 2019). The proposed models do not explicitly consider configurational decisions related to the design of the CLSC network, which is the purpose of this research.

Design and planning for a resilient and viable supply chain

A pandemic can wreak havoc in supply chains, as witnessed in the COVID-19 crisis. In particular, this extraordinary long-term disruptive event demonstrated that the so far known resiliency strategies, namely multiple sourcing, backup suppliers, fortification, etc. could not be enough to protect supply chains in such occurrences. The issue of improving supply chain resilience, adaptability and survivability under such extraordinary disruptions has since then attracted the attention of many scholars and practitioners. Ivanov (2020) introduces a new notion that attributes to a supply chain a special property, the capability to survive and adapt to long-term disruptions by reconfiguring its structure and replanning its performance, namely the viability of the supply chain. Although many works have been recently devoted to defining, understanding and theorizing this novel concept (Ivanov, 2020; Ivanov and Dolgui, 2021; Ruel e al., 2021, to list a few), the latter needs further exploration as the particular criteria that allow for reaching supply chain viability are still not clearly identified. For example, an extensive literature has been dedicated to the design of resilient and/or

sustainable supply chain. How to extend these models to ensure supply chain viability? Which criteria should be incorporated in the design model to reach viability?

The design and planning for resilient and viable supply chains prone to severe disruptions, is at the heart of some of my ongoing works and will constitute one of my research projects in the near future.

In a first work, with Xavier Brusset and Davide La Torre (SKEMA Business School), we studied how the effort invested in terms of implementing protective measures (beyond those imposed by the government) within a production plant could increase its resilience and ensure production continuity (Brusset et al., 2022). This work is presently extended to take into account the service level of suppliers during the crisis period (i.e. the reliability of delivering the quantity ordered in full and on time). The originality of these works is twofold: (1) they integrate an epidemiological model with a production planning model; (2) they introduce the implementation of protective measures as a new resilience strategy for supply chains in pandemic context. In particular, the developed models are recommended for labor-intensive industries, such as the meat industry.

In addition, we are developing an approach for planning the meat supply chain in pandemic context. Indeed, the COVID-19 crisis unveiled the vulnerability of the meat supply chain, one of the most impacted supply chains by this pandemic crisis. The successive demand and supply shocks, the perishability of meat, facility closures in the sequel of workers' infections, substantially weaken the supply chain performance. In the existing literature, a few works handle demand forecasting and supply forecasting in a pandemic context such as the COVID-19. In this research, we propose a comprehensive two-stage approach that embeds a mathematical model for meat supply chain planning and demand and supply forecasting models. One of the contributions remains in identifying the most suitable models for predicting the demand and the supply based on the quality of the planning decisions. A case study is used to evaluate the proposed approach. Managerial insights are drawn in order to help meat supply chain managers adjusting the forecasting and planning models in pandemic context.

Recently, with Xavier Brusset, Davide La Torre, Marco Repetto (SKEMA Business School), and Dmiry Ivanov (Berlin School of Economics and Law), we investigate supplier selection problem considering the novel settings of a pandemic crisis, as the COVID-19 outbreak. We devise a model for supplier selection integrating ripple effect analysis and epidemic modelling. More specifically, the proposed prescriptive forward-looking model provides supply chain managers with the optimal choice over a planning horizon among subsets of interchangeable suppliers and corresponding orders; which will maximize demand satisfaction given their prices, lead times, exposure to COVID-19 infection, and upstream suppliers' risk exposure. Results demonstrate that our model can help reconfigure a supply chain and mitigate the ripple effect that stems from reduced production because of infected workers.

In future research, we are going to investigate the design of viable multi-echelon supply chains. For that, we started by addressing the design of a four-echelon pharmaceutical supply chain network prone to severe disruptions. We intend to explore the effect of (1) technology including digitalization, manufacturing and warehouse process automation, (2) product substitutability, and (3) diversification of the supplier base on supply chain resiliency, viability and cost, especially in pandemic context. Novel models and solution approaches will

be devised to account for new problem features, including the criteria to achieve supply chain viability.

As mentioned above, these research projects will be the subject of research proposals submitted to funding programmes that support research and innovation projects (such as projects ANR, PHC Utique projects, etc.). In addition, in these research projects, we plan to involve industrial partners in order to enhance their socio-economic impact. Setting up and carrying out applied research projects, co-funded by industrial partners, is one of our short- and medium-term objectives.

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