POLYTECHNIQUE MONTRÉAL
affiliée à l'Université de Montréal

Méthodes exactes et approchées pour le problème de planification des soins à domicile

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Thèse présentée en vue de l'obtention du diplôme de *Philosophiæ Doctor*
Mathématiques

Mai 2020

POLYTECHNIQUE MONTRÉAL
affiliée à l'Université de Montréal

Cette thèse intitulée :

Méthodes exactes et approchées pour le problème de planification des soins à domicile

présentée par **Florian GRENOUILLEAU**
en vue de l'obtention du diplôme de *Philosophiæ Doctor*
a été dûment acceptée par le jury d'examen constitué de :

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Nadia LAHRICHI, membre et codirectrice de recherche
Jorge MENDOZA, membre
Stefan NICKEL, membre externe

DÉDICACE

À la beauté du monde,

Qu'elle puisse avoir la chance de perdurer.

"Les hommes n'atteignent en fin de compte que ce qu'ils visent.

Aussi, dussent-ils manquer sur-le-champ leur but,

mieux vaut pour eux viser quelque chose de haut"

Henry David Thoreau

REMERCIEMENTS

Je souhaite tout d'abord remercier mes directeurs de recherche : Louis-Martin Rousseau et Nadia Lahrichi. Je suis conscient de la chance que j'ai eu de pouvoir travailler avec eux durant ces quatre années. Merci pour leurs encouragements et pour leur soutien, aussi bien sur le plan académique que personnel. Si j'ai pris autant de plaisir à faire cette thèse, c'est en grande partie grâce à eux.

Merci aussi à toutes les personnes avec qui j'ai eu la chance de travailler durant cette thèse. Je pense notamment à Antoine Legrain, à David, Pierre et Jonathan d'Alayacare ainsi qu'à John Hooker et Willem-Jan van Hoeve de Carnegie Mellon. Je remercie aussi toutes ces personnes du CIRRELT qui ont fait en sorte que mon doctorat se passe le mieux possible. Je pense en particulier à Lucie L'heureux et Lucie-Nathalie Cournoyer.

Ensuite, j'aimerais remercier Stefan Nickel d'avoir accepté d'être membre de mon jury de thèse et d'évaluer mes travaux. Merci aux autres membres de ce jury, Michel Gendreau et Jorge Mendoza, d'avoir été présents lors de mon oral de proposition de recherche et d'accepter, aujourd'hui, d'évaluer mes travaux de thèse.

Parce qu'une thèse est aussi une aventure humaine, j'aimerais remercier toutes les personnes qui m'ont entouré durant ces années. Du pavillon André Aisenstadt, je pense à Menel, Adrien, Antoine, Matthieu et évidemment Alexis. Je remercie aussi mes camarades de NEIPA que sont Ben, Charles, Lucas et Claudio, le groupe des pirates avec Eliot, Antoine, Thomas, Clément et Josselin et mes amis de Carnegie Mellon, Arash, Musa et Franco. Je souhaiterais aussi remercier ces personnes qui m'ont soutenu dans les moments compliqués de ce doctorat et qui m'ont fait grandir pendant ces quatre années à Montréal, je pense ici à Anastasia, Olivier, Simon, Etienne, Ricci et Xavier. Enfin, merci à Marianne de m'avoir accompagné durant ces derniers mois, ton soutien m'a été précieux.

Pour conclure, j'aimerais remercier ma famille. Malgré la distance, vous avez toujours été présents durant ces quatre années. Merci à mes parents de m'avoir permis de faire les études que je souhaitais et de m'avoir toujours soutenu et encouragé dans mes choix. Si je suis ici aujourd'hui, c'est aussi grâce à vous.

RÉSUMÉ

De par le vieillissement de la population ainsi que le souhait des patients de rester le plus longtemps possible chez eux, auprès de leur famille, la dernière décennie a vu émerger la démocratisation des soins à domicile. Ces services peuvent prendre différentes formes telles que des soins infirmiers (piqûres, changement de pansement), de l'aide à la personne (pour prendre un bain, pour manger) ou encore du soutien psychologique. Au-delà du confort de vie qu'ils permettent chez les patients, ces soins à domicile donnent aussi la possibilité aux gouvernements de réduire le flux de patient dans les hôpitaux, de décentraliser les décisions de soins et de réduire le coût de prise en charge des patients.

Néanmoins, afin de prendre en compte un maximum de patients tout en gardant un haut niveau de service, il a été montré qu'une planification des visites faite à la main était sous-optimale. Pour parer à cela, de nombreux outils d'aide à la décision ont été développés durant les vingt dernières années. Ces outils, capables de prendre en compte les nombreuses contraintes métier rencontrées par les agences de soins à domicile, permettent de créer en quelques secondes ou quelques minutes, des horaires hebdomadaires optimisés pour des dizaines d'employés. Cette thèse porte sur l'élaboration de ces outils d'aide à la décision et sur l'amélioration des processus opérationnels des agences de soins à domicile. Ces améliorations permettent alors de prendre en charge plus de patients, tout en conservant un haut niveau de service et de bonnes conditions de travail pour le personnel infirmier.

Dans la première partie de cette thèse, nous présentons un travail réalisé en collaboration avec une compagnie montréalaise, Alayacare. Dans ce projet, nous listons l'ensemble des contraintes métier rencontrées pour les agences de soins à domicile et nous développons une modélisation du problème sous la forme d'un partitionnement d'ensemble. Pour résoudre le problème, nous développons une matheuristique, se décomposant en deux grandes parties. Tout d'abord un algorithme à voisinage large (LNS) est développé afin d'itérativement générer de nouvelles solutions réalisables et déterminer de nouveaux horaires hebdomadaires possibles pour les soignants. Ensuite, une résolution de la relaxation linéaire du problème de partitionnement d'ensemble, basée sur les horaires trouvés précédemment, est appelée. Sur des instances réelles issues de notre partenaire industriel, cette méthode de résolution a montré que l'on pouvait réduire de 37% le temps de trajet total, mais aussi augmenter de 16% la continuité des soins entre les patients et le personnel soignant.

Dans la seconde partie de cette thèse, nous mettons l'emphase sur l'importance d'avoir une régularité dans les heures et jours de visites des patients. Pour cela, nous prenons en compte

le fait que les patients restent plusieurs semaines dans le système des agences de soins à domicile et donc, lors de l'acceptation de nouveaux patients, il faut prendre en compte les contraintes associées aux patients existants (jours et heures de visite, personne soignante affectée). L'objectif est alors d'accepter le plus de nouveaux patients possibles, tout en gardant les horaires des patients existants inchangés. Afin de résoudre ce problème, nous reprenons et améliorons une décomposition de Benders et nous développons l'idée d'utiliser des patterns de visites pour les patients (comprenant les jours et heures de visite ainsi que l'employé affecté). Les expérimentations faites sur des instances réelles de la littérature montrent que notre nouvelle formulation permet de réduire drastiquement les temps de calcul. Enfin, nous montrons que pour les instances les plus difficiles à résoudre, nous pouvons adapter la LNS présentée dans l'article 1 afin d'obtenir les solutions optimales pour un temps de calcul ne dépassant pas les 20 secondes.

Enfin, le troisième projet de cette thèse consiste à prendre en compte l'aspect dynamique du problème. En effet, nous avons expliqué précédemment que certains patients restaient dans le système durant plusieurs semaines, conservant leurs jours et heures de visites ainsi que leur personnel soignant affecté. Dans cette dernière partie, nous prenons un horizon roulant sur plus d'un an et étudions l'impact des décisions d'acceptation et de planification prises chaque semaine, sur le nombre de visites moyen. Dans ce contexte, nous recevons donc plusieurs offres de patients chaque jour et nous devons décider si le patient peut être accepté et si oui, qui le visitera, quels jours et à quelle heure. Pour cela, nous développons différentes heuristiques et mettons l'emphase sur les effets positifs que permet la flexibilité lors de la planification des visites. Cette flexibilité vient dans un premier temps du moment auquel nous prenons la décision pour l'acceptation des patients (à la réception de l'offre, à la fin de la journée, à la fin de la semaine). L'autre flexibilité vient du fait que l'on va non pas attribuer une heure exacte de visite au patient pour l'ensemble de son plan de soin, mais plutôt une fenêtre de temps, de soixante minutes par exemple, dans laquelle il sera visité. Les résultats de ces différentes heuristiques ainsi que des différentes flexibilités montrent que, sans modifications massives des processus de décision des agences, il est possible d'accepter jusqu'à 12% de visites en plus chaque semaine.

ABSTRACT

Due to the population's aging and people's will to stay at home with family and friends, the last decade has been the decade of home health care services democratization. Those home care services have different aspects such as nursing acts (injection, band-aid replacement), personnal support (bathing, cooking) or social work for the psychological support of the patients. Beyond the fact that those services positively impact patients' life, they also give governments the possibility of reducing flows of patients in the hospitals, decentralize the decisions and reduce the costs.

Nevertheless, keeping up a high level of service for the patients is challenging and it has been shown that the manual scheduling of the visits by the head nurses usually leads to sub-optimal solutions. To cope with this issue, decision-making tools have been developed during the last decades in order to help the home care agencies in this scheduling task. These tools, capable to take into account a large set of practical constraints, allow the users to quickly (in a few seconds or minutes) and efficiently design weekly visit schedules for dozens of nurses. This thesis focuses on the elaboration of efficient decision-making tools and resolution methods in the context of home health care services.

In the first part of this thesis, we present a work realised in colalboration with a company from Montréal, Alayacare. In this project, we list the different practical constraints met by their users (worldwide home care agencies) and we propose a set partitioning-based formulation. In order to solve the problem, we propose a matheuristic, composed of two main elements. Firstly, a large neighborhood search (LNS) method is implemented, allowing to iteratively generate new feasible solutions and retrieve a set of feasible weekly schedules for the different nurses. Secondly, a relaxed version of the set partitioning is solved using the weekly schedules previously found. On real instances provided by our industrial partner, experiments show that our method allows to reduce by 37% the travel time and increase by 16% the continuity of care between the patients and the nurses.

In the second part of this thesis, we focus on the patients' visits' recurrency aspect. To do so, we take into account the fact that patients stay multiple weeks in home care agencies' system and so, when we accept new patients, we have to take into account resource constraints from the existing patients (visit time and days, assigned nurse). The objective is then to maximize the number of new patients accepted without modifying old patients' assignment and scheduling. In order to solve this problem, we extend a Benders decomposition and propose a new decomposition using visit patterns (composed of visit time and days and an

assigned caregiver). Computational experiments show that our new decomposition allows to dramatically reduce the computation times on benchmark instances. For the largest instances, we show that we can adapt the LNS proposed in the first paper using visit patterns and solve optimally all the instances in less than 20 seconds.

Finally, the third research projet consists in taking into account the dynamic aspect of the home health care services. Indeed, we previously presented the fact that patients stay multiple weeks in the system and so have to be taken as constraints when accepting new patients. In this last part of the thesis, we take into account the rolling horizon aspect of the problem (on more than a year) and we study the impact of the weekly decisions over time. The metric corresponds to the maximization of the average number of weekly visits. In this context, we receive multiple patient offers per day and we have to decide which patients we can accept and how they will be scheduled. To solve this problem, we propose different heuristics and focus on the impact of flexibility during the acceptance and scheduling process. On the one hand, this flexibility corresponds to the moment the decision is taken (when the offer is received, at the end of the day, at the end of the week). On the other hand, we also study flexibility on the visit time and propose not to assign the patients an exact visit time, but rather a visit time window. Results show that those heuristics and the flexiblity we propose allow the home care agencies, without drastic modification of their processes, to dramatically increase the average number of weekly visits with up to 12%.

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CHAPITRE 1 INTRODUCTION

Durant les dernières décennies, les conditions de vie de l'ensemble de la population mondiale se sont grandement améliorées, permettant entre autres une augmentation de l'espérance de vie. Ce phénomène, corrélé au baby-boom des pays du Nord, a amené les Nations Unies à prédire que d'ici 2050, le nombre de personnes ayant 60 ans ou plus allait doubler pour atteindre 1.5 milliard d'individus [1]. Si l'on prend le cas du Canada, en 2015, 16.1% de la population canadienne avait 65 ans ou plus avec 5,780,900 personnes. Ce chiffre devrait progresser pour atteindre 20.1% de la population en 2024 [2].

Or, avec l'âge, apparaissent souvent des maladies chroniques, les personnes qui en souffrent requièrent alors de nombreux soins, et ce sur le long terme. Encore une fois au Canada, entre 75% et 80% des personnes âgées de 65 ans ou plus sont atteints d'au moins une maladie chronique [3]. Afin de proposer les meilleurs soins de santé aux Canadiens, l'Association Médicale Canadienne travaille actuellement sur deux objectifs majeurs : créer une société qui soit la plus adaptée aux personnes âgées et développer un continuum de soins permettant d'accompagner les ainés dans leurs problèmes de santé et leur permettre d'avoir un accès simple et efficace à l'ensemble des spécialistes de santé. Ces soins ont cependant un coût, d'après la Banque Mondiale [4] : en 2016, 10% du PIB mondial était alloué aux dépenses de santé. Ces chiffres atteignent entre autres, 10.5% du PIB pour le Canada, 11.5% pour la France et 17.7% pour les États-Unis.

Parmi l'ensemble des services de santé offerts aux personnes âgées, les soins à domicile ont reçu une grande attention depuis une dizaine d'années aussi bien en termes de financements gouvernementaux que du point de vue de la recherche académique. Ces soins à domicile peuvent prendre différentes formes telles que des soins infirmiers (piqûres, changement de pansement), de l'aide à la personne (pour prendre un bain, pour manger) ou encore de la simple présence pour de l'aide psychologique. Ces soins à domicile ont peu à peu montré l'importance qu'ils recouvraient et l'impact qu'ils pouvaient avoir sur la vie des patients. En effet, du fait de ces soins, les patients peuvent rester à la maison, continuer à garder leurs habitudes de vie et rester entourés de leur famille au lieu d'être au milieu de l'agitation des hôpitaux.

Ces soins à domicile permettent aussi de réduire le flux de patient dans les hôpitaux afin de garder des ressources pour les cas les plus urgents et éviter l'infection entre patients. Du point de vue des gouvernements, les soins à domicile permettent de décentraliser les décisions et d'apporter un plan de soin propre à chaque patient. Enfin, les soins à domicile permettent une large réduction du coût d'hospitalisation. Dans [5], les auteurs montrent que le coût journalier d'un patient à l'hôpital en Ontario est de 842$ et ce coût descend à 42$ lorsque le patient est pris en charge à domicile.

En ce qui concerne la demande canadienne en soins à domicile, le Conference Board du Canada a estimé que 2,4 millions de Canadiens âgés de 65 ans ou plus auront besoin de soins à domicile d'ici 2026. Cela représente une augmentation de 71% comparativement à la demande de 2011. Le coût global associé à ces soins à domicile va passer de $29,3 milliards en 2011 à $184,2 milliards en 2046 [6]. Cette accélération de la demande et des coûts qui lui sont associés se retrouve dans la plupart des pays industrialisés. Aux États-Unis, on observe qu'en 2010, environ 12 millions d'individus ont reçu des soins à domicile [7]. D'un point de vue économique, aux États-Unis encore, il a été prédit une augmentation de 21% du nombre d'emplois dans le domaine de la santé sur la période 2014-2024. Cela représente 3,8 millions d'emplois créés. L'industrie des soins à domicile est celle ayant la plus importante croissance sur cette même période [8].

De ce contexte des soins à domicile, il est important de noter que le personnel infirmier constitue un des éléments fondamentaux du système et donc prendre soin du personnel et rendre leurs journées de travail les plus agréables et efficaces possible devient une priorité pour de nombreuses agences de soins à domicile [9]. Entre autres, la prise en compte des facteurs de stress et la meilleure répartition de la charge de travail sont devenues des enjeux cruciaux afin d'éviter un renouvellement de personnel très élevé, atteignant plus de 80% chaque année [10]. En place de l'aspect humain, chaque remplacement de personnel amène à des coûts pouvant atteindre 2600$ (recherche de la personne, entretien, formation) [11]. Depuis plusieurs années maintenant, de nombreux chercheurs ont montré qu'un changement de politique était nécessaire afin d'améliorer les conditions de travail des soignants à domicile et conserver une grande qualité dans les soins prodigués aux patients [12].

Au vu de cette augmentation de la demande en soins à domicile, le rôle des agences devient primordial et ces dernières tentent continuellement d'améliorer leurs processus opérationnels afin de servir plus de patients, tout en conservant une haute qualité de service pour leurs patients et de bonnes conditions de travail pour leur personnel. Par souci de simplification, le terme "infirmière" utilisé dans la suite du document recouvrira l'ensemble du personnel soignant.

Un des enjeux majeurs de ces agences consiste à créer les plannings de soins. Cette planification peut alors se définir en deux grandes parties : l'affectation des patients aux infirmières, et la création des tournées des infirmières, i.e., définir l'ordre dans lequel elles vont visiter les patients et à quelle heure chaque patient va être vu.

Comme nous le verrons dans cette thèse, la génération des horaires des infirmières est une tâche complexe, au sein de laquelle de nombreux enjeux sont à prendre en compte. Premièrement, les besoins des patients doivent être considérés. Cela consiste alors à tenir compte de leurs disponibilités, le nombre de visites dont ils ont besoin, le type de soins particuliers qu'ils requièrent ou encore leurs préférences concernant la personne qui les visite. Ensuite, les contraintes des infirmières doivent être intégrées au problème. On peut alors retrouver un nombre d'heures de travail minimum ou maximum sur la semaine, des disponibilités particulières ou encore la prise en compte de préférences envers certains patients. Enfin, certains enjeux sont associés aux agences de soins à domicile. On devra alors maximiser les revenus de l'agence (réduire les coûts de transport, augmenter le nombre de patients visités) tout en assurant un haut niveau de service et en respectant l'ensemble des conditions de travail du personnel infirmier.

Actuellement, encore beaucoup d'agences de soins à domicile créent ces horaires manuellement. Les infirmières en chef ainsi que les coordonnateurs prennent alors tous les dossiers des patients et tentent de déterminer quelle est la meilleure répartition de ces derniers par rapport aux disponibilités des infirmières. Au-delà du fait que ce processus soit long et fastidieux, il est aussi évident que la complexité du problème mène à des plannings qui sont sous-optimaux et pour lesquels l'allocation des ressources pourrait être grandement améliorée.

C'est sur ce problème de création des horaires que porte cette thèse de doctorat. L'objectif de cette thèse est alors de développer des algorithmes permettant la prise en compte de l'ensemble des contraintes métier rencontrées par les agences de soins à domicile et de permettre la génération de plannings efficients pour la visite des patients. En plus de leur efficacité, ces algorithmes ont aussi la particularité d'avoir des temps de calcul très courts (de quelques secondes à une dizaine de minutes) et donnent donc la possibilité d'être lancés avec de nombreux critères à optimiser, afin de trouver la solution qui correspond le mieux aux besoins et aux attentes des agences.

Nous verrons dans cette thèse, l'ensemble des gains que peuvent apporter des algorithmes d'optimisation dans le contexte des soins à domicile. Nous montrerons que ces algorithmes sont capables de prendre en compte un éventail très large de contraintes (article 1), mais aussi de résoudre en quelques centièmes de secondes des problèmes d'affectation et de routage (article 2). Enfin, nous verrons que ces algorithmes peuvent aussi considérer l'aspect dynamique du problème,i,e, le fait que chaque semaine des dizaines de patients intègrent et quittent les agences de soins à domicile. Dans ce contexte, nous montrerons que la prise en compte d'une certaine flexibilité dans le moment de prise de décision par les agences peut avoir un impact majeur sur le nombre de patients acceptés dans le système (article 3).

Cette thèse est structurée de la manière suivante. Le chapitre 2 présente une revue de la littérature existante autour du problème de planification des soins à domicile. Le chapitre 3 présente les enjeux ainsi que les méthodes de résolutions associées à chacun des articles de la thèse. Le chapitre 4 présente l'article "A set partitioning heuristic for the home health care routing and scheduling problem" publié dans European Journal of Operational Research. Le chapitre 5 présente l'article "New decomposition methods for home care scheduling with predefined visits" publié dans Computers & Operations Research. Le chapitre 6 présente l'article "The Dynamic Home Health Care Scheduling Problem : The Value of Flexibility" soumis à Health Care Management Science. Le chapitre 7 présente une discussion générale des trois articles de la thèse. Enfin, le chapitre 8 donne les conclusions de la thèse.

CHAPITRE 2 REVUE DE LITTÉRATURE

Ce chapitre présente la revue de littérature entourant le problème de planification des soins à domicile. Cette revue de littérature s'articule autour de quatre axes. La section 2.1 introduit les différentes parties prenantes du problème ainsi que les contraintes et objectifs qui leur sont associés. La section 2.2 présente les différentes façons de formuler le problème et d'en appréhender la complexité. La section 2.3 décrit les principales méthodes d'optimisation qui ont été développées pour résoudre notre problème. Enfin, le positionnement des travaux de cette thèse de doctorat est décrit dans la section 2.4.

Avant toute chose, il est important de noter que le problème de planification des soins à domicile est un problème qui n'a pas de définition unique dans la littérature. Cela vient en partie du fait que les contraintes et les objectifs pris en compte lors de sa résolution dépendent du contexte, du pays dans lequel les auteurs placent leur recherche. De plus, même si la communauté semble valider le terme *home health care routing and scheduling problem*, de nombreux autres termes sont utilisés pour nommer le même problème tels que : *Home health care delivery* [13], *traveling therapists* [14] ou encore *Home Health Care Problem* [15].

On notera aussi que deux articles de revue de littérature majeurs ont été publiés en 2017 [16, 17] et on invite donc le lecteur à se référer à ces articles pour une présentation plus détaillée de certains points présentés dans ce chapitre.

2.1 Perspective de chaque partie prenante

Dans cette section, nous présentons les enjeux qui existent, en termes de contraintes et d'objectifs, pour les trois parties prenantes de notre problème que sont : les patients, les infirmières (représentant l'ensemble du personnel soignant) et les agences de soins à domicile. Nous aborderons alors les notions de disponibilités (pour les patients et les infirmières), de contraintes dues aux contrats de travail ou encore l'ensemble des coûts que doivent prendre en compte les agences de soins à domicile.

2.1.1 Contraintes et objectifs reliés aux patients

Les patients sont au cœur du problème que nous souhaitons résoudre. Pour chacun d'entre eux, nous avons toujours une localisation ainsi qu'un certain nombre de visites à planifier sur la semaine. Par la suite, différents aspects logistiques doivent être pris en compte pour prodiguer le meilleur soin possible.

Tout d'abord, les disponibilités du patient doivent être considérées. Pour certains d'entre eux, les jours de visites seront prédéfinis [14] ou devront respecter certains patterns (p.e, mardi-jeudi ou bien lundi-mercredi-vendredi) [13, 18], mais dans la grande majorité des travaux publiés, les patients sont considérés comme disponibles toute la semaine [19–21]. Ces disponibilités sont aussi souvent prises en compte sous la forme de fenêtres de temps. Ces fenêtres de temps peuvent être soit dures [20, 22] ou souples [23–25].

Ensuite, l'affectation des patients doit prendre en compte leurs besoins spécifiques. Certains auront besoin d'une piqûre, d'autres d'un changement de pansement, à ces tâches correspond alors un certain niveau de compétence demandé pour réaliser correctement le soin [26–28]. Un patient peut aussi avoir des préférences envers certaines infirmières [29] et certaines affectations peuvent être interdites dues par exemple à un événement passé entre le patient et l'infirmière [30, 31].

Enfin, un élément majeur pour les patients, est la prise en compte de l'interdépendance qu'il peut exister entre leurs visites. Cette interdépendance se retrouve dans deux types de situations. D'une part, certains patients ont besoin de plusieurs visites dans la même journée et il peut arriver qu'un temps minimum ou maximum soit requis entre ces visites [32, 33]. En outre, des visites peuvent nécessiter deux infirmières simultanément [34, 35]. D'autre part, l'interdépendance entre les visites peut être prise en compte sous la forme de la continuité des soins. Cette contrainte, considérée comme centrale dans le contexte de la santé, correspond au fait de conserver une même planification des visites d'un patient pour l'ensemble de son plan de soin. Cela peut correspondre au fait d'affecter toujours la même infirmière, de le visiter les mêmes jours chaque semaine ou encore de le visiter à la même heure. Cette continuité des soins permet de rassurer le patient, de créer une relation forte avec la personne soignante et par cela, d'obtenir un haut niveau de service. Cette contrainte peut être considérée sous la forme d'une contrainte souple ou dure [36,37]. Le problème se rapproche alors d'un *consistent vehicle routing problem* [38]. Dans certains cas, la continuité des soins est prise en compte sur de longues périodes de temps et alors le patient reçoit la même affectation pour l'ensemble de son plan de soin [39,40]. Enfin, certains auteurs introduisent la continuité des soins comme un nombre maximal d'infirmières différentes que l'on peut attribuer aux visites d'un patient [41].

En ce qui concerne les patients dans le problème que nous étudions, nous pouvons donc résumer en expliquant que l'objectif est de prendre en compte l'ensemble des contraintes issues de leurs plans de soins (nombre de visites, nécessité de certaines compétences, disponibilités à certains moments de la journée) tout en maximisant leur expérience de prise en charge (maximisation de leurs préférences concernant la personne soignante ou le moment de la visite, maximisation de la continuité des soins).

2.1.2 Contraintes et objectifs reliés au personnel soignant

Dans le problème que nous étudions, la gestion du personnel infirmier constitue aussi un élément essentiel. Tout comme les patients, certaines contraintes métier et certaines métriques à optimiser leur sont propres.

Premièrement, nous devons considérer les contrats de travail ainsi que les disponibilités de chaque infirmière. Il existe alors des situations dans lesquelles certaines infirmières travaillent à temps plein, d'autres à temps partiel et d'autres encore sont remplaçantes et reçoivent des heures lorsqu'un manque de ressources se fait sentir [37, 42]. On peut aussi avoir à prendre en compte le fait que certaines infirmières requièrent un temps de travail minimum et maximum dans leurs semaines de travail [15, 43]. Certaines d'entre elles ont des jours ou des quarts de travail spécifiques que l'on doit respecter [44, 45]. Enfin, pour la partie concernant l'affectation aux patients, le respect des compétences propres à chaque infirmière doit être considéré [46, 47].

Deuxièmement, il a été montré que le taux de renouvellement des employés était très élevé dans le contexte des soins à domicile, pouvant atteindre jusqu'à 82% par an [10], chaque remplacement de personnel pouvant coûter jusqu'à 2600$ [11]. Pour éviter cela, nous essayons d'intégrer le bien-être des infirmières dans la planification des visites. Cela se fait en planifiant des pauses durant les tournées [48–50] ou en s'assurant qu'un temps de repos suffisant existe entre deux quarts de travail [26]. Certains travaux ont tenté d'estimer la difficulté psychologique (*burnout level* en anglais) associée à chaque visite et de répartir au mieux cette difficulté sur l'ensemble des infirmières [51]. Cet équilibre de la charge de travail entre les infirmières constitue l'enjeu majeur de certains articles [21, 52].

Pour conclure sur le personnel soignant, il apparaît que la résolution du problème va devoir prendre en compte l'ensemble des contraintes issues des contrats de travail (temps de repos, compétences spécifiques, disponibilités), tout en mettant en place les meilleures conditions de travail pour les infirmières (équilibre des charges de travail, préférences envers certains patients, régularité dans les quarts de travail).

2.1.3 Contraintes et objectifs reliés aux agences de soins à domicile

La troisième et dernière partie à prendre en compte lors de la résolution de notre problème est celle concernant les agences de soins à domicile. Certaines contraintes techniques leur sont rattachées et leur objectif principal est, pour les agences privées, de maximiser leurs revenus et pour les agences publiques, de minimiser leurs coûts, tout en conservant un haut niveau de service.

Dans un premier temps, nous devons donc prendre en compte les contraintes de ressources des agences. Pour cela, nous devons respecter la répartition des infirmières par district [53–55]. Ensuite, il peut arriver que plusieurs moyens de transport soient à la disposition des infirmières (marche, voiture, transport en commun) [56, 57] et que les temps de trajet inter-patients soient variables en fonction du moment de la journée [27, 58].

Dans un second temps, une grande partie des agences souhaitent maximiser leurs bénéfices. Pour cela, elles augmentent le nombre de visites planifiées [59,60] ou maximisent l'acceptation des patients les plus payants [61, 62]. Ensuite, ces mêmes agences essayent de minimiser leurs coûts en réduisant les coûts de transport [63, 64], le nombre d'infirmières nécessaires [49, 64], les heures supplémentaires [65, 66] ou en limitant la sous-traitance de certaines visites [51]. Récemment, certains travaux ont aussi tenté de prendre en compte les enjeux écologiques en minimisant l'émission de gaz à effet de serre lors de la planification des visites [67, 68].

Pour cette troisième partie prenante que constituent les agences de soins à domicile, il apparaît donc que l'objectif va être de maximiser les revenus de ces agences tout en minimisant les coûts et en respectant l'ensemble des contraintes réglementaires vis-à-vis de leur personnel.

Du fait de l'ensemble des enjeux contradictoires qu'il peut exister entre les patients, les infirmières et les agences, le problème de planification des soins à domicile est complexe et peut être modéliser de nombreuses façons. De plus, les fonctions objectifs de ces problèmes sont souvent multi-critères et il est compliqué de déterminer une hiérarchie entre ces différentes métriques.

2.2 Pluralité des représentations du problème

Dans cette section, nous présentons les différentes représentations du problème. Nous montrons tout d'abord que différents horizons de temps peuvent être utilisés. Ensuite, la prise en compte d'aspects non-déterministes est introduite. Enfin, nous introduisons les différentes façons d'appréhender la multiplicité des fonctions objectifs.

2.2.1 Les différentes échelles de temps

La planification des soins à domicile est aussi complexe de par les échelles de temps avec lesquelles les agences ont à travailler. Nous allons voir dans cette partie quelles sont ces échelles de temps et comment elles peuvent s'imbriquer les unes dans les autres.

Tout d'abord, la plupart des agences de soins à domicile ont un modèle d'affaires dans lequel elles reçoivent des offres de prise en charge de patient. Ces agences doivent alors décider si elles peuvent accepter le patient dans leur système (ou bien soit le mettre sur liste d'attente ou le référer à une autre agence) et comment le patient sera visité durant l'intégralité de son plan de soin. Dans ce contexte, le problème de planification est résolu à chaque nouvelle offre de patient. Le problème est alors étudié de façon dynamique [69]. Pour résoudre ce problème, différentes heuristiques ont été développées [59], certaines anticipant les futures demandes sous la forme de scénarios [40, 70].

Ensuite, on peut observer qu'une bonne partie des travaux publiés s'intéressent à la résolution quotidienne du problème [71, 72]. Dans ce contexte, l'acceptation des patients est rarement prise en compte et nous avons un ensemble de patients que l'on tente de planifier tout en assurant les contraintes de ressources infirmières. Cette configuration se rapproche alors d'un problème de tournées de véhicules avec fenêtre de temps [73, 74] avec certaines contraintes propres au domaine de la santé (compétences des infirmières, dépendance entre les visites). La minimisation du temps de trajet est d'ailleurs l'objectif de la plupart des papiers résolvant le problème pour une journée [75, 76].

Enfin, un autre large pan de la recherche s'est intéressé à résoudre le problème sur la semaine [77, 78]. Le fait de planifier sur plusieurs jours permet de prendre en compte les notions de patterns de visites pour les patients [18], de continuité des soins [22, 55] ou encore le temps de travail minimum ou maximum alloué aux infirmières [41, 79].

En observant la littérature et les articles qui ont été publiés ces dernières années, on observe tout de même que la tendance est à la complexification du problème et donc que les travaux les plus récents portent sur des horizons de temps longs tels que la semaine ou le mois.

2.2.2 Prise en compte des aspects non déterministes

En plus de ces différents pas de temps lors de la prise de décision, nous pouvons aussi observer la prise en compte de paramètres non-déterministes pour certaines formulations du problème. On peut notamment citer les travaux prenant en compte les aspects stochastiques et robustes entourant la planification des visites à domicile.

En ce qui concerne les aspects stochastiques, la source d'incertitude la plus présente dans la littérature est celle portant sur la durée du service chez le patient [75,80]. En effet, cette durée est soumise à l'état du patient, aussi bien physique que psychologique, qui peut changer d'un jour à l'autre et l'infirmière doit alors s'adapter à la réalité de chacun des patients qu'elle visite. Les autres sources d'incertitude sont celles portant sur le temps de trajet entre deux patients qui peuvent dépendre du trafic [28, 45], sur l'annulation possible de la visite par le patient [65, 81] ou encore sur la quantité de médicaments dont aura besoin le patient [82].

Pour résoudre ces problèmes stochastiques, différentes méthodes sont proposées dans la littérature. Au niveau de la formulation, on retrouve des programmes linéaires stochastiques [65, 80] ou encore des modèles mathématiques prenant en compte le *chance-constraint* de certains facteurs aléatoires [82, 83]. D'autre part, certains auteurs présentent le problème sous la forme de chaine de Markov [84] ou utilisent des scénarii pour anticiper les différentes occurences des paramètres stochastiques [75]. D'autres travaux ont étudié la prise en compte de certaines méthodes de résolution robustes. Parmi eux, des modèles reposants sur des *cardinality constraints* [55, 85, 86] ou un autre utilisant un budget d'incertitude et des métaheuristiques [87].

2.2.3 Gestion des objectifs

Nous avons vu précédemment que de nombreuses métriques sont à prendre en compte simultanément lorsque l'on planifie des soins à domicile. Malgré tout, nous trouvons dans la littérature certains travaux ne prenant en compte qu'un seul élément dans leur fonction objectif. Les auteurs minimisent alors uniquement le temps de trajet [24, 88, 89], le temps de travail [26], égalisent la charge de travail entre les infirmières [81, 90] ou encore maximisent le nombre de visites [13].

Néanmoins, dans la majorité des cas, les travaux tentent de prendre en compte l'aspect multi-critère du problème. Se pose alors la question à savoir si certains objectifs devraient être priorisés par rapport à d'autres (ajouter une visite supplémentaire plutôt que réduire le temps de trajet par exemple). Dans ce contexte, de nombreux auteurs ont fait le choix d'utiliser la pondération des différents facteurs à optimiser dans une fonction objectif unique [91], certains allant jusqu'à utiliser 13 métriques dans leur fonction objectif [56]. D'autres travaux ont quant à eux étudié la possibilité d'une hiérarchie lexicographique entre les différents objectifs [25, 31], l'utilisation de frontières de Pareto [29, 92] ou encore une hybridation de ces deux dernières stratégies [93].

2.3 Les principales méthodes de résolution

Dans cette section, nous présentons succinctement les différentes méthodes de résolution qui ont été développées. Pour cela, une énumération des méthodes exactes et approchées résolvant le problème de planification des soins à domicile est faite.

Du fait de la complexité et de l'hétérogénéité du problème, les méthodes exactes sont souvent utilisées pour des problèmes de petite taille. Ces méthodes de résolution servent alors de références pour s'assurer de l'efficacité de solutions heuristiques. Parmi ces résolutions exactes, on retrouve une large partie des auteurs qui utilisent des solveurs mathématiques tels que Cplex ou Gurobi [60,78,90,94,95]. Les autres méthodes exactes correspondent aux algorithmes de *branch-and-price(-and-cut)* [26, 45, 96] ou encore aux décompositions de Benders [13].

On retrouve ensuite les méthodes approchées avec notamment les heuristiques. De par la décomposition naturelle du problème entre la partie affectation et la partie routage, des approches en deux phases ont été implémentées [91, 97]. Aussi, certains auteurs ont présenté des algorithmes basés sur de la recherche locale [77, 98].

Dans un second temps, on peut observer que de nombreuses métaheuristiques ont été développées pour résoudre notre problème. On retrouve alors les métaheuristiques utilisées fréquemment pour résoudre les tournées de véhicule telles que les recherches à voisinage variable (VNS) [35], la recherche taboue [15, 99–101] ou le recuit simulé [63, 102]. De plus, des méthodes utilisant le principe des colonies de fourmis [103] et la recherche d'harmonie [104] ont été développées.

Enfin, la troisième classe de méthodes approchées correspond à celle des matheuristiques. Ces approches se placent à la frontière entre la programmation mathématique et les métaheuristiques et permettent d'allier les qualités de chacune de ces méthodes. Parmi ces stratégies, on retrouve des combinaisons entre des résolutions exactes à l'aide de solveurs mathématiques et des heuristiques constructives [24], de la recherche à voisinage large [20] ou de VNS [44]. Dans [105], une série de programmes linéaires est résolue séquentiellement. Il est intéressant de relever le fait que certaines des matheuristiques développées dans la littérature sont capables de résoudre des problèmes avec des milliers de visites [36, 64, 106].

2.4 Positionnement des travaux de la thèse

Comme décrit dans les sections précédentes, le problème de planification des soins à domicile est un problème complexe mettant en jeu de nombreux acteurs. De plus, une multitude de contraintes et d'objectifs doivent être pris en compte pour répondre aux besoins de chacun de ces acteurs.

De par cette multitude de paramètres, aucune définition unique du problème n'a été proposée par l'ensemble de la communauté scientifique. En effet, malgré les dizaines d'articles publiés cette dernière décennie, il apparait que chaque groupe de recherche travaille sur une version différente du problème avec des contraintes et des objectifs qui lui sont propres. La bibliographie se représente alors non pas comme un grand ensemble dans lequel les auteurs comparent leurs méthodes et cherchent à s'inspirer les uns des autres, mais plutôt comme de petits "ilots de recherche", définis par la prise en compte de certains paramètres du problème.

Le premier projet de cette thèse va tenter d'aller à l'encontre de cette tendance, et ce de trois manières différentes. Tout d'abord, nous avons collaboré avec des agences de soins à domicile afin de comprendre les enjeux majeurs qu'elles rencontrent et définir un problème comprenant les contraintes et objectifs qui correspondent à la grande majorité de ceux rencontrés par les agences à travers le monde. Ensuite, la méthode de résolution que nous avons développé (recherche à voisinage large (LNS)) est une méthode flexible, dans laquelle les contraintes peuvent être ajoutées et supprimées facilement afin d'être comparées à d'autres méthodes de la littérature. Enfin, parce qu'aucun jeu d'instance ne couvrait le problème que nous traitions, nous avons créé de nouveaux jeux d'instances et nous espérons que par le futur, l'ensemble de la communauté scientifique utilisera ce jeu d'instance pour comparer les différentes méthodes.

Nos discussions avec les différentes agences nous ont aussi montré que le fait de planifier l'ensemble des visites sans prendre en compte celles précédemment acceptées est très rare. C'est pourquoi nous avons tourné notre travail de recherche vers la prise en compte de l'aspect dynamique du problème et le fait que l'on doit prendre des décisions de planification tout en intégrant la continuité des soins et le fait que certains patients existent dans le système et utilisent certaines ressources.

Dans cette optique, le second travail de recherche porte sur l'élaboration de méthodes de résolution pour résoudre le problème d'acceptation et d'affectation de patients, prenant en compte certains patients existants. Dans ce second projet, nous montrons qu'une décomposition de Benders utilisant des patterns de visites peut permettre de résoudre très rapidement une très grande majorité des instances. Pour les instances plus complexes, nous montrons qu'encore une fois, la flexibilité et l'efficacité d'une LNS permettent de rapidement résoudre le problème à l'optimal.

Enfin, le troisième projet de cette thèse va plus loin et résout le problème non pas sur une semaine, mais sur plus d'une année et analyse l'impact des décisions hebdomadaires dans le contexte d'un horizon roulant. Nous tentons dans ce projet de modifier le paradigme de pensée des agences en analysant l'impact de l'ajout d'une certaine flexibilité dans leurs processus de décision. Cette flexibilité provient du moment auquel les agences prennent leurs décisions (à chaque offre de patient, en fin de journée, en fin de semaine) mais aussi de l'affectation horaire que l'on offre aux patients (affectation d'un horaire fixe ou affectation d'une fenêtre de temps). Ces travaux montrent alors que de petits changements dans les processus de décision des agences peuvent leur permettre d'augmenter drastiquement le nombre de visites hebdomadaires tout en conservant un haut niveau de service.

CHAPITRE 3 ORGANISATION DE LA THÈSE

Comme nous l'avons vu dans la revue de littérature du chapitre 2, le problème de planification des soins à domicile est un problème complexe que l'on peut appréhender de nombreuses façons. Cette thèse de doctorat va décrire et résoudre trois différentes formulations du problème avec pour chacune, des angles d'attaque et des enjeux différents.

Le chapitre 4 présente une formulation du problème très proche des réalités du terrain. Cet article présente un travail que nous avons effectué avec la compagnie Alayacare, une compagnie informatique montréalaise. Depuis plusieurs années maintenant, Alayacare développe un logiciel d'aide à la gestion de données pour les agences de soins à domicile. Dans un souci d'amélioration continue, Alayacare avait le souhait de développer un outil d'aide à la décision permettant aux infirmières en chef des agences ou aux coordinateurs, de planifier rapidement des dizaines voire des centaines de visites, et ce en prenant en compte l'ensemble des contraintes métier. Nous avons donc décidé de collaborer avec cette compagnie afin d'avoir accès à un réel contexte de formulation du problème ainsi qu'à des données réelles issues des agences partenaires. Pour résoudre ce problème, nous avons formulé ce dernier sous la forme d'un partitionnement d'ensembles (SP), pour lequel les variables représentent les plannings hebdomadaires possibles pour chacune des infirmières. Ces plannings renferment alors un ensemble de patients affectés ainsi que les jours et l'heure de visite pour chacun des patients. Ce SP est ensuite utilisé au sein d'une matheuristique, appelant itérativement une méthode de résolution à large voisinage (LNS) et la résolution du SP relaxé. La combinaison d'une part, de la LNS pour créer des solutions réalisables et générer des plannings réalisables, et d'autre part de la résolution du SP en utilisant ces mêmes plannings, nous a permis de lier efficacité et rapidité afin de résoudre des instances réelles en moins de dix minutes (tâche qui pouvait prendre plusieurs heures auparavant). Les résultats expérimentaux ont aussi montré que sur les instances réelles de l'agence partenaire, notre méthode de résolution permettait de réduire de 37% les temps de trajet des infirmières tout en augmentant de 16% la continuité des soins. Ce projet de recherche a été publié en 2018 dans *European Journal of Operational Research* et a remporté le prix de la pratique de la Société Canadienne de Recherche Opérationnelle la même année.

Dans le chapitre 5, c'est une autre facette du problème à laquelle nous nous intéressons. En effet, tandis que le premier projet partait de plannings vides et planifiait l'ensemble des patients utilisant l'ensemble des infirmières, le second présente une autre réalité des agences de soins à domicile. Dans ce second contexte, nous étudions la situation dans laquelle certains patients sont déjà présents dans le système de l'agence, ils ont donc leur infirmière affectée, leurs jours et heure de visite et on prend comme hypothèse que ces valeurs ne peuvent être modifiées du fait de la continuité des soins. L'objectif est alors, à partir des offres de patients que l'agence a reçues au cours de la semaine, de maximiser le nombre de patients qui peuvent être acceptés tout en gardant intacts les patients existants. Pour résoudre ce problème, nous présentons deux décompositions de Benders ainsi qu'une décomposition de Dantzig-Wolfe se basant sur les patterns de visite possibles de chacun des nouveaux patients (e.g, visites les mardis-jeudis à 15h avec une infirmière donnée). Pour ce qui est des décompositions de Benders, les problèmes maitres sont résolus à l'aide de CPLEX tandis que les sous-problèmes prenant en compte les temps de trajet et la charge de travail hebdomadaire, sont résolus avec CP Optimizer. Enfin, la décomposition de Dantzig-Wolfe est résolue d'une manière similaire au premier projet, utilisant une LNS basée sur les patterns de visites possibles pour chacun des patients. Les résultats montrent que notre nouvelle décomposition de Benders permet une diminution drastique du temps de calcul pour la grande majorité des instances. Néanmoins, ces temps de calcul tendent à augmenter rapidement (jusqu'à une heure de temps de calcul pour certaines instances) avec le nombre de patterns. Pour pallier à ce problème, la méthode utilisant la LNS montre de très bons résultats puisqu'elle permet de trouver l'ensemble des solutions optimales en moins de 20 secondes. Ce projet a été publié en 2019 dans *Computers & Operations Research*.

Le chapitre 6 présente quant à lui le dernier projet de cette thèse. Dans ce troisième projet, nous reprenons les contraintes de continuité du second projet (patients existants avec des affectations que l'on ne peut modifier) en prenant en compte l'horizon roulant. L'objectif est alors de maximiser le nombre de visites hebdomadaire moyen. Dans ce contexte, les méthodes que nous développons sont des heuristiques et l'objectif majeur de ce projet est de tester différentes stratégies que peuvent utiliser les agences lors de l'acceptation et la planification des nouveaux patients. En termes de flexibilité, nous étudions deux éléments. Le premier est le moment auquel l'agence prend la décision d'accepter ou non une offre de patient. Dans la littérature, on observe que cette décision peut se prendre à trois moments distincts que sont : le moment de réception de l'offre de patient, à la fin de la journée ou encore à la fin de la semaine. On comprend que plus l'agence se donne du temps pour prendre ces décisions d'acceptation et de planification, plus elle a accès à l'ensemble des offres de patients afin d'optimiser l'affectation des patients sur la semaine. La seconde flexibilité que nous prenons en compte est le fait d'affecter non pas un horaire de visite fixe aux patients, mais une fenêtre de temps. Cela permet d'ajuster chaque semaine l'horaire de chacun des patients afin de maximiser le nombre de visites. Les fenêtres de temps étant fixes pour l'ensemble du plan de soin du patient et restant de petite taille (entre 30 minutes et 2 heures), elles permettent de continuer d'offrir un haut niveau de service aux patients tout en donnant une plus grande flexibilité aux agences. Nos expérimentations montrent que ces flexibilités permettent des améliorations du nombre de visites hebdomadaires pouvant aller jusqu'à 12% d'amélioration. Cet article a été soumis à Health Care Management Science en juin 2020.

Les résultats et limitations de ces travaux sont discutés dans le chapitre 7. Enfin, les conclusions de la thèse sont présentées dans le chapitre 8.

CHAPITRE 4 ARTICLE 1 : A SET PARTITIONING HEURISTIC FOR THE HOME HEALTH CARE ROUTING AND SCHEDULING PROBLEM

F. Grenouilleau, A. Legrain, N. Lahrichi et L-M. Rousseau ont écrit cet article et l'ont publié en 2019 dans European Journal of Operational Research

4.1 Introduction

Home health care services improve patients' quality of life by helping them remain independent and in their own homes, often surrounded by family and friends, while maintaining their regular habits. From a governmental point of view, home care services decrease hospital congestion by freeing up hospital beds, which also results in reducing costs for these institutions [107]. In 2012, in Canada, more than 2.2 million people received home care services [108]. These services are various : from personal support (bathing, dressing, housekeeping) to more specific tasks such as insulin injection or wound care. Due to the variety of tasks required, different medical specialties and skills are needed (e.g., personal social worker or nurse).

In this paper, we investigate the home health care routing and scheduling problem (HHCRSP) within a practical context. This problem is interested in determining the assignment of a set of home visits to a set of caregivers over the course of a week and the routing of these caregivers' workdays. The HHCRSP can be described as a multi-depot vehicle routing problem (MDVRP) with time windows and time-dependent travel issues. Moreover, the home care context adds constraints focusing on the caregivers' skills and the patients' requirements (both mandatory and optional), as well as the management of the caregivers' work time contracts. Finally, the HHCRSP has a major concern which is the continuity of care, corresponding to the upkeep of a strong patient-caregiver relationship.

In this work, we present a set partitioning heuristic (SPH) to address the weekly version of the HHCRSP. This method is based on the heuristic concentration principle [109]. The goal of our SPH is to solve a set partitioning formulation of the HHCRSP using the columns (feasible routes) generated by a Large Neighborhood Search (LNS) [110]. Due to the necessity to produce high quality solutions in a small computational time, the SPH solves a linear relaxation of the set partitioning formulation and a constructive heuristic is then applied to build an integer solution based on the solution found. This paper presents three major contributions. First, the proposed method takes into account a larger set of practical constraints and solves instances covering up to 430 visits, over the course of a week, in less than 10 minutes. Second, we propose a relaxed heuristic concentration approach that combines the global perspective of a mathematical program with the efficiency of a heuristic approach. Finally, we propose new LNS' operators, specifically designed for the HHCRSP, which permit the extension of the search space to find new and improved solutions.

To assess the quality of the proposed method, we have evaluated it performance against a classic LNS approach. Furthermore, as our research's context differs from existing benchmarks, and that reproducibility is of major importance in research, we provide and make public a set of realistic generated instances. We hope that this benchmark will help to homogenize the research about the HHCRSP and help the future authors to compare their methods.

The paper is organized as follows. Section 4.2 presents the literature review on the HHCRSP. Section 4.3 details the problem and its formulation. Section 4.4 describes our approach and Section 4.5 shows the computational results on generated and real instances. Finally, conclusions are drawn in Section 4.6.

4.2 Literature review

From our knowledge, the routing and scheduling optimization in the home health care context is a 20 years old problem [42, 111]. According to the existing literature, we observe that no standard version of the problem exists. Authors use different constraints and objectives. This plurality, usually due to the authors's country's home care management, makes it difficult to compare the existing methods.

The HHCRSP was originally solved on a daily planning horizon. Then, it has evolved to integrate more practical constraints such as the maximization of the patients and caregivers' preferences [29], the balance of the workload [23], visits incompatibilities [61], shared visits [35], multiple modes of transportation [56] or even the time-dependent travel time [27]. Thereafter, the HHCRSP has been extended to a weekly horizon that allows for better coping with the reality of some constraints, such as the patients' care plan and/or the continuity of care. Some methods using branch-and-price [96], branch-and-price-and-cut [26], cardinality constraints [112] integer linear based method [51,113] have been proposed, but the complexity of the problem leads to scalability issues.

To deal with these issues, methods based on heuristics or meta-heuristics have been developed using frameworks such as large neighborhood search [19], memetic algorithm [114], ant colony optimization [115], two-phase algorithm [18], or harmony search [104]. In [22], the problem is split in two : the *master problem*, which uses a constructive heuristic and an ALNS to build a feasible assignment of the visits, and the *operational problem*, which integrates the last minute changes (e.g., visit cancellation or sick caregiver) into the current schedule with an insertion heuristic and a tabu-search. Finally, [25] propose a two-phase method based on a set partitioning formulation. The first phase produces pools of visit patterns and solves the patterns' assignment using Cplex. Then, the second phase improves the best patterns' assignment with a local search procedure that swaps patients' visits to reduce travel time and maximize patients and nurses' preferences.

For more references, we refer the reader to two comprehensive surveys published recently [16, 17]. For an overview on the multi-day HHCRSP (features and classic constraints), we refer the reader to Table 4.1. We highlight for each paper the main characteristics of the problem, and constraints are classified either as hard (H) or soft (S). Last column indicates the instances' availability. According to this table, we observe that we tackle a richer version of the problem than most of the existing literature. In the similar work of [25], instances are not available. We fill this gap by providing new benchmark to the community (http ://dx.doi.org/10.17632/cbgt59hnhk.1).

Table 4.1 Characteristics of the multi-day HHCRSP literature

	Features						Constraints				
Article	Travel cost	Workload Balance	Time-dependent	Patient's preferences	Caregiver's preferences	Continuity of care	Work time contracts	Time windows	Qualifications	Unscheduled visits	Instances available
[96]	S				S			S	H	H	
[26]							H	H	H	H	X
[112]	S	S				H	H		H	H	
[51]				S		S			H	S	
[113]	S						H	H	H	H	
[19]	S						H	H	H	S	
[115]	S						H	H	H		
[18]	S	S				H			H	H	
[104]	S				H		H		H	H	X
[22]	S					S	S	H	H	S	
[25]				S		H	H	S	S	H	
Our approach	S		H	S	S	S	S	H	H	S	X

4.3 Problem definition

The home health care routing and scheduling problem can be described as a "multi-attribute" vehicle routing problem as it considers many features (e.g., patients' requirements, caregivers' skills, time-dependent travel times, and contracted working hours). We define the sets P of patients and C of caregivers. The objective is to determine patient-to-caregiver assignments and build the caregivers' routes over the horizon of H days ($H = 7$ in our context) according to the required number of visits of the patients. The caregivers' assignments must take into account patients' mandatory (e.g., specialty) and optional (e.g., language) requirements and caregivers' skills and characteristics (e.g., gender). (Note that in the remainder of the paper, caregivers characteristics will be included in the set of skills for the sake of simplicity). The routing part of the problem must cope with patients' availability (days and time windows) and caregivers' work shifts. Caregivers' work contracts (i.e., minimum and maximum amount of working time per day and week) have to be managed as well. Finally, the impact of traffic delays on travel time are taken into account, through a time-dependent distance matrix.

For each patient $p \in P$, we define a number n_p of required visits of duration dur_p, a subset $D_p \subseteq [1, ..., H]$ of available days and a hard time-window $[e_p^d, l_p^d]$ for each available day $d \in D_p$. Moreover, we also define two lists M_p and O_p that respectively contain the mandatory and optional requirements. The optional requirements could be described as patient's preferences about, for example, the gender or the language spoken by the assigned caregiver. For each caregiver $c \in C$, we similarly define a list E_c of skills, a soft minimum $\underline{w}_c^w$ and maximum $\overline{w}_c^w$, working hours over the week, and a subset $D_c \subseteq [1, ..., H]$ of workdays. Each of these workdays d also has a time-window $[a_c^d, b_c^d]$ and a soft minimum $\underline{w}_c^d$ and maximum $\overline{w}_c^d$ of working hours. Every patient and caregiver have their home location (respectively l_p and l_c) that belongs to a set L of possible zip codes. Finally, the continuity of care measures the strength of a patient-caregiver relationship with a score $CC_{p,c}$. This is based on the number of times that the caregiver c has been assigned to the past visits of patient p.

We propose to formulate the HHCRSP as a set partitioning problem (SPP) that aims at selecting the best routes for each caregiver c among a set Ω of daily feasible caregivers' routes. We also define the subsets $\Omega_d \subset \Omega$ and $\Omega_c \subset \Omega$ that correspond to the routes associated respectively to day d and caregiver c. Each route $\omega \in \Omega$ is defined by a set of visited patients. Implicitly, each route ensures the respect of the patients' mandatory requirements, the caregivers' skills, the time-windows and the time-dependent travel times for all the visited patients. To each route, we compute a cost based on : 1) the number of missing optional requirements (defined as the number of optional requirements of patient (O_p) minus the intersection between sets O_p and E_c, where c is the caregiver assigned to the route ω) ; 2) a travel time tt_ω ; 3) a score for continuity of care, and 4) a length len_ω penalty (this captures the minimum or maximum daily working hours for each caregiver).

The score for continuity of care f_1 is given by :

$$f_1(CC_{p,c}) = \begin{cases} 1 & \text{if } \ CC_{p,c} = 0 \\ \frac{2}{3} & \text{if } \ 1 \leq CC_{p,c} \leq 2 \\ \frac{1}{3} & \text{otherwise} \end{cases}$$

and, the working hours penalty function f_2 is described as follows :

$$f_2(len_\omega) = \max(0,\ \underline{w}_d - len_\omega,\ len_\omega - \overline{w}_d)$$

The cost c_ω of each route $\omega \in \Omega$ is therefore defined as a weighted sum :

$$c_\omega = \gamma_1 . \sum_{p \in P} a_{\omega,p}(|O_p| - |O_p \cap E_c|) + \gamma_2 . tt_\omega + \gamma_3 . \sum_{p \in P} a_{\omega,p} . f_1(CC_{p,c}) + \gamma_4 . f_2(len_\omega),$$

where $a_{\omega,p}$ equals to 1 if the route ω visits patient p and $\gamma_1, ...\gamma_4$ correspond to the weight of each soft constraint and capture the significance of each objective function's component.

The decision variables of the problem are given by :

- x_ω which equals 1 if the route ω is selected, 0 otherwise ;
- o_c which measures the weekly overtime for caregiver c ;
- u_c which also measures the weekly idle time for caregiver c. This corresponds to the number of working hours not used in the caregiver's week, i.e, the difference between the minimal amount of working hours and the actual amount of scheduled hours ;
- z_p which counts the number of unscheduled visits for patient p.

The corresponding SPP formulation is defined as follows :

$$(SPP) : \min \quad \sum_{\omega \in \Omega} c_\omega x_\omega + \beta_1 . \sum_{c \in C} (o_c + u_c) + \beta_2 . \sum_{p \in P} z_p \tag{4.1}$$

$$\begin{aligned}
\text{subject to} : \sum_{\omega \in \Omega_d} a_{\omega,p} x_\omega &\leq 1 \qquad \forall p \in P, d \in D_p && (4.2)\\
\sum_{\omega \in \Omega} a_{\omega,p} x_\omega + z_p &= n_p \qquad \forall p \in P && (4.3)\\
\sum_{\omega \in \Omega_d \cap \Omega_c} x_\omega &\leq 1 \qquad \forall c \in C, d \in D_c && (4.4)\\
\sum_{\omega \in \Omega} len_\omega x_\omega + u_c &\geq \underline{w}_c^w \qquad \forall c \in C && (4.5)\\
\sum_{\omega \in \Omega} len_\omega x_\omega - o_c &\leq \overline{w}_c^w \qquad \forall c \in C && (4.6)\\
x_\omega &\in \{0,1\} \qquad \forall \omega \in \Omega && (4.7)\\
z_p &\geq 0 \qquad \forall p \in P && (4.8)\\
o_c, u_c &\geq 0 \qquad \forall c \in C && (4.9)
\end{aligned}$$

The objective function (4.1) corresponds to a weighted sum of costs associated, respectively, to the routes, the weekly caregivers' overtimes and idle time and the unscheduled visits. Weights β_1 and β_2 capture the significance of the second and third objective function's components. Constraints (4.2) ensure that patient p is visited a maximum of once per day, Constraints (4.3) count the number of unscheduled visits per patient. Then, Constraints (4.4) ensure that no more than one route per day is assigned to each caregiver. Finally, Constraints (4.5) – (4.6) measure, respectively, the weekly idle time and overtime. The domains of the variables are defined by Constraints (4.7) – (4.9).

One should note that required number of visits for each patient is a soft constraint. In practice, agencies may outsource the visits they can not provide. Finally, we consider single visits per day. Our model is easy to extend to multiple visits.

4.4 Solution Method

In this section, we present the set partitioning heuristic (SPH). The proposed SPH is a matheuristic based on the resolution of the SPP presented in the section 4.3. This method is based on the heuristic concentration principle [109]. The aim of the heuristic concentration is to keep the best solutions found by a heuristic procedure and then use a set partitioning that combines parts of these solutions to create a better one. This combination of heuristic and exact approaches have already been used for the VRPTW [116, 117]. In our method, the possible SPP's routes are found using a Large Neighborhood Search (LNS).

4.4.1 Set Partitioning Resolution

The resolution of a set partitioning model is difficult and can be computationally expensive ([96], [26]). The industrial context of this project however required relatively short solution time, basically less than 10 minutes. To address this challenge, we solve a relaxation of the proposed SPP model ($Relaxed_{SPP}$) and reconstruct the integer solution using a constructive heuristic ($Heur_{SPP}$). The $Relaxed_{SPP}$ corresponds to the resolution of the proposed SPP while relaxing the integrity of the decision variables x_ω, generating the fractional variables $\bar{x}_\omega$. After the resolution of the $Relaxed_{SPP}$, the $Heur_{SPP}$ procedure is called to build an integer solution according to the resultant relaxed values $\bar{x}_\omega$. An overview of the method is given by the Algorithm 1.

Algorithm 1: $Heur_{SPP}$

```
Create the list L^Ω̄, copy of the routes in Ω, sorted in decreasing order of the
  values x̄_ω from the last Relaxed_SPP
Empty solution s
forall route ω in L^Ω̄ do
    forall patient visit v in ω's visit list do
        if The patient of the visit v has all his/her visits scheduled in s then
            remove v from ω's visit list
    if ω's visit list is not empty then
        Reschedule ω with the remaining visits
        Insert the route ω in s
if The solution s is better than the best found solution then
    Update the best found solution with s
```

As presented in Algorithm 1, $Heur_{SPP}$ creates an integer solution based on the fractional one found by the previous $Relaxed_{SPP}$. First, we sort the existing routes $\overline{\Omega}$ by their value $\bar{x}_\omega$ and store them in the list $L^{\bar{\Omega}}$. Then a constructive method is applied starting from an empty solution s. Iteratively, we select the next route r in the list and remove from r the patients for which, all the visits are already scheduled in s. If the route is not empty, we determine the visit times for the remaining patients in the route r and insert r in s. At the end of the algorithm, if the built solution s is better than the best one found during the previous SPH's iterations, we update the best solution with s.

4.4.2 LNS-based route generation

In order to quickly generate a set of high-quality routes, a Large Neighborhood Search (LNS) method is developed. On top of the continuous generation of feasible caregivers' routes, the LNS also allows to gradually improve the best found solution by using a set of classic and problem-specific operators. The found routes are then used to solve the proposed $Relaxed_{SPP}$.

The LNS [110] is a meta-heuristic using the $ruin - and - recreate$ principle [118]. This method, starting from an initial solution, iteratively destroys a part of the current solution, then repairs it in order to improve its quality. The current and best solutions are then updated if necessary. A full description of the LNS can be found in [119]. In the following subsections, we present the main components of our LNS. In particular, we present the specific operators that we have developed to cope with some HHCRSP's difficulties.

Initial solution

In order to create the initial feasible solution, a lowest-cost insertion method is used. We first sort the patients in decreasing order of their visits' durations, then, following this order, we try to insert the patient's visits at the lowest cost. The patients with unscheduled visits are stored in a list until the first LNS iteration. In our context, the possibility to have unscheduled visits ensures to always have a feasible solution (in the worst case, all the visits are unscheduled and all the caregivers' routes are empty).

Classic LNS operators

In our LNS' implementation, we use a mix of both classic and new operators for the destruction/repair operations. For the destruction procedure, the classic operators are $WorstRemoval$, $RandomRemoval$ from [120] and the $RelatedRemoval$ from [110]. For the repair procedure, the classic operators are the $Greedy\ Heuristic$, $regret$-2 and $regret$-3 from [120].

New LNS operators

In order to focus the search on some difficult aspects of the problem, some problem-specific destroy and repair operators have been implemented in the LNS.

New destroy operators Let us recall that q, the number of destroyed visits, is randomly selected at each LNS' iteration. The developed destroy operators are as follows :

1. The *ServiceRemoval* operator randomly selects a patient and removes all his/her scheduled visits. This process is repeated until at least q visits are removed. This new operator permits a reset of the assigned visit days of the patient and potentially creates a new pattern of visits during the repair part.
2. The *FlexibleAvailRemoval* operator deletes from the current schedule the patients with the highest flexibility (i.e., highest value of $\frac{|D_p|}{n_p}$). Iteratively, the most flexible patient is selected and all its scheduled visits are removed from the current schedule. The patients list is scanned this way until q visits are removed.
3. The *DualRemoval* operator uses the dual values from the last $Relaxed_{SPP}$ resolution. Based on constraints (4.3), this operator sorts the patients in decreasing order of their dual values, then iteratively selects the patient at the top of the list (lowest dual value), and removes his/her visits. The process is repeated until q visits are removed like the other destroy operators.

New repair operators For the proposed LNS, two new repair operators have been created :

1. The *RandomService* operator randomly chooses one of the patients for which some visits are not scheduled. A lowest-cost insertion logic is used to schedule his/her visits over the horizon. This process is repeated until every patient with missing visits has been tested.
2. The *DualRepair* operator focuses on the patients with the highest dual values. It sorts the patient in decreasing order of their dual values, based on constraints (4.3) of the last $Relaxed_{SPP}$'s resolution. Then, the operator follows this ordered list and tries to schedule as many visits as possible for each patient using again a lowest-cost insertion logic.

Due to the fact that the dual values come from the $Relaxed_{SPP}$, the dual operators (*DualRemoval*, *DualRepair*) can't be used in the first LNS's segment (first 1,000 iterations). They are introduced in the operators lists at the end of the first $Relaxed_{SPP}$. Note that the dual values remain unchanged until the following $Relaxed_{SPP}$ is solved.

Range of destruction

The number q of visits destroyed at each iteration is randomly drawn in a range $[min\_percent, max\_percent] * Sched_s$ where $Sched_s$ is the number of visits scheduled in the impacted solution s.

Solution Analysis

After the destroy and repair procedures, the created solution is analyzed to decide if its quality is good enough to be kept as a best or current solution. Three cases may occur in this context :

1. the new solution is better than the best found, the LNS updates the best and current solutions with the new one ;
2. the new solution is better than the current solution, only the current solution is updated ;
3. the new solution is worse than the current solution, a simulated annealing accept criterion is then used to either accept or refuse it.

This simulated annealing accept criterion [121] accepts the new solution with a probability $e^{-\frac{f(s_{new})-f(s_{cur})}{T}}$ where $f(s_{new})$ and $f(s_{cur})$ are respectively the value of the new and current solutions. The value T is the current temperature of the problem which decreases at each simulated annealing call, according to the relation subscript $T_{n+1} = T_n \times c$ where $0 < c < 1$ is the decrease coefficient. According to [120], the decrease coefficient c and the initial temperature T_0 are set to 0.99975 and $1.05 \times f(s_0)$, respectively, where s_0 is the initial solution.

Termination criterion

The SPH ends when reaching either a maximum number of LNS' iterations or a maximum computational time.

Management of the time-dependent travel time

In order to adapt to practical settings, we include the time-dependent travel times between the patients' locations. In our implementation, we use a dynamic computation of the time-dependent travel times based on the algorithm described by [122]. This algorithm computes the traffic-dependent travel times between two locations according to the departure time. It is based on a stepwise speed functions ; the adjustment of speed between two periods of time ensures the respect of the FIFO principle.

4.4.3 Method's overview

Now that we have presented our method's two main components (SPP's resolution and LNS-based route generation), we can now give the overview of our set partitioning heuristic

(SPH). A SPH's description is given by the Algorithm 2. The first part of the algorithm is based on the LNS' procedure described earlier (initial solution, destruction, repair, analysis). Then, at the end of each segment (i.e., a block of 1,000 iterations in our case), a sub-procedure is called. This procedure solves the $Relaxed_{SPP}$ and applies the $Heur_{SPP}$ presented in the subsection 4.4.1.

Algorithm 2: SPH

```
Find an initial feasible solution ;
while No termination criteria met do
    for A segment of 1,000 iterations do
        s ← currentSolution ;
        Select and apply a destroy operator on s ;
        Select and apply a repair operator on s ;
        Analyze the solution s ;
    Solve Relaxed_SPP ;
    Apply Heur_SPP ;
Return the best found solution ;
```

4.5 Computational Results

This section presenting some computational experiments is divided into two parts. The first set of experiments assesses the suitability of the overall SPH, by studying the effectiveness of the new operators with respect to the classical ones and examining the impact of the proposed set partitioning resolution ($Relaxed_{SPP}$ then $Heur_{SPP}$). In the second part, we analyze the performance of SPH on real instances provided by our industrial partner. The proposed algorithm has been implemented in C++ and all the tests are run on an Intel(R) Xeon(R) (duo core) X5675 3.07GHz, with 96 GB RAM and running on Linux operating system. We use the solver CPLEX, version 12.6.1. to solve $Relaxed_{SPP}$. All the experiments are run on a single thread. The termination criterion are set to 10 minutes and 10^5 LNS' iterations. The *min_percent* and *max_percent* have been respectively set to 2% and 5%. Finally, the weights (γ_1,γ_2,γ_3,γ_4,β_1,β_2,) have been fixed after preliminary evaluations in collaboration with Alayacare (refer to Appendix, Table 4.9 for the values.

4.5.1 Experiments on generated-instances

In order to test the proposed SPH, we have based our analysis on a benchmark of 60 instances : three sets (Small, Medium, Large) of 20 instances corresponding to the different problem's sizes that must be solved by the algorithm. An overview of the instances' characteristics is given in the table 4.2. Instances can be downloaded from : http ://dx.doi.org/10.17632/cbgt59hnhk.1

Table 4.2 Characteristics of the generated instances

Instance	Patient	Visits	Caregiver	Workdays
Small	40	120	5	25
Medium	80	225	10	45
Large	150	430	20	90

These sets have been randomly generated based on real instances' characteristics provided by our industrial partner and each value has a predefined range. The instances' generation is based on 5 different requirements/skills, 141 possible locations, and several parameters described in Tables 4.3.

Table 4.3 Employees' parameters for the generated instances

Parameter	Name	Minimum	Maximum
n_p	Number of visits	1	7
dur_p	Duration of visits (in min)	40	60
$\|M_p\|$	Mandatory requirements	1	2
$\|O_p\|$	Optional requirements	0	2
$\frac{l_p^d - e_p^d}{dur_p}$	Time-window's size	2	4
$\underline{w}_c^w$	Minimum week working hours (in min)	0	600
$\overline{w}_c^w$	Maximum week working hours (in min)	1200	2400
$b_c^d - a_c^d$	time-window's size (in min)	420	720
$\underline{w}_c^d$	Minimum day working hours (in min)	0	$30\% \cdot (b_c^d - a_c^d)$
$\overline{w}_c^d$	Maximum day working hours (in min)	$80\% \cdot (b_c^d - a_c^d)$	$100\% \cdot (b_c^d - a_c^d)$
$\|E_c\|$	Skills list	2	3

In order to observe the impact of the proposed operators, we define 2 groups of operators :

— CL : The classic operators with $WorstRemoval$, *RandomRemoval*, *RelatedRemoval* for the destroy part and *Greedy Heuristic*, *regret-2* and *regret-3* for the repair ones.

— NW : The new operators : $ServiceRemoval$, $FlexibleAvailRemoval$ and $DualRemoval$ for the destroy operators, $RandomService$ and $DualRepair$ for the repair ones. These operators necessitate the resolution of the $Relaxed_{SPP}$.

Moreover, to test the impact of the $Heur_{SPP}$, we distinguish the use or not of this algorithm.

For this analysis, 10 runs of each instance have been computed for three different scenarios (CL, CL + NW and CL + NW + $Heur_{SPP}$). The presented results are based on the average of the best found solutions' costs over the 10 runs. Figures 4.1 and 4.2 present the comparison of the three scenarios. The values correspond to the gap between each scenario's value and the value of the CL one. According to these results, we can observe that, on average, the new operators ($CL+NW$ scenario), by extending the search space, find better solutions and reduce the solutions' cost for the small, medium and large instances by respectively 7.63%, 10.06% and 2.34% (see tables 4.5, 4.6 and 4.7 in Appendix). The reduced improvements produced by the new operators on the large instances could be due to the reduced number of iterations done (see table 4.8 in Appendix). This reduction of the number of iteration (32211 for CL to 24101 for $CL+NW$) is caused by the time spent in the resolution of $Relaxed_{SPP}$ at each end of segment. Furthermore, we can observe that the $Heur_{SPP}$ ($CL+NW+Heur_{SPP}$ scenario) is able to find the best solutions for all instances : the improvements for the three instances' sets are respectively 13.76%, 20.82% and 14.39%. According to these observations, we'll keep the $CL + NW + Heur_{SPP}$ scenario for the real instances' resolution.

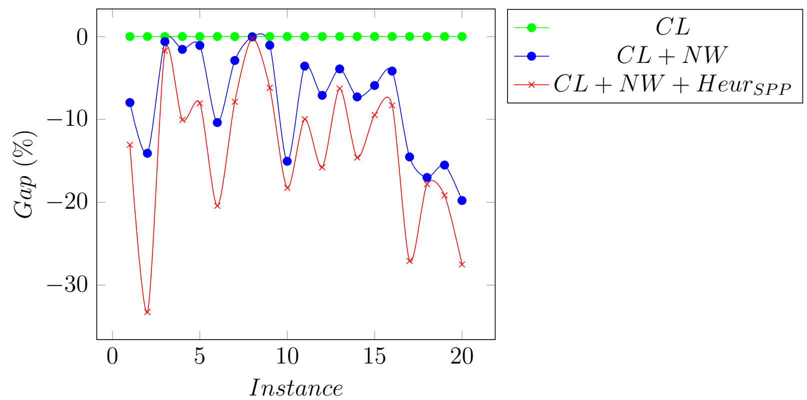

Figure 4.1 Comparison of the cost for the small instances

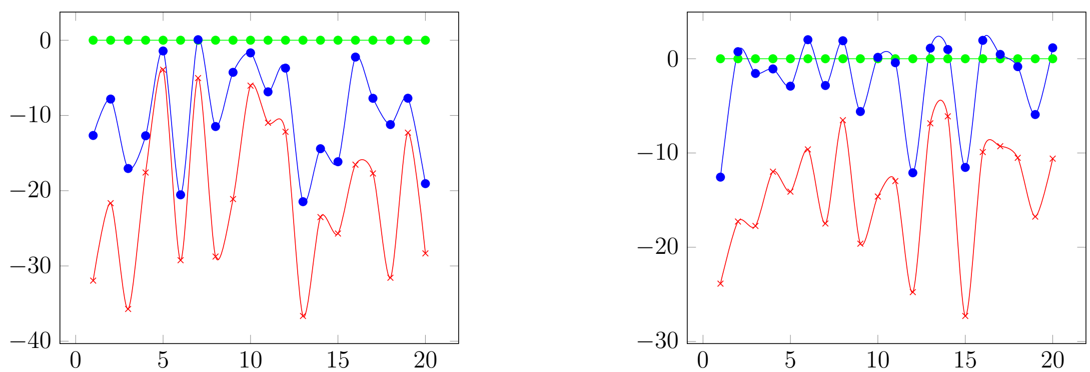

Figure 4.2 Comparison of the cost for the medium (left) and large (right) instances

4.5.2 Real-World Instances

In this section, we describe the tests performed on instances from one of Alayacare's clients. For the studied client, the objective was to analyze the improvements both in terms of travel time and continuity of care provided by the proposed method. In these experiments, 4 instances representing 4 different weeks have been used. These instances are described as $P\_V\_C\_R$ where P is the number of patients, V the number of visits, C the number of caregivers and R the number of routes (number of workdays). For these instances, the chosen patients were homogeneous, so the same requirements were needed. The available days correspond to actual patients' visits' days (i.e. $|D_p| = n_p$ for each patient). The patients' time windows were designed around their actual visit times. For the employees, their workdays, work time contracts and time windows were given by the client.The figure 4.3 presents the distribution of the number of visits per patient for the real instances. According to this figure, the majority of patients only need 1 or 2 visits per week.

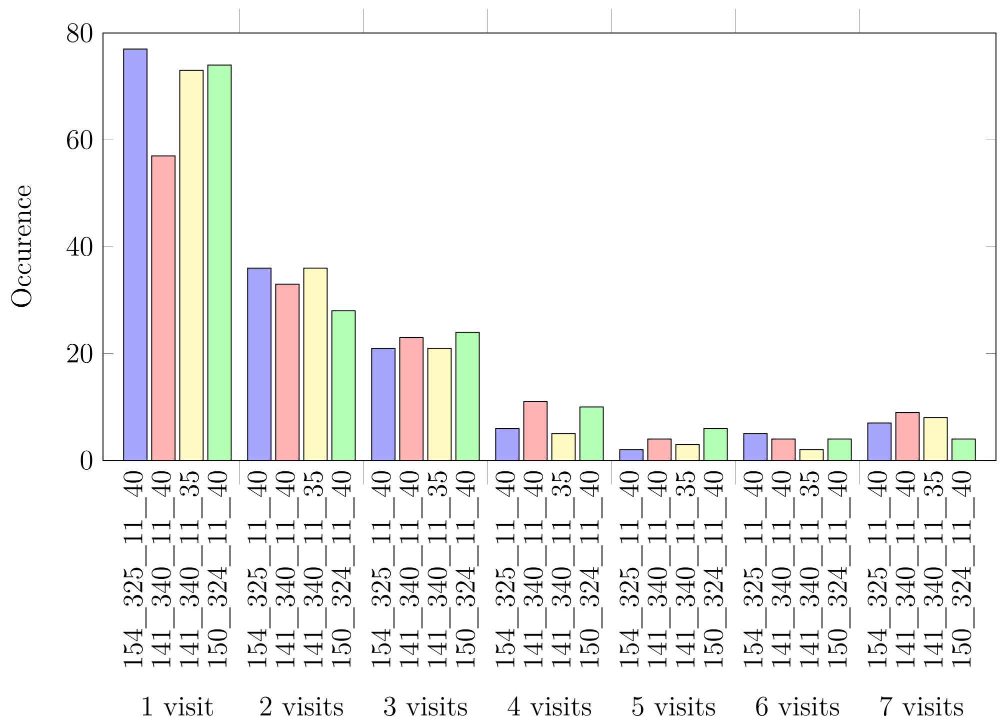

Figure 4.3 Distribution of the number of visit per patient

A comparison of Alayacare's current client solutions and our SPH's solutions on these 4 instances is presented in Table 4.4. According to the client's will, we focus here on two major indicators, the total travel time (TT) and the continuity of care (CC, i.e., the percentage of scheduled visits for which the patient p and the caregiver c have $CC_{p,c} \neq 0$).

Table 4.4 Comparison of the actual solutions with those produced by our approach

	Current solution		SPH**'s solution**		Δ	
Instance	TT	CC	TT	CC	TT	CC
154_325_11_40	4361.16	60%	**2431.62**	**75.94%**	-44.24%	+15.94%
141_340_11_40	4549.03	62.33%	**2833.18**	**79.05%**	-37.72%	+16.72%
148_311_11_35	3832.94	71.69%	**2571.29**	**85.98 %**	-32.92%	+14.29%
150_324_11_40	3686.57	64.43%	**2464.22**	**82.10%**	-33.16%	+17.67%
Mean	4107.43	64.61%	2575.08	80.77%	**-37.01%**	**+16.16%**

According to the Table 4.4, our approach improves the solutions both in terms of travel time and continuity of care. On average, the proposed algorithm reduces the total travel time by 37.01% and increases the continuity of care by 16.16%. These results show that the use of such method by Alayacare's clients could lead to large improvement in term of costs reduction and quality of service.

4.6 Conclusions

The HHCRSP is a complex problem due to the simultaneous management of the assignment (requirements, skills, continuity of care) and routing (travel time, work time contracts, impact of the traffic) constraints. Nevertheless, we have proposed a set partitioning heuristic able to cope with all these requirements. The presented method is firstly based on a set partitioning formulation of the problem. The resolution of this set partitioning is done in two phases : the resolution of the relaxation ($Relaxed_{SPP}$) followed by a constructive heuristic ($Heur_{SPP}$). To populate the SPP's columns, we developed a LNS procedure. This LNS has three benefits, it allows us : to generate possible routes for the SPP, to always have a feasible primal solution and, during the segments, to continuously improve the best found solution. To extend the LNS' search space, five new operators have also been proposed.

According to the results, we observed that the new operators and the constructive heuristic permit a dramatic reduction in term of solutions' costs for the generated instances (respectively 13.76%, 20.82% and 14.39% for the small, medium and large sets). On the real instances, the algorithm permitted, on average, a 37% reduction in travel time and a 16% increase in the continuity of care. The developed method has been approved by our industrial partner, integrated in their software, and used by Alayacare's clients around the world (Canada, USA, Australia, Singapore) since November 2017.

Acknowledgment

We thank our industrial partner Alayacare for their precious collaboration, confidence and financial support together with the grant agencies MITACS and MEDTEQ. This project has received the Canadian Operational Research Society's practice prize in June 2018.

Appendix

Table 4.5 Comparison of the scenarios for the small instances

	CL	CL + NW		CL + NW + $Heur_{SPP}$	
	Value	Value	Gap	Value	Gap
Small_01	753650.31	693571.5086	**-7.97%**	655170.3155	**-13.07%**
Small_02	388578.40	333827.24	**-14.09%**	259383.96	**-33.25%**
Small_03	261321.75	259734.41	**-0.61%**	256827.88	**-1.72%**
Small_04	307137.08	302363.23	**-1.55%**	276264.58	**-10.05%**
Small_05	324180.21	320682.19	**-1.08%**	298047.69	**-8.06%**
Small_06	602088.16	539567.85	**-10.38%**	479109.71	**-20.43%**
Small_07	273176.12	265288.10	**-2.89%**	251640.48	**-7.88%**
Small_08	1528431.83	1527824.96	**-0.04%**	1524747.94	**-0.24%**
Small_09	394693.73	390526.27	**-1.06%**	370272.71	**-6.19%**
Small_10	469118.08	398505.77	**-15.05%**	383520.66	**-18.25%**
Small_11	283330.11	273207.25	**-3.57%**	255041.27	**-9.98%**
Small_12	938840.89	872176.95	**-7.10%**	790714.41	**-15.78%**
Small_13	244551.83	234983.10	**-3.91%**	229196.10	**-6.28%**
Small_14	860348.70	797670.64	**-7.29%**	734774.10	**-14.60%**
Small_15	993613.49	934921.45	**-5.91%**	899489.84	**-9.47%**
Small_16	447580.61	428907.60	**-4.17%**	410401.47	**-8.31%**
Small_17	1096303.37	937055.30	**-14.53%**	799396.40	**-27.08%**
Small_18	559169.93	464071.39	**-17.01%**	459508.10	**-17.82%**
Small_19	521073.62	440239.02	**-15.51%**	421205.03	**-19.17%**
Small_20	881554.92	715901.54	**-18.79%**	639114.14	**-27.50%**
Mean Gap			**-7.63%**		**-13.76%**

Table 4.6 Comparison of the scenarios for the medium instances

	CL	CL + NW		CL + NW + $Heur_{SPP}$	
	Value	Value	Gap	Value	Gap
Medium_01	1588963.97	1387766.74	**-12.66%**	1081305.18	**-31.95%**
Medium_02	828816.02	764033.19	**-7.82%**	649277.75	**-21.66%**
Medium_03	1286191.22	1066939.71	**-17.05%**	826778.72	**-35.72%**
Medium_04	800638.52	698931.17	**-12.70%**	659917.34	**-17.58%**
Medium_05	618752.83	609918.10	**-1.43%**	594481.40	**-3.92%**
Medium_06	887273.58	704931.93	**-20.55%**	627804.64	**-29.24%**
Medium_07	888716.31	889382.71	0.07%	844053.29	**-5.03%**
Medium_08	785631.13	695492.88	**-11.47%**	559769.34	**-28.75%**
Medium_09	685023.22	655755.50	**-4.27%**	540411.70	**-21.11%**
Medium_10	786320.41	773141.13	**-1.68%**	738833.99	**-6.04%**
Medium_11	937630.59	873310.67	**-6.86%**	834727.72	**-10.97%**
Medium_12	596877.70	574721.15	**-3.71%**	524259.20	**-12.17%**
Medium_13	1039973.26	816774.91	**-21.46%**	658848.83	**-36.65%**
Medium_14	708509.23	606313.06	**-14.42%**	541961.29	**-23.51%**
Medium_15	801160.06	671760.95	**-16.15%**	595359.66	**-25.69%**
Medium_16	845822.10	826898.21	**-2.24%**	705922.75	**-16.54%**
Medium_17	776339.87	716435.76	**-7.72%**	638842.83	**-17.71%**
Medium_18	2207257.99	1933365.62	**-12.41%**	1510478.67	**-31.57%**
Medium_19	607654.99	560813.02	**-7.71%**	532946.69	**-12.29%**
Medium_20	844354.06	683449.57	**-19.06%**	605117.08	**-28.33%**
Mean Gap			**-10.06%**		**-20.82%**

Table 4.7 Comparison of the scenarios for the large instances

	CL	CL + NW		CL + NW + $Heur_{SPP}$	
	Value	Value	Gap	Value	Gap
Large_01	1315840.27	1150528.85	**-12.56%**	1001922.79	**-23.86%**
Large_02	1271025.39	1280565.37	0.75%	1051504.59	**-17.27%**
Large_03	1275166.17	1255270.51	**-1.56%**	1048994.79	**-17.74%**
Large_04	1349729.93	1335133.74	**-1.08%**	1188032.84	**-11.98%**
Large_05	1252057.51	1215604.27	**-2.91%**	1075480.95	**-14.10%**
Large_06	1163047.20	1186513.28	2.02%	1051132.77	**-9.62%**
Large_07	1171658.52	1138382.32	**-2.84%**	966833.28	**-17.48%**
Large_08	1022707.50	1042276.78	1.91%	956056.27	**-6.52%**
Large_09	1253375.63	1183201.19	**-5.60%**	1007451.18	**-19.62%**
Large_10	1128399.05	1130063.19	0.15%	963391.38	**-14.62%**
Large_11	1249775.60	1244545.95	**-0.42%**	1087580.95	**-12.98%**
Large_12	1270174.66	1116505.44	**-12.10%**	955662.29	**-24.76%**
Large_13	1058909.80	1070766.14	1.12%	986339.54	**-6.85%**
Large_14	988281.59	997946.76	0.98%	927882.28	**-6.11%**
Large_15	1545000.49	1366852.11	**-11.53%**	1123416.86	**-27.29%**
Large_16	1239669.08	1263805.39	1.95%	1116903.18	**-9.90%**
Large_17	1036061.19	1040816.36	0.46%	939885.29	**-9.28%**
Large_18	1042017.09	1033234.67	**-0.84%**	932547.24	**-10.51%**
Large_19	1250220.56	1176267.76	**-5.92%**	1040813.51	**-16.75%**
Large_20	1128135.80	1141223.34	1.16%	1008533.86	**-10.60%**
Mean Gap			**-2.34%**		**-14.39%**

Table 4.8 Comparison of the computation time and number of iteration for the three scenarios (Average over the 10 runs)

	CL		CL + NW		CL + NW + Heur	
	time (s)	Iterations	time (s)	Iterations	time (s)	Iterations
Small_Instances	149.8	100000	164.9	100000	163.8	100000
Medium_Instances	517.5	98607	597.6	79834	584	84928
Large_Instances	600	32211	600	24101	600	24258

Table 4.9 Values of the weights used in the objective functions

Weight	γ_1	γ_2	γ_3	γ_4	β_1	β_2
Value	1000	30	1000	100	100	50000

CHAPITRE 5 ARTICLE 2 : NEW DECOMPOSITION METHODS FOR HOME CARE SCHEDULING WITH PREDIFINED VISITS

F. Grenouilleau, N. Lahrichi et L-M. Rousseau ont écrit cet article et l'ont publié en 2020 dans Computers & Operations Research

5.1 Introduction

Due to population aging and the Canadian government's plan to decentralize care, the demand for home care services has significantly increased during the last decade [108]. These services allow the patients to stay in their own homes for as long as possible. From the government's point of view, home care services reduce the patient flow in hospitals and reduce the cost of care [107].

In this context, the home care agencies receive new patient requests everyday and continuously try to better manage their resources in order to serve them while maintaining a high level of service. Due to this resources' management, the scheduling decisions are becoming crucial in order to keep a high acceptance rate and be able to maximize the agency's revenues. In this work, we are interested in the home care scheduling with predefined visits (*HCS-PV*). This problem can be described as follows ; each week some patients leave the agencies' system (end of the care plan, problem requiring a hospital admission, etc.) and thus, agencies have to decide how many new patients they can accept and how the patients will be assigned to the providers and scheduled. In order to conserve a high continuity of care (i.e. a strong patient-provider relationship), the schedules for the patients already present in the system (named *existing patients*) have to stay unchanged (same assigned provider, same visit time and days). To efficiently solve the problem, the home care agencies usually split the patients per area and solve the scheduling problems per team of providers (5 to 15 providers). Moreover, most of the agencies are still creating the schedules by hand while trying to take into account all the constraints simultaneously. This usually leads to suboptimal solutions and usually requires a large amount of time for the schedulers. To help them in this task, more and more researchers attempt to develop efficient optimization methods taking into account the practical constraints met by the home care agencies while producing high quality solutions in a short amount of time in order to be used in practice.

According to the literature, the proposed *HCS-PV* can be described as a variant of the home health care routing and scheduling problem (HHCRSP), a 20 years old problem ([111], [42]).

To the best of our knowledge, no standard version of the *HHCRSP* exists (different constraints and/or objectives) but it is usually respresented as a rich vehicle routing problem. This plurality of modeling, which originates from the countries' home care management policies, makes it difficult to compare the existing methods. In our case, the *HCS-PV* is close to a consistent VRP with home care specific constraints.

The HHCRSP (see [16], [17] for two comprehensive surveys) was originally solved on a daily planning horizon. It, then, has evolved to integrate more practical constraints such as the maximization of the patients and caregivers' preferences [29], the balance of the workload [23], shared visits [35] or even the time-dependent travel time [27]. Thereafter, the HHCRSP has been extended to a weekly horizon that allows for better coping with the reality of some constraints, such as the patients' care plan and/or the continuity of care. Some exact methods [26,51,96,113] have been proposed. Nevertheless, the complexity of the problem often leads to scalability issues. In order to cope with those issues, recent works apply metaheuristic-based methods [18, 19, 104, 114, 115, 123]. Those methods allow to solve large problems but do not offer any proof of convergence or optimality gap.

Recently, [13] have proposed a new method to solve the *HCS-PV* based on a logic-based Benders decomposition (*LBBD*). The proposed method decomposes the problem in two parts, the acceptance and assignments of the patient is done in a master problem while the feasibility of the scheduling constraints (time windows, travel times, etc.) is checked in independent subproblems. Based on their computational experiments, the proposed *LBBD* outperforms the classical mixed-integer formulation in terms of computation time. Nevertheless, on large instances, the proposed *LBBD* does not seem robust and the computation time quickly increases with the size of the instances. In this work, we propose to extend the idea of solving the *HCS-PV* using Benders decompositions by introducing novel master and subproblem decompositions in order to reduce the computation time. This computation time's reduction will allow the home care agencies to solve larger problems and use the proposed methods on a daily basis.

In this paper, the contributions are as follows. We firstly propose a new algorithm for the subproblem of the *LBBD* formulation presented in [13]. It decomposes the subproblem to make it easier to solve. Secondly, we present a new *LBBD* formulation with additional variables. The new variables correspond to visit patterns for the patients ; they combine the assigned provider, the visit days, and the visit times in a single variable so that most of the constraints can be handled in the master problem. Finally, we propose a new matheuristic method based on a Dantzig–Wolfe formulation (DWF) and a large neighborhood search (LNS). This matheuristic iteratively solves the problem using *LNS* and then solves the *DWF* using the providers' schedules found during the *LNS* iterations. Our computational experiments show that the matheuristic finds all the optimal solutions of the benchmark instances in less than 20 seconds.

The remainder of this paper is as follows. Section 5.2 defines the problem. Section 5.3 presents the mathematical formulations and Section 5.4 describes our matheuristic. Section 5.5 presents the computational results and Section 5.6 provides concluding remarks.

5.2 Problem definition

HCS-PV considers a patient set P and maximizes the number of scheduled patients given a set of available providers A on a 5-days horizon. For each scheduled patient, we must determine the assigned provider, the visit days, and the visit time. These decisions must take into account the existing patients ; the scheduled visits for these patients cannot be modified for continuity of care purposes. In the home care context, continuity of care involves always sending the same provider at the same time to the same patient, to build a relationship between them and to improve the patient's experience. Figure 5.1 gives an example of a provider's schedule and a possible slot for a new patient requiring two visits per week.

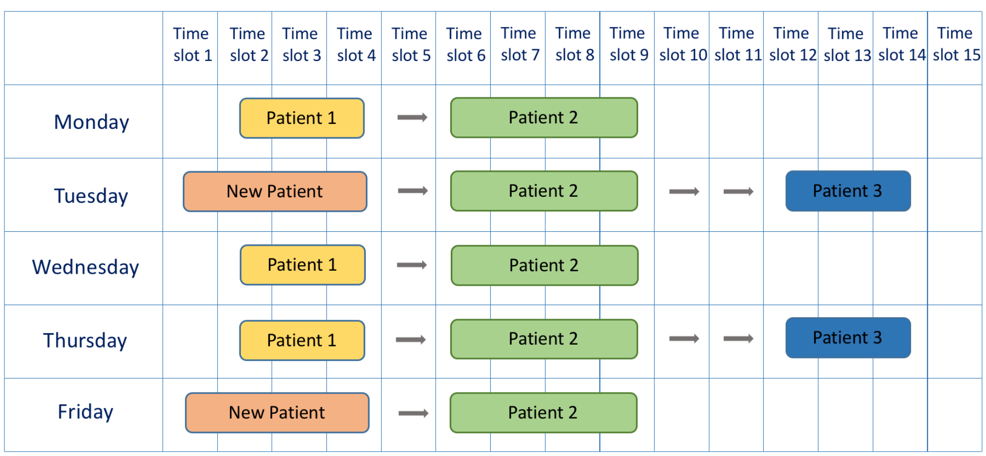

Figure 5.1 Possible assignment for a new patient requiring two visits per week.

Various assignment and routing constraints must be taken into account. Each patient is assigned to a single provider, and the visit times must be the same throughout the week (visit consistency). There are also restrictions on the travel time, the available time windows for the patients and providers, and the maximum weekly working time for the providers. Formally, each patient p has a required number of visits $v_p \in [1, 5]$, a level of qualification required Q_p, a visit duration dur_p, a location l_p and a time window $[r_p, d_p]$ in which he/she must be visited. Moreover, some patients have special requirements, e.g., they may need a specified duration between visits. For example, a patient could require two visits with at least one day between the visits. In this case, the visit days Monday-Wednesday or Tuesday-Friday will be allowed but the visit days Tuesday-Wednesday or Thursday-Friday will be forbidden. For this constraint we define the set K_p, representing all the combination of visit days which are allowed for patient p. Finally, each provider a has a location l_a, a working time window $[r_a, d_a]$, a qualification level Q_a and a maximum weekly working time $\overline{W_a}$. The working time only comprises the time between the start of the first patient and the end of the last patient for each work day. A summary of these parameters is given in Table 5.1.

Table 5.1 Description of the problem's parameters

Parameter	Description
P	Set of patients
A	Set of providers
v_p	Number of visits required
Q_p	Required level of qualification
dur_p	Duration per visit
l_p	Patient's location
$[r_p, d_p]$	Patient's time window (same every day)
K_p	Feasible combination of visit days
l_a	Provider's location
$[r_a, d_a]$	Provider's time window (same every day)
Q_a	Provider's qualification level
$\overline{W_a}$	Maximum work time over the week

5.3 Mathematical formulations

In this section, we present different formulations for the proposed problem. The goal here is to use those different formulations in order to tackle the problem in different ways and analyze if some computation time reductions are observed. Firstly, we recall the formulation introduced by [13]. This formulation corresponds to a natural Benders decomposition for the problem, with the assignments in the master problem and the scheduling in the subproblems. Secondly, we propose an alternative subproblem for this first formulation using two steps of resolution. Thirdly, we propose a new Benders formulation using pattern of visits as variable, this formulation's objective is to have more constraints in the master problem in order to potentially improve the resolution time. Finally, we propose a classical Dantzig-Wolfe resolution based on the providers' weekly schedules.

5.3.1 Assignment-based LBBD

This first formulation [13] uses a *LBBD* [124], which derives from the classical Benders decomposition [125]. The classical Benders method decomposes the problem into two parts (master problem and subproblem). It iteratively solves the master problem and checks the feasibility and optimality of the solution in the subproblems. If necessary, the subproblem generates feasibility and/or optimality cuts, and these cuts are added to the master problem. The process stops when the generated solution is optimal or the problem is proved infeasible. The Benders subproblems are linear programs, but in the *LBBD* the subproblem is a feasibility check based on the inference dual. In order to ease the comprehension of this first model, the variables presented in the subsequent sections are summarized in Table 5.4. in the Appendix.

Master problem

In this first *LBBD*, the master problem corresponds to an assignment problem defining the visited patients and their visited days as well as the patient-provider assignments. We define three sets of decision variables : δ_p is set to 1 if patient p is visited and 0 otherwise ; $x_{a,p}$ is 1 if patient p is visited by provider a and 0 otherwise ; and $y_{a,p,d}$ equals 1 if patient p is visited by provider a on day d. If there are restrictions on which days patients can be scheduled, we manage this with the constraint $\mathbf{y} \in K_p$.

The master problem (MP) is as follows :

$$(MP) : \max \sum_{p \in P} \delta_p \tag{5.1}$$

$$\begin{aligned}
\text{subject to : } \sum_{a \in A} x_{a,p} &= \delta_p \qquad \forall p \in P && (5.2)\\
y_{a,p,d} &\leq x_{a,p} \qquad \forall a \in A, \forall p \in P, \forall d \in D && (5.3)\\
\sum_{a \in A} \sum_{d \in D} y_{a,p,d} &= v_p \delta_p \qquad \forall p \in P && (5.4)\\
x_{a,p} &= 0 \qquad \forall a \in A, \forall p \in P, Q_p \nsubseteq Q_a && (5.5)\\
\mathbf{y} &\in K_p \qquad \forall p \in P && (5.6)\\
\delta_p, x_{a,p}, y_{a,p,d} &\in \{0,1\} \qquad \forall a \in A, \forall p \in P, \forall d \in D && (5.7)
\end{aligned}$$

In MP, the objective function (5.1) maximizes the number of patients visited. Constraints (5.2) and (5.3) are the convexity constraints that link the variables, and constraints (5.4) enforce the required number of visits per patient. Constraints (5.5) ensure that requirements and skills are respected, and constraints (5.6) control the sets of days allowed for each patient. Finally, constraints (5.7) are the binary restrictions.

Subproblem

The subproblem determines if the assignment found by MP is feasible according to the scheduling constraints : synchronization of the visits, travel time, time windows and maximum worktime. In case of infeasibility, *no-good cuts* (on the $y_{a,p,d}$ variables) are added to the master problem. We define a subproblem SP_a for each provider a. Each SP_a corresponds to a multiple-day traveling salesman problem with time windows, and it is solved using constraint programming. For each *SP*, we define $P_{(SP_a)}$ the set of assigned patients and $P_{(SP_a),d}$ the set of patients assigned per day d to provider a. In addition, we define sequencing variables $\pi_{d,v}$ which correspond to the patient p's location visited in the v^{th} position on day d, with $p \in P_{(SP_a),d}$. These variables also take into account the fact that each route must start and end at the provider's location l_a. Moreover, we introduce the variables s_p corresponding to the visit time for patient p and the parameter V_d equal to the number of patient visited the day d (i.e, $|P_{(SP_a),d}|$). Finally, we restrain the patients' time windows according to the provider's one by defining $r'_p = max(r_a, r_p)$ and $d'_p = min(d_a, d_p)$. We define a subproblem for each provider as follows :

$$
\begin{aligned}
& (SP_a) : \max 0 && && (5.8)\\
& \pi_{d,1} = l_a, \pi_{d,V_d+2} = l_a && \forall d \in D && (5.9)\\
\text{s.t. } & all\_different\{\pi_{d,v} | v = 1,..,V_d+2\} && \forall d \in D && (5.10)\\
& r'_p \leq s_p \leq d'_p - dur_p && \forall p \in P_{(SP_a)} && (5.11)\\
& s_{\pi_{d,v}} + dur_{\pi_{d,v}} + t_{\pi_{d,v},\pi_{d,v+1}} \leq s_{\pi_{d,v+1}} && \forall d \in D, v = 1,..,V_d+1 && (5.12)\\
& \sum_{d \in D} (s_{\pi_{d,V_d+1}} + dur_{\pi_{d,V_d+1}} - s_{\pi_{d,2}}) \leq \overline{W_a} && && (5.13)\\
& \pi_{d,v} \in P_{(SP_a),d} \cup l_a && \forall d \in D, v = 1,..,V_d+2 && (5.14)
\end{aligned}
$$

In this formulation, the objective function (5.8) is 0 because we simply want to check that a solution exists. Constraints (5.9) ensure that the provider starts and ends each day at his/her home. This means that for each day, the tour start at $v = 1$, ends at $v = V_d + 2$ and the first patient is visited at the position $v = 2$ and the last patient at position $v = V_d + 1$. Constraints (5.10) ensure that all the locations are visited and constraints (5.11) enforce the patients' time windows. The travel time constraints are taken into account by constraints (5.12) and the maximum working time by constraints (5.13). Finally, the variables' domains are defined by constraints (5.14).

5.3.2 Two-steps subproblem

As described in the previous section, the subproblem SP_a is defined for each provider a individually and has to cope with all the routing constraints (travel time, visit consistency, overtime, time windows). Depending on the problem's difficulty (size of the time windows, number of patient to schedule), this simultaneous management of all those constraints could lead to an excessive computation time. In order to avoid this issue, we propose an alternative subproblem resolution allowing to split the resolution in two steps. The first step will only check the travel time and time windows constraints, the second will solve the whole subproblem as proposed in the previous section. To describe this two-steps subproblem, we introduce the constraint programming formulation of the daily problem. The daily subproblem $(SP_{a,d})$ is as follows.

$$
\begin{aligned}
& (SP_{a,d}) : \max 0 && && (5.15)\\
\text{s.t. } & all\_different\{\pi_v | v = 1, .., V_d + 2\} && && (5.16)\\
& \pi_1 = l_a, \pi_{V_d+2} = l_a && && (5.17)\\
& r'_p \leq s_p \leq d'_p - dur_p && \forall p \in P_{(SP_a),d} && (5.18)\\
& s_{\pi_v} + dur_{\pi_v} + t_{\pi_v,\pi_{v+1}} \leq s_{\pi_{v+1}} && v = 1, .., V_d + 1 && (5.19)\\
& \pi_v \in P_{(SP_a),d} \cup l_a \cup l_{a'} && v = 1, .., V_d + 2 && (5.20)
\end{aligned}
$$

According to this formulation, the alternative subproblem now first solves the problem for each day independently $(SP_{a,d})$. The provider's maximum weekly working time and consistency constraints are not considered (constraints 5.11 and 5.13). If a feasible route is found for each day, we solve the full subproblem (SP_a), otherwise a feasibility cut is created for each non-feasible day.

5.3.3 Pattern-based LBBD

As described previously, the master problem proposed in [13] manages the acceptances/assignments and all the routing constraints are managed in the subproblems. In this section, we present a second Benders decomposition. The idea here is to move most of the constraints from the subproblems to the master one. This modification could help the master problem to better "understand" the problem and so more easily find interesting integer solutions in order to reduce the computation time. As a reminder, in order to define a feasible solution, we must determine for each accepted patient, the assigned provider, the set of visit days, and the visit time. In the second formulation, we combine these decisions into a new variable.

We introduce the concept of a visit pattern ω. That includes all of these four elements : a patient p_ω, an assigned provider a_ω, a set of visit days D_ω, and a visit time s_ω. In comparison with the previous master problem, the pattern ω could be seen as a concatenation of the $x_{a,p}$ and $y_{a,p,d}$ variables. The problem involves assigning a pattern $\omega \in \Omega_p$ to each patient, where Ω_p is a set containing all the feasible visit patterns for patient p, with $\cup_{p \in P} \Omega_p = \Omega$. Because the schedules of the existing patients can't be modified, we can compute in advance the set of feasible patterns for each patient, thus generating the set Ω containing all the feasible patterns. To do so, for each patient (p), each provider (a), each time index (t) and each combination (C) of $\binom{5}{v_p}$ days respecting the patient's K_p set, we check if the pattern made of provider a, visit time t, and visit days C is feasible for patient p, according to the provider a's available visit slots.

Master problem

We now present the new *LBBD* formulation based on Ω. Variable δ_p still corresponds to the patient acceptance and let x_ω be 1 if visit pattern ω is selected. Finally, $tt_{\omega,\omega'}$ corresponds to the travel time between the patient locations associated with patterns ω and ω'.

$$(PBF) : \max \sum_{p \in P} \delta_p \tag{5.21}$$

$$\text{s.t. } \delta_p = \sum_{\omega_p \in \Omega_p} x_{\omega_p} \qquad \forall p \in P \tag{5.22}$$

$$x_\omega + x_{\omega'} \leq 1 \qquad \forall (\omega, \omega') \in \Omega, D_\omega \cap D_{\omega'} \neq \emptyset, s_\omega + tt_{\omega,\omega'} > s_{\omega'} \tag{5.23}$$

$$\delta_p \in \{0, 1\} \qquad \forall p \in P \tag{5.24}$$

$$x_\omega \in \{0, 1\} \qquad \forall \omega \in \Omega \tag{5.25}$$

Let PBF be the new pattern-based formulation. The master problem is a set covering problem defined by (5.21)–(5.25). The objective function (5.21) maximizes the number of patients visited. Constraints (5.22) are the convexity constraints that link the decision variables, and constraints (5.23) enforce the travel time between patients. Constraints (5.24)–(5.25) are the binary restrictions. This new master problem includes all the constraints (single provider-to-patient assignment, consistent visits, required number of visits, travel time, patient's requirements) except for the restrictions on the providers' working time, which are enforced in the subproblems.

Subproblem

The subproblems are described as follows. For each provider a, the subproblem retrieves the list of selected patterns and computes for each day the total worktime (time between the start of the earliest visit and the end of the latest one). If the sum of these work times is greater than $\overline{W_a}$, a feasibility cut is added to the master problem. We provide a procedure in polynomial time as described in Algorithm 3.

Algorithm 3: Subproblem solution (for provider a)

```
sum_work_time = 0 ;
for each day d do
    Retrieve the list L_d of assigned patterns containing d;
    Sort L_d by increasing order of visit times and build the route r_d;
    sum_work_time += r_d's work time;
if sum_work_time > W̄_a then
    Create a no-good cut on the assigned patterns;
```

5.3.4 Dantzig-Wolfe decomposition

As described in the introduction, the branch-and-price methods have been widely used to solve the home health care scheduling problem ([96], [26]). Moreover, in the previous section, we have shown that each patient schedule can be represented by a pattern. For each feasible solution, we can define the provider's schedule by the subset of patterns that has been assigned to this provider. Therefore, a provider's schedule consists of visit patterns that satisfy travel and work-time constraints. We use this aggregation of patterns (i.e. the schedules) to build the third formulation, a Dantzig-Wolfe decomposition.

We introduce Λ, the set of feasible providers' schedules, and Λ_a the subset of feasible schedules for provider a (with $\Lambda = \cup_{\Lambda_a}$). Let n_λ be the number of patients visited by schedule $\lambda \in \Lambda$. Let $v_{\lambda,p}$ equal to 1 if patient p is visited by schedule λ and 0 otherwise. Finally, we define the decision variable x_λ, which equals 1 if provider's schedule λ is selected and 0 otherwise.

The assignment set partitioning formulation (ASP) is a Dantzig–Wolfe decomposition and is stated as follows :

$$(ASP) : \max \sum_{\lambda \in \Lambda} n_\lambda x_\lambda \tag{5.26}$$

$$\text{s.t.} \sum_{\lambda \in \Lambda_a} x_\lambda \leq 1 \qquad \forall a \in A \tag{5.27}$$

$$\sum_{\lambda \in \Lambda} v_{\lambda,p} x_\lambda \leq 1 \qquad \forall p \in P \tag{5.28}$$

$$x_\lambda \in \{0, 1\} \qquad \forall \lambda \in \Lambda \tag{5.29}$$

The objective function (5.26) maximizes the number of patients scheduled. Constraints (5.27) ensure that there is at most one schedule per provider, and constraints (5.28) ensure that there is at most one schedule per patient. Finally, constraints (5.29) are the binary restrictions.

5.4 Visit pattern matheuristic

In this section, we present a visit pattern matheuristic based on the formulation proposed in Section 5.3.4 and a large neighborhood search (LNS). The *LNS* [110] is a metaheuristic using the *ruin-and-recreate* principle [118]. This iterative method destroys some parts of the solution and then repairs it to improve its quality. The current and best solutions are then updated if necessary.

According to the literature ([126], [127], [123]), matheuristics provide a good balance between the solution quality of an exact method and the short computation time of metaheuristics. In the proposed matheuristic, the idea is to use the providers' schedules as variables which can be generated using the *LNS* procedure. During the *LNS*' iterations, all the encountered feasible weekly schedules are kept in a list. After a certain number of iterations, the *LNS* stops and then we solve (5.26) – (5.29) using the retrieved schedules. If a better solution is found by the set partitioning, the *LNS*' best solution is updated and another round of *LNS* iterations is run. A similar matheuristic framework has been introduced in [123].

5.4.1 Overview of visit pattern matheuristic

Algorithm 4 gives an overview of the visit-pattern matheuristic (VPM). We first create an initial solution and then iteratively remove part of the solution using a removal operator and rebuild it using a repair operator. We then analyze the temporary solution (S_t) to see if it improves the best found solution (S^*) or if the acceptance rule (simulated annealing in our context) accepts it as the current solution (S_c). We solve the set partitioning problem based on Λ every 2000 iterations and update the current and best solutions if necessary. The implementation details are given in Section 5.4.2

Algorithm 4: VPM

```
Create the initial solution S_c;
Set the best found solution S* to S_c;
Create the empty set of providers' weekly schedules Λ;
while termination criterion not met do
    S_t ← S_c;
    Apply removal operator to S_t;
    Apply repair operator to S_t;
    Add the found schedules to Λ;
    if S_t is accepted then
        S_c ← S_t;
    if S_t is better than S* then
        S* ← S_t;
    if total_iteration % 2000 = 0 then
        S_sp ← Solve ASP based on Λ;
        if S_sp better than S* then
            S* ← S_sp;
            S_c ← S_sp;
```

5.4.2 Implementation details

We now present the implementation details of our *LNS* algorithm. We first build the initial solution using a greedy approach (see Algorithm 5). This algorithm starts by creating the actual schedules per provider by inserting all the existing patients. Then, iteratively, a new patient is randomly chosen and all his/her possible insertions (feasible visit patterns assignments) are computed. If at least one assignment is feasible, the patient is accepted and the method assigns the pattern generating the lowest increase in terms of travel time. The procedure is repeated until all the new patients are processed.

Algorithm 5: Initial Solution

Create P', a copy of the patient set P;
Create the solution S_0 with fixed visit patterns per provider;
while *P' is not empty* **do**
  Randomly select patient p from P';
  Remove p from P';
  Find all the feasible insertions I_p for p's visit patterns;
  if *I_p is not empty* **then**
    Apply to S_0 the insertion giving the smallest increase of travel time;
  return solution S_0;

In terms of operators, we have adapted the classical removal and destroy operators from [110] and [120]. These operators work on the feasible visit patterns described in Section 5.3.3. We list the operators here with brief descriptions. The removal operator [120] removes q patients per iteration, and we set q to 30% of the number of scheduled patients. We define $C_{p,n}$ to be the increase in the travel time arising from the insertion of patient p's nth best option.

Random removal This operator randomly selects q scheduled patients and removes their visit patterns from the solution.

Worst removal This operator computes, for each patient, the improvement in the travel time if the patient's visit pattern is removed. It then removes the q patients with the highest values.

Related removal This operator randomly selects a patient and removes his/her visit pattern. Then it removes the $q-1$ most closely related patients. In our implementation, the relation between two patients is based on the percentage of shared time windows and the required number of visits : $R(p,p') = \frac{[r_p,d_p]\cap[r_{p'},d_{p'}]}{d_p-r_p} + min(1, \frac{v_{p'}}{v_p})$.

Random repair This operator randomly selects an unscheduled patient p, computes the possible insertions of p's visit patterns, and applies the insertion with the lowest cost. This operation is repeated until all the unscheduled patients have been tested.

Greedy repair This operator iteratively computes the possible insertions for the unscheduled patients and applies the insertion associated with the smallest increase of travel time. This operation is repeated until there are no more possible insertions.

Regret repair This operator iteratively computes the possible insertions of the unscheduled patients and applies the best insertion for the patient with the highest regret value. Patient p's regret value is $C_{p,2} - C_{p,1}$.

During the *LNS*, the acceptance rule determines if the created solution can be accepted as the new current solution. It is based on simulated annealing as described in [120]. We set our initial temperature to $1.05 * f(S_0)$ and the decreasing temperature c to 0.99975. Finally, the termination of our *LNS* algorithm is based on two termination criteria : we stop after 20,000 iterations or 20 seconds of computation.

5.5 Computational results

In this section, we present experiments that compare the efficiency of all the proposed methods (two-steps subproblem, the pattern-based formulation and the matheuristic). To provide an extensive comparison, we have re-implemented the method proposed in [13]. We refer to their formulation as *Heching* and we use the 57 provided instances. These instances are based on real-data provided by a home care agency from Pennsylvania, US. Each instance contains 60 patients and 6 providers. Over those 60 patients, between 8 and 30 are "new" and a decision of acceptance or not has to be taken for these patients. The provided instances are split into three sets :

— *Classical* : Instances provided by their industrial partner ;

— *Narrow* : Based on the *Classical* instances, with narrower patient time windows ;

— *Fewer* : Based on the *Classical* instances, with fewer visits per patient.

We implemented the methods in C++ and performed the tests on a 2.7 GHz Intel Core i5 Macbook, with 16 Gb RAM using only one core. We solve the master problems (5.1)–(5.7) and (5.21)–(5.25) using Cplex 12.7.1 and the subproblems (5.8)–(5.14) and (5.15)–(5.20) using CP Optimizer version 12.7. Finally, for the *LBBD*s, the maximum computation time is set to 3600 s per instance.

5.5.1 Efficiency of the *LBBD* formulations

We now analyze the impact of the two-steps subproblem (5.3.2) and the pattern-based formulation (PBF). The results are given in Table 5.2. The first two columns present the instance name, the number of new patients and the number of patients accepted in the optimal solution. The *CPU* column gives the computation time in seconds. Finally, for *PBF*, *Nb Pattern* gives the number of feasible patterns computed and *TL* is the time limit (3600 s).

We observe that using the two-steps subproblem dramatically reduces the computation time (-36.14%) and outperforms *Heching* for 51 of 55 solved instances. In addition, according to Figure 5.2, *Heching*' subproblem has a failure rate (*Heching - Inf SubP*) of 80.65% in average while the two-steps subproblem only calls the whole subproblem (*Two_Steps - Call SubP*) 30.70% of the time and the subproblem is infeasible (*Two_Steps - Inf SubP*) only for 28.74% of those calls.

For the *Classical* and *Narrow* instances, the *PBF* dramatically outperforms the model proposed in [13] even with the two-steps subproblem. The *PBF* solves all the *Classical* instances in less than 9 s and all the *Narrow* instances in less than 2 s. However, for the *Fewer* instances containing more than 25 new patients, we observe a large increase of computation time compared to *Heching*. This issue is due to the increase in the number of generated patterns and therefore the size of the set partitioning problem. Nevertheless, *PBF* solves all the benchmark instances.

Table 5.2 Results for the two-steps subproblem and visit pattern formulation

		Heching	Alt. Subp.		PBF		
Instance	New / Accepted	CPU (s)	CPU (s)	% Improvement	CPU (s)	% Improvement	Nb Pattern
Classic_8	8/8	1.05	0.59	-43.81%	**0.01**	-99.05%	277
Classic_9	9/8	0.96	0.71	-26.04%	**0.01**	-98.96%	276
Classic_10	10/9	1.34	0.83	-38.06%	**0.02**	-98.51%	358
Classic_11	11/10	1.26	1.15	-8.73%	**0.02**	-98.41%	405
Classic_12	12/11	1.53	1.42	-7.19%	**0.02**	-98.69%	441
Classic_13	13/12	2.12	0.85	-59.91%	**0.05**	-97.64%	551
Classic_14	14/12	8.85	5.75	-35.03%	**0.11**	-98.76%	690
Classic_15	15/13	8.79	6.30	-28.33%	**0.11**	-98.75%	724
Classic_16	16/14	14.27	6.06	-57.53%	**0.16**	-98.88%	865
Classic_17	17/16	12.81	11.54	-9.91%	**0.45**	-96.49%	1171
Classic_18	18/16	22.14	14.11	-36.27%	**0.53**	-97.61%	1214
Classic_19	19/17	31.93	30.79	-3.57%	**0.87**	-97.28%	1275
Classic_20	20/17	97.78	47.67	-51.25%	**0.7**	-99.28%	1325
Classic_21	21/19	210.34	86.18	-59.03%	**1.2**	-99.43%	1403
Classic_22	22/20	185.70	96.46	-48.06%	**0.91**	-99.51%	1535
Classic_23	23/21	1048.01	1557.68	48.63%	**5.31**	-99.49%	1913
Classic_24	24/22	TL	TL	/	**5.32**	/	2032
Classic_25	25/24	646.88	676.69	4.61%	**3.3**	-99.49%	2309
Classic_26	26/25	2088.62	532.45	-74.51%	**8.44**	-99.60%	2543
Fewer_12	12/10	1.25	1.03	-17.60%	**0.07**	-94.40%	998
Fewer_13	13/11	1.23	1.11	-9.76%	**0.09**	-92.68%	1158
Fewer_14	14/12	2.15	1.35	-37.21%	**0.12**	-94.42%	1230
Fewer_15	15/13	1.82	1.15	-36.81%	**0.22**	-87.91%	1584
Fewer_16	16/14	2.20	1.58	-28.18%	**0.3**	-86.36%	1671
Fewer_17	17/15	2.92	2.43	-16.78%	**0.56**	-80.82%	1989
Fewer_18	18/16	3.87	2.08	-46.25%	**0.68**	-82.43%	2109
Fewer_19	19/17	4.04	3.35	-17.08%	**1.54**	-61.88%	2484
Fewer_20	20/19	4.78	2.11	-55.86%	**2.02**	-57.74%	2645
Fewer_21	21/20	4.63	2.39	-48.38%	**2.12**	-54.21%	2954
Fewer_22	22/21	4.85	**2.28**	-52.99%	2.53	-47.84%	3459
Fewer_23	23/23	11.05	**1.75**	-84.16%	5.98	-45.88%	3693
Fewer_24	24/24	4.78	**2.55**	-46.65%	4.12	-13.81%	3991
Fewer_25	25/25	19.16	**3.25**	-83.04%	5.61	-70.72%	4536
Fewer_26	26/26	5.09	**1.59**	-68.76%	5.61	10.22%	4875
Fewer_27	27/27	21.70	**4.27**	-80.32%	29.74	37.05%	4950
Fewer_28	28/28	49.97	**13.64**	-72.70%	125.98	152.11%	5108
Fewer_29	29/28	78.30	**21.17**	-72.96%	83.68	6.87%	5196
Fewer_30	30/29	398.6	**221.64**	-44.40%	3530.71	785.78%	5318
Narrow_8	8/7	0.95	0.67	-29.47%	**0.01**	-98.95%	243
Narrow_9	9/8	1.33	0.88	-33.83%	**0.01**	-99.25%	242
Narrow_10	10/9	1.67	0.75	-55.09%	**0.01**	-99.40%	296
Narrow_11	11/10	1.29	0.79	-38.76%	**0.01**	-99.22%	308
Narrow_12	12/11	0.97	1.03	6.19%	**0.01**	-98.97%	348
Narrow_13	13/12	2.16	0.98	-54.63%	**0.02**	-99.07%	394
Narrow_14	14/13	4.51	4.25	-5.76%	**0.04**	-99.11%	543
Narrow_15	15/14	4.08	2.20	-46.08%	**0.04**	-99.02%	568
Narrow_16	16/15	6.80	3.80	-44.12%	**0.08**	-98.82%	692
Narrow_17	17/16	7.38	4.50	-39.02%	**0.14**	-98.10%	823
Narrow_18	18/16	14.90	7.58	-49.13%	**0.24**	-98.39%	842
Narrow_19	19/17	17.81	11.41	-35.93%	**0.25**	-98.60%	846
Narrow_20	20/17	23.46	25.05	6.78%	**0.49**	-97.91%	860
Narrow_21	21/18	34.24	25.47	-25.61%	**0.54**	-98.42%	878
Narrow_22	22/19	73.74	68.79	-6.71%	**0.5**	-99.32%	948
Narrow_23	23/21	190.47	129.74	-31.88%	**1.23**	-99.35%	1212
Narrow_24	24/22	674.33	401.60	-40.44%	**1.13**	-99.83%	1317
Narrow_25	25/23	TL	TL	/	**1.38**	/	1452
Narrow_26	26/25	1303.29	1169.51	-10.26%	**1.89**	-99.85%	1594
Average				**-36.14%**		**-64.30%**	

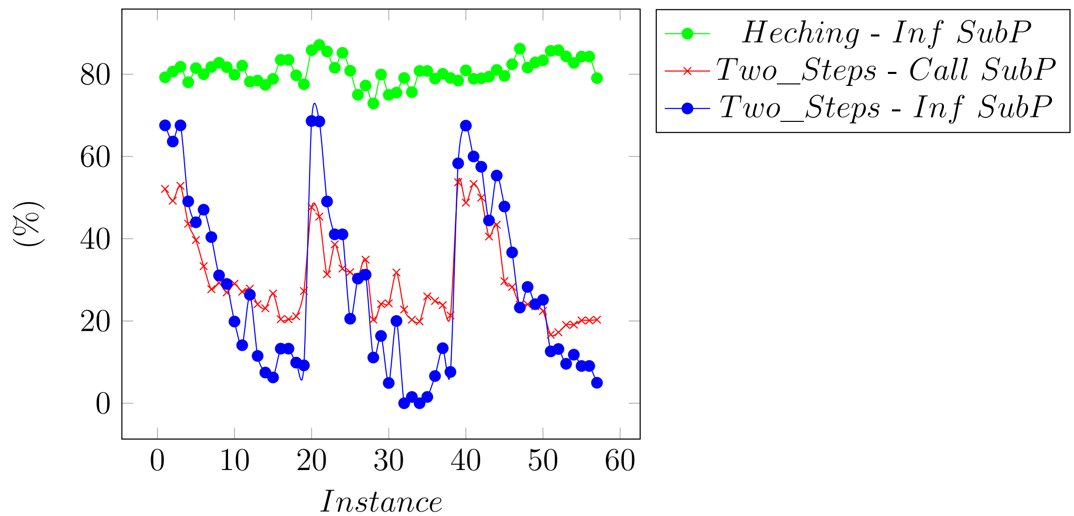

Figure 5.2 Comparison of the failure rates during the full subproblems resolutions

5.5.2 Efficiency of the matheuristic

In this section, we test the visit pattern matheuristic (VPM) proposed in Section 5.4. To do this, we solve the instances with the classical *LNS* (i.e., without the set partitioning resolution) and with the *VPM*. The results are given in Table 5.3. The columns Best and CPU Best correspond to the best found solution and the time (in seconds) at which this solution was found. The *LNS* optimally solves 37 of the 57 instances in less than 20 s or 20,000 iterations. With the same termination criteria, the *VPM* finds the optimal solution for all the instances. For most of the instances (51), the *VPM* finds the best solution in the first 10 s.

Table 5.3 Results for the matheuristic

		Heching et al.	LNS			VPM		
Instance	Optimal Solution	CT	Best Solution	CT	Time Best Solution	Best Solution	CT	Time Best Solution
Classic_8	60	1.05	**60**	8.3	**0.06**	**60**	8.44	**0.06**
Classic_9	59	0.96	**59**	8.32	**0.16**	**59**	8.44	**0.16**
Classic_10	59	1.34	**59**	9.18	**0.01**	**59**	9.59	**0.01**
Classic_11	59	1.26	**59**	11.85	**0.11**	**59**	12.1	**0.11**
Classic_12	59	1.53	**59**	13.41	**0.01**	**59**	13.99	**0.01**
Classic_13	59	2.12	**59**	16.21	**0.03**	**59**	14.92	**0.03**
Classic_14	58	8.85	**58**	19.03	**0.05**	**58**	18.76	**0.05**
Classic_15	58	8.79	**58**	18.51	**0.03**	**58**	18.92	**0.03**
Classic_16	58	14.27	**58**	20	**0.06**	**58**	20	**0.06**
Classic_17	59	12.81	**59**	20	17.03	**59**	20	**4.16**
Classic_18	58	22.14	**58**	20	**0.7**	**58**	20	0.75
Classic_19	58	31.93	**58**	20	**3.12**	**58**	20	3.17
Classic_20	57	97.78	**57**	20	**0.02**	**57**	20	0.03
Classic_21	58	210.34	57	20	5.53	**58**	20	**10.49**
Classic_22	58	185.7	57	20	4.01	**58**	20	**5.58**
Classic_23	58	1048.01	57	20	1.12	**58**	20	**6.88**
Classic_24	58	TL	**58**	20	**3.5**	**58**	20	3.52
Classic_25	59	646.88	58	20	8.35	**59**	20	**16.18**
Classic_26	59	2088.62	57	20	0.68	**59**	20	**9.14**
Fewer_12	58	1.25	**58**	20	**0.16**	**58**	20	**0.16**
Fewer_13	58	1.23	**58**	20	**0.04**	**58**	20	**0.04**
Fewer_14	58	2.15	**58**	20	0.02	**58**	20	**0.01**
Fewer_15	58	1.82	**58**	20	**1.01**	**58**	20	1.03
Fewer_16	58	2.2	**58**	20	**0.09**	**58**	20	**0.09**
Fewer_17	58	2.92	**58**	20	**0.09**	**58**	20	0.1
Fewer_18	58	3.87	**58**	20	**0.15**	**58**	20	**0.15**
Fewer_19	58	4.04	**58**	20	**1.04**	**58**	20	**1.04**
Fewer_20	59	**4.78**	**58**	20	0.25	**59**	20	6.29
Fewer_21	59	4.63	**59**	20	**1.69**	**59**	20	1.96
Fewer_22	59	4.85	**59**	20	5.26	**59**	20	**4.83**
Fewer_23	60	11.05	59	20	0.16	**60**	20	**8.79**
Fewer_24	60	4.78	**60**	20	0.84	**60**	20	**0.8**
Fewer_25	60	19.16	**60**	20	16.66	**60**	20	**9.61**
Fewer_26	60	**5.09**	**60**	20	12.62	**60**	20	10.41
Fewer_27	60	21.7	59	20	0.29	**60**	20	**11.19**
Fewer_28	60	49.97	59	20	3.84	**60**	20	**12.2**
Fewer_29	59	78.3	**59**	20	9.99	**59**	20	**9.45**
Fewer_30	59	398.6	58	20	7.55	**59**	20	**13.93**
Narrow_8	60	0.95	**60**	8.22	**0.03**	**60**	7.9	**0.03**
Narrow_9	59	1.33	**59**	8.23	0.25	**59**	8	**0.24**
Narrow_10	59	1.67	**59**	9.79	**0.18**	**59**	9.86	**0.18**
Narrow_11	59	1.29	**59**	9.97	**0.2**	**59**	10.98	0.22
Narrow_12	59	0.97	**59**	11.67	**0.79**	**59**	11.39	**0.79**
Narrow_13	59	2.16	**59**	12.57	**0.11**	**59**	12.51	**0.11**
Narrow_14	59	4.51	58	14.94	0.01	**59**	14.86	**1.73**
Narrow_15	59	4.08	58	15.65	0.97	**59**	16.17	**1.81**
Narrow_16	59	6.8	58	20	0.18	**59**	20	**2.28**
Narrow_17	59	7.38	58	20	0.68	**59**	20	**2.73**
Narrow_18	58	14.9	**58**	20	10.59	**58**	20	**2.98**
Narrow_19	58	17.81	57	20	1.68	**58**	20	**3.3**
Narrow_20	57	23.46	56	20	0.62	**57**	20	**3.47**
Narrow_21	57	34.24	56	20	0.74	**57**	20	**3.49**
Narrow_22	57	73.74	**57**	20	16.93	**57**	20	**3.67**
Narrow_23	58	190.47	57	20	11.72	**58**	20	**9.35**
Narrow_24	58	674.33	57	20	11.86	**58**	20	**10.46**
Narrow_25	58	TL	**58**	20	8.39	**58**	20	**5.48**
Narrow_26	59	1303.29	57	20	1.81	**59**	20	**13.46**

5.6 Conclusions

The *HCS-PV* is a complex problem that home care agencies have to solve every week. The goal is to assign and schedule a set of new patients given a set of providers while taking into account the patients already present in the system. Each patient has a required number of visits and can be assigned to only one provider. The visit times must be the same for the entire horizon, and each provider has a maximum working time.

To solve this problem, we have extended the work of [13]. First, we proposed a two-stage subproblem. Then, we presented a new *LBBD* based on visit patterns that includes more constraints in the master problem. Finally, we introduced a Dantzig-Wolfe formulation and developed a matheuristic based on *LNS*.

When computed on real instances from agencies in Pennsylvania provided in [13] our computational experiments show that our two-steps subproblem reduces the average computation time by 34%, while the new pattern-based formulation solves all the benchmark instances (53 out of the 57 instances are solved in less that 10 s). Finally, our matheuristic solves all the instances in less than 20 s. These results lead to two main observations. On the one hand, the pattern-based formulation, due to its speed, could allow the home care agencies to solve larger problems (especially in the $Classic$ and $Narrow$ contexts). Agencies will be able to take into account more providers simultaneously and this could potentially help them improve their offer of service. On the other hand, if the problems become too large, the proposed matheuristic seems to be a good alternative to achieve speed and efficiency. According to the experiments, the proposed matheuristic could allow the agencies to "play" with the algorithm in order to test different parameters (modification of the time windows, set of providers taken into account). This could help them to test different options and optimize their level of service.

In future research, we consider extending the problem to include more practical constraints such as the possibility of having two providers required for the same visits or breaks in the providers' schedules. Finally, we think that solving this problem for only one week is not realistic enough and so, we would like to work on a dynamic version of this problem in order to solve it on a rolling horizon and analyze the impact of the decisions over time.

Acknowledgment

We thank Aliza Heching, John Hooker, and Ryo Kimura for providing access to the benchmark instances. This work has been supported by the Natural Sciences and Engineering Research Council of Canada.

Appendix

Table 5.4 Description of the Benders decomposition's parameters

	Element	Description
Master Problem	δ_p	Patient p is accepted
	$x_{a,p}$	Provider a is assigned to the patient p
	$y_{a,p,d}$	Patient p is visited by provider a the day d
	y	List of feasible $y_{a,p,d}$ values according to visit day K_p
Subproblem	SP_a	Subproblem for the provider a
	$P_{(SP_a)}$	List of patients currently assigned to a ($x_{a,p}*$)
	$P_{(SP_a),d}$	List of patients visited the day d ($y_{a,p,d}*$)
	$\pi_{d,v}$	Ordering variables representing provider's route on day d
	s_p	Visit time for the patient p
	$t_{\pi_{d,v},\pi_{d,v'}}$	Travel time between the locations $\pi_{d,v}$ and $\pi_{d,v'}$

CHAPITRE 6 ARTICLE 3 : THE DYNAMIC HOME HEALTH CARE SCHEDULING PROBLEM : THE VALUE OF FLEXIBILITY

F. Grenouilleau, N. Lahrichi et L-M. Rousseau ont écrit cet article et l'ont soumis en Juin 2020 au journal Health Care Management Science.

6.1 Introduction

During the past decades, living conditions worldwide have dramatically increased, leading to an increase in life expectancy. According to the United Nations, the number of persons aged 60 or older will double by 2050, reaching 1.5 billion [1]. While increased life expectancy is viewed as a positive trend, a large elderly population also presents serious challenges, especially in terms of healthcare needs. Those needs correspond to the use of medicines, appointments with multiple healthcare professionals or even the requirement of home health care services. In 2010, 12 millions people received home care services in North America [128] and 2.2 millions Canadians received home care services in 2012 [129], corresponding to 6.3% of the population. From the home care agencies' point of view, this increase in demand creates challenges in term of resource management, as they seek to serve an increasing number of patients while maintaining a high quality of service.

Home health care routing and scheduling for a set of patients consists of determining the assignment of patient visits to a set of caregivers, and determining the most efficient daily schedules for those caregivers. The type of care delivered to patients is diverse. It can correspond to nursing care, such as injections and medication management, but also personal support with bathing, housekeeping or even meal preparation. Due to increasing demand for home health care services in many countries, this optimization problem has received much attention during the past decade [16, 17, 130].

In practice, this problem is highly dynamic. Every week, patients leave the system (i.e., their home care plan is terminated, or they require hospitalization, etc.) and new patient referrals are sent to the agencies. For each referral, many decisions must be made. First, the agency has to decide if the patient can be accepted or not. Then, the agency has to assign a nurse, a visit time and visit days for the patient. During this assignment process, the main constraint is related to continuity of care. This constraint consists of scheduling the same nurse, on the same days, at the same time, for the duration of the patient's care plan. This constraint is fundamental in the home care context and allows for the development of a strong relationship between the patient and the assigned nurse, which helps maintain a high level of service. Solving the dynamic home health care routing and scheduling problem (DHHCRSP) consists of making dynamic acceptance, routing and scheduling decisions on a rolling horizon, in order to maximize the average number of weekly visits.

This paper investigates two flexibility policies, which propose different *modi operandi* the home care agencies could use to increase their number of weekly visits. First, the decision to accept and schedule a new patient can be postponed until the end of the day, or even the end of the week, rather than deciding immediately as each patient offer is received. Postponing this decision would allow agencies to batch patients' offers and optimize their acceptance and scheduling decisions. A second policy we study in this paper is the assignment of a visit time window to the patient's care plan, as opposed to assigning an exact visit time. This means that instead of telling the patient that he will be visited at 9am, for example we would tell him that the visit time will be between 8.30am and 9.30am. This simple policy shift would relax the visit time constraint from continuity of care, while maintaining a high level of service for patients.

The contributions of this paper are twofold. First, we show the value of postponing the decision moment for accepting and scheduling a new patient. We develop a constructive heuristic and a large neighborhood search to efficiently accept and schedule new patients. Next, we present the dramatic increase in the number of weekly visits provided by the assignment of visit time windows. To support this claim, multiple sensitivity analyses of time window length and insertion criteria are computed.

The rest of the paper is organized as follows. The definition of the problem and previous work related to it are given in Section 6.2. Section 6.3 presents the proposed flexible policies, while resolution methods are described in Section 6.4. Section 6.5 contains the computational experiments and sensitivity analyses. Conclusions are summarized in Section 6.6.

6.2 Problem Definition and related work

= Every week, patients leave home health care agencies' systems (i.e., they are re-admitted to a hospital, their care plan ends, etc.). This frees up some of the agencies' resources, prompting them to select new patients to accept and serve. In this section, we provide a comprehensive definition of the problem and present its related work from the literature.

6.2.1 Problem Definition

The dynamic home health care routing and scheduling problem (DHHCRSP) for a home health agency consists of determining, on a weekly basis, which patient referrals an agency can accept and integrate into its system. When accepted, scheduling decisions must be made for the patient. Those decisions concern the assigned nurse, the visit time and the visit days. This problem is closely linked to the classical home health care routing and scheduling problem [16, 17].

In this context, we define the set of patients P and for each patient p, we have a required number of visits per week n_p, a care plan length c_p in weeks, a visit duration d_p, a location l_p and a level of nursing skill required for the patient s_p. From a practical perspective, all of this information is contained in the referral offers received by the agency. Based on this information, the agency then decides whether to accept the patient or not.

To serve the patients, a set of nurses N is introduced. For each nurse $n \in N$, we have a given location l_n, a daily time window tw_n during which they are available to work and a level of qualification s_n. Considering a rolling horizon, the objective for the home care agencies is to maximize the average number of patient visits per week, while respecting a set of practical constraints.

Agencies must be able to provide the required number of visits per patient, ensure the nurses' availability, the travel time between the patients and provide nurses who possess the required qualifications.

A primary challenge in the home care context is the constraint of continuity of care, sometimes called loyalty. In our context, this constraint corresponds to assigning a unique nurse, a unique visit time and a unique set of visit days to the patient when he is accepted. Those values will stay unchanged for the duration of the patient's care plan. This constraint ensures a strong relationship between the patient and the nurse, leading to a high level of service. Due to this constraint, decisions made by the agency upon each patient's acceptance have a profound impact on the agency's resource allocation in the ensuing weeks.

Formally, we define for each patient p the set of possible visit patterns Ω_p. Each pattern $\omega_p \in \Omega_p$ is defined by an assigned nurse n_{ω_p}, a visit time v_{ω_p}, a set of visit days D_{ω_p} and a set W_{ω_p} of active weeks corresponding to the weeks during which the patient has to be visited. Next, we introduce the set $\overline{A}$ of conflicting patterns. A pair $(\omega_p, \omega_{p'})$ is a disjunctive pair if $n_{\omega_p} = n_{\omega_{p'}}$, $D_{\omega_p} \cap D_{\omega_{p'}} \neq \emptyset$, $W_{\omega_p} \cap W_{\omega_{p'}} \neq \emptyset$ and $v_{\omega_p} + d_p + tt_{l_p,l_{p'}} > v_{\omega_{p'}}$ where $tt_{l_p,l_{p'}}$ corresponds to the travel time between both patients' locations. Finally, the decision variables x_{ω_p} equal 1 if the pattern ω_p is selected, 0 otherwise and the offline DHHCRSP can be formulated as follows :

$$(DHHCRSP): \max \sum_{p \in P} \sum_{\omega_p \in \Omega_p} n_p x_{\omega_p} \tag{6.1}$$

$$\text{s.t.} \sum_{\omega_p \in \Omega_p} x_{\omega_p} \leq 1 \qquad \forall p \in P \tag{6.2}$$

$$x_{\omega_p} + x_{\omega_{p'}} \leq 1 \qquad \forall (\omega_p, \omega_{p'}) \in \overline{A} \tag{6.3}$$

$$x_{\omega_p} \in \{0, 1\} \qquad \forall p \in P, \forall \omega_p \in \Omega_p \tag{6.4}$$

The objective function (6.1) maximizes the number of patients' visits scheduled. Constraints (6.2) ensure that there is at most one selected pattern per patient, and constraints (6.3) ensure that the conflicting pairs of pattern cannot be selected together. Finally, constraints (6.4) correspond to variables' domain specification.

6.2.2 Related work

A fundamental aspect of this problem is deciding which patients to accept while taking into account hard continuity of care (same days, same nurse, same time). This problem has been solved on a weekly horizon by [13]. In this paper, the number of accepted patients is maximized. The authors presented a mixed-integer program formulation and developed a logic-based Benders decomposition to solve the problem.

This work was further extended by [131]. In this paper, authors proposed formulating the possible assignments using visit patterns, and showed that the computation time can be dramatically reduced using those patterns in a logic-based Benders decomposition. They also showed that for the real instances proposed in [13], all optimal solutions can be found in less than 20 seconds using the patterns with a large neighborhood search.

A second aspect of our problem is taking into account the rolling horizon and the decisions' impact over time. This aspect of the problem, was first studied by [132]. In this paper, patients are split to different classes according to their characteristics, and the author maximizes the number of accepted patients over a 12-week horizon. To solve the problem, a stochastic linear programming model is proposed, wherein only the patient to nurse assignment is considered, ignoring the scheduling part. In [133], the authors solved the same problem and allowed for different decisions, such as accepting or rejecting the patient or putting the patient on a waiting list. They developed Markov decisions processes in order to cope with the problem.

The first paper to address both scheduling and assignment on a rolling horizon is [59]. In this paper, the authors developed different constructive heuristics (based on distance and resource capacity) in order to accept and schedule new patients. The acceptance decision has to be made when the patient offers arrive, and the agency's objective is to maximize the average number of weekly visits, considering only one nurse. The same problem is further developed in [70], where authors developed a scenario-based heuristic in order to anticipate the patient referrals and make better decisions. This scenario-based approach has since been extended to a multiple-nurses version in [40].

In reviewing the existing literature, it appears the DHHCRSP has been studied within a restrained context. Acceptance and scheduling decisions are always made when the patient offer arrives, and the heuristics are mostly based on minimizing the increase in travel time [59,70]. In this work, we propose exploring other alternatives, and we develop new acceptance and scheduling policies in order to give home care agencies the possibility of modifying their *modi operandi* and potentially increasing their number of weekly visits.

6.3 Development of flexible policies

In this section, we present two policies that allow more flexibility in the home care agencies' decision-making process. The first policy concerns the moment the agencies make their acceptance and scheduling decisions, the second focuses on the allocation of visit time windows to the patient.

6.3.1 Delaying the decision moment

In the previous section, we observed that to solve the DHHCRSP, decision-makers usually make the acceptance and scheduling decision for the patient the moment the referral is received [59, 70]. The main benefit of this *modus operandi* is to quickly inform the patient whether he can be scheduled by the agency or not. Nevertheless, in the literature studying home care services, we observe that the problem is usually solved on a daily [32,75] or weekly basis [20, 25].

According to those observations, we propose a strategy of delaying the decision moment for the acceptance and scheduling of patients. This delay would allow agencies to batch patient referrals in a waiting list and could create new opportunities. First, having a more complete picture of requests allows agencies to accept the most interesting patients, i.e., the ones with the largest number of visits. Next, because all the scheduling decisions will be made simultaneously, the agencies can optimize the nurses' schedules while minimizing travel times and maximizing the resources available for the ensuing weeks.

In order to test this idea, we compare three decision moments. The agencies can make their decision : when the patient's referral is received, at the end of each day or at the end of each week.

6.3.2 Allowing the assignment of time windows

In Section 6.2, we observed that the continuity of care is a main constraint for home care services. Visits to the patient by the same nurse, on the same days, at the same time, is required for the duration of the patient's care plan. This constraint allows for the formation of a strong relationship between the nurse and the patient, and gives the patient the opportunity to easily organize his week around the scheduled visits.

The second policy we introduce is to relax a part of this continuity of care. More specifically, we propose assigning a visit time window rather than a specific visit time to the patient. In this context, the patient would not have a visit scheduled for 9am, but would be promised a visit during a window of time, for example 8.30am-9.30am.

According to our discussions with home care agencies, assigning such tight time windows would not have a significant impact on patient satisfaction or on the level of service. On the other hand, those time windows would give the agencies a great deal of flexibility, allowing them to optimize visit scheduling and potentially schedule more visits per week.

6.4 Resolution Methods

In order to study the proposed policies, new resolution methods must be developed. In this section, we present two innovative methods in order to solve the DHHCRSP using the proposed policies. To assess the quality of these methods, we compare them to two existing methods, a greedy heuristic from [59] and a scenario-based method from [70].

6.4.1 Greedy

This first heuristic was developed in [59]. This resolution method makes a greedy decision every time a new referral arrives in the system. Initially developed for a unique nurse, this algorithm has been extended to take into account multiple nurses [70]. In this algorithm, if a possible insertion is found for the new patient, this patient is accepted and the criterion for the assignment corresponds to the minimization of the increase in travel time. A detailed description of this algorithm is given by Algorithm 6.

Algorithm 6: Request Greedy

for *each referral* r *arriving in the system* **do**
- Retrieve the current solution s
- Compute the list of possible insertions for the patient
- **if** *at least one possible insertion exists* **then**
  - Assign the patient the insertion minimizing the increase of travel time
- **else**
  - Reject the patient

6.4.2 Scenario-based approach

The second heuristic found in the literature is the scenario-based approach (SBA) developed by [70]. In this method, the acceptance-assignment decision is made every time a new referral arrives at the agency, and the following process is used. First, the current weekly schedules are retrieved and scenarios of possible future referrals are created. Those scenarios take into account the average distribution of patients with one, two or three visits and the geographical distribution of those patients. Then, each scenario is solved using an iterative cheapest insertion heuristic. If the patient is accepted in at least one scenario, then the patient is accepted and the assignment values correspond to the most frequently assigned ones over the scenarios in which the patient has been accepted. Algorithm 7 gives the method's overview.

Algorithm 7: Request Scenarios

for *each referral* r *arriving in the system* **do**
- Retrieve the current solution s
- Generate a set of demand scenarios
- Solve each scenario using an iterative cheapest insertion heuristic
- **if** *at least one scenario accepts and schedules* r **then**
  - Accept the patient
  - Assign the patient to the nurse, days and time the most used over all the insertions
- **else**
  - Reject the patient

6.4.3 Large patients based heuristic (LPBH)

In our context, the main objective is to maximize the average number of weekly visits over the horizon. When taking into account the possibility of solving the DHHCRSP problem daily or weekly, [40] have shown that simply extending their algorithm to wait until the end of the week, and then applying their scenario-based method, is inefficient.

A policy to maximize the average number of weekly visits could be to first assign the patients who require the greatest number of visits. For each week (or day) of the horizon, we define the sets of patients L_n corresponding to the new patients who arrived during the current week (or day) and who require n visits (in our case, we have L_1, L_2 and L_3). As described in Algorithm 8, we then process the sets L_n in decreasing order of n and iteratively assign the cheapest patient in the weekly schedules. This new heuristic method is described in Algorithm 8.

Algorithm 8: Large patients based heuristic (LPBH)

```
for each week w (or day d) of the horizon do
    for each list L_n in decreasing order of n do
        Retrieve the current solution s
        while we can find a patient from L_n to insert do
            Compute the insertion i with the patient p from L_n leading to the lowest
              increase in travel time
            Apply the insertion i to s
            Remove p from the list L_n
```

Large neighborhood search

In previous works [123, 131], we have shown that large neighborhood search (LNS) methods [118, 120] allow us to efficiently solve the home health care routing and scheduling problem for a single week. Specifically, this method has proved to work well on problems considering hard continuity of care [131].

In this work, we have extended the proposed method to iteratively solve the scheduling problem on a weekly basis. At the end of each week, the referrals are batched and the LNS is run according to those referrals and the current nurses' schedules. In order to correctly evaluate the problem via the LNS, the objective function is decomposed lexicographically. First the number of visits is maximized, then the total travel time is minimized.

In term of operators, destruction is done using the classical random and worst operators (based on the travel time created by the patient). A third destruction operator removes patients with fewer visits. The pseudo-code for this last operator is given in Algorithm 9.

Algorithm 9: No. visits destruction operator

```
Retrieve np, the number of patient to remove from the current solution
Create the lists L1, L2 and L3, containing the patient referrals with respectively one,
  two and three visits
Remove 50%np patients from L1 from the current solution
Remove 30%np patients from L2 from the current solution
Remove 20%np patients from L3 from the current solution
Return the current solution
```

For the repair operators, the classical greedy and regret operators (based on increase in travel time) have been developed and the last repair operator corresponds to the large patients based heuristic defined by Algorithm 8. In the proposed LNS, the destruction/repair process is repeated for 3000 iterations.

6.5 Computational experiments

In this section, we test the proposed resolution methods. First, we analyze the impact of the decision moment on quality of the solutions. Then, we run experiments on the second flexibility policy, the time window allocation. Finally, sensitivity analyses are performed to investigate the time window allocation policy more thoroughly.

6.5.1 Instance Generation

In order to test the different resolution methods, we have generated sets of instances according to different parameters. Those parameters include : the number of nurses, the arrival rate for patient referrals, the restrained set of possible visit days for the patients, the length of the care plan and the qualification level required by the patients. Those parameters are similar to the ones used in [40] and are defined as follows :

— Arrival rate for referrals (in minutes) : This parameter corresponds to an exponential distribution, and rates have been selected based on discussions we had with home care agencies in order to have a realistic picture of weekly demand.

— Feasible visit days : The feasible visit days for patients are defined by the *Day_Set* parameter. If *Day_Set* $= 1$, all the combinations of days are possible for the patient, if *Day_Set* $= 2$, only combinations with no consecutive days are feasible. For example, for patients requiring two visits per week, the possible combinations of days will be Mon.-Wed., Mon.-Thurs., Mon.-Fri., Tues.-Thurs., Tues.-Fri. and Wed.-Fri. and for patients requiring three visits, the only feasible combination of visit days will be Mon.-Wed.-Fri.

— Care plan length : For a given instance, the length of the patients' care plan is homogeneous. Two care plan lengths are studied over the sets of instances, 4 weeks and 8 weeks.

— Qualification level : This parameter is defined by $Qual$. If $Qual = 1$, then a special skill is required by 40% of the patients and only 30% of the nurses have this skill.

Six nurses are used in each instance. This number corresponds to the average size of nurse groups agencies create when splitting employees by district or by groups of patients. Preliminary experiments have shown that instances with a different number of nurses lead to the same experimental observations as the ones with six nurses. Similar to [40], these nurses work homogeneous schedules of 510 minutes per day, five days per week, and the days are divided into 15 minute slots. The patients, and nurses' location are randomly selected from a 60x60 square. The horizon corresponds to 72 consecutive weeks with a warm-up of 8 weeks using Bennett's algorithm.

For each combination Day_Set/Care_plan_length/Qual, we generate instances with seven different arrival rates, and we run each resolution method 10 times per instance. In order to assess the quality of the proposed methods, we re-implemented the methods from [59] (Greedy) and [70] (SBA). We implemented the methods in C++ and performed the tests on a 2.7GHz Intel Core i5 Macbook, with 16Gb RAM and only one core.

6.5.2 Decision moment

We first analyse the impact of the decision moment on the resulting number of visits per week and the average travel time between two visits.

For instances with a 4-week care plan duration (Table 6.1), we observe that, using the LPBH, the average number of weekly visits increases with flexibility (+1.08% improvement for the day, +5.07% for the week compared to Greedy). Moreover, we observe that the LNS allows for additional improvement in term of average weekly visits (+8.08%). For instances with an 8-week care plan (Table 6.2), we observe the same behaviour. The average number of weekly visits increases with the flexibility (+0.59% of improvement for the day, +2.48% for the week) and the LNS remains the best resolution method (+3.74%).

Concerning travel times (Table 6.3), we observe that the average travel time between two patients is reduced when flexibility increases. Batching patient referrals until the end of the day reduces the travel time by 1.99% compared to Greedy. This travel time reduction reaches 8.57% when the problem is solved weekly, and 9.97% when the LNS is used.

Table 6.1 Average number of weekly visits, care plan = 4 weeks

Day_Set	Qual	Interval	Greedy	SBA	Day LPBH	Week LPBH	LNS
1	0	120	150.79	155.56	153.13	159.24	**167.29**
		140	143.45	145.62	144.75	149.58	**155.73**
		160	135.64	136.27	135.93	139.8	**144.45**
		180	127.91	128.37	128.58	130.72	**134.71**
		200	120.42	120.26	120.56	121.37	**124.53**
		220	112.75	112.77	112.65	113.28	**115.51**
		240	105.84	106	105.94	106.39	**107.36**
	1	120	135.46	137.58	135.77	140.18	**146.84**
		140	125.26	126.91	126	128.11	**134.29**
		160	116.61	117.47	117	117.51	**122.88**
		180	106.98	108.25	107	107.59	**112.11**
		200	98.4	99.8	98.21	98.89	**102.98**
		220	91.37	92.88	91.81	91.74	**94.96**
		240	85.15	86.46	85.32	85.3	**88.43**
2	0	120	139.37	144.44	143.01	158.24	**163.78**
		140	127.89	134.05	131.72	145.31	**150.68**
		160	118.53	123.67	122.94	134.58	**137.86**
		180	113.98	116.27	115.26	124.4	**128**
		200	106.32	110.11	108.94	115.83	**118.98**
		220	102.17	103.59	103.95	109.55	**111.48**
		240	97.48	99	98.62	102.7	**104.05**
	1	120	123.16	127.62	126.17	135.77	**142.13**
		140	114.65	117.96	116.67	124.18	**128.57**
		160	106.44	109.51	108.4	114.3	**118.56**
		180	100.67	102.71	101.66	105.03	**109.52**
		200	93.43	94.98	94.33	96.98	**100.64**
		220	88.37	89.79	88.15	90.76	**92.92**
		240	82.77	84.08	82.9	84.61	**87.31**
Average			113.26	115.43	114.48	119	**123.09**
Gap				1.91%	1.08%	5.07%	**8.68%**

Table 6.2 Average number of weekly visits, care plan = 8 weeks

Day_Set	Qual	Interval	Greedy	SBA	Day LPBH	Week LPBH	LNS
1	0	320	133.67	133.61	134.08	136.12	**138.7**
		340	129.84	130.37	129.8	131.54	**133.31**
		360	126.87	126.86	127.91	128.14	**130.16**
		380	123.27	122.29	122.3	124.2	**125.77**
		400	118.9	119	118.64	119.25	**121.48**
		420	115.36	115.7	115.6	116.31	**117.41**
		440	111.53	111.79	111.58	113.09	**113.52**
	1	320	115.49	115.73	115.78	116.91	**118.67**
		340	111.26	111.37	111.23	111.2	**113.84**
		360	106.83	108.05	106.36	107.24	**109.51**
		380	102.65	102.55	102.41	102.48	**105.15**
		400	98.92	99.88	98.32	98.88	**100.63**
		420	95.16	95.88	95.38	95.11	**96.69**
		440	90.92	91.97	91.6	91.79	**93.13**
2	0	320	117.56	120.45	121.24	127.12	**128.34**
		340	116.62	116.34	118.19	122.86	**123.82**
		360	113.17	115.34	114.29	118.68	**120.08**
		380	108.7	109.52	111.24	115.12	**116.24**
		400	107.41	107.75	107.83	**112.15**	112.04
		420	104.46	105.21	104.91	**108.94**	108.7
		440	100.13	101.37	100.97	**105.37**	105.25
	1	320	105.44	108.17	107.65	110.81	**112.31**
		340	102.94	104.7	103.15	106.99	**108.06**
		360	99.74	101.24	100.39	102.39	**103.38**
		380	96.61	97.57	97.85	99.13	**99.86**
		400	92.71	93.75	93.08	95.14	**96.73**
		420	89.79	91.2	91	91.68	**93.47**
		440	86.48	87.7	87.56	88.83	**89.23**
Average			107.94	108.76	108.58	110.62	**111.98**
Gap				0.76%	0.59%	2.48%	**3.74%**

Table 6.3 Average travel time

Care Plan	Day Set	Qual	Greedy	SBA	Day LPBH	Week LPBH	LNS
4	1	0	18.06	16.98	17.66	16.23	**15.73**
		1	19.14	18.60	18.72	17.36	**17.36**
	2	0	19.29	17.31	18.69	16.99	**16.20**
		1	20.73	19.54	20.14	18.41	**18.23**
8	1	0	18.24	18.32	18.09	17.15	**16.87**
		1	18.73	18.60	18.58	17.82	**17.75**
	2	0	19.51	18.96	19.06	17.86	**17.45**
		1	20.45	20.23	20.13	**19.11**	19.17
Average			19.27	18.57	18.88	17.62	**17.35**
Gap				-3.64%	-1.99%	-8.57%	**-9.97%**

6.5.3 Time Window Allocation

In the previous section, we demonstrated improvements both in terms of the number of visits per week and travel times made possible by postponing the moment acceptance and scheduling decisions are made. In the next part of our experiment, we will extend this flexibility by allowing agencies to assign patients a visit time window, as opposed to an exact visit time. The same instances are used and the time window is set to 60 minutes. In the following tables, the instances' names correspond to the parameters' values associated with the tuple CarePlanDuration_DaySet_Qual_Interval.

In order to test this algorithm, we solved the same instances from the previous section. Tables 6.4, 6.5 and 6.6 present the results. For these experiments, we compared the introduction of flexible time windows (i.e., allowing for a 1-hour interval) using the different decision moments. When the decision is made upon receipt of a request, we compare our results to Greedy, when decisions are made daily, we compare our results to Daily LPBH and finally, when decisions are made weekly, we compare our results to LNS.

According to the results, we observe different behaviours. When a decision is made upon receipt of each request, we observe that allowing a 1-hour time-window for visits improves solutions by almost 7% for both sets of instances. This improvement is almost equivalent when decisions are made daily. Another great impact is observed when we allow decisions to be made at the end of the week, with an average increase of +3.94% and +5.90% (corresponding approximately 5-6 additional visits per week). Table 4 and 5 clearly shows that introducing flexibility in the appointment time brings a lot of value to the agencies even if travel times are longer (Table 6.6).

Table 6.4 Average no. of weekly visits with time windows, care plan = 4 weeks

	Request			Day			Week		
Instance	Greedy	Request TW	Gap	Day LPBH	Day TW	Gap	LNS	Week TW	Gap
4_1_0_120	150.79	167.37	**11.00%**	153.13	170.47	**11.32%**	167.29	179.22	**7.13%**
4_1_0_140	143.45	159.27	**11.03%**	144.75	160.98	**11.21%**	155.73	166.99	**7.23%**
4_1_0_160	135.64	148.81	**9.71%**	135.93	148.51	**9.25%**	144.45	153.10	**5.99%**
4_1_0_180	127.91	137.81	**7.74%**	128.58	138.47	**7.69%**	134.71	140.24	**4.10%**
4_1_0_200	120.42	126.19	**4.79%**	120.56	126.60	**5.01%**	124.53	127.12	**2.08%**
4_1_0_220	112.75	116.09	**2.96%**	112.65	116.21	**3.16%**	115.51	116.40	**0.77%**
4_1_0_240	105.84	107.61	**1.67%**	105.94	107.57	**1.54%**	107.36	107.63	**0.25%**
4_1_1_120	135.46	149.42	**10.31%**	135.77	150.92	**11.16%**	146.84	154.07	**4.93%**
4_1_1_140	125.26	138.04	**10.21%**	126.00	138.13	**9.63%**	134.29	140.67	**4.75%**
4_1_1_160	116.61	127.22	**9.11%**	117.00	127.43	**8.92%**	122.88	129.02	**4.99%**
4_1_1_180	106.98	116.57	**8.97%**	107.00	116.76	**9.12%**	112.11	117.76	**5.04%**
4_1_1_200	98.40	106.51	**8.25%**	98.21	106.71	**8.65%**	102.98	107.31	**4.21%**
4_1_1_220	91.37	99.05	**8.40%**	91.81	98.98	**7.81%**	94.96	99.71	**5.00%**
4_1_1_240	85.15	91.85	**7.87%**	85.32	91.82	**7.63%**	88.43	92.06	**4.11%**
4_2_0_120	139.37	146.82	**5.35%**	143.01	154.22	**7.84%**	163.78	171.74	**4.86%**
4_2_0_140	127.89	136.27	**6.55%**	131.72	140.17	**6.41%**	150.68	156.63	**3.95%**
4_2_0_160	118.53	125.91	**6.22%**	122.94	130.64	**6.26%**	137.86	143.79	**4.30%**
4_2_0_180	113.98	118.90	**4.31%**	115.26	122.87	**6.61%**	128.00	132.26	**3.33%**
4_2_0_200	106.32	113.01	**6.29%**	108.94	115.10	**5.66%**	118.98	122.21	**2.72%**
4_2_0_220	102.17	106.69	**4.43%**	103.95	108.27	**4.16%**	111.48	113.57	**1.87%**
4_2_0_240	97.48	101.02	**3.63%**	98.62	102.80	**4.24%**	104.05	105.44	**1.34%**
4_2_1_120	123.16	132.88	**7.89%**	126.17	136.19	**7.94%**	142.13	147.93	**4.08%**
4_2_1_140	114.65	122.60	**6.93%**	116.67	127.35	**9.16%**	128.57	134.93	**4.95%**
4_2_1_160	106.44	113.71	**6.83%**	108.40	115.65	**6.69%**	118.56	123.63	**4.27%**
4_2_1_180	100.67	106.44	**5.74%**	101.66	108.12	**6.35%**	109.52	113.31	**3.46%**
4_2_1_200	93.43	98.50	**5.42%**	94.33	100.36	**6.40%**	100.64	103.71	**3.05%**
4_2_1_220	88.37	92.37	**4.54%**	88.15	93.19	**5.71%**	92.92	96.26	**3.60%**
Average	114.39	122.48	**6.89%**	115.65	124.24	**7.24%**	124.42	129.51	**3.94%**

Table 6.5 Average no. of weekly visits with time windows, care plan = 4 weeks

	Request			Day			Week		
Instance	Greedy	Request TW	Gap	Day LPBH	Day TW	Gap	LNS	Week TW	Gap
8_1_0_320	133.67	147.03	**10.00%**	134.08	146.82	**9.51%**	138.70	150.45	**8.47%**
8_1_0_340	129.84	141.91	**9.30%**	129.80	142.37	**9.69%**	133.31	144.41	**8.33%**
8_1_0_360	126.87	135.88	**7.10%**	127.91	137.09	**7.17%**	130.16	137.73	**5.82%**
8_1_0_380	123.27	131.35	**6.56%**	122.30	131.28	**7.34%**	125.77	132.19	**5.11%**
8_1_0_400	118.90	126.05	**6.02%**	118.64	126.20	**6.37%**	121.48	126.38	**4.03%**
8_1_0_420	115.36	121.18	**5.05%**	115.60	121.11	**4.77%**	117.41	121.68	**3.63%**
8_1_0_440	111.53	116.31	**4.29%**	111.58	116.00	**3.96%**	113.52	116.04	**2.21%**
8_1_1_320	115.49	126.02	**9.11%**	115.78	126.15	**8.96%**	118.67	127.48	**7.42%**
8_1_1_340	111.26	121.17	**8.91%**	111.23	121.64	**9.36%**	113.84	122.38	**7.50%**
8_1_1_360	106.83	115.86	**8.45%**	106.36	116.35	**9.40%**	109.51	116.80	**6.66%**
8_1_1_380	102.65	110.68	**7.82%**	102.41	111.01	**8.40%**	105.15	111.98	**6.50%**
8_1_1_400	98.92	107.08	**8.25%**	98.32	106.81	**8.63%**	100.63	107.23	**6.56%**
8_1_1_420	95.16	102.24	**7.44%**	95.38	102.72	**7.70%**	96.69	103.35	**6.89%**
8_1_1_440	90.92	98.65	**8.50%**	91.60	98.42	**7.45%**	93.13	98.76	**6.04%**
8_2_0_320	117.56	124.54	**5.94%**	121.24	126.07	**3.98%**	128.34	136.85	**6.63%**
8_2_0_340	116.62	122.26	**4.83%**	118.19	123.12	**4.17%**	123.82	131.58	**6.26%**
8_2_0_360	113.17	119.15	**5.28%**	114.29	120.99	**5.86%**	120.08	127.53	**6.21%**
8_2_0_380	108.70	114.98	**5.78%**	111.24	117.65	**5.76%**	116.24	122.63	**5.49%**
8_2_0_400	107.41	112.07	**4.34%**	107.83	112.57	**4.40%**	112.04	118.48	**5.74%**
8_2_0_420	104.46	109.02	**4.37%**	104.91	110.59	**5.41%**	108.70	113.54	**4.46%**
8_2_0_440	100.13	105.55	**5.42%**	100.97	106.78	**5.76%**	105.25	110.22	**4.72%**
8_2_1_320	105.44	112.64	**6.84%**	107.65	114.37	**6.24%**	112.31	119.34	**6.26%**
8_2_1_340	102.94	108.04	**4.95%**	103.15	111.01	**7.62%**	108.06	114.85	**6.28%**
8_2_1_360	99.74	105.31	**5.59%**	100.39	107.01	**6.59%**	103.38	109.89	**6.29%**
8_2_1_380	96.61	101.28	**4.83%**	97.85	103.07	**5.34%**	99.86	105.93	**6.07%**
8_2_1_400	92.71	98.53	**6.27%**	93.08	99.69	**7.11%**	96.73	101.77	**5.21%**
8_2_1_420	89.79	94.55	**5.30%**	91.00	95.86	**5.34%**	93.47	98.02	**4.87%**
8_2_1_440	86.48	92.25	**6.67%**	87.56	91.85	**4.90%**	89.23	94.17	**5.53%**
Average	107.94	115.06	**6.54%**	108.58	115.88	**6.68%**	111.98	118.63	**5.90%**

Table 6.6 Average travel time (compared to LNS' solutions)

Care Plan	Day Set	Qual	LNS	Request TW	Day TW	Week TW
4	1	0	**15.73**	+31.38%	+26.59%	+12.58%
		1	**17.36**	+27.10%	+23.41%	+14.05%
	2	0	**16.20**	+34.83%	+29.59%	+14.35%
		1	**18.23**	+27.39%	+24.09%	+13.86%
8	1	0	**16.87**	+22.17%	+20.95%	+12.19%
		1	**17.75**	+21.67%	+20.61%	+14.84%
	2	0	**17.45**	+25.65%	+23.24%	+13.30%
		1	**19.17**	+20.77%	+18.30%	+12.46%
Average			**17.35**	+26.37%	+23.35%	+13.45%

Figure 6.1 shows the resolution methods' quality according to Greedy. We observe three clusters of methods, the first one composed of SBA and Day LPBH, the second with Request

TW, Day TW and LNS and the last cluster with Week TW. According to this figure, it appears that if the home care agencies want to improve their *modus operandi*, the most efficient change would be to use the Request TW method and then allow themselves to solve the problem on a weekly basis to then use the Weekly TW method.

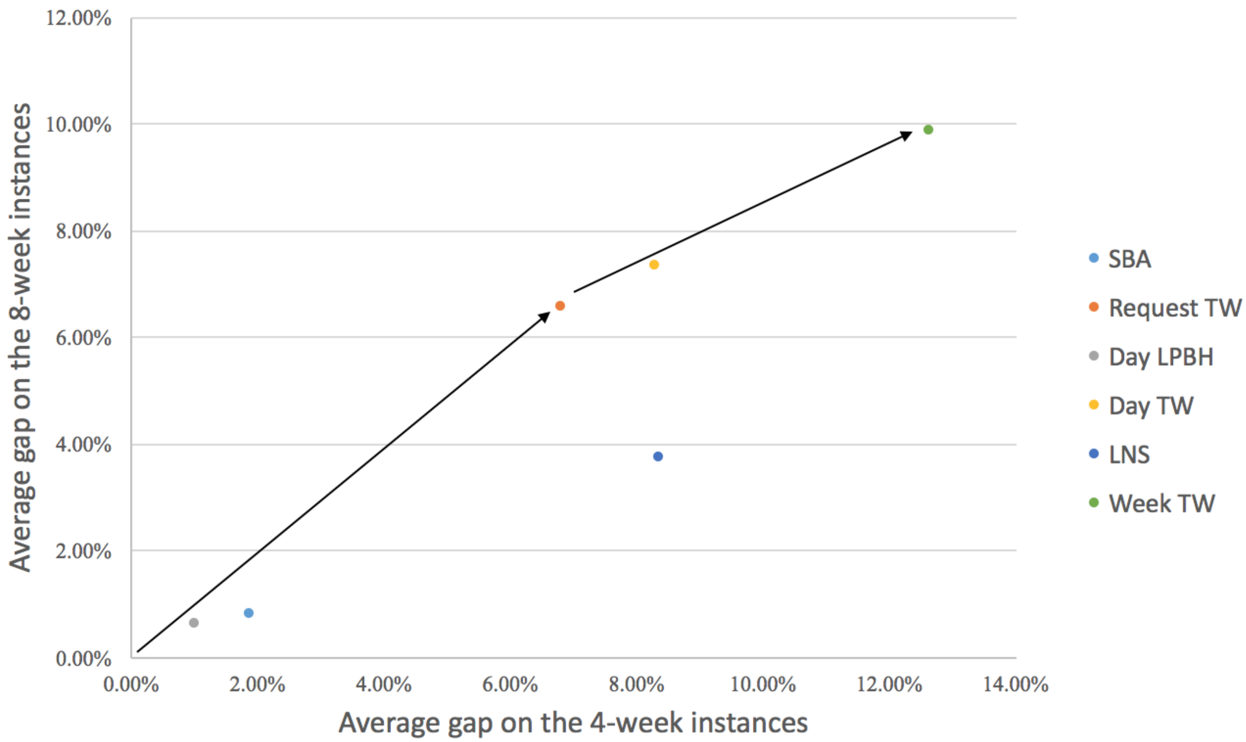

Figure 6.1 Gap to Bennett's solutions

6.5.4 Sensitivity Analysis

We now conduct some sensitivity analyses of the proposed time-window allocation extension. We first analyze the impact of modifying the insertion criterion in the heuristic, then we analyze the impact of modifying the size of the allocated time windows.

Firstly, we observe that when inserting a new patient with a specific time-window into a route, the effective size of the time window in the route depends on the time windows of the previous and next patients. Indeed, the concept of forward time slack developed in [134] describes how for each insertion with a time window constraint, we can define minimum and maximum start time values depending on the visits already included in the route. As shown in Figure 6.2, the new patient has a potential time window of 8.30am-10.30am (length = 120 min), but when testing the insertion in the route we observe that the effective time window is 9.15am-10am (effective length = 45 min). In the long term, it may be preferable to insert this new patient at a position in which the time window's effective length is closer to 120 min.

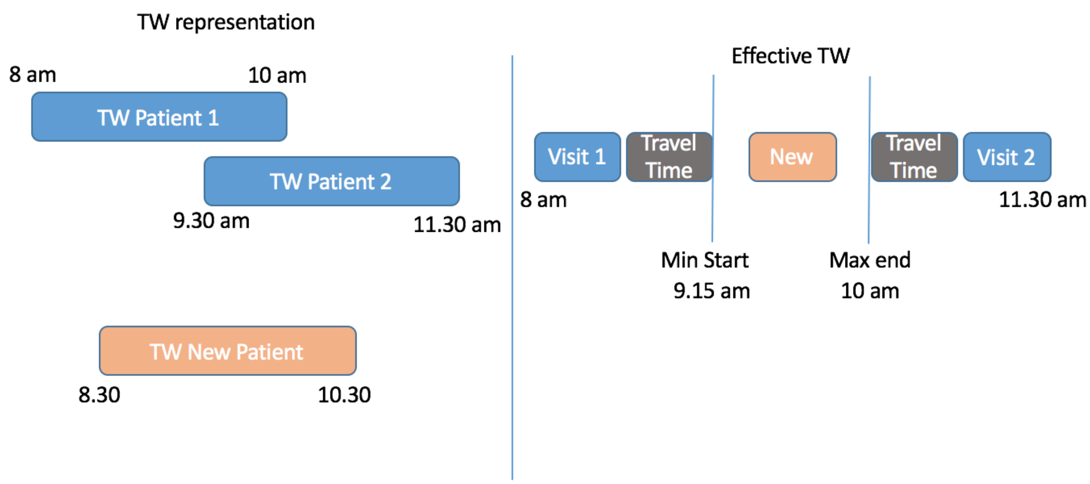

Figure 6.2 Representation of the forward time slack

In order to analyze the impact of the effective time windows, we compare the existing insertion criterion (minimizing the travel time increase) with a new lexicographic objective, first maximizing the size of the effective time window and then minimizing the travel time for a given insertion. Tables 6.7 and 6.8 present the results. For each decison moment, we show the average number of visits using the previous insertion criterion (TT) and the new one ($Lexico$). We observe that for every decision moment, using the new objective function results in an increase in the number of weekly visits. The greatest improvements are for the request-based decision moment, with increases of +3.65% for the 4-week instances and +3.33% for the 8-week instances.

Table 6.7 Comparison of both objective functions, care plan = 4 weeks

			Request			Day			Week		
Day_Set	Qual	Interval	TT	Lexico	Gap	TT	Lexico	Gap	TT	Lexico	Gap
1	0	120	167.37	168.51	**0.68%**	170.47	172.20	**1.01%**	179.22	179.97	**0.42%**
		140	159.27	159.48	**0.13%**	160.98	161.54	**0.35%**	166.99	166.31	-0.41%
		160	148.81	148.62	-0.13%	148.51	149.96	**0.98%**	153.10	151.85	-0.81%
		180	137.81	137.83	**0.02%**	138.47	138.51	**0.03%**	140.24	139.63	-0.43%
		200	126.19	126.23	**0.03%**	126.60	126.48	-0.09%	127.12	126.52	-0.47%
		220	116.09	116.01	-0.07%	116.21	116.16	-0.04%	116.40	116.00	-0.34%
		240	107.61	107.57	-0.04%	107.57	107.50	-0.07%	107.63	107.48	-0.14%
	1	120	149.42	150.15	**0.49%**	150.92	152.02	**0.73%**	154.07	155.00	**0.60%**
		140	138.04	138.18	**0.10%**	138.13	139.28	**0.83%**	140.67	140.76	**0.07%**
		160	127.22	126.83	-0.31%	127.43	127.64	**0.16%**	129.02	128.57	-0.35%
		180	116.57	116.41	-0.14%	116.76	116.74	-0.02%	117.76	117.60	-0.14%
		200	106.51	105.91	-0.57%	106.71	106.83	**0.10%**	107.31	107.01	-0.28%
		220	99.05	99.08	**0.03%**	98.98	98.95	-0.03%	99.71	99.27	-0.44%
		240	91.85	91.85	**0.00%**	91.82	91.95	**0.14%**	92.06	92.40	**0.37%**
2	0	120	146.82	161.75	**10.17%**	154.22	167.51	**8.62%**	171.74	178.14	**3.73%**
		140	136.27	151.46	**11.15%**	140.17	155.59	**11.00%**	156.63	163.31	**4.26%**
		160	125.91	140.77	**11.81%**	130.64	143.84	**10.11%**	143.79	149.70	**4.11%**
		180	118.90	130.81	**10.02%**	122.87	133.18	**8.39%**	132.26	136.97	**3.56%**
		200	113.01	121.00	**7.06%**	115.10	122.97	**6.84%**	122.21	124.64	**1.99%**
		220	106.69	112.80	**5.72%**	108.27	113.67	**4.98%**	113.57	115.11	**1.36%**
		240	101.02	105.11	**4.04%**	102.80	105.96	**3.07%**	105.44	106.86	**1.35%**
	1	120	132.88	144.25	**8.56%**	136.19	147.84	**8.55%**	147.93	153.53	**3.79%**
		140	122.60	132.35	**7.96%**	127.35	135.09	**6.08%**	134.93	139.06	**3.06%**
		160	113.71	121.73	**7.05%**	115.65	123.48	**6.77%**	123.63	126.47	**2.29%**
		180	106.44	112.47	**5.66%**	108.12	113.77	**5.23%**	113.31	115.72	**2.13%**
		200	98.50	103.29	**4.87%**	100.36	103.91	**3.54%**	103.71	105.66	**1.88%**
		220	92.37	95.88	**3.79%**	93.19	96.85	**3.92%**	96.26	97.80	**1.60%**
		240	86.68	90.16	**4.02%**	87.97	90.31	**2.66%**	90.22	91.27	**1.16%**
Average			121.20	125.59	**3.65%**	122.95	127.13	**3.35%**	128.10	129.74	**1.21%**

Table 6.8 Comparison of both objective functions, care plan = 8 weeks

			Request			Day			Week		
Day_Set	Qual	Interval	TT	Lexico	Gap	TT	Lexico	Gap	TT	Lexico	Gap
1	0	120	147.03	146.95	-0.05%	146.82	147.35	**0.36%**	150.45	149.61	-0.56%
		140	141.91	141.63	-0.20%	142.37	142.18	-0.13%	144.41	143.86	-0.39%
		160	135.88	136.80	**0.68%**	137.09	136.80	-0.21%	137.73	138.01	**0.20%**
		180	131.35	130.44	-0.69%	131.28	130.78	-0.38%	132.19	131.50	-0.53%
		200	126.05	125.57	-0.38%	126.20	125.89	-0.24%	126.38	126.24	-0.11%
		220	121.18	120.83	-0.29%	121.11	120.98	-0.11%	121.68	120.92	-0.62%
		240	116.31	115.92	-0.33%	116.00	115.42	-0.50%	116.04	116.25	**0.18%**
	1	120	126.02	125.81	-0.16%	126.15	126.16	**0.01%**	127.48	126.73	-0.59%
		140	121.17	120.74	-0.36%	121.64	120.90	-0.61%	122.38	121.62	-0.62%
		160	115.86	115.06	-0.69%	116.35	116.39	**0.04%**	116.80	115.86	-0.81%
		180	110.68	110.75	**0.06%**	111.01	110.88	-0.12%	111.98	111.68	-0.28%
		200	107.08	106.46	-0.59%	106.81	107.00	**0.18%**	107.23	107.14	-0.08%
		220	102.24	102.13	-0.11%	102.72	102.37	-0.34%	103.35	102.51	-0.82%
		240	98.65	98.59	-0.05%	98.42	98.35	-0.07%	98.76	98.67	-0.09%
2	0	120	124.54	139.12	**11.70%**	126.07	141.07	**11.90%**	136.85	145.47	**6.30%**
		140	122.26	134.56	**10.06%**	123.12	135.08	**9.72%**	131.58	140.12	**6.49%**
		160	119.15	129.62	**8.79%**	120.99	130.62	**7.96%**	127.53	134.14	**5.18%**
		180	114.98	125.17	**8.86%**	117.65	125.40	**6.59%**	122.63	128.18	**4.53%**
		200	112.07	120.04	**7.12%**	112.57	121.21	**7.67%**	118.48	122.75	**3.60%**
		220	109.02	115.94	**6.35%**	110.59	117.18	**5.96%**	113.54	118.06	**3.98%**
		240	105.55	111.50	**5.64%**	106.78	112.76	**5.60%**	110.22	113.41	**2.89%**
	1	120	112.64	120.72	**7.17%**	114.37	121.65	**6.37%**	119.34	124.07	**3.96%**
		140	108.04	116.15	**7.51%**	111.01	117.18	**5.56%**	114.85	118.48	**3.17%**
		160	105.31	111.33	**5.72%**	107.01	112.19	**4.84%**	109.89	113.66	**3.43%**
		180	101.28	106.99	**5.64%**	103.07	107.30	**4.10%**	105.93	108.97	**2.87%**
		200	98.53	102.87	**4.41%**	99.69	103.52	**3.84%**	101.77	104.39	**2.57%**
		220	94.55	98.48	**4.16%**	95.86	99.15	**3.44%**	98.02	100.30	**2.32%**
		240	92.25	95.27	**3.28%**	91.85	95.40	**3.87%**	94.17	96.60	**2.58%**
Average			115.06	118.77	**3.33%**	115.88	119.33	**3.05%**	118.63	120.69	**1.74%**

Finally, this last sensitivity analysis investigates the impact of the time window's size on the quality of the solutions. In order to study this parameter, we ran the proposed instances using four different time window sizes : 30 minutes, 1 hour, 2 hours and 4 hours. The results, split by decision moment, are shown in Figures 6.3, 6.4 and 6.5. According to those figures, we observe that the improvements compared to Greedy increase asymptotically with the size of the time windows.

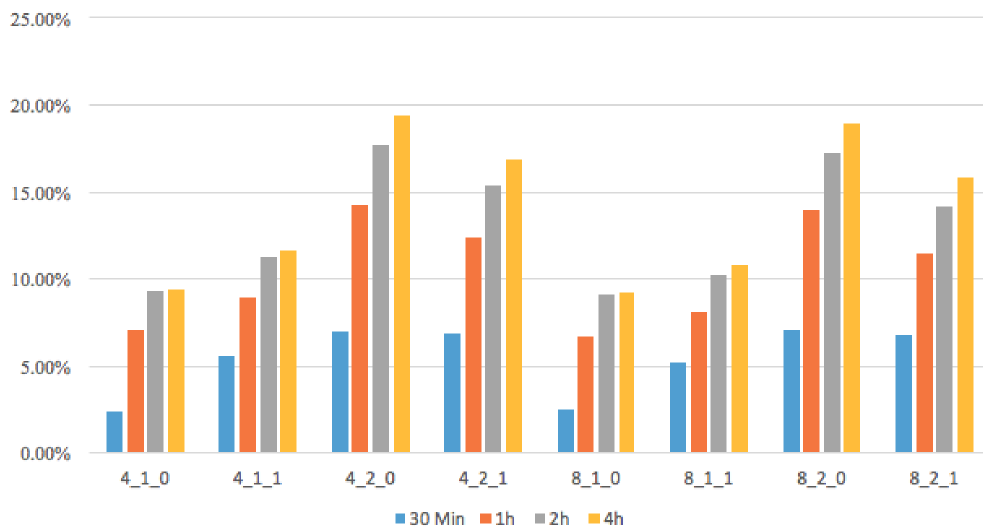

Figure 6.3 Gap to Greedy according to TW size (Request)

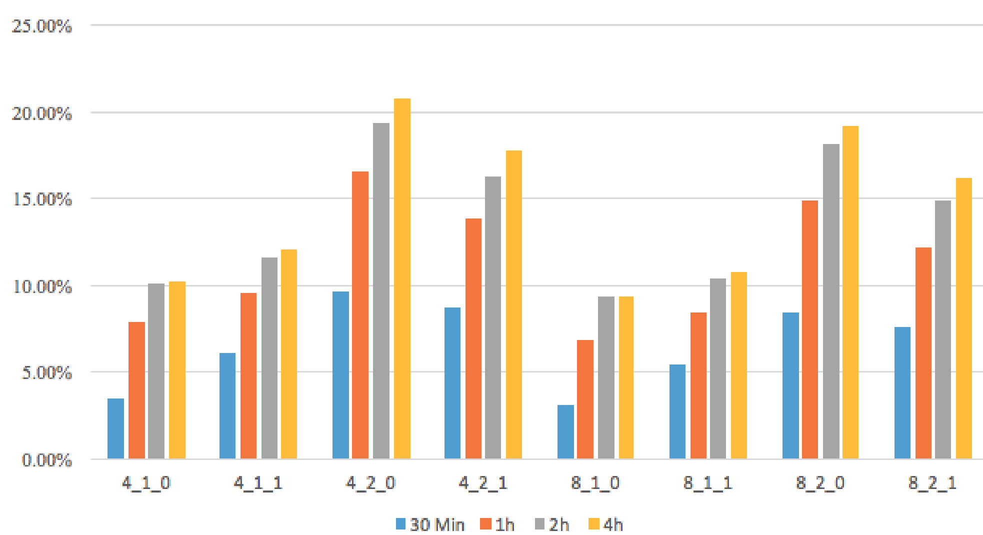

Figure 6.4 Gap to Greedy according to TW size (Day)

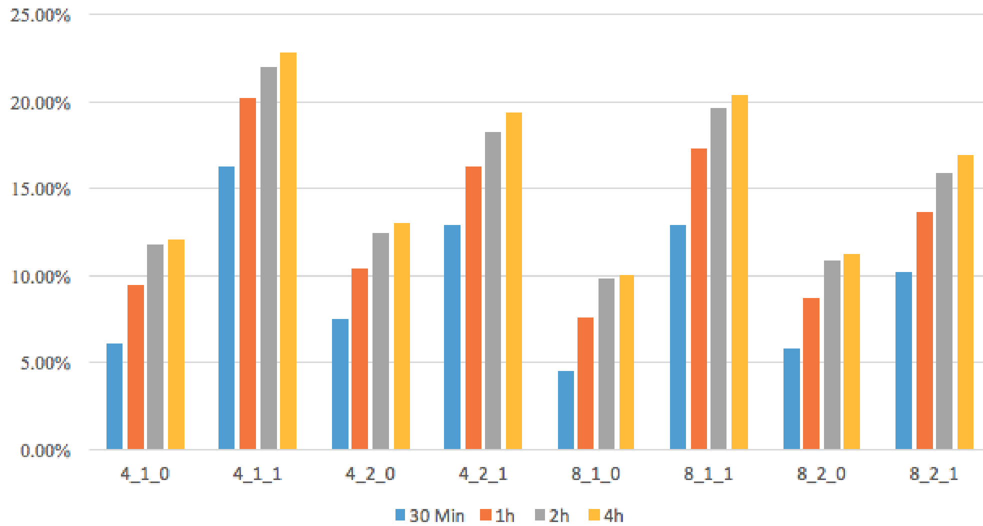

Figure 6.5 Gap to Greedy according to TW size (Week)

6.6 Conclusions

In this paper, we studied the dynamic home health care routing and scheduling problem. For home care agencies, this problem consists of deciding, for each new patient referral, if the patient can be accepted in the system and how the patient will be scheduled. We have shown that one of the main constraints of this problem is the hard continuity of care. This constraint consists of keeping the patients' assignment values (assigned nurse, visit days, visit time) consistent for the duration of their care plan.

In order to solve this problem on a rolling horizon, we proposed different flexibility policies that home care agencies may use in order to maximize the number of weekly visits. In this context, we first presented the impact of delaying the decision moment by batching patient referrals on a daily or weekly basis. This policy gives the agencies more information about patient referrals and allows them to assign patients more efficiently. We have shown that increasing the flexibility of the decision moment improves the quality of solutions, and the best method to solve the weekly version is the LNS.

Second, we investigated the possibility of assigning visit time windows to patients instead of an exact visit time. By adding flexibility to visit time, we have demonstrated dramatic improvements in terms of the number of weekly visits, even when the decision moment lacks flexibility, and a decision must be made immediately every time a new referral arrives. Some sensitivity analyses have shown that, using this second policy, a lexicographic insertion criterion focusing on the effective time window sizes and the 1 hour time windows are the best parameters, allowing numerous additional weekly visits while maintaining a high level of service.

Compliance with ethical standards

This work was supported by the Natural Sciences and Engineering Research Council of Canada. There is no conflict of interest between the authors and other agencies or persons. Finally, this article does not contain any studies with human participants or animals performed.

CHAPITRE 7 DISCUSSION GÉNÉRALE

Dans cette thèse, nous avons traité le problème de planification des soins à domicile. À partir de cette problématique, nous avons proposé trois formulations de problème ainsi que différentes approches de résolution. Dans ce chapitre, nous revenons sur l'ensemble des formulations et approches présentées et nous tentons d'identifier les limites de nos travaux ainsi que les améliorations qui pourraient leur être apportées.

7.1 Synthèse des travaux

À travers les travaux que nous avons présenté, nous avons pu observer que le problème de planification des tournées d'infirmières à domicile était un problème complexe, pouvant prendre de nombreuses formes. Ces différences de formulation dépendent généralement du contexte de l'étude et de l'horizon temporel sur lequel les auteurs souhaitent résoudre le problème. Nos travaux ne dérogent pas à cette règle et lors de cette thèse, nous avons présenté trois formulations différentes du problème, avec des variations en termes de contraintes et de fonctions objectifs.

Dans le chapitre 4, nous avons présenté une étude réalisée en collaboration avec une compagnie Montréalaise, Alayacare. Cette compagnie a développé un logiciel pour aider les agences de soins à domicile à mieux gérer leurs données et améliorer leurs processus opérationnels. Cette collaboration nous a permis d'avoir un contact direct avec de nombreuses agences et donc de pouvoir comprendre leurs problématiques, les contraintes qu'elles rencontraient quotidiennement. Pour résoudre ce problème, nous avons proposé une formulation sous la forme d'un partitionnement d'ensembles (SP), dans lequel les variables correspondent à une journée de travail pour une infirmière et décrit alors l'ensemble des patients visités et l'ordre dans lequel ces derniers sont visités. S'agissant de la méthode de résolution, nous avons fait le choix de nous tourner vers une matheuristique combinant une recherche à voisinage large (LNS) et une résolution relaxée du SP utilisant les journées de travail trouvées lors des itérations de la LNS. D'après les expérimentations que nous avons réalisées, nous avons montré que la méthode proposée permettait une large amélioration comparée à une LNS classique et, sur des instances réelles issues de notre partenaire industriel, nous avons montré que notre méthode permettait de réduire de 37% les temps de trajet, mais aussi d'augmenter de 16% la relation patient-infirmière.

Dans le chapitre 5, nous avons continué à travailler sur un horizon hebdomadaire, mais nous avons mis l'emphase sur la contrainte de continuité des soins, contrainte primordiale dans le contexte des soins à domicile. Pour rappel, cette contrainte correspond au fait de créer une routine dans les visites des patients et donc d'essayer de planifier toujours la même infirmière, les mêmes jours de visites ou la même heure de visite. Cette considération permet d'augmenter le niveau de service pour les patients et fait en sorte de renforcer la relation entre le patient et l'infirmière. Dans le cas du chapitre 5, cette contrainte de continuité était dure dans le sens où l'on ne pouvait modifier l'infirmière affectée, les jours, ni l'heure de visites pour l'ensemble des patients déjà présents dans le système de l'agence de soins à domicile. Nous nous retrouvons alors avec un ensemble d'offres de patients, pour chacun de ces patients nous devons décider si oui ou non nous pouvons l'accepter et si oui, quand est-ce que ce patient sera visité et par qui. L'objectif est alors de maximiser le nombre de nouveaux patients que nous pouvons accepter. Deux décompositions de Benders et une décomposition de Dantzig-Wolfe ont été présentées pour ce problème. La résolution de ces formulations s'est faite à l'aide de Cplex et CP Optimizer pour les décompositions de Benders et grâce à une nouvelle version de la LNS présentée dans le chapitre 4 pour la décomposition de Dantzig-Wolfe. Les expérimentations montrent que la seconde décomposition de Benders permet de trouver l'ensemble des solutions optimales, et ce dans un temps très restreint (moins d'une seconde) pour la majorité des instances. Enfin, la LNS montre encore une fois son efficacité puisqu'elle permet de trouver l'ensemble des solutions optimales en moins de 20 secondes.

Dans le chapitre 6, nous avons continué à mettre l'emphase sur la continuité des soins, mais nous avons quitté la résolution hebdomadaire pour travailler sur un horizon roulant de plusieurs dizaines de semaines. Dans ce contexte, l'objectif de l'étude était de déterminer l'impact des décisions d'acceptation et de planification des patients sur la disponibilité des ressources pour les semaines suivantes. L'objectif est alors de maximiser le nombre moyen de visites par semaine. Dans ce travail, nous présentons deux stratégies de prises de décisions que pourraient mettre en place les agences de soins à domicile afin d'augmenter le nombre de visites par semaine tout en modifiant que très leurs modus operandi. La première stratégie consiste à ne pas prendre la décision vis-à-vis d'une offre de patient à la réception de cette offre. L'idée est alors d'attendre la fin de la journée ou la fin de la semaine pour prendre les décisions d'acceptation et de planification des patients. Le fait d'attendre permet alors d'avoir une vue d'ensemble des patients possibles et donc d'optimiser les tournées des infirmières pour planifier le plus de visite. La seconde stratégie porte elle sur la relaxation d'une partie de la contrainte de continuité des soins. Dans cette stratégie nous proposons non pas de donner une heure de visite fixe aux patients, heure de visite qui restera inchangée pour l'ensemble de leur plan de soin, mais plutôt d'affecter aux patients des fenêtres de temps dans lesquelles ils seront visités. Un patient ne sera donc plus visité à 9h, mais dans la fenêtre [8h30,9h30]. À partir de jeux d'instances que nous avons générés, nos expérimentations montrent l'efficacité des stratégies proposées avec +12% de visites sur une base hebdomadaire.

7.2 Limitations de la solution proposée et améliorations futures

Nous allons maintenant mettre en exergue les différentes limitations des solutions proposées ainsi que de possibles améliorations.

Concernant le problème étudié dans le chapitre 4, une des principales limitations est le fait que la fonction objectif contient de nombreux critères, souvent contradictoires. Il est compliqué de comparer différentes solutions puisqu'aucun ordre n'est donné entre les différents objectifs. Pour contrer cela, il pourrait être intéressant de réduire la fonction objectif à au plus trois critères et de concentrer la résolution du problème sur ces trois critères. Il est en effet possible par exemple que le nombre minimal et maximal d'heures travaillées ne soient pas des critères de premier ordre et que l'on puisse réduire la complexité de la fonction objectif en les retirant.

Pour ce qui est du chapitre 5, la limitation principale que l'on pourrait mettre en relief est le fait que nous prenons en compte que très peu de contraintes métier. En effet, seuls le nombre de visites ainsi que la continuité des soins sont pris en compte. Le temps de trajet des infirmières est considéré comme une contrainte dure dans les sous-problèmes et aucune contrainte de disponibilités n'est présentée pour les patients. Pour remédier à ces enjeux, il serait intéressant d'étendre le problème avec plus de contraintes et observer comment les décompositions de Benders se comportent lorsque la complexité du problème augmente. Enfin, des instances de taille plus importantes pourraient être résolues afin, encore une fois, de tester le comportement des méthodes de résolutions proposées face à des instances plus compliquées.

Dans le chapitre 6, une critique qui pourrait être faite à nos travaux est le fait de ne pas avoir développé l'idée d'utiliser des scénarios pour prédire les futures offres de patient et ainsi potentiellement prendre de meilleures décisions. Ce choix de ne pas prendre en compte le futur a été fait pour simplifier les stratégies et proposer aux agences des modifications de leurs modus operandi qui soient les plus simples possible à mettre en place, tout en restant efficaces. Dans le futur, il serait donc intéressant de pousser cette idée de scénarios afin de permettre aux agences d'avoir un arsenal complet de stratégies de résolution et une comparaison de l'efficacité de chacune de ces stratégies de résolution.

Nous allons maintenant nous tourner vers une analyse plus globale de la thèse. Tout d'abord, il apparaît que les instances que nous avons créé et publié dans le premier article ne sont pas utilisées dans les deux suivants. Cela est dû au fait que dans les deux articles suivants, nous

nous sommes intéressés à la continuité des soins dans un cadre très spécifique et donc les premières instances ne pouvaient pas être utilisées. Au niveau des instances, on observe aussi que le papier 3 n'utilise pas d'instances réelles, elles sont générées en suivant les paramètres d'un papier existant dans la littérature. Une amélioration possible de cette thèse serait alors d'essayer d'homogénéiser l'utilisation des instances pour avoir une base de comparaison des méthodes plus solide.

Enfin, une dernière nuance que nous pouvons apporter à cette thèse est le fait que le temps de trajet est toujours utilisé dans nos travaux, notamment comme un critère à optimiser (Article 1 et 3). Or, il existe certaines agences de soins à domicile pour qui cette contrainte de temps de trajet ne constitue pas un élément important de la planification. En effet, pour ces agences, les temps de trajets des infirmières ne sont pas pris en compte et donc seul compte pour elles le nombre de visites hebdomadaires. Une amélioration possible de nos travaux serait alors de pousser un peu plus la partie affectation des patients et des visites et mitiger l'impact que peut avoir le temps de trajet sur la qualité des solutions produites.

CHAPITRE 8 CONCLUSION ET RECOMMANDATIONS

Dans cette thèse, nous nous sommes intéressés au problème de planification des soins à domicile. Nous avons montré que ce problème était complexe de par l'ensemble des contraintes à prendre en compte, mais aussi de par la multiplicité des contextes de recherche. Les travaux de cette thèse font écho à cette pluralité de contexte et présentent trois formulations distinctes du problème.

Dans un premier temps, nous avons développé une méthode pour résoudre un problème de planification hebdomadaire prenant en compte un très grand nombre des contraintes métier rencontrées par les agences de soins à domicile. Nous avons alors développé une matheuristique faisant le pont entre une méthode de recherche à voisinage large et un partitionnement d'ensembles. Sur des instances réelles, cette méthode a permis de réduire de 37% les temps de trajet et d'augmenter de 16% la relation patient-infirmière.

Ensuite, nous avons mis l'emphase sur la contrainte de continuité des soins et le fait, pour les agences, d'accepter de nouveaux patients tout en gardant inchangés, les affectations, jours de visites et heures de visites des patients existants. Pour cela, deux décompositions de Benders et une décomposition de Dantzig-Wolfe ont été proposées. En particulier, la décomposition de Benders se basant sur des patterns de visites pour les patients a montré son efficacité en résolvant une majorité des instances en moins d'une seconde. La méthode de résolution issue décomposition de Dantzig-Wolfe permet quant à elle de résoudre toutes les instances en moins de 20 secondes.

Enfin, nous avons présenté le problème dans un contexte d'horizon roulant et nous avons mis en place différentes stratégies de planification que les agences peuvent utiliser pour augmenter leur nombre de visites hebdomadaires. Parmi ces stratégies, nous avons dans un premier temps proposé de différer le moment de la prise de décision concernant l'acceptation de nouveaux patients. Dans un second temps, nous avons mis en place une affectation de fenêtre de temps pour le moment des visites, en substitution à l'affectation d'un horaire fixe pour l'ensemble du plan de soin des patients. Les expérimentations effectuées avec ces deux stratégies ont prouvé une augmentation du nombre de visites hebdomadaire pouvant atteindre 12% pour les agences de soins à domicile.

Cette thèse est le fruit de quatre années de travail. Au-delà du plaisir que j'ai pris à travailler sur ces projets de recherche, j'espère qu'une partie de ces travaux pourront être utilisés par les agences de soins à domicile afin de les aider dans leur tâche et d'augmenter la qualité des soins pour les patients ainsi que les conditions de travail pour le personnel infirmier. Cette envie de résoudre des problèmes pratiques ayant un impact sur la société est la raison pour laquelle j'ai fait ce doctorat et c'est le chemin que je souhaite continuer à emprunter pour la suite de ma carrière.

"Ce qu'il y a de mieux dans ce monde, de plus beau, de plus excitant,

ce sont les commencements"

Jean D'Ormesson

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