A tabu search-based heuristic for the dynamic oil distribution problem

Mémoire

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Résumé

Ce mémoire traite l'intégration dynamique des opérations de gestion des stocks et du transport avec la présence d'un évènement perturbateur, qui est la livraison urgente sur appel imprévue. En s'inspirant du cadre général de l'industrie énergétique et la distribution de l'huile à chauffage en particulier, après une revue de littérature exhaustive des problèmes de tournées de véhicules dynamiques et stockage-routage, nous introduisons une nouvelle variante qui cadre le problème dynamique de stockage-routage avec livraisons sur appel. Notre démarche de traitement s'est devisée en deux grandes étapes. Une première étape, statique et déterministe, s'est focalisée sur la description et la formulation mathématique du problème en se basant sur la programmation linéaire mixte et une résolution exacte à travers l'algorithme de *branch-and-cut*. Pour le besoin de l'intégration dynamique des livraisons incertaines sur appel dans un temps d'exécution raisonnable, une deuxième étape dynamique s'est concentrée sur le développement d'une heuristique basée sur la recherche tabou avec la configuration de deux politiques dynamiques de contrôle qui étudient les possibilités d'insérer les visites dynamiques soit dans la route en cours d'exécution ou dans celle de la période suivante dans le cas échéant. 72 instances ont été générées, et des analyses ont été menées sur différents facteurs qui peuvent influencer le taux de service des clients dynamiques aussi que les coûts d'opération.

Mots clés: problème de routage-stockage; problème de tournées de véhicules dynamiques; livraisons sur appel; politiques de contrôle dynamiques.

Abstract

This thesis deals with the dynamic integration of inventory management and transportation operations with the uncertain event of unplanned deliveries following urgent calls. Inspired by the general framework of the energy industry and the distribution of heating oil, in particular, a comprehensive literature review of both problems of dynamic vehicle routing and inventory-routing are conducted. We then introduce a new variant, called the dynamic inventory-routing problem with customer requests. Our solution approach has been divided into two main steps. A static and deterministic first step focused on the mathematical description and formulation of the problem based on a mixed-integer programming model and the development of an exact solution approach through a branch and cut algorithm. Then, to dynamically integrate uncertain on-call deliveries in a reasonable execution time, a second dynamic step is established to develop a heuristic, based on tabu search, with the configuration of two dynamic control policies that consider the possibilities of inserting dynamic visits either in the route under the execution or in that of the following period. 72 instances are generated, and analyses are conducted on various factors that can influence the service level for dynamic customers and operation costs.

Keywords: Inventory routing problem; dynamic vehicle routing problem; dynamic customer requests; dynamic policies.

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Avant-propos

Ce travail de recherche porte sur l'optimisation dynamique de l'activité de distribution de l'huile à chauffage et a comme principale contribution un article scientifique intitulé « Dynamic inventory routing problem with customer requests».

Les coauteurs de cet article ont contribué à ce travail à travers leur expertise, leurs propositions avisées et leur support continu pour l'accomplissement de l'article ainsi que du mémoire. Les coauteurs sont :

- **Maryam Darvish**, Professeure adjointe
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- **Jacques Renaud**, Professeur titulaire
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A titre de premier auteur, j'ai réalisé cet article en effectuant la revue de littérature, tous les tests préliminaires et les analyses des résultats, ainsi que sa rédaction complète.

L'article sera éventuellement soumis pour publication.

Introduction générale

L'industrie énergétique contribue directement au développement de l'économie canadienne en représentant plus de 10% du produit intérieur brut (PIB) en 2018, tout en produisant, transformant et distribuant différents produits énergétiques (Gouvernement.CA, 2020). Ce secteur présente la particularité de l'étendue de sa chaîne de valeur ainsi que la complexité de son réseau d'intervenants. Dans ce contexte de gestion décentralisée des activités, les entreprises œuvrant dans ce domaine font face à plusieurs défis à savoir la fluctuation des prix du pétrole brut, la fluctuation de la demande avec les pics hivernaux (le chauffage des locaux a représenté 64% de la consommation énergétique résiduelle annuelle des québécois en 2016) (Whitmore and Pineau, 2018), et les limites de capacité de stockage surtout au niveau de l'activité de distribution du pétrole raffiné ou gaz liquide aux consommateurs finaux (une capacité qui ne dépasse pas un maximum de l'équivalent de deux jours du pic de la demande) (Whitmore and Pineau, 2018). En prenant l'exemple du propane, les grands distributeurs s'approvisionnent directement des terminaux à travers la voie ferrée ou routière.

Quoique les capacités de stockage soient toujours réduites à cause des coûts élevés d'installation, ces distributeurs, disposent généralement de leurs propres espaces et installations de stockage qui comportent des grands réservoirs à partir desquels les camions-citernes de livraison sont remplis. Cette dépendance au transport routier ou ferroviaire rend la distribution en aval particulièrement vulnérable aux retards d'approvisionnement ou de livraison aux clients finaux étant donné que la neige peut bloquer ou ralentir l'accès aux terminaux, aux espaces de stockage et aussi aux localisations des utilisateurs finaux (NEB, 2014).

Ces fournisseurs énergétiques se chargent aussi de surveiller les niveaux des stocks dans les réservoirs de leurs clients et s'assurent de leur réapprovisionnement en cas de risque de rupture. Avec le progrès technologique, certains fournisseurs investissent dans l'installation de réservoirs intelligents avec des capteurs qui permettent le suivi en temps réel de la consommation de leurs clients (Superior, 2021). Ce genre d'activité est généralement géré par des contrats à prix fixes qui englobent les frais de location ou achat des réservoirs ainsi que les opérations occasionnelles de réapprovisionnement (CAA-Québec, 2021). Ce genre de fournisseur gère aussi une autre catégorie de clients qui préfèrent des livraisons sur appel et des paiements au prix de détail courant lors du remplissage du réservoir. À ce niveau, ces distributeurs font face aussi à d'autres défis de gestion de la demande incertaine et de livraisons dynamiques sur appel. Quoique le changement d'un fournisseur à un autre du même secteur soit assez rare vu les frais d'installation et les restrictions contractuelles, tout refus de répondre à une demande imprévue, pourra engendrer l'insatisfaction des clients, et leur désintérêt pour cette alternative énergétique moins polluante et moins coûteuse face à l'électricité et au gaz naturel (NEB, 2014).

La problématique étudiée

Dans ce mémoire, nous nous focalisons sur le dernier maillon de la chaîne de valeur énergétique, tout en mettant le point sur l'activité de distribution de l'huile de chauffage ou tout autre type de produit énergétique liquide qui nécessite la disponibilité de réservoirs de stockage chez les clients. Ceci se concrétise en réalité par les activités de réapprovisionnement des stations-service ou les réservoirs positionnés aux locaux résidentiels, commerciaux ou institutionnels.

Pour garder un certain niveau de compétitivité, l'intégration logistique et le partage d'information sont parmi les piliers les plus primordiaux dans ce domaine. Quoique l'intégration des activités de stockage et routage a été bien adoptée dans la gestion des flux de distribution énergétique, les mécanismes de prise de décision de la logistique traditionnelle se sont toujours basés sur la condition de la disponibilité d'une information complète pour garantir l'efficacité des résultats. L'intégration des activités de gestion des stocks et du transport fait toujours référence en littérature au problème du stockage-routage ou *Inventory Routing Problem* (IRP). Tout en présumant que tous les paramètres du problème sont déterministes et statiques, la version classique de l'IRP vise la minimisation des coûts communs de stockage et transport.

Face à une réalité bien marquée par l'incertitude et le dynamisme, le planificateur se trouve contraint par le temps et aura besoin toujours d'avoir une solution rapide du nouveau problème au moment d'apparition des nouvelles informations, ainsi que la possibilité de tester des scénarios avant de choisir l'action à entreprendre (Psaraftis, 1988).

La motivation de ce travail consiste ainsi à proposer un outil qui permettra d'adapter ce système de stockage-routage aux nouveaux besoins dynamiques et incertains de la livraison sur appel tout en gardant un certain équilibre avec les besoins engendrés par le mécanisme de réapprovisionnement intégré.

Dans ce contexte dynamique d'apparition de nouveaux clients lors des livraisons, nous traiterons plus précisément les questions de recherche suivantes :

- Comment intégrer la livraison sur appel dans le contexte de l'IRP,
- Quelle approche adopter pour pouvoir prendre en compte l'arrivée incertaine et dynamique des appels des clients,
- Quelles politiques de contrôle sont adéquates pour la gestion des appels dynamiques des clients dans le contexte de l'IRP,
- Quels impacts apporte l'intégration des appels dynamiques des clients et la considéra-

tion de leurs taux de service sur l'efficacité économique du problème.

Méthodologie

Afin de traiter ce problème, et apporter des éléments de réponse aux questions de recherche, nous allons tout d'abord effectuer une revue de littérature qui permettra de positionner notre problème dans la littérature scientifique étant donné qu'il présente la particularité de combiner deux sous-problèmes qui sont connus et qui font partie des deux familles de tournées de véhicules dynamiques (*Dynamic Vehicle Routing Problem*-DVRP) et l'IRP.
Ensuite, nous allons proposer deux versions de notre problème. Une première version *déterministe* et *statique* sera présentée, qui suppose la présence d'une information complète sur les périodes d'appel et les quantités à commander par les clients dynamiques. Ceci se concrétise par la proposition d'une formulation mathématique et sa résolution sur le solveur CPLEX en utilisant des instances tirées de la littérature et adaptées aux spécificités de notre problème. Ceci sera suivi par une deuxième version *dynamique* qui se base sur le développement d'une heuristique et deux politiques de contrôle pour l'intégration des appels dynamiques des clients. Après une étape de test de performance de notre heuristique, nous allons proposer une analyse de sensibilité à travers l'application de notre heuristique ainsi que les politiques de contrôle sur 72 instances générées. Cette analyse de sensibilité servira par la suite à analyser l'impact du choix de la politique de contrôle ainsi que d'autres facteurs sur la qualité des solutions.

Organisation du mémoire

Dans ce qui suit, nous proposons dans le Chapitre 1 une étude bibliographique exhaustive sur le DVRP qui va mener à proposer une taxonomie des différentes caractéristiques dynamiques des problèmes de tournées de véhicules étudiées jusqu'à ce jour en littérature. Ce chapitre proposera aussi une classification des méthodes de résolution développées suivant les critères de la qualité de l'information disponible (déterministe ou stochastique) et l'approche de résolution (hors ligne ou en ligne). Dans le Chapitre 2, et suite à la présentation d'une brève revue de littérature de l'IRP, nous introduisons notre problème étudié et ses particularités qui seront par la suite suivis par la présentation de nos approches de résolution dans les deux versions, statique et dynamique. Après une analyse des résultats nous proposons dans le dernier chapitre une conclusion générale qui englobe une synthèse de tout le travail, les contributions, ainsi que des pistes de recherche futures sur le sujet.

Chapitre 1

Models and solution algorithms for real-time vehicle routing problems

1.1 Résumé

Le développement des technologies de l'information a permis de suivre, de traiter et de partager l'information changeante en temps réel. À la suite de ces progrès technologiques, il y a eu un intérêt accru à adopter la version dynamique du problème de tournées de véhicules au cours des dernières années. Dans ce travail, nous présentons une taxonomie des caractéristiques dynamiques des problèmes de routage récemment étudiés. Les caractéristiques physiques, temporelles, spatiales et de planification sont incluses. Deuxièmement, nous proposons une classification des modèles et des méthodes de résolution utilisées en se basant sur deux critères : l'approche de résolution et la qualité de l'information.

1.2 Abstract

The development of information technologies has made it possible to track, process, and share changing information in real-time. As a result of this technological advances in recent years, there has been a growing interest in adopting the dynamic version of the vehicle routing problem. In this work, first, we present a taxonomy of dynamic characteristics of recently studied routing problems. Physical, temporal, spatial, and planning characteristics are considered. Second, we propose a classification of the applied models and solution methods based on two criteria: solution approach and information quality.

1.3 Introduction

To cope with the ever-changing business environment, companies need to be more responsive and flexible. With the development of information and communications technologies (ICTs), a growing research interest has been observed over the past three decades in treating the dynamism of distribution challenges. The dynamic vehicle routing problem (DVRP), as a variant of the vehicle routing problem (VRP) relies on dynamic or real-time information. This variant covers several important applications, namely pick-up and delivery, waste collection, dial-a-ride, ride-sharing taxis, ambulance logistics, and winter gritting. However, unlike the classic VRP, the dynamic version requires real-time information inputs, e.g., customer demand, location, travel time, vehicle positions, traffic status, etc., and advanced communication tools for drivers and planners.

To deepen the understanding of the concepts, we refer the readers to previously published literature reviews [see (Psaraftis, 1995; Gendreau et al., 1996; Ghiani et al., 2003; Pillac et al., 2013; Psaraftis et al., 2016; Ritzinger et al., 2016)] which provide insights on differences between the classic VRP and its dynamic version, the degree of dynamism, and the value of information.

This chapter aims to review recent models and algorithms proposed for the DVRP. Our purpose is not to include an exhaustive list of all the techniques developed, but to focus on the main trends in the literature and to identify avenues for future research.

The contributions of this work are mainly twofold. First, we propose a taxonomy of the DVRP. Second, we classify the solution methods with regard to two criteria: the quality of the available information and the solution approach adopted.

The remainder of this chapter is organized as follows: Section 1.4 presents the concepts, definitions, and taxonomy of the main characteristics considered in the DVRP literature for the last three decades. Section 1.5 focuses on the solution methods found in the literature. The goal is to propose a classification that can be used as a guideline for the choice of the solution algorithm. Our concluding remarks are given in Section 1.6 where we also enumerate a list of potential research avenues.

1.4 Definitions and taxonomy

We first present the DVRP's definition in Section 1.4.1. Then, we list its characteristics in Section 1.4.2.

1.4.1 Definition

The DVRP, also known in the literature as the real-time or online routing problem, is a variant of the classic VRP. It owes its roots to a level of uncertainty and information changing over time. For instance, in discrete-time planning, solving this problem optimally during a given planning period does not guarantee the robustness of this solution for the following periods. This is due to the inherent dynamism in the decision environment.

Dealing with any stochastic/dynamic problem, the main concerns are: *What* form of change is expected, *When* it may happen, and *How* accurate real-time decisions can be made. This section focuses on answering the first two questions, and Section 1.5 is devoted to the third one.

New information may affect all inputs (or parameters) of the problem at any planning period. The widely discussed sources of uncertainty in the literature are mainly the volatility of the demand, such as variations in the number of unserved customers (Gendreau et al., 2006), customers pick-up/delivery time windows (Srour et al., 2018; Voccia et al., 2019), or customers locations (Reyes et al., 2017). Another form of uncertainty concerns the transition in supply, manifested by the change in the number of available vehicles (Angelelli et al., 2016), their speeds, capacities (Archetti et al., 2020), and locations (Bertsimas et al., 2019). Less attention has been given to uncertainty due to external factors. These changes are limited to, for example, variations in travel times (Fleischmann et al., 2004) and arrival rate of customers' requests (Ichoua et al., 2006) (with little consideration of their temporal-spatial density and disparity). This is with the intention to indirectly capture some impacts of the congestion and peak traffic periods (Ghiani et al., 2009; Bopardikar and Srivastava, 2019).

To date, many variants of the DVRP exist in the literature. Each problem is viewed as a specific case by taking into account a different combination of parameters and assumptions, which can be grouped into four main categories: physical, temporal, location, and planning characteristics. In what follows, we provide a summary of research conducted for each category.

1.4.2 Characteristics

Physical characteristics This category covers the vehicle's characteristics, the depot, and products or services provided. Different combinations of these characteristics may generate various problems with specific challenges. Angelelli et al. (2016) introduced the stochastic dynamic traveling purchaser problem (SDTPP) in the objective to optimize procurement-routing decisions of a purchaser visiting different markets, where the volume of available products decreases over time. This problem arises in the daily procurement of multiple products available in limited quantities on several markets, as perishable food in restaurants or locally purchased spare parts for industrial companies. As with multiple products, routes planners may deal with various services such as installing, repairing or emergency services. This is echoed in the literature under different categories of problems, such as the dynamic traveling repairman problem (DTRP) (Bertsimas and Van-Ryzin, 1989). The objective is to minimize the waiting time of upcoming calls for service until they are fulfilled. In this context, the planner faces dynamic arrival of customers' requests that need to be assigned to a specific vehicle according to different criteria, such as locations of customers and vehicles. In such cases, vehicles are usually heterogeneous concerning the available equipment, capacity, or competency level of the technician assigned to it.

As in static routing problems, the vehicle capacity in DVRPs can be considered unlimited, limited to a certain predefined amount, or shared. The shared capacity is widely adopted in city logistics problems assuming door-to-door deliveries as ride-sharing systems. By matching drivers and riders to the same itineraries, the objectives are to reduce trip expenses, maximize vehicle occupation, and decrease gas emissions. The dynamic version considers updating system inputs such as drivers and riders status and their current positions (Agatz et al., 2012; Homsi et al., 2021).

Temporal characteristics The time dimension is crucial in DVRPs. It was manifested in the DVRP literature by incorporating temporal parameters in objective functions and/or as part of the studied problem's constraints. This category covers various types of time windows. Regarding VRPs with time windows (VRPTW), customers' time windows are common in a variety of real-world applications, including school bus routing, repairman scheduling, and e-commerce distribution. As a result, the customer's time window restricts the earliest and latest times to begin and end service at the customer's location (Cordeau et al., 2001). Hard time windows refer to cases when the servicing vehicle is not allowed to violate time window constraints, such as starting earlier or finishing the service later. However, soft or mixed time windows, consider the possibility of failing to meet at least one of them.

Due to the incorporation of real-time customer requests occurring during routes execution, the VRPTW in its dynamic version (DVRPTW) appears to be more difficult to solve. Soft time constraints are more commonly used in this context, with time-dependent penalties reflecting customer dissatisfaction (Barkaoui et al., 2015). Time windows can also refer to other contexts, such as dynamic pick-up and delivery problems (DPDP), in which the planner is confronted with the dynamic arrival of customer requests that include pick-up and drop-off locations as well as preferred pick-up time. To group them, and assuming some customer flexibility, each pick-up time is then assigned to a time window that specifies the earliest and latest time to complete the pick-up (Ichoua et al., 2006; Srour et al., 2018).

The depot opening time window is another type of time constraint. Routing decisions in the case of same-day delivery problems take into account a departure from and a return to the depot within a predetermined time window. In dynamic situations, a mixed time window is more commonly used. When a new customer request is received, it can be assigned to an available vehicle in the depot. The charged vehicle has the option of leaving the depot immediately or waiting for potential incoming requests. However, once leaving, it must return to the depot before the deadline (Voccia et al., 2019).

Other temporal parameters have become more relevant with the development of DVRPs. We recognize that travel, on-site service, and waiting times explicitly demonstrate the temporal uncertainty encountered when dealing with DVRPs, mainly when service levels and response time to changes are considered (Ichoua et al., 2006; Ferrucci et al., 2013; Srour et al., 2018). This is because, in reality, at least one of the previously mentioned parameters remains unknown (or imprecisely known) until operations are performed (Srour et al., 2018). To address temporal uncertainty, time-dependent distributions and/or stochastic methods are usually adopted (Ritzinger et al., 2016). More details on solution methods are presented in Section 1.5.

Location characteristics The most common customer locations handled by VRPs are the customer addresses from which they require pick-up, delivery, or both services. However, in reality, the customer's location may change over time. For example, in last-mile deliveries, a customer's absence at the delivery time results in multiple visits following those missed deliveries and inefficient delivery systems due to a significant increase in the number of kilometers traveled, particularly in residential areas. To accommodate changes in customer location, the VRP with roaming delivery locations is introduced to promote vehicle trunk deliveries applications instead of home deliveries. This variant takes into account a customer's geographical profile rather than an exact and unique location. The geographical profile specifies the appropriate time and place for a delivery based on a set of time-dependent locations that correspond to time windows during which the customer's vehicle remains in the same location (Reyes et al., 2017).

Similarly, other locations were considered in different studied DVRPs, such as waiting locations, also known in the literature as *"idle points"*. They are usually adopted in highly dynamic problems, such as DPDP and DTRP, for daily delivery management. First, customer locations are aggregated into geographical zones, and the planning horizon is divided into time periods within a day. Waiting points can then be strategically defined based on the stochastic arrival rates of customer requests corresponding to each zone. When a vehicle arrives at a customer location before its time window, it can be redirected to an appropriate waiting location to serve a potential customer in the meantime (Ichoua et al., 2006). Other types of locations arise from recourse actions such as refueling locations in the event of a vehicle breakdown (Bertsimas and Van-Ryzin, 1991) and waste disposal stations where demand is realized only when the vehicle arrives at the point of collection (Pillac et al., 2018; Bopardikar and Srivastava, 2019).

Planning characteristics The planning task in DVRPs depends on several criteria: the planning horizon, the available information, the degree of dynamism of the problem, the arrival rate of customers' requests, and strategies applied. Assuming generally discrete-time planning, researchers consider finite, infinite, or double (short and long-term) planning horizon. In the literature, the double planning horizon is discussed in two ways. Psaraftis (1988) used a long-term rolling horizon by dynamically redefining a short-term horizon. On the other hand, Mitrovic-Minic et al. (2004) used a solution method with a different objective for each planning horizon. On the short-term planning horizon, the total distance is minimized. However, the goal of the long-term planning horizon is to minimize a linear function of distance and time.

The availability and quality of information are also critical factors influencing the robustness of dynamic schedules. It is possible that some parameters are available just locally. In the case

of waste collection, for example, the exact waste level may be revealed only when the vehicle arrives at the tank's location. However, as technology advances, information becomes more widely available, allowing planners to obtain global and continuous data on inventory levels, traffic conditions, etc. Furthermore, during route planning and execution, data such as vehicle number and capacity may be deterministic and certain. Inventory levels and demand could be stochastic and derived from forecasts or predefined distribution functions. However, as the plan is carried out, such stochastic input must be revised and updated (Psaraftis, 1995).
Any DVRP can be classified into three categories based on the degree of dynamism proposed by Larsen et al. (2007): low, medium, and highly dynamic. A first *Effective Degree of Dynamism* is calculated based on four factors: the number of real-time requests and their arrival times, the total number of requests, and the planning horizon. This metric assesses the degree of dynamism based on the time distribution of dynamic request arrivals. Larsen et al. (2007) adapted this measure for the DVRPTW by incorporating time windows in such a way that they reflect the required reaction time. To this extent, the more dynamic the problem is, the more crucial anticipation and reaction time become.
In response to the need for quick reaction times and anticipation tools, many of strategies have been developed in the literature, including the waiting strategy, deviation strategy, assignment and redeployment strategy and rejection strategy.

The waiting strategy can be adapted, depending on the availability of certain information, such as aggregating customer locations and distribution areas into geographic zones, splitting the planning horizon into time intervals, and estimating the arrival rate of customer requests for each time interval and geographic zone combination. It is common to assume in the DVRP literature that the arrival rate of customers' requests follows an independent Poisson process for each zone (Ichoua et al., 2006). With all of those details, as well as a real-time track of vehicle positions, the planner may be able to determine whether it is better to require a vehicle to wait in its current position rather than directing it to its next planned destination belonging to another zone if it seems that new customer requests are likely to appear in the neighborhood. It is also worth noting that the effectiveness of this strategy depends on determining the appropriate to wait time. If it is too short, it may not be possible for forecasted requests to be fulfilled in time. If it is too long, the vehicle may remain waiting for an extended period of time, allowing service requests in other zones to accumulate (Ichoua et al., 2006).

Unlike the waiting strategy, the deviation strategy can be used in extremely dynamic situations where the vehicle can be directed to a new destination to serve an immediate request, even if it is already on its way to a planned one (Ichoua et al., 2000). In this context, Gendreau et al. (2001) proposed a redeployment strategy in the emergency ambulances dispatching problem, where reaction time is strongly related to saving lives. Each patient call is rated based on its urgency, which is determined by the patient's medical condition. Then, vehicles are assigned to cover all available demand positions within a 15-minute radius and the most urgent requests within a 7-minute radius. As a result, the redeployment strategy was designed to relocate ambulances in such a way that if a vehicle is already assigned to a less urgent request, it can be reassigned to an urgent one if a set of predefined criteria is met.

A summary of the previous characteristics is presented in Table 1.1. The taxonomy combines the four families of location, physical, temporal, and planning characteristics. Each column in this table presents a distinct characteristic for each corresponding family.

1.5 Models and methods

First, we present different models and methods applied to solve DVRPs. Then, we classify them according to the solution approach and the quality of available information.

1.5.1 Modelling concerns

Although research on the DVRP is rapidly growing, the main emphasis has been on designing more competitive algorithms in terms of performance and solution quality (Ulmer et al., 2020). In the absence of a modeling framework and benchmark, we can quickly recognize diversified modeling approaches dealing with various constraints, variables, objective functions, and approximate solution methods. All of which complicates any attempt to compare results and limit the role of mathematical models provided to the following axes:

- a tool to formalize the description of the problem under study,
- a tool to compare an approximate solution of the dynamic problem against the optimal solution of the static and deterministic version,
- a tool to allow identification of an initial solution for a metaheuristic solution method.

Moreover, the widely used word *dynamic* in the literature creates confusion among a dynamic problem, a dynamic model, and a dynamic application. A problem is considered dynamic if at least one of its parameters is defined as a function of time. Mainly, there are two categories of dynamic problems: dynamic data problems and time-dependent data problems (Powell et al., 1995). In the first category, we tackle problems where the information changes during the planning horizon, such as immediate customer requests or traffic conditions. The second category relies on known data, which is also a function of time, such as time-dependent VRPs. A model is dynamic when it explicitly treats the change of information over time based on the system's states and interactions between them during the decision process. Finally, a dynamic application refers to a static model which is resolved repeatedly as the information is revealed (Powell et al., 1995).

1.5.2 Solution approaches

After defining the problem, choosing the right solution approach is a crucial task. This selection mainly relies on the quality of the available data (deterministic or stochastic) and the choice between online or offline solution approaches.

TABLE 1.1 – The DVRP's taxonomy

Location characteristics					
Customer locations	**Idle points**	**Idle point locations**			
Static	Considered	Static			
Dynamic	Not considered	Dynamic			
Physical characteristics					
Vehicle's capacity	**Fleet's type**	**Fleet's size**	**Depots**	**Products/service**	
Limited	Heterogeneous	Unique	Unique	Unique	
Unlimited	Homogenous	Multiple	Multiple	Multiple	
Shared					
Time characteristics					
Customers' time windows	**Travel time**	**On-site service time**	**Depot time window**	**Waiting time**	
Soft	Static	Static	Predefined	Considered	
Hard	Dynamic	Dynamic	Not considered	Not considered	
Mixed					
Planning characteristics					
Planning horizon	**Availability of information**	**Quality of information**	**Degree of dynamism**	**Request arrival rate**	**Planning strategies**
Finite	Local	Deterministic	Low	Heavy	Waiting
Infinite	Global	Stochastic	Medium	Light	Deviation
Double			High		Rejection

Dynamic and deterministic information

In the absence of any stochastic information, re-optimization has been the most widely used approach to the DVRP. This approach has the benefit of adopting the already mastered models and methods applied in static routing problems (Ulmer et al., 2020). It was introduced following two different solution processes: periodic re-optimization or continuous re-optimization (Pillac et al., 2013).

Periodic re-optimization Periodic re-optimization is based on splitting the time horizon into k epochs uniformly (offline re-optimization) or randomly by immediate events (online re-optimization). In the offline case, at the beginning of each epoch, an update of the current system state (current vehicle locations, assigned, not yet served, or unassigned customers, etc.) is carried out. According to the new system state, we face a static problem similar to the classic VRP. Over the first epoch, the routes resulting from solving the static problem will be applied. Any update will not be recognized until the start of the next epoch. This approach is more suited for problems with a low degree of dynamism since it tends to accumulate customer requests until the end of each epoch to achieve more flexibility against longer reaction times (Larsen et al., 2007; Pillac et al., 2013). Psaraftis (1988) applied a periodic re-optimization heuristic for a dynamic routing problem of cargo ships under military emergency. In such situations of military mobilization, the objective is to allocate cargoes to ships so as to ensure that cargoes arrive at their destination as planned in a certain time window, respect the specificity of each cargo, ship and port, avoid congestion in ports, and ensure the maximal utilization of ships. To consider the dynamic change in inputs, a predefined system updating parameters are set, in a way, in each epoch of time, the system inputs are updated and a re-optimization process is launched.

By addressing changes immediately, the second approach, the online re-optimization, is more reactive. In fact, a re-optimization process is launched by the arrival of any new customer request, and a static VRP is solved according to the new system state. In order to avoid any costly insertions, this approach usually involves a rejection strategy (Gendreau et al., 1999).

Continuous re-optimization The continuous re-optimization is appropriate for medium to high dynamic problems with more limited time windows and an important proportion of real-time requests compared to the total number of customers. Bank ATM terminal repair (Van-Anholt et al., 2016; Van-Der-Heide et al., 2020) and emergency services, such as ambulance dispatching (Gendreau et al., 2001), are examples of these categories (Larsen et al., 2007). In these contexts, the time between two successive events should be best exploited. Thus, the optimization process runs continuously and saves the best solutions in an adaptive memory for potential system updates. It stops with each new event by adding a new customer request in the set of unserved customers or more simply by the end of on-site service. A new problem is then identified, and a solution process is restarted with the appropriate initial solution already saved.

In these three re-optimization cases (offline, online and continuous re-optimization), a linear programming model is implemented by considering the particularities of the problem studied and is likely to be solved by the methods developed previously for the static VRP (Psaraftis, 1988). The optimal solution is often limited to small instances, particularly considering the execution time challenge. Thus, besides applying the column generation method (Chen and Xu, 2006; Hvattum et al., 2007), the use of a combination of construction and improvement heuristics, as well as local search metaheuristics are quite common (Ghiani et al., 2003; Montemanni et al., 2005; Gendreau et al., 2006; Ritzinger and Puchinger, 2013), and more precisely, the parallel implementation of the tabu search (Gendreau et al., 1999; Ozbaygin and Savelsbergh, 2019).

Dynamic and stochastic information

In the presence of stochastic information, the dynamic problem can be handled through historical or probabilistic data. By focusing on these data in the solution process, two approaches have been developed in the literature: offline or online stochastic and dynamic planning.

Offline stochastic & dynamic planning It is a proactive approach (offline), often referred to as the a priori approach. The decision process begins at period 0 before any changes in inputs. It is mainly based on listing possible change scenarios using stochastic information to complete the routing plans appropriate to each scenario. These plans will then be executed (but without any update) as the information changes in real-time.

The widely used formulations for the proactive decision processes are the Markov decision process (MDP) and the stochastic-dynamic programming, where initial and final states, transitions, post-decision state and decision policies are defined. To overcome the dimensionality issues, approximate solution methods are developed based on the rollout algorithm (Ulmer et al., 2019), value function approximation with a lookup table (Powell, 2007), and dedicated algorithms as learning algorithms (Klapp et al., 2018; Ulmer et al., 2019).

Online stochastic & dynamic planning It is referred to as the a-posteriori or reactive (online) approach. The solution process is initiated every time the information is updated. A solution quality improvement process will proceed in the lapse of time between two events (this depends on the method used, the degree of dynamism, and mainly the reaction time required).

For the reactive process decision, the modeling approaches developed in the literature are multi-stage stochastic modeling approach (Angelelli et al., 2016), multi-scenario approach (Powell, 2007), sampling approach (Bent and Van-Hentenryck, 2004; Pillac et al., 2012, 2013), mixed-integer modeling approach (Liu, 2019; Carvalho et al., 2020) and queuing approach

(Zhang et al., 2018). Regarding the solution methods, a wide range of specific heuristics was developed as the center of gravity heuristic, fixed routes, online expectation algorithm, branch-and-regret heuristic (Thomas, 2007; Van-Hentenryck et al., 2010; Ghiani et al., 2012; Ritzinger et al., 2016). Moreover, a thread of adequate local search and insertion methods are developed as dynamic stochastic variable neighborhood search (DSVNS) (Gutjahr et al., 2007), adaptive VNS, and anticipatory insertion heuristics (Hvattum et al., 2007; Azi et al., 2012; Ghiani et al., 2012; Pillac et al., 2012).

A summary of our proposed classification for solution methods is presented in Table 1.2. The rows mention the two solution approaches adopted in literature which are either the online or the offline approach. The columns show the quality of information that can be deterministic or stochastic. For each combination of solution approach and quality of information, we indicate the models and solution methods generally applied in the literature.

Table 1.2 – Models and solution methods

		Quality of information			
		Deterministic		Stochastic	
		Modeling approach	Solution algorithms	Modeling approach	Solution algorithms
Solution approach	Online	LP	Construction heurstics Improvement heursitcs Local search heruistics (TS, VNS)	MSSP MSA, Sampling based MSA, SSA Rolling horizon based approach+MIP	PFA algorithm DVNS, AVNS Specific heureustics: CG, AI, FR, OEA, CA, RA
			Population heuristics (GA, ACA)	Queuing	Hybrid adaptive predictive control approach Branch-and-regret heureustic
	Offline			MDP SDP	Approximate linear programming+ roullout algorithm Approximate dynamic programming VFA+lookup table+ Q-learning algoithm

Linear Programming (LP)	Tabu search (TS) Variable neighborhood search (VNS) Genetic algorithm (GA) Ant colony algorithm (ACA)	Multi-stage Stochastic planning (MSSP) Multi Scenario Approach (MSA) Sample scenario approach (SSA) Mixed-integer programming (MIP) Markov decision process (MDP) Stochastic dynamic programming (SDP)	Policy function approximation (PFA) Dynamic stochastic variable neighberhood search (DSVNS) Adaptive variable neighborhood search (AVNS) Center of gravity heuristic (CG) Anticipatory insertion heuristic (AI) Fixed-route heuristic (FR) Online expectation algorithm (OEA) Consensus algorithm (CA) Regret algorithm (RA) Value function approximation (VFA)

1.6 Conclusions

Even though research on dynamic routing problems has grown in recent years, it lacks a guiding framework that summarizes all characteristics and matches the problem's solution approach to the appropriate solution method to use. This difficulty arises first from confusion of how the term *dynamic* is used in the literature. As mentioned in Section 1.5.1, the various interpretations result in multiple perspectives on the same problem and, as a result, multiple solution methods. Second, each problem addressed in the literature considers different particularities and characteristics, increasing subjectivity and making it difficult to generalize one's approach to solve other problems. In terms of solution methods, we realized that the use of re-optimization-based-solution approach in the context of low dynamic problems is commonly used. Such a solution approach allows the application of static solution methods in a dynamic context while maintaining the quality of the results. However, as the problem becomes more dynamic, methods used to solve it diverge, making it more challenging to adapt an exact solution approach in a context where reaction time to change is crucial.

In this chapter, we attempted to present a general and precise literature review for real-time VRPs in order to enhance future research in this area by proposing a taxonomy of the main dynamic characteristics considered in recent research and a classification of solution methods based on the adopted solution approach and the quality of the available information. Many research and ideas were already developed, but a wide range of research avenues have yet to be explored. Below we mention some of them:

- **Stochastic and dynamic problems:** More attention should be paid to stochastic and dynamic problems in the literature. The most common characteristics used in recent studies are dynamic demand or stochastic customer requests assumed to follow a Poisson process. Travel times, for example, have always been important in transportation problems, and taking into account real-time travel time changes can make dynamic and stochastic problems more realistic.
- **Environmental issues:** Considering greenhouse gas emissions reduction goals by adapting speed as a decision variable and adding congestion costs to influence the route choice.
- **Disruption management:** Considering the cases of simultaneous events of disruption, for example, vehicle breakdown and product unavailability.

Chapitre 2

Dynamic inventory routing problem with customer requests

2.1 Résumé

Ce chapitre traite l'intégration des décisions dynamiques de routage-stockage dans le contexte de l'industrie des produits pétroliers. Inspirés par une situation réelle d'une entreprise de distribution de l'huile à chauffage, nous introduisons le problème dynamique de routage-stockage avec les appels des clients (DIRPCR) comme variante du problème bien connu de routage-stockage (IRP). Plus précisément, nous considérons un fournisseur qui gère le réapprovisionnement des réservoirs des clients réguliers et l'arrivée dynamique des demandes imprévues de livraisons pour le même jour. Nous proposons une heuristique basée sur la recherche tabou et deux politiques dynamiques pour intégrer les demandes urgentes imprévues sur un horizon mobile. Les résultats de l'étude indiquent que cet algorithme fonctionne bien dans un contexte dynamique. De plus, dans le cadre des différentes expérimentations menées, nous avons présenté des recommandations pour d'autres recherches futures et pour des directives managériales.

2.2 Abstract

This chapter addresses the integration of dynamic inventory-routing decisions in the context of the petroleum industry. Inspired by a real-world case, we introduce the dynamic inventory routing problem with customers' requests as a variant of the well-known inventory routing problem. Specifically, we consider a supplier that manages the replenishment of regular customers' tanks and the dynamic arrival of unplanned requests for same-day deliveries. We propose a tabu search-based heuristic and two dynamic policies to integrate the incoming requests in a rolling horizon manner. The results of the study indicate that this algorithm performs well in a dynamic context. Also, based on different experiments conducted, we

present recommendations for further research avenues and provide managerial guidelines.

2.3 Introduction

The Oil Distribution Problem (ODP) is a real-world problem faced by companies active in the petroleum products industry. They plan the distribution, monitoring, and replenishment of oil or any liquid that needs to be consumed daily and stored in dedicated tanks directly positioned in customers' locations. In addition to residential heating oil deliveries, we can also address this problem by replenishing gas stations. Most researchers viewed the ODP as an inventory routing problem (IRP) since the supplier handles the customer's inventory to avoid any stock-outs. However, another stream of research ignores inventory costs and focuses only on transportation planning. Therefore, they study the ODP as a multi-period vehicle routing problem.

This work is motivated first by the social side of the oil distribution problem. In winter, distributing heating oil or liquefied natural gas is a life necessity, and any stock-out can put people's lives in danger. Moreover, oil distribution is undoubtedly viewed as a second alternative for electricity, but it is crucial to ensure energy equity between regions and offer stability between seasons. Thus, proposing decision making techniques to reduce oil distribution costs may motivate companies to maintain providing this alternative. Although this problem has been studied in the literature for almost three decades, there has always been a lack of research considering more realistic assumptions. As a result, we will concentrate mainly on two points in this chapter:

- A solution approach that handles urgent unplanned deliveries quickly by offering same-day or next-day delivery. A quantity-dependent penalty will also be used to avoid dynamic request rejection and to maximize service level in other ways.
- A sophisticated analysis will be conducted to investigate the effects of increasing penalty or opportunity cost, vehicle capacity, and customer dispersion on service levels and operational costs in order to propose managerial recommendations to better serve customers while maintaining efficiency and competitivity.

Inspired by an actual oil distribution company, this work adopts an inventory routing approach to solve the problem by introducing a new variant of the classic IRP to deal with the dynamic arrival of customers' requests. By studying deterministic and dynamic versions of the problem, our goal is to solve large instances of this problem efficiently and quickly by appropriately integrating the dynamic requests, using a heuristic approach and reactive policies.

The remainder of this chapter is organized as follows. Section 2.4 presents a literature review on the most relevant papers related to the IRP. Section 2.5 introduces our variant of the IRP and focuses on the description and formulation of the problem in its deterministic version. Section 2.6 deals with the dynamic version of the problem by presenting the tabu search-based algorithm and two dynamic policies to integrate urgent customers' requests. Section 2.7

starts by enumerating the preliminary tests to evaluate the heuristic's performance and to set its parameters. Next, we provide information on how instances are generated and present the final results. Finally, Section 2.8 is dedicated to the concluding remarks, recommendations, and potential research avenues.

2.4 Literature review

The literature on the IRP is broad. In what follows, we give a brief overview of relevant works. For further classifications and extensive literature reviews, we refer the interested reader to Andersson et al. (2010) and Coelho et al. (2014b). The classic version of the IRP aims to minimize operation costs by assigning customers to delivery days of a predefined planning horizon, allocating quantities to deliver according to an inventory holding policy and customers' consumption rates, to finally generate the appropriate routes. Operation costs usually include supplier and customer inventory holding and transportation costs. In some real-world situations, the operational costs are reduced to only transportation costs, for example, when the supplier and customer belong to the same company, or when the supplier deals directly with final customers, e.g., heating oil distribution, waste collection, or vending machines replenishment. The IRP is a tactical planning problem that aims to capture the effect of the short-term decisions on long-term costs. Earlier research has focused on determining optimal delivery days from which penalties or incentives are incurred in case a delivery is postponed or advanced. In this context, Dror et al. (1985); Dror and Trudeau (1986) and Dror and Ball (1987) proposed a two-step IRP with deterministic and stochastic consumption rates (with normal distribution variations). After determining each customer's optimal delivery period in accordance with the Order Up to level (OU) policy, the first step of the assignment divides customers into mandatory and optional categories. Customers are considered *mandatory* when they risk running out of stock if no delivery is planned on the current planning period, otherwise they are considered *optional*. The second step, assuming the presence of a single truck, optimizes the generated daily routes by solving a modified Traveling Salesman Problem (TSP) iteratively over the planning horizon with a constructive heuristic and an objective function to minimize traveling costs including:

- a penalty cost in case of delivering a mandatory customer significantly earlier than the optimal delivery date (the goal here is to postpone the delivery of a mandatory customer until the optimal delivery date, to consolidate deliveries),
- a bonus for delivering an optional customer before the planned delivery date (the goal here is to encourage advancing the delivery of optional customers, if they are located in a mandatory customer's neighborhood to avoid a costly delivery in the near future).

Considering inventory holding costs and different inventory policies, Archetti et al. (2007) solved the IRP optimally with a *branch-and-cut* (B&C) algorithm. Experiments were conducted to conclude that:

(i) The saving in costs is more effective with a longer planning horizon due to reduced transportation costs. With a longer planning horizon, more chances can appear to coordinate and consolidate shipments,

(ii) The saving in costs can be improved by relaxing the constraints on the delivered quantities. More precisely, the widely used OU policy, despite its simplicity, appears to be rigid and generates high inventory levels in some cases. Thus, applying other flexible policies according to the specificities of the problem under study may be relevant.

Desaulniers et al. (2016) applied the maximum-level (ML) policy to an IRP with single supplier, and known customers' consumption rates. By fixing an upper bound for the quantity to deliver in each period, and an *extreme* route delivery pattern that takes into account full tank refills with the possibility of a one-time partial refill during the planning horizon, the problem was formulated as a mixed-integer program (MIP) with the objective to minimize the sum of the traveling and inventory holding costs at the supplier and the customers. The holding costs depend on the remaining inventory at the end of each period. The problem was solved with a branch-price-and-cut algorithm applied to the benchmark instances proposed by Coelho and Laporte (2014). They finally concluded that the ML policy outperforms the OU and is more flexible and challenging to solve.

Another research stream focused on managing stochastic demand by incorporating additional costs of recourse actions in case of a planning mismatch. Trudeau and Dror (1992) presented an IRP with demands that become known once the vehicle reaches the customer's location. Such operations' efficiency is measured by an average of delivered quantity per hour of distribution. According to an estimated value of the demand, two sets of mandatory and optional customers are generated for daily deliveries on a weekly planning horizon. The optional customers are assigned according to their proximity to the mandatory ones. In case of a route failure (lack of vehicle capacity), an emergency delivery service is performed to refill the tank and charge a stock-out cost. Based on a single vehicle problem and to manage demand stochasticity and transportation capacity violation, Coelho et al. (2014a) proposed two options for recourse actions as follows: outsource direct deliveries for route failures caused by vehicle capacity violation and lateral emergency transshipments between customers, in case a customer faces a shortage. In both cases, the supplier incurs a distance and volume-dependent cost.

Less attention has been paid to dynamism in the context of the IRP. The literature mainly assumes stochastic or random and stationary or non-stationary demands that change during the planning horizon. Based on a set of known customers, different approaches have been developed to balance dynamic demands and uncertainty with a focus on inventory management effects (Roldán et al., 2016). Solyalı et al. (2012) proposed a robust optimization approach to solve an IRP with dynamic uncertain demand and unknown probability distribution. Considering a stationary random demand Bertazzi et al. (2013) used dynamic programming to model a stochastic IRP by minimizing the expected transportation, inventory and penalty costs and a hybrid rollout algorithm to solve it. Consequently, the literature on dynamic inventory routing optimization remains rather scant. In fact, the dynamic parameter considered on dynamic IRPs is mainly customer demand. For example, Brinkmann et al. (2020) discuss the management of bike-sharing systems by dealing with stochastic and dynamic IRP. They modeled the problem by using a Markov decision process to minimize the unmet demand by relocating bikes between stations. Different experiments highlighted the importance of the coordination between anticipate and reactive actions in managing dynamic and stochastic systems. However, research on other dynamic parameters is limited. For example, Rahimi (2017) introduced a perishable multi-commodity IRP with demand and traffic condition variation. He considered a bi-objective mathematical formulation by maximizing revenues against inventory holding, ordering, and transportation costs on the one hand and reducing accident rates with the produced noise emissions per vehicle on the other. He also proposed a heuristic to solve the dynamic version of the problem according to a re-optimization process that considers real-time updating of demand and traffic condition.

The dynamic inventory routing problem (DIRP), as we present in this work, is a combination of the vendor-managed inventory (VMI) and the dynamic vehicle routing problem (DVRP) (see Figure 2.1). It is based on uncertain events that trigger changes. However, besides the stochastic and/or dynamic demand, it is crucial to consider other parameters to handle DIRP concerning more realistic situations. In this problem we deal, for example, with dynamic transportation lead times due to changing traffic conditions, and dynamic customer locations. Specifically, in this work, we focus on the dynamic arrival of customers' requests.

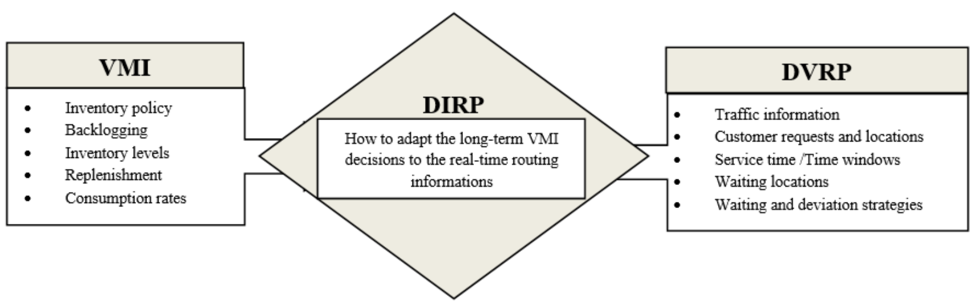

FIGURE 2.1 – DIRP in relation to the VMI and the DVRP

2.5 Problem description and formulation

In this section, we introduce the dynamic inventory routing problem with customer requests (DIRPCR) which is a new variant of the classic IRP by allowing the dynamic arrival of customer requests during the planning horizon. In Section 2.5.1, we present a detailed description of the problem. Then, we propose a mathematical formulation for its deterministic version in Section 2.5.2.

2.5.1 Problem description

The DIRPCR can be defined on an undirected graph ($\mathcal{V}$,$\mathcal{E}$) where $\mathcal{V}$ represents the set of vertices, and $\mathcal{E}$ the set of weighted edges (i, j) relating pairs of vertices according to a non-negative travel cost C_{ij}. $\mathcal{S}$ is the set of visited nodes and $\mathcal{E}(\mathcal{S}) = \{(i, j) \in \mathcal{E} | i \in \mathcal{S}, j \in \mathcal{S}\}$

The set $\mathcal{V}$ of vertices is composed of a node 0 representing the supplier and a subset $\mathcal{V}'= \{1, ..., n\}$ of the customers. $\mathcal{V}'$ is partitioned into two subsets of VMI and Self-Monitoring (SM) customers, respectively $\mathcal{V}_{vmi}$, $\mathcal{V}_{sm}$. VMI customers are contractual customers that maintain a long-term partnership with the supplier and delegate the total monitoring of their inventory replenishment via a monthly billing of the generated expenses. SM customers may also be contractual customers but they have usually reduced consumption rates and prefer self-monitoring their inventory. In other situations, an SM customer may be a price-dependent customer who avoids long-term contracts and switches for the supplier with the most competitive price. In both cases, an SM customer is in-charge of inventory monitoring and each time an urgent order is passed, its delivery cannot exceed one day from the date of ordering. It is important to note that SM customers can be proactive in real-world situations by placing orders prior to the stock-out period. However, dealing with same-day or next-day delivery requests is usually more disturbing and challenging. Thus, in this work, we only consider urgent requests to be fulfilled on the same or next-day, which need some reactive policies to be appropriately integrated.

A vehicle of capacity Q is assumed to be available at the depot. Considering a double discretized planning horizon, the supplier operates in two steps. First, he/she frames a master plan for VMI customers in a long-term horizon $\mathcal{T}$ of H days (i.e., for weekly or monthly updates). Considering an OU inventory policy, its initial inventory I_{0t} and periodic receptions r_{0t}, the supplier monitors the inventory replenishment of the VMI customers based on their initial inventory levels I_{it}, the known consumption rates r_{it} and the inventory holding capacity U_i for each customer $i \in \mathcal{V}_{vmi}$. Second, the supplier deals with the integration of the dynamic arrival of the SM customer requests in the short-term horizon $\mathcal{P} \in \mathcal{T}$ of a single day p (i.e., for daily updates). Thus, a request of an SM customer i is defined by an order day p_i, and an ordered quantity γ_i.

The objective is to determine delivery routes to minimize the operation costs, avoid stock-outs for VMI customers and integrate the maximum number of SM customer requests, by considering the following points:

- each route starts and ends at the depot,
- an opportunity cost is incurred to the supplier every time an SM customer request is rejected,
- the vehicle capacity is respected,
- the supplier inventory level is respected,

- the OU policy is respected.

2.5.2 Problem formulation

We present the deterministic formulation of this problem by including VMI customers with stationary consumption rates ($r_{it} = r_i, \forall t \in \mathcal{T}/\{0\}$) and a known list of SM customers orders that we either accept to fulfill on the same order day p_i, or reject and face a quantity-dependent penalty $\sigma\gamma_i$. At this level, we present a modified version of the IRP model proposed in Archetti et al. (2007) to deal with the problem at hand.

The main modifications are:

- as the supplier is dealing with final customers, and the objective is to reduce distribution costs, we do not include the inventory holding costs in our model. However, we consider the update of inventory levels, and the necessary constraints to avoid stock-outs according to the OU policy.
- as we consider different types of customers, we add constraints to integrate the SM customers orders.
- a quantity-dependent opportunity cost is considered if an SM customer is rejected, using a penalty coefficient σ.
- to avoid starting a new delivery planning cycle with stock-out cases, we consider a planning horizon of $H + 1$ periods, which refers to $\mathcal{T} = \{1, ..., H+1\}$.

The variables are:

- I_{lt}: the inventory level at location l at the start of each period t.
- q_{it}: represent the quantity delivered to each customer i during period t.
- y_{lt}: represent a binary variable equal to 1 if location l is visited at period t, and 0 otherwise.
- x_{ij}^t: represent the number of times edge $(i, j) \in \mathcal{E}$ is used in period $t \in \mathcal{T}$.

$$\text{minimize} \quad \sum_{(i,j)\in\mathcal{E}} \sum_{t\in\mathcal{T}} C_{ij} x_{ij}^t + \sigma \sum_{i\in\mathcal{V}_{sm}} \sum_{p\in\mathcal{P}} \gamma_i (1 - y_{ip}) \tag{2.1}$$

subject to

$$I_{0t} = I_{0,t-1} + r_{0,t-1} - \sum_{i\in\mathcal{V}'} q_{i,t-1}, \forall t \in \mathcal{T} \tag{2.2}$$

$$I_{0t} \geq \sum_{i\in\mathcal{V}'} q_{it}, \forall t \in \mathcal{T} \tag{2.3}$$

$$I_{it} = I_{i,t-1} - r_{i,t-1} + q_{i,t-1}, \forall i \in \mathcal{V}_{vmi}, \forall t \in \mathcal{T} \tag{2.4}$$

$$q_{it} \leq U_i - I_{it}, \forall i \in \mathcal{V}_{vmi}, \forall t \in \mathcal{T} \tag{2.5}$$

$$q_{it} \geq U_i y_{it} - I_{it}, \forall i \in \mathcal{V}_{vmi}, \forall t \in \mathcal{T} \tag{2.6}$$

$$q_{it} \leq U_i y_{it}, \forall i \in \mathcal{V}_{vmi}, \forall t \in \mathcal{T} \tag{2.7}$$

$$\sum_{i \in \mathcal{V}'} q_{it} \leq Q y_{0t}, \forall t \in \mathcal{T} \tag{2.8}$$

$$q_{it} = \gamma_i y_{it}, \forall t = p_i, \forall i \in \mathcal{V}_{sm} \tag{2.9}$$

$$\sum_{t \in \mathcal{T}} y_{it} \leq 1, \forall i \in \mathcal{V}_{sm} \tag{2.10}$$

$$\sum_{j:(i,j) \in \mathcal{E}} x_{ij}^t = 2 y_{it}, \forall i \in \mathcal{V}, \forall t \in \mathcal{T} \tag{2.11}$$

$$\sum_{(i,j) \in \mathcal{E}(\mathcal{S})} x_{ij}^t \leq \sum_{(i) \in \mathcal{S}} y_{it} - y_{st}, \mathcal{S} \subseteq \mathcal{V}', \forall s \in \mathcal{S}, \forall t \in \mathcal{T} \tag{2.12}$$

$$y_{it} \in \{0, 1\}, \forall i \in \mathcal{V}, \forall t \in \mathcal{T} \tag{2.13}$$

$$q_{it} \geq 0, \forall i \in \mathcal{V}', \forall t \in \mathcal{T} \tag{2.14}$$

$$I_{it} \geq 0, \forall i \in \mathcal{V}, \forall t \in \mathcal{T} \tag{2.15}$$

$$x_{ij}^t \in \{0, 1\}, i, j \in \mathcal{V}', \forall t \in \mathcal{T} \tag{2.16}$$

$$x_{0j}^t \in \{0, 1, 2\}, j \in \mathcal{V}', \forall t \in \mathcal{T} \tag{2.17}$$

The objective function (2.1) minimizes the sum of transportation costs for every scheduled delivery to any customer in the planning horizon and the opportunity cost for rejecting the delivery of SM customers. Constraints (2.2)-(2.4) are the inventory conservation constraints. Adopting an OU policy, constraints (2.5)-(2.7) impose that each delivery to a customer must refill the tank to its maximum level which depends on the capacity of the tank (U_i) and the already existing oil level in it (I_{it}). Constraints (2.8) ensure the vehicle capacity is respected. Constraints (2.9)-(2.10) consider SM customers' requests, by enforcing visiting each one of them just during the predetermined delivery date p_i and delivering the exact requested quantity γ_i. Constraints (2.11)-(2.12) are the routing constraints. Constraints (2.11) are the degree constraints for each node on the planning horizon. Constraints (2.12) are the subtour elimination constraints which stipulate the availability of two edge disjoint paths to reach each visited node via the source one (the depot)(Fischetti et al., 1998; Archetti et al., 2014). Finally, constraints (2.13)-(2.17) define the domain and nature of the variables.

Since our focus is on the dynamic aspect of the problem by considering the dynamic arrival of SM customer requests during route execution, and handling real-time decisions, we propose a heuristic approach.

We present in Section 2.6, a tabu search-based heuristic to handle plan updates, as well as two different policies to integrate the dynamic customer requests in the solution process. Consequently, an SM customer can get a real-time reply by either accepting his request and integrating his order on the delivery plan of the same or next day, or by rejecting it in a way to be able to look for another supplier immediately.

2.6 Solution algorithm

Tabu search (TS) is known as an effective method for solving the classical VRP and its variants (Rego and Roucairol, 1995; Renaud et al., 1996; Bolduc et al., 2010) as well as the IRP (Chiang and Russell, 2004; Archetti et al., 2012). Therefore, we have developed a tabu search-based heuristic to solve the dynamic version of our problem.

The TS is an approximate algorithm that is used to solve NP-hard problems in a reasonable amount of time by finding near-optimal solutions. Exploiting local search tools, TS covers the search space $\mathcal{A}$ by moving from a current solution a to its neighbor a', which is not forbidden to visit according to a permanently updated tabu list. The application of the appropriate type of tabu list, the tenure parameter value, and the use of specific techniques such as aspiration or jump techniques are all important factors in TS performance. Moreover, TS has the advantage of not exploring all possible solutions, but instead, it selects the more promising neighbors to handle wisely the local optimums. More details about the tabu search algorithm can be found in Glover (1986).
Before delving into the functionality, it is necessary to highlight the various basic elements of our heuristics.

2.6.1 Heuristic components

The first step in the development of our algorithm is based on defining the following components based on definitions found in Glover and Taillard (1993) and Osman and Wassan (2002):

(i) **tabu list:** has the role of saving some characteristics of conducted moves on a current solution for a certain number of iterations. Stored attributes are used to uniquely identify each move and then define its status at each iteration. In fact, once a move is added to the tabu list, it cannot be used again until the tabu status expires. For instance, a move that inserts customer i into a route of period t is identified in the tabu list based on three elements: move operator, customer, and period numbers.

(ii) **tabu tenure:** is the parameter that defines how many iterations a move remains in the tabu list.

(iii) **move operator:** has the role to make a change in the current solution. We used four different move operators: *Add*, *Remove*, *Move*, and *Swap*, which will be explained in detail in Section 2.6.2

(iv) **stopping criteria:** is the rule that allows deciding when the solution process should be terminated.

(v) **reactive tabu list:** is considered reactive if it dynamically changes the tenure parameter value based on the ongoing search process. If unimproving moves are generated repeatedly and consecutively, the tenure parameter value is gradually increased to force the search solution process to be moved to another area. When successively improved moves are generated, the tenure parameter value is reduced to spread the search in the same area.

(vi) **aspiration criteria:** adopting this technique allows to override a move's tabu status if it generates a better solution than the current best one. As a result, even if it is on the tabu list, a promoting move is always chosen.

2.6.2 Heuristic design

Our algorithm is designed based on three main procedures: initialization, move, and improvement. The general scheme is presented in Figure 2.2.

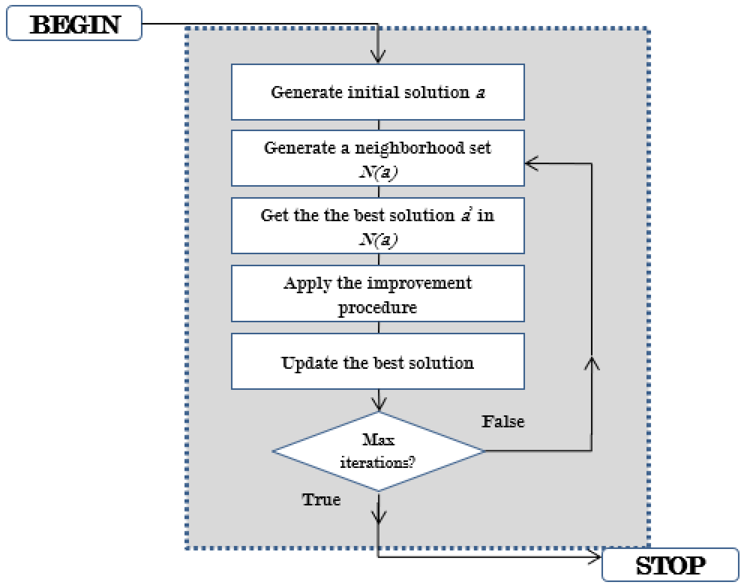

FIGURE 2.2 – Overview of the tabu search-based algorithm

Initialization procedure

Inspired by the work of Dror and Ball (1987), initially and in a rolling horizon manner we calculate for each VMI customer $i \in \mathcal{V}_{vmi}$ a coverage parameter f_{it} which represents the number of periods that the available oil level in the tank can cover the consumption over the planning horizon. The optimal solution of an OU policy suggests that each customer should be visited at its stock-out period and get refilled to the maximum level. Knowing the consumption rates r_{it}, and the starting level of oil I_{it} for each period t, f_{it} is determined for each customer $i \in \mathcal{V}_{vmi}$ and for every period $t \in \mathcal{T}$ as depicted by the function f_{it} in (2.18):

$$f_{it} = I_{it}/r_{it}, \forall i \in \mathcal{V}_{vmi}, \forall t \in \mathcal{T} \tag{2.18}$$

After assigning VMI customers to their stock-out periods, we assign each SM customer i $\forall i \in \mathcal{V}_{sm}$ to its predefined delivery date which is equivalent to its order day p_i.

Delivering all VMI customers in their stock-out period guarantees reducing deliveries frequencies and transportation costs, but may violate vehicle capacity and supplier inventory levels. Such infeasible solutions are considered admissible as initial solutions. Specifically, each solution is considered admissible if it guarantees the absence of customers stock-out and over-stock situations in every planning period while not necessarily respecting vehicle capacity and supplier inventory levels constraints throughout the entire planning horizon, which we consider to be a relaxation of our modelling constraints (supply inventory levels, vehicle capacity, and SM customers deliveries). However, every generated admissible solution is penalized based on an evaluation function as described in the following Section 2.6.2.

An initial solution $a \in \mathcal{A}$ is then considered by respecting the numerical order of customers, that is, the first assigned customer to a route is the first one to be visited.

The pseudo code of the initialization procedure is presented in Algorithm 2.1.

Algorithm 2.1 Initialization procedure pseudo code

while $t \leq H + 1$ **do**
    for each customer $i \in \mathcal{V}$' **do**
        if $i \in \mathcal{V}_{vmi}$ and $f_{it} < 1$ **then**
            $q_{it} \leftarrow U_i - I_{it}$
        else $i \in \mathcal{V}_{sm}$ and p_i=t
            $q_{it} \leftarrow \gamma_i$
        end if
    end for
end while

At this point, it is important to note that assigning SM customers during the initialization procedure is only used to test the deterministic version of our heuristic. In the dynamic version, however, after preparing an initial plan of only VMI customers deliveries, we assign SM customers dynamically based on developed control policies as presented in Section 2.6.3.

Move procedure

The move procedure is designed based on the previous application of the TS to the IRP in Archetti et al. (2012). After generating an initial solution a $\in \mathcal{A}$, the move procedure generates the corresponding neighborhood set $\mathcal{N}$(a) and selects the best solution a' $\in \mathcal{N}$(a).

The neighborhood set $\mathcal{N}$(a) is created according to four types of moves: *Add*, *Remove*, *Move*, and *Swap*.

- *Add*(i,t) considers the current solution a and randomly chooses customer i and period t who is not assigned to and inserts i in the route at t by the cheapest insertion method. *Add* is considered valid under three conditions. First, we assign a VMI customer to a period that is not already assigned to it. Second, we assign an SM customer i to the predefined delivery date p_i. Third, the new assignment would keep the current solution at least admissible.
- *Remove*(i,t) considers the current solution a and randomly chooses a customer i from the list of customers to visit on a selected period t, removes it from the route, and links its predecessor to its successor. *Remove* is considered valid just when we remove a customer from a period that is already assigned to, it remains at least another scheduled delivery for each VMI customer and when the removal of the planned delivery would keep the current solution at least admissible.

The two other types of moves can be viewed as combinations of the above mentioned ones.

- *Move*(i, t, t') can be considered as the application of a *remove* move on the current solution a, followed by and an *add* move. In fact the *move* removes a visit of customer i from period t and adds a new visit to the same customer in another period t'.

- *Swap*(i, t, i', t') can also be considered as simultaneous *remove* and *add* moves, but for two customers which removes a visit to customer i from period t and adds a new one to period t', and in the opposite way, removes a visit to customer i' from period t' and adds a new one to period t.

Given that VMI customers may be visited more than once over the planning horizon, and based on the initial plan resulted from the initialization step, the application of the various types of moves alters the frequency and interval between visits. In fact, *Add*(i,t) has the role of increasing the frequency of visits to customer i by scheduling a new visit on period t to which is not already assigned. For instance, if we consider a three-period planning horizon, a customer i may already be assigned to be visited on period 1, but by using the *Add* move type, we can add another visit on period 2 or 3 except for period 1 which is already assigned to it. As a result, the frequency of visits to customer i increases to 2. Moreover, *Remove*(i,t) has the role of decreasing this frequency, by removing an already scheduled visit to customer i on period t. However, *Move*(i, t, t') and *Swap*(i, t, i', t') do not affect the frequency of visits but the interval between them. For example, suppose we have a six-period planning horizon and a customer i is already scheduled to be visited twice during periods 1 and 4. By using a *Move* move we can increase the interval between the two visits by fixing the visit scheduled for period 1 and postponing the visit scheduled for period 4 to period 5 by *Move*(i, 4, 5) or 6 by *Move*(i, 4, 6). We can also shorten the interval between those two visits by either fixing the visit scheduled for period 1 and advancing the visit scheduled for period 4 to its predecessors (period 3 by *Move*(i, 4, 3) or period 2 by *Move*(i, 4, 2)) or fixing the visit scheduled for period 4 and postponing the visit scheduled for period 1 to its successors (period 2 by *Move*(i, 1, 2) or period 3 by *Move*(i, 1, 3)).

To ensure that a generated solution remains at least admissible, the same quantity should be deducted from the next delivery when we add a visit to a chosen customer, if there is a next one. In the opposite way, the same quantity to deduce when we remove a visit from a chosen customer, should be added to the next delivery, if there is a next one.

The neighborhood $\mathcal{N}$(a) is generated from a by applying the above moves, and by relaxing vehicle capacity, supplier inventory level and SM customers' requests constraints. To choose the best solution $a' \in \mathcal{N}$(a), an evaluation function $\mathcal{F}$(a) is then used to penalize any infeasible but admissible solution as follows (see Function 2.19):

- k_t(a): transportation cost of solution a in period t,
- Q_t(a): total quantity delivered in period t by using a unique vehicle with a capacity Q,
- I_t(a): the supplier inventory level in period t,
- $Q_{sm,t}$(a): The total quantity delivered to SM customers in period t,
- α, β, σ: vehicle capacity, supply stock-out, and SM customers rejection constraints violation parameters,

- $[\cdot]^{+} = max(.,0)$,

$$\mathcal{F}(a) = \sum_{t\in\mathcal{T}} k_t(a) + \alpha \sum_{t\in\mathcal{T}} [Q_t(a) - Q]^{+} + \beta\,[-I_{0t}(a)]^{+} + \sigma \sum_{t\in\mathcal{T}} \left[\sum_{i\in\mathcal{V}_{sm}} \gamma_i - Q_{sm,t}(a) \right]^{+} \quad (2.19)$$

The current and the best solutions are then updated according to the evaluation step results, and the best move is added to a reactive tabu list with a dynamic length and tenure parameters values.

Algorithm 2.2 Move procedure pseudo code

Inputs: MaxIter, MaxMoves
Apply the initialization procedure to generate an initial solution a
$A_{best} \leftarrow a$
$CurrentIter \leftarrow 1$
$CurrentMove \leftarrow 1$
while $CurrentIter \leq MaxIter$ **do**
    while $CurrentMove \leq MaxMoves$ **do**
        Generate all feasible and/or admissible moves and update $\mathcal{N}$(a)
    end while
    Evaluate all solutions in $\mathcal{N}$(a) and choose the best one (a')
    if $a' < A_{best}$ **then**
        $A_{best} \leftarrow a'$
    end if
end while

Improvement procedure

This procedure is used on the one hand as a guiding tool to avoid generating and evaluating all admissible solutions at each iteration and to improve execution time. On the other hand, it is applied with the aim of consolidation and reduction of visit frequencies. At this level, we consider a priority of visit categorizations (as seen in Dror and Ball (1987)) for VMI customers, by distinguishing the mandatory ones from the optional ones according the their on-hand oil levels. A customer is considered mandatory, when she/he is assigned to a stock-out period t^*. Thus, we cannot postpone planned visits for any of next periods $t > t^*$. A customer is considered optional, when she/he is assigned to a period $t < t^*$. These visits can either be postponed to a period t' where $t < t' \leq t^*$ or advanced further to period t" where $1 < t" < t$. The first improvement step focuses on emptying the last period $(H + 1)$ by choosing the appropriate scheduled visit moves according to customers categories. Pushing back the visits to the previous periods may generate more admissible but infeasible solutions with respect to vehicle capacity and supply inventory level violations. The next step focuses on those periods with capacity violations, by choosing either to advance the delivery of mandatory customers to a previous period or to postpone the visit of optional customers to the next one. The last step focuses on reducing unnecessary visits during the first period. As we assume the availability of a certain oil level in all VMI customer tanks on period 0, *Remove* or *Move* type movements

are privileged to push forward any optional customer visit to the next period.
In addition to the guiding process, we apply specific versions of 2 and 3-Opt algorithms for daily TSP optimization (referred to respectively as 2-Opt-sv and 3-Opt-sv hereafter). In fact, we adopted a neighborhood-based configuration as detailed in Martin et al. (1991) which has the advantage of not considering all possible edges by avoiding far positioned edge exchanges and privileging edge exchanges of nodes in the same neighborhood (Algorithms 2.3 and 2.4). As a result, those versions are chosen to improve execution time.
As indicated by the Algorithms 2.3 and 2.4, in order to be able to apply them on various tours generated throughout the planning horizon, the following elements should be available:

- *tour*, represents the sequence of customers' visits on the route generated for each planning period. For instance, $tour[i] = \omega$, denotes that i will be the ωth customer to visit.
- symmetric distance matrix $d[i][j]$
- neighborhood matrix $nbhd[i][j]$, generated by sorting each row in d_{ij} in a non-decreasing order. For large instances, we can reduce the neighborhood matrix to a λ-neighborhood matrix, where λ refers to each customer's first λ nearest neighbors. For instance, $nbhd[i][k] = c$, denotes that customer c is the kth neighbor of i.
- $MinLink$ refers to the value of the shortest link between all $(i, j) \in \mathcal{E}$ where i, $j \in tour$
- $MaxLink$ refers to the longest link between all $(i, j) \in \mathcal{E}$ where i, $j \in tour$. Throughout the optimization process, this value should be updated.

Regarding the 2-Opt-sv, in Algorithm 2.3 shown below, u, v, z, w, are nodes in *tour*, and u_1, v_1, z_1, w_1 are their corresponding positions. We begin by looping through these nodes in *tour*. Taking the first node u in *tour* and its successor v, we look then for the closest neighbor to u, which is w and its successor z. Then, we should determine whether linking u to its neighbor w will not increase the total distance of the route. Finally, we perform an intra-route swap by exchanging the edges (u, v) and (w, z) with (u, w) and (v, z) in a *tour*.

Algorithm 2.3 2-Opt-sv pseudo code

Inputs:
- route list: *tour*,
- route size: *RS*,
- neighborhood matrix: *nbhd*,
- distance matrix: $d[i][j]$,
- Shortest distance in tour: $MinLink$,
- longest distance in tour: $MaxLink$

boolean hastourChanged=true
while $hastourChanged = true$ **do**
    $hastourChanged = false$
    for each position $u_1 \in tour$ **do**
        $v_1 = (u_1 + RS - 1)\%RS$
        $u = tour[u_1]$
        $v = tour[v_1]$
        for each position $k \in nbhd[u]$ **do**
            $w_1 = Index(nbhd[u][k])$ ▷ w_1 gets the position of the kth neighbor of u in *tour*
            $z_1 = (w_1 + RS - 1)\%RS$
            $w = tour[w_1]$
            $z = tour[z_1\%RS]$
            if $d[u][w] + MinLink > d[u][v] + MaxLink$ **then**
                $break$ ▷ break out of k loop and go to next u_1
            end if
            if $d[u][w] + d[v][z] < d[u][v] + d[w][z])$ **then**
                $Swap(v, w)$ ▷ exchange the edges (u,v) and (w,z) by (u,w) and (v,z) in *tour*
                $hastourChanged = true$
                $break$ ▷ break out of k loop and go to next u_1
            end if
        end for
    end for
end while

The same logic is followed by the 3-Opt-sv Algorithm 2.4 but with 6 nodes instead of 4. b, u, v, w, z and d are nodes in *tour*, and b_1, u_1, v_1, w_1, z_1, d_1 are their corresponding positions in *tour*. Starting from the edge (u, v), we loop on both neighbors of u and v, checking each time if linking u and v to each neighbor will improve the route transportation cost in relation to the *MinLink* and *MaxLink* values. Following that, we use an intra-route swap to reduce the overall distance between the 6 nodes.

Algorithm 2.4 3-Opt-sv pseudo code

```
Inputs:
    • route list: tour,
    • route size: RS,
    • neighborhood matrix: nbhd,
    • distance matrix: d[i][j],
    • Shortest distance in tour: MinLink,
    • longest distance in tour: MaxLink
boolean hastourChanged=true
double d(uv, bd, wz) = 0
while hastourChanged = true do
    hastourChanged = false
    for each position u1 ∈ tour do
        v1 = (u1 + RS − 1)%RS
        u = tour[u1]
        v = tour[v1]
        for each position k ∈ nbhd[v] do
            z1 = Index(nbhd[v][k])          ▷ w1 gets the position of the kth neighbor of v in tour
            w1 = (z1 + RS − 1)%RS
            z = tour[z1]
            w = tour[w1]
            if d[v][z] + 2 × MinLink > d[v][u] + 2 × MaxLink then
                break                       ▷ break out of k loop and go to next u1
            end if
            if d[v][z] + 2 × MinLink > d[v][u] + d[w][z] + MaxLink then
                continue
            end if
            for each position k1 ∈ nbhd[u] do
                d1 = Index(nbhd[d][k1])     ▷ d1 gets the position of the k1th neighbor of u in tour
                b1 = (d1 + RS − 1)%RS
                b = tour[b1]
                d = tour[d1]
                if d[v][z] + d[u][d] + MinLink > d[v][u] + d[w][z] + MaxLink then
                    break                   ▷ break out of k1 loop and go to next k
                end if
                d(uv, bd, wz) = d[u][v] + d[b][d] + d[w][z]
                if d[u][d] + d[v][z] + d[b][w] < d(uv, bd, wz) then
                    Swap(u, z)      ▷ exchange the edges (u,v) and (w,z) by (v,z) and (w,u) in tour
                    Swap(w, d)      ▷ exchange the edges (b,d) and (w,u) by (d,u) and (b,w) in tour
                                    ▷ which result in the exchange of edges (u,v), (w,z) and (b,d) by (v,z), (d,u) and (b,w) in tour
                    hastourChanged = true
                    break           ▷ break out of k and k1 loops and go to next ui
                end if
            end for
        end for
    end for
end while
```

2.6.3 Dynamic policies

The TS-based heuristic can be used to solve the DIRPCR under two different proposed policies: *Rerouting* and *Reassignment*. These policies' role is to use a different reactive pattern to integrate SM customers' requests into the a priori plan, either in the same routing period or the next.

Rerouting policy

This policy focuses on inserting SM customers in same-day delivery and avoiding pre-established delivery plan changes. According to this policy, the SM customers' requests are revealed just during route executions. After a given SM customer request becomes known, an evaluation step is incurred to check if adding an SM customer on the current route on the one hand will not cause supply stock-out and transportation capacity violations and increase transportation costs extensively against opportunity ones on the other hand. Assuming that the vehicle leaves the depot with a full load, the SM customer is either added at the end of the current route or rejected to incur a quantity-dependent opportunity cost. This same procedure is repeated by checking and updating capacities and route visits, each time an SM customer request is accepted until the set of SM customers is empty. We have to mention that adding the SM customer in a position other than the last one to a route under execution needs a real-time track, update, and record of all the parameters during the route execution such as the vehicle position and the status of customers. However, this detailed and real-time monitoring procedure requires sophisticated ICTs use, which is not always the case in real-world applications.

Reassignment policy

This policy avoids same-day deliveries to allow SM customer requests integration in a better position on the route for the following delivery period. After receiving an SM customer i request in period p_i, we add it with the cheapest insertion to the planned route of the next period p_i+1, we update the remaining vehicle capacity and supplier residual inventory level, and we launch a new assignment cycle starting from p_i+1 and ending in period $H+1$.

According to both policies, SM customers' requests may be rejected for three reasons: vehicle or supply inventory level violations or cost increase. The latter refers to situations where adding an SM customer may generate higher transportation costs than the opportunity cost.

After the reassignment step, we continue revealing SM customers' requests and deciding on VMI customers' possibilities to postpone, advance, or reject some SM requests and incur an opportunity cost until the end of the planning horizon.

2.7 Computational experiments

Our experiments are divided into two steps. The first step is dedicated to what we call "the deterministic version" of the problem and a second step for "the dynamic version".

2.7.1 Preliminary tests

The first step was to make preliminary tests on our heuristic to set up different parameters and evaluate its performance as an approximate solution method against an exact approach for solving the deterministic version. The preliminary tests are made on modified versions of Archetti et al. (2007) instances. In the context of solving classic IRPs, the authors proposed 160 instances divided into four classes regarding planning horizon length and inventory holding costs. They were generated randomly according to uniform distribution within different ranges of parameters. Thus, the number of customers varies from 5 to 50 with Euclidean positions to plan their deliveries on three or six-period planning horizons according to specified vehicle capacity, periodic reception/consumption rates, maximum inventory levels, and inventory holding unit costs. To be adapted to our problem, we chose three instances with 5, 30, and 50 customers and two different planning horizon sizes of three and six periods. Given that the Archetti et al. (2007) instances were generated based on other criteria unrelated to our work, such as supplier and customer inventory holding costs, we estimated that the three instances chosen were sufficient to assess the heuristic's performance at various variations, whether in terms of the number of customers or the length of the planning horizon.

We considered the already available data as VMI customers' ones, and we added the corresponding SM customers' needed parameters randomly, mainly γ_i, p_i and locations.

For the exact approach, a $B\&C$ algorithm implemented in C++ was tested by using IBM ILOG CPLEX 12.6.1, and run on an Intel Xeon E3-1270 V2 3.5 GHz and 12 GB RAM computer with a maximum running time of two hours.

For the approximate approach, the TS-based heuristic was implemented in Java using and incorporating modifications on the Open TS package released by the COIN-OR foundation, Inc. and developed by Harder et al. (2004).

Parameters setting

For our heuristic, we used a unique tabu list with a length of n^2, where n refers to the total number of customers in an instance. As previously stated, in addition to using an aspiration criterion throughout the entire solution process, a reactive tabu list was incorporated by a dynamic variation of the tabu list tenure parameter. The tenure parameter was initialized to 10, then is decreased by 90%, if a new best solution is reached and increased by 40% if a move does not improve the current solution. In terms of the stopping rule, we chose two criteria: reaching the optimal solution for the deterministic version tests and completing $300\times n$

iterations for the dynamic version application.

During our first tests, we noticed that generating feasible solutions depends on respecting vehicle capacity, which was the most challenging constraint to maintain between iterations (see Table 2.1).

α is the parameter for the vehicle capacity violation penalty, and is initially set to 1. We tested two ways to update it during algorithm execution. A rise to 5 on all iterations, was tested. Then, a dynamic update at every 5 iterations was also incorporated: if the 5 last generated solutions were feasible, then α is reduced by 75%, and if they were infeasible, then it is increased by 50%.

Table 2.1 shows a summary of results by applying our TS-based heuristic on one of the modified instances from Archetti et al. (2007). The instance has a total of 60 customers, 50 of which are VMI customers and 10 of which are SM customers; the planning horizon is of three periods. The first column represents the iteration number, the second column denotes the solution evaluation function value $\mathcal{F}$(a), the third, the fourth, the fifth and the sixth columns, refer to the four elements of $\mathcal{F}$(a) which are the transportation cost (TC), the supply stock-out penalty (SP), the vehicle capacity penalty (VCP), and the opportunity cost of rejecting SM customers (SMCP). The last two columns are the number of generated moves on each iteration and the best chosen move to apply on the next one. For instance, "move(20,4,3)" denotes a *move* type move of customer 20 from period 4 to 3.

Such generated debriefs with each run support in guiding our preliminary tests steps. In the first iteration, an initial solution with a value of 21077 is generated in comparison to an optimal solution value of 5817. Moving customer 20 from period 4 to 3 is chosen to generate the best $\mathcal{F}$(a) out of a total of 27 other moves. After applying this move, the solution value on the second iteration dropped by 34% to 13954.2. *Move* type moves are chosen to apply on the $(H+1)$ planning period from the second iteration until the seventh. Because of the vehicle capacity violation and the concentration of visits on period 3, by the eighth iteration, unfeasible but admissible solutions began to be generated. In fact, successive moves of visits from period 4 to period 3 were chosen until iteration 30. Emptying period 4, accumulated deliveries on period 3, reduced transportation costs by 53% on one side (transportation cost on iteration 30 is 12085.1 instead of 21077 on the first iteration), but increased the penalty due to vehicle capacity violation on the other. On subsequent iterations, and in order to reestablish feasibility, moves are made to balance visits mainly between periods 3 and 2. Finally, at the 48th iteration a solution of value 5991.1 is obtained which is 2.9% from the optimum and 71.5% lower than the initial solution.

TABLE 2.1 – Example of runs for absH3high_5n50 instance

Iter	$\mathcal{F}$(a)	TC	SP	VCP	SMCP	Number of moves	Best Move
i1	21077.0	21077.0	0.0	0.0	0.0	27	move(20,4,3)
i2	13954.2	13954.2	0.0	0.0	0.0	26	move(36,4,3)
i3	13523.4	13523.4	0.0	0.0	0.0	25	move(13,4,3)
i4	13394.8	13394.8	0.0	0.0	0.0	24	move(19,4,3)
i5	13325.2	13325.2	0.0	0.0	0.0	23	move(38,4,3)
i6	13262.6	13262.6	0.0	0.0	0.0	22	move(5,4,3)
i7	13204.9	13204.9	0.0	0.0	0.0	21	move(23,4,3)
i8	13180.9	13155.9	0.0	25.0	0.0	20	move(8,4,3)
i9	13215.4	13140.4	0.0	75.0	0.0	1	K-Opt-sv
i10	13215.4	13140.4	0.0	75.0	0.0	19	move(46,4,3)
i11	13253.0	13118.0	0.0	135.0	0.0	18	move(47,4,3)
i12	13359.5	13159.5	0.0	200.0	0.0	17	move(4,4,3)
i13	13476.8	13151.8	0.0	325.0	0.0	16	move(44,4,3)
i14	13611.3	13001.3	0.0	610.0	0.0	15	move(40,4,3)
i15	13763.3	12988.3	0.0	775.0	0.0	14	move(9,4,3)
i16	13938.5	12898.5	0.0	1040.0	0.0	13	move(17,4,3)
i17	14138.6	12938.6	0.0	1200.0	0.0	12	move(10,4,3)
i18	14358.4	12903.4	0.0	1455.0	0.0	11	move(25,4,3)
i19	14617.7	12742.7	0.0	1875.0	0.0	1	K-Opt-sv
i20	14617.7	12742.7	0.0	1875.0	0.0	10	move(30,4,3)
i21	14893.1	12738.1	0.0	2155.0	0.0	9	move(27,4,3)
i22	15266.2	12836.2	0.0	2430.0	0.0	8	move(32,4,3)
i23	15703.1	12878.1	0.0	2825.0	0.0	7	move(50,4,3)
i24	16156.0	12851.0	0.0	3305.0	0.0	6	move(24,4,3)
i25	16622.5	12832.5	0.0	3790.0	0.0	5	move(29,4,3)
i26	17102.9	12832.9	0.0	4270.0	0.0	4	move(15,4,3)
i27	17541.9	12796.9	0.0	4745.0	0.0	3	move(7,4,3)
i28	18001.1	12836.1	0.0	5165.0	0.0	2	move(34,4,3)
i29	17650.1	12085.1	0.0	5565.0	0.0	1	K-Opt-sv
i30	17650.1	12085.1	0.0	5565.0	0.0	1	move(33,4,3)
i31	19883.5	14133.5	0.0	5750.0	0.0	23	move(37,3,2)
i32	13135.8	8855.8	0.0	4280.0	0.0	44	move(3,3,2)
i33	10327.3	7157.3	0.0	3170.0	0.0	63	move(11,3,2)
i34	8681.5	6711.5	0.0	1970.0	0.0	80	move(42,3,2)
i35	7242.3	6712.3	0.0	530.0	0.0	95	move(41,3,2)
i36	6442.2	6442.2	0.0	0.0	0.0	145	move(32,2,1)
i37	6331.5	6321.5	0.0	10.0	0.0	109	swap(45,3,11,2)
i38	6330.1	6330.1	0.0	0.0	0.0	146	swap(45,2,6,3)
i39	6241.4	6241.4	0.0	0.0	0.0	1	K-Opt-sv
i40	6241.4	6241.4	0.0	0.0	0.0	146	move(47,2,1)
i41	6197.7	6197.7	0.0	0.0	0.0	147	move(47,1,2)
i42	6174.3	6174.3	0.0	0.0	0.0	146	move(35,3,2)
i43	6156.4	6156.4	0.0	0.0	0.0	159	move(50,2,1)
i44	6066.4	6066.4	0.0	0.0	0.0	160	move(44,2,1)
i45	6044.1	6044.1	0.0	0.0	0.0	161	move(4,2,1)
i46	5997.1	5997.1	0.0	0.0	0.0	162	move(13,2,1)
i47	5992.5	5992.5	0.0	0.0	0.0	163	move(48,3,2)
i48	5991.1	5991.1	0.0	0.0	0.0	174	move(18,3,2)

K-Opt-sv incorporation

After setting up parameters, the next step was to test the incorporation of 3-Opt-sv and 2-Opt-sv algorithms in two ways: at first separately with a frequency of application at each certain number of iterations. Then we integrated them into each type of move by applying the chosen move on the current solution followed by a K-Opt-sv operation (either a 2-Opt-sv or a 3-Opt-sv). The evolution of the current solution value during the execution process showed that the 2-Opt-sv performs better than the 3-Opt-sv algorithm in our case compared to the exact solution value (Z^*) (see Figure 2.3).

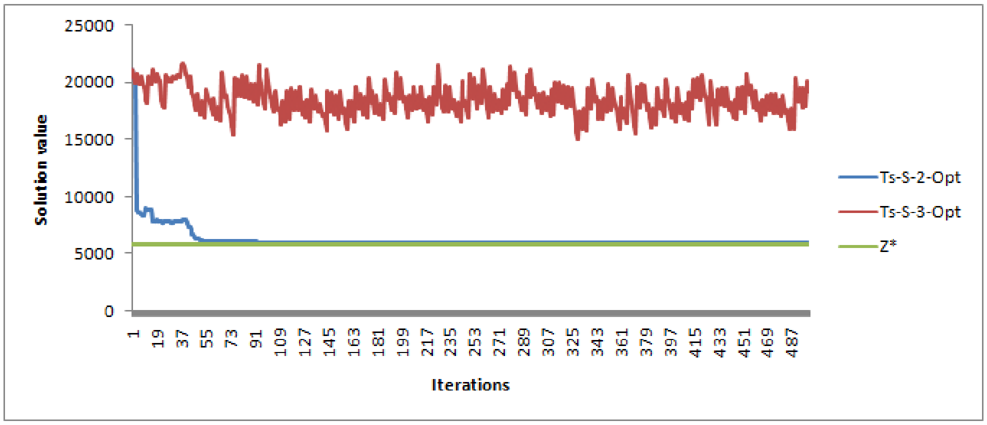

FIGURE 2.3 – Performance of 2-Opt-sv and 3-Opt-sv on absH3high_5n50 instance

Table 2.2 summarizes the results of applying the B&C algorithm as well as the TS algorithm with/without the 2-Opt-sv. The row "B&C" refers to the solution of the deterministic version of our problem assuming full information about both VMI and SM customers. On row "Ts-W-2-opt" we show the results of the tabu search without applying a 2-Opt-sv. The rows "Ts-S-2-opt" show the results of using a tabu search with a separate 2-Opt-sv called at each fixed number of iterations. Finally, the row "Ts-I-2-opt" stands for the results of applying tabu search with an integrated 2-Opt-sv into each move involved in each iteration.

TABLE 2.2 – 2-Opt-sv incorporation

	Instances	absH3high_1n5	absH3high_5n50	absH6low_5n30
	n	8	60	37
	Vmi customers	5	50	30
	Sm customers	3	10	7
	H	3	3	6
	Heuristic initial solution	3030	21077	22576
B&C	z*	2563	5817	8511
	Time (s)	0.08	186.84	721.61
Ts-W-2-Opt	Best Solution	2563	7728	13726
	Time (s)	0.515	5.756	2.917
	Gap (z)	0.0%	32.9%	61.3%
Ts-S-2-Opt	Best Solution	2563	5970	8668
	Time (s)	0.464	3.401	21.996
	Gap (z)	0.0%	2.6%	1.8%
Ts-I-2-Opt	Best Solution	2563	6000	9584
	Time (s)	0.826	10.452	4.383
	Gap (z)	0.0%	3.1%	12.6%

It is shown that in general, incorporating a 2-Opt-sv in a tabu search process makes a significant improvement. Indeed, without a 2-Opt-sv, the heuristic solution value generated a 32% gap on an instance of 50 customers and three periods of planning horizon. In addition, it generates a 61% gap on an instance of 30 customers and a six-period planning horizon. By using a 2-Opt-sv algorithm at a specific frequency during the execution of the TS, solution gaps were reduced to 1% and 2%, respectively (see the "Ts-S-2-Opt" row on Table 2.2). However, when the 2-Opt-sv is included in each move execution, solution gaps increase by 10% (see "Ts-I-2-Opt" row on Table 2.2). We, therefore, decided that the TS with a separate 2-Opt-sv was the best configuration to use.

The preliminary results also show that the application frequency of the 2-Opt-sv (referred to as "f" in Figures 2.4 and 2.5) widely impacts its performance. As shown in Figures 2.4 and 2.5, the 2-Opt-sv when applied separately, performs better, especially, on instances with larger planning horizons, and that the larger it gets, more intervals we need between two successive 2-Opt-sv. According to those results, we fixed a frequency of three for three-period instances and a frequency of forty for six-period ones.

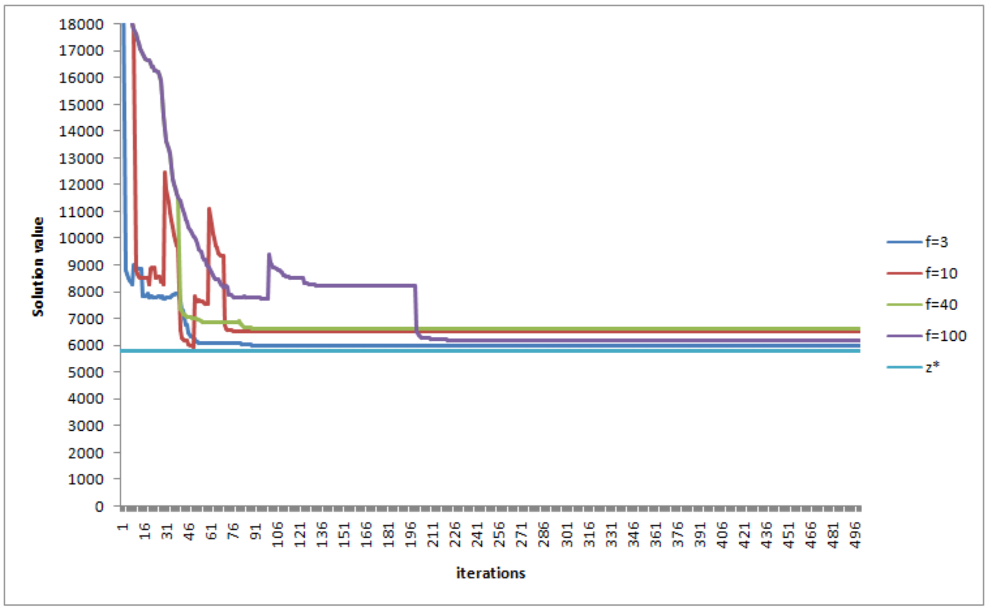

FIGURE 2.4 – Variations of 2-Opt-sv frequency on three-period instances

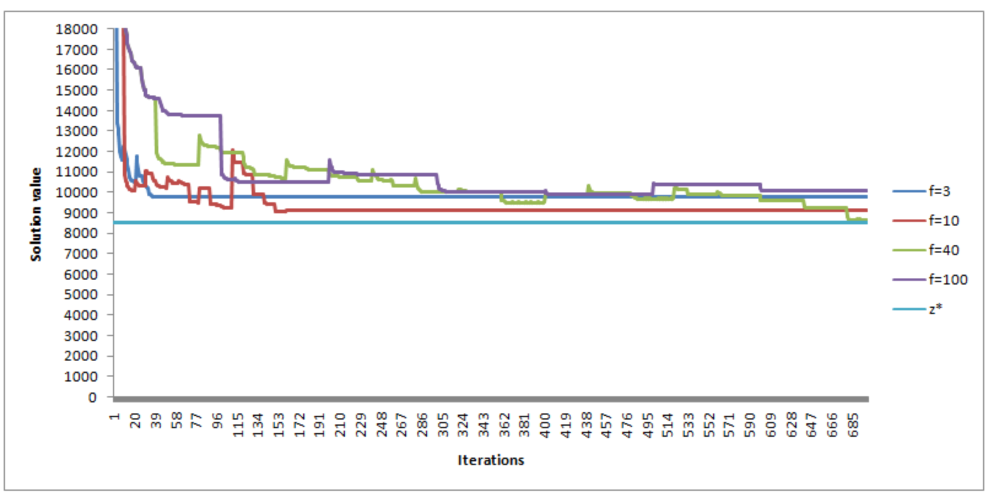

FIGURE 2.5 – Variations of 2-Opt-sv frequency on six-period instances

2.7.2 Instance generation

In this section, we present a description of the instances generated following Archetti et al. (2007). Four groups of instances were generated and named "IRPDC-a-b-c-d" with "a" for the planning horizon, "b" for the number of VMI customers, "c" for instance group, and "d" for the percentage of SM customers. Each group contains 18 instances resulting from different combinations of the following parameters:

- planning horizon length H: 3, 6 periods,
- VMI customers set size $\mathcal{V}_{vmi}$: $\{30, 50, 100\}$,
- SM customers set size $\mathcal{V}_{sm}$: $k \times \mathcal{V}_{vmi}$ with $k \in \{10\%, 25\%, 50\%\}$,
- travel cost C_{ij}: represented by the euclidean distance $\sqrt{(X_i - X_j)^2 + (Y_i - Y_j)^2}$ between points (X_i, Y_i) and (X_j, Y_j) which are generated uniformly and randomly in the interval $[0, 500]$, or clustered according to the depot position and a radius of 50,
- SM customer i delivery date $p_i \in \mathcal{T}$: an integer number generated randomly in the interval $[1,H]$,
- SM customer i ordered quantity γ_i, $\forall\ i \in \mathcal{V}_{sm}$: randomly generated in the interval $[10, 100]$,
- vehicle capacity Q: $\frac{3}{2} \times \sum_{i \in \mathcal{V}_{vmi}} r_{it}$, or $2 \times \sum_{i \in \mathcal{V}_{vmi}} r_{it}$,
- consumption rates r_{it}, i in $\mathcal{V}_{vmi}$: randomly generated in the interval $[10, 100]$,
- VMI customer i inventory holding capacity U_i, $i \in \mathcal{V}_{vmi}$: $g \times r_{it}$ where g is an integer generated randomly in $[1,H]$,
- VMI customer i initial inventory level I_{i0}: U_i-r_{it},
- supplier's initial inventory level I_{00}: $\sum_{i \in \mathcal{V}_{vmi}} U_i$, $i \in \mathcal{V}_{vmi}$,
- supplier's periodic reception r_{0t}: $\sum_{i \in \mathcal{V}_{vmi}} r_{it}$, $i \in \mathcal{V}_{vmi}$.

The specificity of the first group of instances lies in the uniform random generation of vertex coordinates. Then comes the second group by using the same data and just increasing the vehicle capacity. Next, the third group considers clustered customer positions against randomly generated ones for supplier and SM customers. Finally, the fourth group is similar to the third group with the difference of increasing the vehicle capacity. In Tables 2.3 and 2.4, we present the characteristics of each group of instances. Columns 1-8 provide information on different parameters used for each instance.

Precisely, the first column presents the group number, the second one the name of the instance, the third one the number of customers, the fourth one the number of VMI customers, the fifth one the number of SM customers, the sixth one the planning horizon, the seventh one the percentage of the incorporated SM customers, next the vehicle capacity.

Table 2.3 – Characteristics of the first and second groups of instances with uniform customers dispersion

	Instances	$\mid \mathcal{V}' \mid$	$\lvert\mathcal{V}_{vmi}\rvert$	$\lvert\mathcal{V}_{sm}\rvert$	H	% SM customers	Q
Group 1	IRPDC-3-30-1-10	33	30	3	3	10	low
	IRPDC-3-30-1-25	38	30	7	3	25	
	IRPDC-3-30-1-50	45	30	15	3	50	
	IRPDC-3-50-1-10	55	50	5	3	10	
	IRPDC-3-50-1-25	63	50	12	3	25	
	IRPDC-3-50-1-50	75	50	25	3	50	
	IRPDC-3-100-1-10	110	100	10	3	10	
	IRPDC-3-100-1-25	125	100	25	3	25	
	IRPDC-3-100-1-50	150	100	50	3	50	
	IRPDC-6-30-1-10	33	30	3	6	10	
	IRPDC-6-30-1-25	38	30	7	6	25	
	IRPDC-6-30-1-50	45	30	15	6	50	
	IRPDC-6-50-1-10	55	50	5	6	10	
	IRPDC-6-50-1-25	63	50	12	6	25	
	IRPDC-6-50-1-50	75	50	25	6	50	
	IRPDC-6-100-1-10	110	100	10	6	10	
	IRPDC-6-100-1-25	125	100	25	6	25	
	IRPDC-6-100-1-50	150	100	50	6	50	
Group 2	IRPDC-3-30-2-10	33	30	3	3	10	high
	IRPDC-3-30-2-25	38	30	7	3	25	
	IRPDC-3-30-2-50	45	30	15	3	50	
	IRPDC-3-50-2-10	55	50	5	3	10	
	IRPDC-3-50-2-25	63	50	12	3	25	
	IRPDC-3-50-2-50	75	50	25	3	50	
	IRPDC-3-100-2-10	110	100	10	3	10	
	IRPDC-3-100-2-25	125	100	25	3	25	
	IRPDC-3-100-2-50	150	100	50	3	50	
	IRPDC-6-30-2-10	33	30	3	6	10	
	IRPDC-6-30-2-25	38	30	7	6	25	
	IRPDC-6-30-2-50	45	30	15	6	50	
	IRPDC-6-50-2-10	55	50	5	6	10	
	IRPDC-6-50-2-25	63	50	12	6	25	
	IRPDC-6-50-2-50	75	50	25	6	50	
	IRPDC-6-100-2-10	110	100	10	6	10	
	IRPDC-6-100-2-25	125	100	25	6	25	
	IRPDC-6-100-2-50	150	100	50	6	50	

Table 2.4 – Characteristics of the third and fourth groups of instances with clustered customers dispersion

	Instances	$\lvert\mathcal{V}'\rvert$	$\lvert\mathcal{V}_{vmi}\rvert$	$\lvert\mathcal{V}_{sm}\rvert$	H	% SM customers	Q
Group 3	IRPDC-3-30-3-10	33	30	3	3	10	low
	IRPDC-3-30-3-25	38	30	7	3	25	
	IRPDC-3-30-3-50	45	30	15	3	50	
	IRPDC-3-50-3-10	55	50	5	3	10	
	IRPDC-3-50-3-25	63	50	12	3	25	
	IRPDC-3-50-3-50	75	50	25	3	50	
	IRPDC-3-100-3-10	110	100	10	3	10	
	IRPDC-3-100-3-25	125	100	25	3	25	
	IRPDC-3-100-3-50	150	100	50	3	50	
	IRPDC-6-30-3-10	33	30	3	6	10	
	IRPDC-6-30-3-25	38	30	7	6	25	
	IRPDC-6-30-3-50	45	30	15	6	50	
	IRPDC-6-50-3-10	55	50	5	6	10	
	IRPDC-6-50-3-25	63	50	12	6	25	
	IRPDC-6-50-3-50	75	50	25	6	50	
	IRPDC-6-100-3-10	110	100	10	6	10	
	IRPDC-6-100-3-25	125	100	25	6	25	
	IRPDC-6-100-3-50	150	100	50	6	50	
Group 4	IRPDC-3-30-4-10	33	30	3	3	10	high
	IRPDC-3-30-4-25	38	30	7	3	25	
	IRPDC-3-30-4-50	45	30	15	3	50	
	IRPDC-3-50-4-10	55	50	5	3	10	
	IRPDC-3-50-4-25	63	50	12	3	25	
	IRPDC-3-50-4-50	75	50	25	3	50	
	IRPDC-3-100-4-10	110	100	10	3	10	
	IRPDC-3-100-4-25	125	100	25	3	25	
	IRPDC-3-100-4-50	150	100	50	3	50	
	IRPDC-6-30-4-10	33	30	3	6	10	
	IRPDC-6-30-4-25	38	30	7	6	25	
	IRPDC-6-30-4-50	45	30	15	6	50	
	IRPDC-6-50-4-10	55	50	5	6	10	
	IRPDC-6-50-4-25	63	50	12	6	25	
	IRPDC-6-50-4-50	75	50	25	6	50	
	IRPDC-6-100-4-10	110	100	10	6	10	
	IRPDC-6-100-4-25	125	100	25	6	25	
	IRPDC-6-100-4-50	150	100	50	6	50	

2.7.3 Results and analysis

This section aims to present and analyze the results obtained from our computational experiments and compare the performance of the proposed dynamic policies according to operational costs and SM customers service levels. Final results are shown in Tables 2.5-2.20. They show the results of applying *Rerouting* and *Reassignment* policies on the four distinct groups of instances with different vehicle capacity or opportunity cost coefficient σ (from 1 to 25) values and changing the dispersion of VMI customer locations (from uniform to clustered).

A first category of results focuses on presenting operational costs, heuristic running time and rejection levels of SM customers' requests. Those results are summarized in Tables 2.5-2.8-2.11-2.14-2.17-2.20 where columns 2-5 present the results of adopting the *Reassignment policy* and applying the developed heuristic on each instance. In particular, column 2 presents the solution value, column 3 the running time (in seconds), column 4 the number of rejected SM customers (noted as $\mathcal{R}_{sm}$), and column 5 the percentage of SM customers rejection calculated as the fraction of the number of rejected ones by the total number of SM customers. Columns 6-9 show the results of adopting the *Rerouting policy* and applying the developed heuristic on each instance.

The second category of results concentrates on rejection reasons of SM customers' requests and their percentages. Those results are summarized in Tables 2.6-2.7-2.9-2.10-2.12-2.13-2.15-2.16-2.18-2.19-2.21-2.22. According to the planning horizon length H, column 1 enumerates the SM customers request periods, column 2 enumerates the SM customers delivery periods, column 3 mentions the total number of SM customers rejected requests due to cost reasons in all instances combined and the column 4 is related to the number of SM customers rejected requests due to vehicle capacity limitation, column 5 shows the number of accepted SM customers on each period. As mentioned before, an SM customer request is rejected due to cost reasons when the marginal transportation cost of accepting the request exceeds the opportunity cost of rejecting it. Also, an SM customer request is rejected due to vehicle capacity restriction when the quantity ordered exceeds the residual vehicle capacity.

VMI customers uniform dispersion

Table 2.5 shows that there is a significant difference between the two dynamic policies. In fact, the *Reassignment* policy generated an average of 58% of rejected dynamic requests, compared to 99.6% for the *Rerouting* policy. However, the *Reassignment* policy resulted in higher operational costs, averaging 10035.40 versus 8132.43 for the *Rerouting* policy. Moreover, adopting a *Reassignment* policy guarantees more flexibility and better integration of SM customers than the *Rerouting* one. The results also show that the performance of the *Reassignment* policy depends on the overall number of VMI customers: the higher the number of VMI customers in an instance, the lower the rejection number and percentage of SM customers. In fact, operational costs and service levels depend extensively on the locations of VMI customers on one side and the number and positions of SM customers on the other side. For instance, as shown in Table 2.5, applying the *Reassignment* policy on three-period instances generated the lowest rejection rate of 40% with 100 VMI customers and 25 SM customers to insert against 100% rejection rate with 30 VMI customers and 7 SM customers to insert. On six-period instances, the lowest rejection levels were also noted on instances of 50 and 100 VMI customers. However, operational costs depend also on the length of the planning horizon when a *Reassignment* is adopted by generating lower costs on six-period instances than three-period ones, even with an equal number of customers. For example, considering the instance "IRPDC-3-100-1-50" (150 customers and three-period planning horizon), inserting 16 SM customers generated an operational cost of 20109.26 against 16445.36 for inserting 28 SM customers concerning the instance "IRPDC-6-100-1-50" (150 customers and six-period planning horizon). As a result, the *Reassignment* policy allows inserting more SM customers with longer planning horizons by re-checking the prior plan and so the frequency of visits of VMI customers and the interval between them on each period of the planning horizon.

Adopting a *Rerouting* policy does not show good results for integrating SM customers: a 100% rejection level is recorded for most instances. These results show that assigning SM customers at the end of the route under execution depends firstly on customers locations and secondly on the residual vehicle capacity. In fact, with randomly generated customers and a reduced opportunity cost coefficient, inserting an SM customer rarely results in a marginal transportation cost that is less than the potential opportunity cost. Moreover, as we do not consider returns to depot to refill the vehicle, SM customer requests may be rejected due to lower residual vehicle capacity, particularly during the final periods when there is usually a concentration of VMI customer deliveries and a lower residual vehicle capacity at the end of routes.

TABLE 2.5 – Dynamic policies results of first group instances (σ=1, Q=Low)

	Reassignment policy				Rerouting policy			
Instances	**Solution value**	**Time (s)**	$\mathcal{R}_{sm}$	**% rejection**	**Solution value**	**Time (s)**	$\mathcal{R}_{sm}$	**% rejection**
IRPDC-3-30-1-10	3584.24	3.15	2	67%	3519.72	4.48	3	100%
IRPDC-3-30-1-25	3643.70	2.51	7	100%	4146.88	4.83	7	100%
IRPDC-3-30-1-50	4374.13	9.33	13	87%	4319.53	6.58	14	93%
IRPDC-3-50-1-10	5953.00	9.64	3	60%	5637.97	9.35	5	100%
IRPDC-3-50-1-25	5169.54	17.66	8	67%	5167.70	15.58	12	100%
IRPDC-3-50-1-50	6263.89	23.84	18	72%	5890.13	12.06	25	100%
IRPDC-3-100-1-10	15094.67	95.41	8	80%	11253.46	92.49	10	100%
IRPDC-3-100-1-25	19588.68	356.27	10	40%	11533.60	117.91	25	100%
IRPDC-3-100-1-50	20109.26	487.47	34	68%	10505.66	96.91	50	100%
IRPDC-6-30-1-10	6775.70	5.29	2	67%	6720.65	6.37	3	100%
IRPDC-6-30-1-25	7069.33	6.58	7	100%	6839.11	6.33	7	100%
IRPDC-6-30-1-50	6278.80	7.50	11	73%	6300.49	5.10	15	100%
IRPDC-6-50-1-10	9733.27	20.39	2	40%	8424.79	28.13	5	100%
IRPDC-6-50-1-25	9477.98	31.17	5	42%	8760.01	20.94	12	100%
IRPDC-6-50-1-50	10149.53	75.58	11	44%	8694.72	21.22	25	100%
IRPDC-6-100-1-10	16171.25	148.75	0	0%	13308.05	123.46	10	100%
IRPDC-6-100-1-25	14754.92	314.22	0	0%	12444.60	105.32	25	100%
IRPDC-6-100-1-50	16445.36	773.73	22	44%	12916.61	138.23	50	100%
Average	10035.40	132.69	9.06	58%	8132.43	45.29	16.83	99.6%

Tables 2.6 and 2.7 provide more details on SM customer assignments respectively according to the *Rerouting* or *Reassignment* policies. Table 2.6 shows that by applying the *Rerouting* policy, more than 70% of SM customers are usually rejected due to cost reasons independently

of the planning horizon. In fact with a default penalty coefficient value of 1, adding SM customers at the end of a current route generates larger transportation cost than the potential opportunity cost. The other SM customer requests are prone to rejection due to vehicle capacity limitation, especially on the last periods of the planning horizon. Table 2.7 shows that the rejection percentages due to cost reasons dropped to 35% by applying the *Reassignment* policy. Nevertheless, its performance depends widely on the planning horizon: the longer it is, the higher the percentage of SM customers added and the lower the percentage of rejection due to vehicle capacity restriction. In fact, on a planning horizon of three periods, 31% rejections are generated due to vehicle capacity limitation, against 5% on six-period planning horizon. Also, 32% of requests are accepted on three-period planning horizon against 61% on six-period one. However, the rejection percentages due to cost reasons are not impacted by the planning horizon length, and it remained around 35% for both situations.

TABLE 2.6 – SM customers status by applying *Rerouting* policy on group 1 instances (σ=1, Q=Low)

		H=3		
Request period	Delivery period	Rejected/Costs	Rejected/Vehicle capacity	Accepted
1	1	42		1
2	2	52		
3	3	36	21	
%		86%	14%	1%
		H=6		
Request period	Delivery period	Rejected/Costs	Rejected/Vehicle capacity	Accepted
1	1	21		
2	2	23		
3	3	25		
4	4	7	24	
5	5	25	6	
6	6	11	10	
%		74%	26%	0%

TABLE 2.7 – SM customers status by applying *Reassignment* policy on group 1 instances (σ=1, Q=Low)

		H=3		
Request period	Delivery period	Rejected/Costs	Rejected/Vehicle capacity	Accepted
1	2	5	1	37
2	3	3	46	3
3	4	48		9
%		37%	31%	32%
		H=6		
Request period	Delivery period	Rejected/Costs	Rejected/Vehicle capacity	Accepted
1	2			21
2	3	6		17
3	4	9		16
4	5	21		10
5	6	8	7	16
6	7	9		12
%		35%	5%	61%

Increasing opportunity cost (σ)

With a higher opportunity cost, the results on Table 2.8 outline an overall decrease on SM customers request rejection for both policies. Increasing σ from the default value of 1 to a greater value of 25, decreased rejection rates from on average 99% to 36% for the *Rerouting* policy and from 58% to 34% for the *Reassignment* policy. This stipulates the fact that with a higher opportunity cost, it becomes more interesting to accept SM customers requests and reduce the possibility of rejection of dynamic requests, except those susceptible to generate higher transportation costs due to their locations. It is also notable that when the percentage of SM customer requests becomes equal to or higher than 25% of VMI customers, the *Rerouting* policy tends to generate lower total operational costs than the *Reassignment* one (see the highlighted cells in Table 2.8). Thus, the more potential SM customer requests, the more suitable it is to integrate them in the same-day delivery. Instead, incorporating them on the following day by updating the delivery plan will incur higher operational costs at the end of the planning horizon.

Tables 2.9 and 2.10 show that increasing the opportunity cost generates lower rejections due to cost reasons. Instead, it generates more rejections due to vehicle capacity, especially for the requests on the last periods of the planning horizon. In other words, the SM customers' requests accepted due to the opportunity cost increase, bring vehicle capacity imbalances later at the end of the planning horizon. The results also show an important improvement in the performance of the *rerouting* policy by increasing the accepted requests percentages from around 0% to 56% and 66% respectively on three-period and six-period planning horizon against a slight increase of 10% on the accepted requests percentage on three-period planning horizon using the *Reassignment* policy.

Table 2.8 – Dynamic policies results for increased σ to 25

	Reassignment policy				Rerouting policy			
Instances	**Solution value**	**Time (s)**	$\mathcal{R}_{sm}$	**% rejection**	**Solution value**	**Time (s)**	$\mathcal{R}_{sm}$	**% rejection**
IRPDC-3-30-1-10	4542.12	2.71	0	0%	3716.15	3.96	1	33%
IRPDC-3-30-1-25	5048.78	2,53	4	57%	3643.70	5.30	3	43%
IRPDC-3-30-1-50	4611.55	9,13	8	53%	4319.53	6.22	5	33%
IRPDC-3-50-1-10	6564.48	8.19	2	40%	5711.69	10.22	2	40%
IRPDC-3-50-1-25	6583.91	13,57	7	58%	4864.95	15.54	4	33%
IRPDC-3-50-1-50	7074.17	31.12	12	48%	5428.94	12.89	15	60%
IRPDC-3-100-1-10	14373.23	84.74	3	30%	13238.26	84.47	5	50%
IRPDC-3-100-1-25	21190.65	367.19	13	52%	11541.82	107.36	7	28%
IRPDC-3-100-1-50	22698.79	460.41	28	56%	12646.34	95.85	25	50%
IRPDC-6-30-1-10	7272.42	5,20	0	0%	6720.65	6.35	1	33%
IRPDC-6-30-1-25	7651.43	7.35	3	43%	6839.11	6.12	2	29%
IRPDC-6-30-1-50	8320.63	7.36	9	60%	6262.13	4.71	6	40%
IRPDC-6-50-1-10	10840.86	20.53	1	20%	8405.22	28.00	2	40%
IRPDC-6-50-1-25	10720.72	31.04	1	8%	8973.17	18.57	3	25%
IRPDC-6-50-1-50	10727.16	70.97	6	24%	8694.72	21.52	8	32%
IRPDC-6-100-1-10	14792.88	152.96	0	0%	15425.05	129.83	2	20%
IRPDC-6-100-1-25	14116.25	304.64	0	0%	12447.12	123.25	5	20%
IRPDC-6-100-1-50	16467.97	773.32	29	58%	12648.89	132.40	23	46%
Average	10755.44	130.72	7.00	34%	8418.19	45.14	6.61	36%

Table 2.9 – SM customers status with *Rerouting policy* after increasing σ to 25

H=3				
Request period	Delivery period	Rejected/Costs	Rejected/Vehicle capacity	Accepted
1	1	8		35
2	2	9	4	39
3	3	7	39	11
%		16%	28%	56%
H=6				
Request period	Delivery period	Rejected/Costs	Rejected/Vehicle capacity	Accepted
1	1	7		14
2	2	2		21
3	3	2		23
4	4	2	25	4
5	5	3	2	26
6	6		9	12
%		11%	24%	66%

Table 2.10 – SM customers status with *Reassignment* policy after increasing σ to 25

H=3				
Request period	Delivery period	Rejected/Costs	Rejected/Vehicle capacity	Accepted
1	2			43
2	3	1	47	4
3	4	29		28
%		20%	31%	49%
H=6				
Request period	Delivery period	Rejected/Costs	Rejected/Vehicle capacity	Accepted
1	2			21
2	3	3		20
3	4	6		19
4	5	14	3	14
5	6	3	14	14
6	7	6		15
%		21%	11%	68%

Increasing Vehicle capacity

Increasing the vehicle capacity while maintaining the opportunity cost low, as shown in Table 2.11 leads to a slight decrease on the average of rejections from 58% to 51% by applying the *Reassignment* policy against no significant improvement by applying the *Rerouting* policy. Results show that rejection levels are lower on six-period instances than three-period ones. However, operational costs tend to be lower just on the largest six-period instances containing between 110 to 150 customers. This demonstrates that, unlike the variation in opportunity cost, vehicle capacity has no direct impact on operational costs. However, the appropriate combination of SM and VMI customers on routes has a greater impact on operational costs. The more VMI customers we have assigned to a route, the easier it is to insert an SM customer at a lower marginal cost by using a *Reassignment* policy, as opposed to a limited improvement for the *Rerouting* policy. In fact, according to the *Rerouting* policy the marginal cost of inserting a new SM customer request is always determined by the location of the last customer on the current route under execution.

TABLE 2.11 – Dynamic policies results for increased vehicle capacity (Q=High)

	Reassignment policy				**Rerouting policy**			
Instances	**Solution value**	**Time (s)**	$\mathcal{R}_{sm}$	**% rejection**	**Solution value**	**Time (s)**	$\mathcal{R}_{sm}$	**% rejection**
IRPDC-3-30-2-10	3871.32	1.16	3	100%	3734.83	1.70	3	100%
IRPDC-3-30-2-25	3690.48	2.22	6	86%	3845.83	3.10	7	100%
IRPDC-3-30-2-50	4598.33	6.13	7	47%	4507.83	3.96	14	93%
IRPDC-3-50-2-10	8153.44	6.54	3	60%	5968.62	3.26	5	100%
IRPDC-3-50-2-25	6668.78	15.16	7	58%	4991.60	9.14	12	100%
IRPDC-3-50-2-50	5826.39	25.10	23	92%	5624.21	2.96	25	100%
IRPDC-3-100-2-10	16781.87	40.62	4	40%	13249.53	7.38	10	100%
IRPDC-3-100-2-25	17552.42	73.54	6	24%	11158.39	40.09	25	100%
IRPDC-3-100-2-50	18181.60	191.05	42	84%	13623.84	30.37	50	100%
IRPDC-6-30-2-10	6384.36	4.79	2	67%	5582.85	7.05	3	100%
IRPDC-6-30-2-25	7246.97	8.99	0	0%	7017.20	4.31	7	100%
IRPDC-6-30-2-50	6796.57	6.91	12	80%	6474.09	4.37	15	100%
IRPDC-6-50-2-10	10060.12	12.45	0	0%	8252.70	14.26	5	100%
IRPDC-6-50-2-25	9596.29	32.06	10	83%	8822.14	20.66	12	100%
IRPDC-6-50-2-50	9786.31	80.42	11	44%	8937.81	23.40	25	100%
IRPDC-6-100-2-10	16401.52	116.44	0	0%	12685.56	102.84	10	100%
IRPDC-6-100-2-25	13824.42	276.59	2	8%	10922.59	77.35	25	100%
IRPDC-6-100-2-50	17834.79	485.63	20	40%	13631.03	81.18	50	100%
Average	10180.89	76.99	8.78	51%	8279.48	24.30	16.83	99.6%

Concerning Tables 2.12 and 2.13 , increasing vehicle capacity helped reduce rejections due to vehicle capacity limitation when the number of customers to visit increased within a period. On three-period instances, where usually there is more concentration of customers within periods, applying a *Reassignment* policy with an extended vehicle capacity reduced such rejections from 31% to 15% and 14% to 1% for the *Rerouting* policy. However, applying any of the two policies, whether on instances of three or six periods, increased rejection levels due to cost reasons even with a low opportunity cost coefficient (σ=1). The results also show that increasing vehicle capacity does not increase SM customers' request acceptance percentage using any of the two policies.

Table 2.12 – SM customers status with *Rerouting* policy after increasing vehicle capacity (Q=High)

		H=3		
Request period	Delivery period	Rejected/Costs	Rejected/Vehicle capacity	Accepted
1	1	42		1
2	2	52		
3	3	56	1	
%		99%	1%	1%
		H=6		
Request period	Delivery period	Rejected/Costs	Rejected/Vehicle capacity	Accepted
1	1	21		0
2	2	23		0
3	3	25		0
4	4	30	1	0
5	5	31		0
6	6	16	5	0
%		96%	4%	0%

Table 2.13 – SM customers status with *Reassignment* policy after increasing vehicle capacity (Q=High)

		H=3		
Request period	Delivery period	Rejected/Costs	Rejected/Vehicle capacity	Accepted
1	2	14		29
2	3	24	15	13
3	4	40	8	9
%		51%	15%	34%
		H=6		
Request period	Delivery period	Rejected/Costs	Rejected/Vehicle capacity	Accepted
1	2	6		15
2	3	10		13
3	4	10	1	14
4	5	9		22
5	6	6	3	22
6	7	12		9
%		35%	3%	63%

VMI customers clustered dispersion

Changing VMI customers' locations to clustered positions has increased the possibility of rejection and the difficulty of integrating SM customers' requests. By applying the *Reassignment* policy, Table 2.14 reveals an increase in rejection rates from an average of 58% with a random and uniform dispersion of VMI customers to 73% when clustered within a radius of 50 around the depot. However, a decrease on operational costs using both policies is noted. Operational costs dropped from an average of 10035.4 to 6631.75 using a *Reassignment* policy and from 8132.43 to 5638.45 using a *Rerouting* policy.

Results also show that for instances with a larger planning horizon and a higher number of VMI customers, rejection rates are lower. In fact, Table 2.16 provides that 32% of requests are accepted on six-period instances against 17% on three-period instances when a *Reassignment*

TABLE 2.14 – Dynamic policies results with clustered VMI customers (σ=1, Q=Low)

	Reassignment policy				Rerouting policy			
Instances	**Solution value**	**Time (s)**	$\mathcal{R}_{sm}$	**% rejection**	**Solution value**	**Time (s)**	$\mathcal{R}_{sm}$	**% rejection**
IRPDC-3-30-3-10	2993.73	3.49	3	100%	2933.65	5.35	3	100%
IRPDC-3-30-3-25	3657.32	4.38	3	43%	3446.40	5.59	7	100%
IRPDC-3-30-3-50	2979.93	9.02	13	87%	2792.88	6.74	15	100%
IRPDC-3-50-3-10	4109.18	5.01	5	100%	3623.33	15.58	5	100%
IRPDC-3-50-3-25	4198.56	14.65	11	92%	3187.91	14.03	12	100%
IRPDC-3-50-3-50	4071.70	21.50	23	92%	3410.19	10.75	25	100%
IRPDC-3-100-3-10	9684.98	71.89	3	30%	5164.26	91.60	10	100%
IRPDC-3-100-3-25	8706.03	138.01	16	64%	6005.73	76.43	25	100%
IRPDC-3-100-3-50	6209.15	412.33	49	98%	6117.35	77.92	49	98%
IRPDC-6-30-3-10	5747.67	5.09	3	100%	5317.56	6.63	3	100%
IRPDC-6-30-3-25	6357.98	6.35	4	57%	6150.61	7.22	7	100%
IRPDC-6-30-3-50	5380.07	12.56	11	73%	5229.53	7.64	15	100%
IRPDC-6-50-3-10	7148.43	12.00	3	60%	6388.31	27.14	5	100%
IRPDC-6-50-3-25	6815.51	25.79	7	58%	6156.05	21.76	12	100%
IRPDC-6-50-3-50	8376.60	54.91	20	80%	6353.43	17.22	25	100%
IRPDC-6-100-3-10	9513.10	168.73	6	60%	9409.23	127.19	10	100%
IRPDC-6-100-3-25	10626.78	306.71	12	48%	9383.78	126.86	25	100%
IRPDC-6-100-3-50	12795.04	760.30	37	74%	10421.98	109.00	50	100%
Average	6631.76	112.93	12.72	73%	5638.45	41.93	16.83	99.9%

policy is applied. On the other hand, concerning vehicle capacity, 30% of requests are rejected due to vehicle capacity limitation on three-period instances against just 8% on six-period instances.

However, a higher transportation cost remains the main reason for rejecting SM customers' requests. It reflected between 53% to 60% of rejection cases within the *Reassignment* policy with a higher level of rejection on the $H+1$ periods of the planning horizon in which usually no VMI customers deliveries are scheduled. As shown in Table 2.15, applying a *Rerouting* policy generates higher rejection levels for operational cost reasons within rates of 80% on three-period instances and 89% on six-period instances. The remaining 20% and 11% of rejections cases are incurred by vehicle capacity violation. They are usually recorded on the last periods of the planning horizon, where there is a higher number of VMI customers scheduled deliveries.

TABLE 2.15 – SM customers status by applying *Rerouting* policy on group 3 instances (σ=1, Q=Low)

		H=3		
Request period	Delivery period	Rejected/Costs	Rejected/Vehicle capacity	Accepted
1	1	39		1
2	2	55		
3	3	27	30	
%		80%	20%	1%
		H=6		
Request period	Delivery period	Rejected/Costs	Rejected/Vehicle capacity	Accepted
1	1	23		0
2	2	30		0
3	3	26		0
4	4	12	9	0
5	5	22	1	0
6	6	22	7	0
%		89%	11%	0%

TABLE 2.16 – SM customers status by applying *Reassignment* policy on group 3 instances (σ=1, Q=Low)

H=3				
Request period	Delivery period	Rejected/Costs	Rejected/Vehicle capacity	Accepted
1	2	24	5	11
2	3	8	41	6
3	4	48		9
%		53%	30%	17%
H=6				
Request period	Delivery period	Rejected/Costs	Rejected/Vehicle capacity	Accepted
1	2	7		16
2	3	20		10
3	4	19	1	6
4	5	18		3
5	6	3	11	9
6	7	24		5
%		60%	8%	32%

Increasing opportunity cost (σ)

Increasing the opportunity cost (σ=25) on the third group instances of clustered VMI customers reflected an overall decrease on rejection levels by using both policies for an average of dynamic requests rejection of 36% as depicted in Table 2.17. Comparing solution values outlines that the *Rerouting* policy generates lower operational costs when applied on small instances of 30 to 50 clustered VMI customers. However, the *Reassignment* policy provides more significant results when used on larger instances with 75 to 150 customers.

TABLE 2.17 – Dynamic policies results with clustered VMI customers and increased σ to 25

	Reassignment policy				Rerouting policy			
Instances	**Solution value**	**Time (s)**	$\mathcal{R}_{sm}$	**% rejection**	**Solution value**	**Time (s)**	$\mathcal{R}_{sm}$	**% rejection**
IRPDC-3-30-3-10	4078.03	3.45	1	33%	2917.25	5.38	1	33%
IRPDC-3-30-3-25	4281.98	4.95	3	43%	3110.69	5.35	6	86%
IRPDC-3-30-3-50	4056.42	9.34	9	60%	2787.53	7.07	5	33%
IRPDC-3-50-3-10	4524.08	5.09	2	40%	3644.70	16.40	2	40%
IRPDC-3-50-3-25	4930.51	17.04	5	42%	3140.63	14.59	3	25%
IRPDC-3-50-3-50	5032.73	24.87	20	80%	3869.22	10.83	13	52%
IRPDC-3-100-3-10	6856.06	72.24	4	40%	6630.10	89.08	3	30%
IRPDC-3-100-3-25	12511.64	143.01	7	28%	7060.37	79.72	15	60%
IRPDC-3-100-3-50	8307.58	341.77	22	44%	5801.80	77.47	24	48%
IRPDC-6-30-3-10	6427.92	5.60	1	33%	5317.56	6.54	0	0%
IRPDC-6-30-3-25	7002.95	6.88	2	29%	6150.61	7.18	3	43%
IRPDC-6-30-3-50	6867.96	11.98	9	60%	5217.97	7.83	5	33%
IRPDC-6-50-3-10	7876.49	12.67	2	40%	6406.74	25.96	1	20%
IRPDC-6-50-3-25	7210.76	25.23	4	33%	6156.05	21.97	2	17%
IRPDC-6-50-3-50	9432.20	55.82	2	8%	7449.59	16.69	5	20%
IRPDC-6-100-3-10	10780.24	198.48	2	20%	8546.63	151.70	4	40%
IRPDC-6-100-3-25	12200.08	299.72	4	16%	9179.34	123.91	10	40%
IRPDC-6-100-3-50	13677.74	878.11	3	6%	10350.92	110.50	17	34%
Average	7558.63	117.57	5.67	36%	5763.21	43.23	6.61	36%

Concerning the reasons of rejection, Tables 2.18-2.19 show that increasing the opportunity cost generates lower dynamic request rejections due to cost reasons in clustered locations context against uniform ones. Instead, it also generates more rejections due to vehicle capacity, especially for the requests on the last periods of the planning horizon.

TABLE 2.18 – SM customers status by applying *Rerouting* policy and increasing σ to 25

H=3				
Request period	Delivery period	Rejected/Costs	Rejected/Vehicle capacity	Accepted
1	1	5		35
2	2	5	10	40
3	3	3	49	5
%		9%	39%	53%
H=6				
Request period	Delivery period	Rejected/Costs	Rejected/Vehicle capacity	Accepted
1	1	2		21
2	2	6		24
3	3			26
4	4	5	12	4
5	5	3	3	17
6	6	3	13	13
%		13%	18%	69%

TABLE 2.19 – SM customers status by applying *Reassignment* policy and increasing σ to 25

H=3				
Request period	Delivery period	Rejected/Costs	Rejected/Vehicle capacity	Accepted
1	2	2	7	31
2	3		52	3
3	4	12		45
%		9%	39%	52%
H=6				
Request period	Delivery period	Rejected/Costs	Rejected/Vehicle capacity	Accepted
1	2			23
2	3	2		28
3	4	2	1	23
4	5	9		12
5	6	2	2	19
6	7	11		18
%		17%	2%	81%

Increasing vehicle capacity:

Increasing the vehicle capacity (σ=1, Q=High) on clustered customer instances generated an increase in rejection levels when applying the *Reassignment* policy. The average rejection level jumped from 51% with uniformly dispersed customers to 70% with clustered ones against no notable change on the overall rejection levels by using the *Rerouting* policy. Vehicle capacity increase also generated lower operational costs on clustered customer instances than those with uniformly dispersed customers.

With regard to Tables 2.21 and 2.22, we note that all rejections are generated due to increased cost reasons and no more due to vehicle capacity limitation.

TABLE 2.20 – Dynamic policies results with clustered VMI customers and increased vehicle capacity (σ=1, Q=High)

	Reassignment policy				Rerouting policy			
	Solution value	**Time (s)**	$\mathcal{R}_{sm}$	**% rejection**	**Solution value**	**Time (s)**	$\mathcal{R}_{sm}$	**% rejection**
IRPDC-3-30-4-10	3123.35	4.35	3	100%	3123.35	4.99	3	100%
IRPDC-3-30-4-25	3324.67	2.26	6	86%	3348.55	1.40	7	100%
IRPDC-3-30-4-50	3295.98	2.95	12	80%	3030.06	1.33	15	100%
IRPDC-3-50-4-10	4466.92	3.35	4	80%	3929.29	2.76	5	100%
IRPDC-3-50-4-25	3651.14	8.74	11	92%	3631.70	2.70	12	100%
IRPDC-3-50-4-50	4387.65	22.09	18	72%	3921.32	3.03	25	100%
IRPDC-3-100-4-10	7070.33	32.36	1	10%	5627.95	8.67	10	100%
IRPDC-3-100-4-25	7382.71	75.80	22	88%	6744.05	10.89	25	100%
IRPDC-3-100-4-50	9414.66	167.94	29	58%	7103.00	9.27	50	100%
IRPDC-6-30-4-10	5845.49	5.45	1	33%	4986.22	4.57	3	100%
IRPDC-6-30-4-25	5786.45	5.32	6	86%	5573.85	6.90	7	100%
IRPDC-6-30-4-50	5289.03	5.80	9	60%	5365.17	4.32	15	100%
IRPDC-6-50-4-10	7789.18	9.78	3	60%	6460.37	20.94	5	100%
IRPDC-6-50-4-25	7443.73	25.27	10	83%	6134.11	17.04	12	100%
IRPDC-6-50-4-50	7909.26	39.72	18	72%	6339.57	10.00	25	100%
IRPDC-6-100-4-10	10228.96	143.60	10	100%	9495.34	108.98	10	100%
IRPDC-6-100-4-25	11471.75	204.67	8	32%	9999.63	100.45	25	100%
IRPDC-6-100-4-50	11592.81	348.11	33	66%	11203.69	30.64	50	100%
Average	6637.45	61.53	11.33	70%	5889.85	19.38	16.89	100%

TABLE 2.21 – SM customers status with *Rerouting* policy after increasing vehicle capacity (σ=1, Q=High)

H=3				
Request period	Delivery period	Rejected/Costs	Rejected/Vehicle capacity	Accepted
1	1	40	0	0
2	2	55	0	0
3	3	57	0	0
%		100%	0%	0%
H=6				
Request period	Delivery period	Rejected/Costs	Rejected/Vehicle capacity	Accepted
1	1	23	0	0
2	2	30	0	0
3	3	26	0	0
4	4	21	0	0
5	5	23	0	0
6	6	29	0	0
%		100%	0%	0%

TABLE 2.22 – SM customers status with *Reassignment* policy after increasing vehicle capacity (σ=1, Q=High)

H=3				
Request period	Delivery period	Rejected/Costs	Rejected/Vehicle capacity	Accepted
1	2	19	0	21
2	3	37	0	18
3	4	50	0	7
%		70%	0%	30%
H=6				
Request period	Delivery period	Rejected/Costs	Rejected/Vehicle capacity	Accepted
1	2	13	0	10
2	3	23	0	7
3	4	20	0	6
4	5	20	0	1
5	6	4	0	19
6	7	18	0	11
%		64%	0%	36%

Table 2.23 summaries all of previously discussed results. The values of the various parameters used in the sensitivity analysis are listed in the columns, along with the group of instances they were applied to. Rows are divided into three families. The first family is dedicated to the parameters we investigated, such as VMI customers dispersion, Vehicle capacity, opportunity cost coefficient σ, and planning horizon length H. The second set of rows is for performance measures linked to the *Rerouting* policy, such as averages of operational costs (solution value), running times, numbers of rejected SM customers (noted as $\mathcal{R}_{sm}$), and rejection rates for SM customers. Furthermore, the rejection rates due to vehicle capacity limitations and costs, as well as the rate of acceptance, are considered. The final family of rows is dedicated for the *Reassignment* policy performance measures.

TABLE 2.23 – Results summary

		Group 1				Group 2		Group 3				Group 4	
Parameters variation	VMI customers dispersion	Uniform						Clustered					
	Vehicle capacity	Low	Low	Low	Low	High	High	Low	Low	Low	Low	High	High
	σ	1	25	1	25	1	1	1	25	1	25	1	1
	H	3	3	6	6	3	6	3	3	6	6	3	6
***Rerouting* policy**	Solution value	8132.43	8418.19	8132.43	8418.19	8279.48	8279.48	5638.45	5763.21	5638.45	5763.21	5889.85	5889.85
	Time (s)	45.29	45.14	45.29	45.14	24.30	24.30	41.93	43.23	41.93	43.23	19.38	19.38
	$\mathcal{R}_{sm}$	16.83	6.61	16.83	6.61	16.83	16.83	16.83	6.61	16.83	6.61	16.89	16.89
	Avg. % rejection	100%	36%	100%	36%	100%	100%	100%	36%	100%	36%	100%	100%
	% Rejection/Costs	86%	16%	74%	11%	99%	96%	80%	9%	89%	13%	100%	100%
	% Rejection/Vehicle capacity	14%	28%	26%	24%	1%	4%	20%	39%	11%	18%	0%	0%
	% Acceptance	1%	56%	0%	66%	1%	0%	1%	53%	0%	69%	0%	0%
***Reassignment* policy**	Solution value	10035.40	10755.44	10035.40	10755.44	10180.89	10180.89	6631.76	7558.63	6631.76	7558.63	6637.45	6637.45
	Time (s)	132.69	130.72	132.69	130.72	76.99	76.99	112.93	117.57	112.93	117.57	61.53	61.53
	$\mathcal{R}_{sm}$	9.06	7.00	9.06	7.00	8.78	8.78	12.72	5.67	12.72	5.67	11.33	11.33
	Avg. % rejection	58%	34%	58%	34%	51%	51%	73%	36%	73%	36%	70%	70%
	% Rejection/Costs	37%	20%	35%	21%	51%	35%	53%	9%	60%	17%	70%	64%
	% Rejection/Vehicle capacity	31%	31%	5%	11%	15%	3%	30%	39%	8%	2%	0%	0%
	% Acceptance	32%	49%	61%	68%	34%	63%	17%	52%	32%	81%	30%	36%

2.8 Conclusions

This chapter investigates a special case of the real-world oil distribution problem. We proposed a new variant that takes into account the dynamic arrival of customer requests by using an inventory routing problem approach (DIRPCR). Focusing on the dynamic specificity of the problem, after framing the definition and mathematical modeling of the DIRPCR, we presented a tabu search-based heuristic as well as two dynamic policies that can be integrated into the heuristic execution process. The results show that the proposed heuristic can handle the short execution time required to outperform the exact approach limitations in dealing with this dynamic problem. In fact, compared to the B&C, our heuristic took lower execution time when applied on instances with different customer set sizes and planning horizon lengths. Also, the proposed heuristic, showed a certain flexibility to be used as a tool to simulate scenarios by applying the *Rerouting* and *Reassignment* dynamic policies to four groups of generated instances distinguished mainly by customers' dispersion and vehicle capacity criteria.

Experimental findings

The generated results provided detailed insights into the interaction between the applied dynamic policies' performance with different configurations of VMI customer dispersion as well as changes in vehicle capacity and opportunity cost parameters. Starting with uniformly distributed customers, the *Reassignment* policy outperformed the *Rerouting* policy in almost all situations. Moreover, the results revealed that the performance of the *Reassignment* policy is affected by the total number of VMI customers and the length of the planning horizon: the larger these factors, the higher the service level. On longer planning horizons, the succession of reassignment cycles allows reviewing the a-priori plan every time a new request is revealed and, as a result, improving the insertion possibilities of SM customers in appropriate positions on the reviewed routes. However, the higher the proportion of SM customers in the total number of customers, the more appropriate it is to integrate them in same-day delivery. Incorporating them the next day by updating the delivery plan, on the other hand, will result in a higher cumulative operational cost at the end of the planning horizon. In fact, as we near the end of the planning horizon, there are fewer opportunities to postpone or advance deliveries to VMI customers, and it becomes more costly to add SM customers. However, the *Rerouting* policy is determined by the last customer location on the current route as well as the residual vehicle capacity. As a result, it usually generates a higher transportation cost than the potential opportunity cost or necessitates extra vehicle capacity, particularly during the last delivery periods when there is a higher concentration of VMI customer deliveries. In this same context, but with a higher opportunity cost, it is critical to implement more selective SM customer criteria or make available dynamic transportation capacity to meet the need for increased transportation capacity at the end of the planning horizon. Instead, SM customers' requests accepted as a result of the opportunity cost increase, result in a vehicle capacity imbalance at the end of the planning horizon.

A clustered VMI customer location configuration reduces operation costs while also lowering SM customer service levels. In particular, accepting SM customer requests, tends to generate higher operation costs due to inadequate uniformly generated SM customer positions compared to clustered VMI customer locations.

In the same context, increasing vehicle capacity reveals that rejection levels are lower on six-period instances than on three-period ones. However, operational costs are typically lower only during the largest six-period instances, which have between 110 and 150 customers. Additionally, increasing vehicle capacity assists in reducing rejections due to vehicle capacity limitation when the number of customers to visit increases within a period. For example, on three-period instances, where there is usually more customer concentration within periods, applying a *Reassignment* policy with an extended vehicle capacity reduces rejections for lack of vehicle capacity, but without any consideration of the marginal transportation cost of accepting SM customers, tends to generate higher operational costs. A higher opportunity cost tends to improve extensively service level and enhance accepting SM customers requests, even if it generates a higher transportation cost, which remains lower than the potential opportunity cost. When comparing solution values, the *Rerouting* policy reduces operational costs when applied to small instances of 30 to 50 clustered VMI customers. However, when used on larger instances of 75 to 150 customers, the *Reassignment* policy produces more significant results. Furthermore, in the context of a high opportunity cost environment, it is demonstrated that it is critical to obtain increased transportation capacity during the final periods of the planning horizon to adapt to an increase in accepted SM customer requests due to the higher opportunity cost.

Managerial recommendations

Based on the findings, we propose the following managerial recommendations:

- **The business environment:** The opportunity cost is influenced by the company's position and the value of the product sold on the market. As a result, it is critical to conduct studies on the company's positioning in relation to competitors offering the same product or another alternative, such as electricity, as well as studies about the fluctuation of sales prices. The availability of this information helps the implementation of appropriate policies for accepting or declining dynamic requests. The geographic dispersion of VMI customers has a direct impact on the operating costs and service levels of dynamic requests. First, the activity territory should be geographically zoned based on the location of VMI customers. Second, a predictive analysis of dynamic requests should be performed to be able to adapt resources in real-time and apply other reactive dynamic policies, such as the integration of returns to the depot to anticipate the arrival of dynamic requests or the integration of waiting times rather than automatically following the a-priori plan.

- **Resources availability:** Throughout our analyses we have noticed that the increase of the transport capacity has limited effects on the quality of results. For instance, it was worthy only in specific situations of planning on a very short term of three periods, which tend to generate a significant concentration of deliveries over time. The second situation involves the accumulation of large number of deliveries in the last planning periods. In the face of this fluctuation in transportation demand, it is first necessary to determine the minimum number of vehicles required to manage the company's static activity, which is the replenishment of VMI customers. Second, it is important to establish a management system for the entire subcontracting activity to ensure flexibility in transport capacity, whether demand is increasing or decreasing, which is heavily influenced by weather conditions.

Further research can be conducted, by investigating parallel computing to get results with more competitive execution time on larger and more complicated scenarios, as well as testing other powerful heuristics such as the adaptive large neighborhood search.

Conclusion générale

Dans ce mémoire, le problème de distribution de l'huile à chauffage a été étudié. Nous avons considéré la particularité de la présence de deux types de clients : des clients VMI dont la gestion du réapprovisionnement de leurs stocks est déléguée au fournisseur, et d'autres clients SM qui gèrent eux-mêmes leurs consommations et expriment leurs besoins à travers des appels dynamiques urgents qui nécessitent une livraison dans le jour même ou le jour suivant. En adoptant une approche de résolution qui s'inspire du cadre classique du problème de stockage-routage (IRP), nous avons défini une nouvelle variante DIRPCR qui traite les livraisons dynamiques sur appel.
Pour étudier ce problème, nous avons commencé par une version statique et déterministe qui suppose que les quantités demandées et les dates de livraison des clients SM sont connues à l'avance. En se basant sur cette hypothèse, nous avons proposé une formulation mathématique de notre problème et nous avons pu par la suite le résoudre avec le solveur CPLEX tout en ayant recours à des versions modifiées des instances d'Archetti et al. (2007) qui ont été appliqué auparavant en littérature sur les IRP.
Ensuite, nous avons entamé la version dynamique de notre problème. Nous avons proposé en premier lieu une heuristique basée sur la recherche tabou. Cette heuristique permet de gérer les décisions d'affectation et routage des clients VMI tout en générant un plan de livraison *a-priori* qui s'étend sur tout l'horizon de planification. En second lieu, nous avons conçu deux politiques dynamiques qui permettent d'intégrer les demandes de livraison sur appel. En effet, en adoptant une approche de ré-optimisation périodique, et en choisissant l'une de nos politiques dynamiques, à chaque période, les demandes des clients dynamiques correspondants sont révélées et des décisions d'acceptation ou de rejet de ces demandes urgentes sont conclues. Cette opération est répétée jusqu'au traitement de toutes les demandes dynamiques sur toutes les périodes de l'horizon de planification.
Finalement, nous avons généré 72 instances qui nous ont permis de mener une analyse extensive sur différents facteurs qui peuvent influencer le coût d'opération et le taux de service des clients dynamiques (SM), à savoir la dispersion des clients VMI, la capacité de transport, et le coût d'opportunité. Certaines recommandations managériales sont énumérées pour orienter les gestionnaires dans leurs décisions de mise en place des systèmes dynamiques de distribution.

Contributions

Dans ce travail, nous avons pu mettre en œuvre le cas où deux types de clients sont présents dans le contexte dynamique de l'IRP et dans le cadre de la distribution su produits énergétiques. En effet, coordonner entre plusieurs systèmes de gestion de besoins de clients est un défi auquel font face les preneurs de décision dans tous les domaines. Quoique les systèmes VMI soient largement adoptés dans les grandes compagnies, les systèmes traditionnels de service à la commande sont toujours présents.
Notre travail est considéré ainsi parmi les premiers qui traitent cette particularité, au moins dans le contexte de distribution de l'huile à chauffage, qui pourra se généraliser facilement sur d'autres domaines et situations réelles.
Nous avons aussi tenté d'adopter une approche de résolution dynamique qui rime avec les besoins réels de la planification des tournées de l'huile à chauffage. En effet, le contexte dynamique nécessite une certaine capacité de réaction rapide face aux changements, et des outils qui permettent de tester des scénarios avant de décider. L'application de différentes politiques de contrôle dynamiques sur notre heuristique et les temps d'exécution rapides ont montré que notre algorithme pourrait être déployé dans une application de gestion de tournées dynamiques et pourrait aussi servir comme un outil de simulation et d'aide à la décision aux planificateurs.
A travers nos analyses, nous avons pu proposer des directives managériales qui peuvent guider toute intention de mise en place de système dynamique de distribution.
Finalement, nous avons proposé une taxonomie qui précise les caractéristiques de base des problèmes de tournées de véhicules dynamiques, ainsi qu'une classification des méthodes de résolution développées en littérature suivant les critères de l'approche de résolution et la qualité de l'information. Ces deux éléments présentent un guide qui facilitera le positionnement des futures recherches sur la thématique de tournées de véhicules dynamiques.

Orientations futures

A travers le travail mené au cours de ce mémoire, nous proposons deux grandes lignes de recherches futures:

(i) **Des recherches en lien avec les méthodes de résolution :** Dans ce travail, nous nous sommes basés sur une ré-optimisation périodique pour intégrer les demandes dynamiques et nous avons supposé que chaque client dynamique accepté pour une livraison dans le même jour d'appel sera inséré à la fin de la route en cours d'exécution. Cette technique utile dans les cas d'absence des données actualisées sur l'état de système (position des véhicules, clients visités et non visités, etc.), limite cependant la performance de la politique de *Reroutage* ou autrement dit les possibilités de livraison dans la même journée. En se servant des progrès technologiques, et le développement des systèmes de géolocalisation, ceci rend facile l'accès aux données nécessaires en temps réel, et permet l'adoption d'une approche plus réactive de ré-optimisation continue avec traitement massif parallèle.

En plus, dans ce travail nous avons configuré deux politiques de contrôle dont une qui vise l'intégration des clients dynamiques au jour même d'appel, et l'autre est liée aux affectations au jour suivant. Sous la condition d'avoir accès aux données actualisées en temps réel, d'autres politiques peuvent être configurées à savoir les politiques de déviation et d'attente et par la suite une analyse comparative plus approfondie peut être menée.

(ii) **Des recherches en lien avec les extensions du problème étudié:** Parmi les extensions prioritaires du problème étudié est l'exploitation de son volet stochastique. En effet, pour bien gérer les problèmes dynamiques, il faut tirer profit des informations stochastiques pour améliorer l'anticipation des changements et par la suite le temps de réaction. Par exemple, avec le développement des domaines des données massives et de l'intelligence artificielle, prévoir la demande des clients dynamiques et la distribution de leurs appels potentiels est devenu à portée de main.

Ensuite, dans notre étude nous avons considéré que le camion part du dépôt avec une occupation maximale. Cependant, quand cette capacité est épuisée, le reste des demandes dynamiques est rejeté. Nous pourrons ainsi étudier une nouvelle configuration qui suppose par exemple la présence des stations intermédiaires ou des retours au dépôt pour rechargement.

Aussi, la considération des contraintes de la logistique urbaine pourrait présenter des extensions intéressantes. Dans notre travail, nos coûts de transport se sont basés sur des distances euclidiennes, alors que l'adoption des données réelles sur la configuration réelle des routes, des détours, ainsi que les niveaux de congestion permetent de rapprocher beaucoup plus les résultats de la réalité.

Finalement, dans ce travail nous nous sommes focalisé sur l'intégration logistique des activités de transport et gestion des stocks tout en supposant un réapprovisionnement périodique et déterministe du fournisseur. Étendre cette intégration pour couvrir les approvisionnents du fournisseur se voit nécessaire étant donné qu'en réalité le maintien de son stock subit les effets du changement des conditions météorologiques et les blocages récurrents des routes d'accès aux terminaux pendant l'hiver.

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