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POLYTECHNIQUE MONTRÉAL

affiliée à l'Université de Montréal

Rolling-horizon Optimization of Operations for Corridor-based M1M Transportation Systems

MARZIEH HAMZEHEI

Département de mathématiques et de génie industriel

Mémoire présenté en vue de l'obtention du diplôme de *Maîtrise ès sciences appliquées*

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Ce mémoire intitulé :

Rolling-horizon Optimization of Operations for Corridor-based M1M Transportation Systems

présenté par **Marzieh HAMZEHEI**

en vue de l'obtention du diplôme de *Maîtrise ès sciences appliquées*

a été dûment accepté par le jury d'examen constitué de :

Michel GAMACHE, président

Michel GENDREAU, membre et directeur de recherche

Teodor Gabriel CRAINIC, membre et codirecteur de recherche

Walter REI, membre et codirecteur de recherche

François SOUMIS, membre

DEDICATION

To my husband, who is the light of my life.

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I would like to express my deepest appreciation to Professor Michel Gendreau as my supervisor for his great guidance, support, patience, and believing in me.

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RÉSUMÉ

Cette étude se concentre sur la planification opérationnelle d'un système de transport basé sur la consolidation dans le contexte d'un système *Many-to-One-to-Many* (*M1M*). Nous travaillons sur le cas particulier d'un système M1M dans lequel le réseau comporte un seul segment. Dans ce système, les demandes des différents expéditeurs doivent être consolidées pour être transportées par les offres sélectionnées des transporteurs pour minimiser le coût total de toutes les parties prenantes impliquées. Pour ce faire, des modèles de planification opérationnelle ont été conçus afin de prendre les décisions optimales de sélection des offres et d'affectation des demandes aux offres.

Dans cette étude, nous considérons deux stratégies pour le processus de prise de décision. La première stratégie est myope et les décisions sont prises exclusivement sur la base des informations connues et disponibles aujourd'hui sans tenir compte de l'avenir, tandis que la seconde est prospective et prend en compte les informations connues et futures. L'objectif est de montrer l'intérêt d'utiliser le modèle qui utilise les informations futures (modèle "look-ahead") par rapport au modèle "myope" dans ce contexte.

Comme nous ne pouvons pas mettre en œuvre les modèles mathématiques et observer le système réel, nous créons un environnement artificiel par le biais d'une simulation informatique. Par conséquent, nous sommes en mesure d'observer comment le système fonctionne en définitive, les politiques étant les règles qui définissent dans quelle mesure les décideurs sont autorisés à modifier leurs décisions antérieures en fonction des nouvelles informations.

Tel qu'indiqué auparavant, nous considérons deux stratégies pour la prise de décision. La première consiste à tirer parti de l'approche à horizon mobile proposée, en simulant les opérations jour après jour à l'aide des modèles d'optimisation pour prendre des décisions au fur et à mesure que le temps passe. La seconde stratégie s'appuie sur la résolution d'un modèle multi-période qui exploite des prévisions sur les demandes et offres de service sur un horizon donné. Les résultats obtenus par les expériences de calcul montrent que la résolution du modèle multi-période serait plus bénéfique et pourrait augmenter la rentabilité de l'ensemble du système grâce à la consolidation et à l'utilisation plus efficace des offres de capacité des transporteurs.

ABSTRACT

This study focuses on the operational planning of a consolidation-based transportation system that happens in the context of the *Many-to-One-to-Many* (*M1M*) system. We work on the special case where the M1M system consists of a single-segment network. In this system, the requests from different shippers must be consolidated into the selected offers of the carriers to minimize the total cost of all involved stakeholders. To do so, operational planning models are designed to make the optimal decisions when selecting the offers and request-to-offer assignments.

In this study, we consider two strategies for the decision-making process. The first strategy is myopic: decisions are made based exclusively on the known information available now without considering the future. The second strategy is a “look-ahead” one, which takes into account both known and future information. The aim is to show the value of using the look-ahead model that uses future information compared to myopic model for this context.

Since we cannot implement the mathematical models and observe the real system, we create an artificial environment, which is done through a computer simulation. Therefore, we are able to observe how the system eventually works with a policy as the rules that defines how much the decision makers are allowed to change their previous decisions given the new information.

As indicated earlier, we are considering two strategies for decision-making. Taking advantage of the proposed rolling-horizon approach, we simulate the operations day after day using the optimization models to make decisions as time advances. The results obtained by carrying out the computational experiments show that solving the multi-period model would be more beneficial compare to the myopic model and it can increase the profitability of the whole system because it achieves a more effective consolidation and more efficient utilization of the carrier capacity offers.

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LIST OF SYMBOLS AND ABBREVIATIONS

IDSP	Intelligent decision support platform
GDP	Gross Domestic Product
M1M	Many-to-One-to-Many
TL	Transportation and logistics
3PL	Third-Party logistics
4PL	Fourth-Party logistics
KPI	Key Performance Indicator

CHAPTER 1 INTRODUCTION

Passengers and freight are able to get to the point where they need to go with the help of transportation and logistics systems (TL). In this way, TL systems play a pivotal role in society's achievements and development. According to Transport Canada's annual report, this sector, as a major economic force, made up 4.5 % ($89 billion) of the Canadian Gross Domestic Product (GDP) in 2019 [1]. However, TL systems may have disturbing impacts on human life in terms of congestion, pollution, and safety. As an example, a total of 21% of Canadian greenhouse gas emissions came from the road transportation sector in 2019 [1]. Thus, social and economic benefits can be improved by effectively managing TL systems.

Freight transportation is one of the most important industries, and its performance is totally dependent upon how the stakeholders manage the movement of goods to ensure a successful operation. For example, without coordination, once shippers are just willing to pay lower delivery costs and carriers are just focusing on earning additional revenues without considering other actors, the results would be poor capacity utilization and empty trips, high transportation costs, high carbon emissions, and delivery delays. In this industry, which continues to evolve and become increasingly competitive, proposing the use of platforms in which shippers and carriers are able to meet their partners and negotiate [2] can address the above-mentioned issues.

An integrated multi-stakeholder freight transport system, called a Many-to-One-to-Many (M1M) was introduced by [3] to reach all the stakeholder's goals simultaneously. In fact, an M1M is a generic word that refers to many transportation systems relevant for a wide gamut of applications such as global, air, maritime, inland, and urban transportation. This system is composed of three essential entities: many shippers, many carriers, and an *intelligent decision support platform* (IDSP) [3]. On the one side of this system, shippers are searching for offers to deliver product loads to the customer location within preferred time windows. On the other hand, carriers are looking for profitable loads. Then, the IDSP, as an intermediary, plans and optimizes the operations in order to meet the needs of all participants in a profitable way. It makes the decisions related to selecting the service offers and shipper requests, request-to-offer assignments, and shipment itineraries [3]. Note that M1M is a decision-making system, in which the IDSP, as a decision support tool, makes the decisions and communicates about the M1M system planning [2]. This system creates a fourwin situation in which carriers obtain more revenue, the delivery cost of shippers decreases, the IDSP makes profits on each transaction, and a smaller environmental footprint is beneficial to society[3].

To manage the activities taking place among all involved stakeholders in this system, strategic, tactical, and operational planning are required [2]. In this research, we are performing a study to better understand operational planning using optimization models. The purpose is to consider the supply and demand sides of this system and match them. For the demand side, we aim to deliver all the requests. For the supply side, we select some regular offers or the spot market to fit the requests with them and to utilize their capacity in an efficient manner [2].

In this study, we analyze in an empirical fashion two possible strategies for making decisions at the operational planning level. The first strategy is a myopic approach in which decisions are made based exclusively on the known information available now without taking into account what might happen later. In the second strategy, decisions made now may have an impact on the future periods, and what will happen in the future may also affect the decisions that are made now [4, 5]. In order to reflect the interactions between known decisions and decisions to be made in the future, we use a multi-period mathematical model proposed by [4] and integrate past, new, and predicted information related to requests and offers into decision processes.

To assess the two approaches within the dynamic informational environment of considered system, we develop a simulation that reproduces how the system could be working eventually. We are simulating the operations day by day, where the sequential operational decisions are made via the use of a rolling-horizon framework. The rolling-horizon framework enables the current, predicted and past contextual information to be iteratively updated.

In the rolling-horizon framework, the linkage of the current period's decisions to the next period's decisions is achievable by defining some policies. In this thesis, we are using a specific policy that only fixes the decisions that are executed. In this policy, we assume that the decisions related to the current period are fixed; they will not change and are implemented. However, other decisions related to the future could be updated.

Finally, the experimental results show that solving a multi-period model would be more beneficial for the consolidation of requests, thus yielding a more efficient utilization of the offers. More precisely, in the multi-period formulation, requests can be assigned to the regular offers in the subsequent periods rather than shipping via the spot market which is a clear advantage of the look-ahead decision-making strategy.

The remainder of this research is structured as follows. We provide a detailed description of the M1M system in Chapter 2. The problem definition is discussed in Chapter 3. Chapter 4 presents a brief review of the related literature. In Chapter 5, the mathematical models, the simulation environment, and the rolling-horizon approach are presented. Chapter 6 presents the generation of instances and computational experiments. Finally, Chapter 7 presents conclusions and directions for future research.

CHAPTER 2 M1M SYSTEM SETTING

This chapter presents the M1M system structure (Many-to-one-to-Many) introduced by [3] and all the definitions and figures are written based on [3]. In Section 2.1, the M1M system and its elements are introduced. We describe the physical network in Section 2.2, the shipper-requests and their attributes in Section 2.3, and the carrier capacity-offers and their features in Section 2.4.

2.1 M1M system and elements

According to [3], M1M is an integrated multi-stakeholder transportation system that is based on consolidation, cooperation and sharing resources. It comprises three main components: the first M refers to many shippers (demand side), the second M refers to the carriers (supply side), and the one is the Intelligent Decision Support Platform (IDSP). The first component, shippers such as wholesalers, producers, and distributors, etc., make requests for the transportation of their product loads from their points of origin to their points of destination in an economical and timely manner. The second component, carriers such as transportation service providers, third-party logistics (3-PLs), and fourth-party logistics (4-PLs) make offers for transportation [2]. Finally, IDSP is an entity in the middle of the system for planning and optimizing operations in order to ensure that the needs of all components are met profitably and simultaneously [2, 3].

The time-dependent requests and offers are available to the system at different points in time. Accordingly, the IDSP receives related information continuously and optimizes the selection of offers and request-to-offer assignments by the consolidating of different shippers requests into the same offers and synchronizing the activities [3]. The communications between all relevant stakeholders, including decision and data exchanges are presented in Figure 2.1 [2, 3].

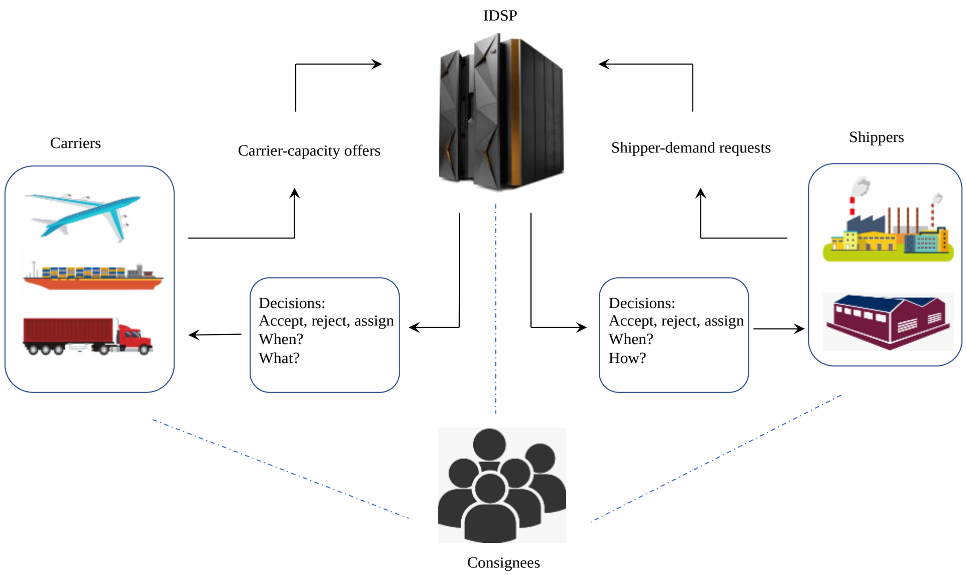

Figure 2.1 M1M system structure [3]

2.2 Physical network

A set of nodes and arcs define the physical network, as illustrated in Figure 2.2 [3]. The nodes consist of service zones, consolidation and transfer terminals that are connected by arcs. Activities happen between zones shown by large disks. The zones also include small disks which represent consignee and shippers' facilities. Each shipment corresponds to a shipper request that originates at a shipper facility and terminates at a consignee facility. Carriers and their facilities (full-truckload motor carrier, less-than-truckload motor carrier, vehicle garage, etc.) could be located in the territory covered by the problem setting [3].

Terminals, represented by the squares, may carry out necessary tasks such as warehousing or cross dock transferring, etc. We assume that terminals can service the zones which are close to them. If the zone is large with important populations and industrial density [2, 3], it can be serviced by more than one terminal. In detail, terminals can provide the full range of services such as:

1) First-mile delivery to receive the shipments from their origins to the outgoing terminals;

2) Unloading inbound requests from incoming vehicles and loading outbound requests to outgoing vehicles;

3) Crossdock movement of requests between different incoming and outgoing vehicles;

4) Warehousing requests that must await the departure of departing vehicles;

5) Last-mile delivery, the final stage, that consists of sending requests for distribution to their final destinations.

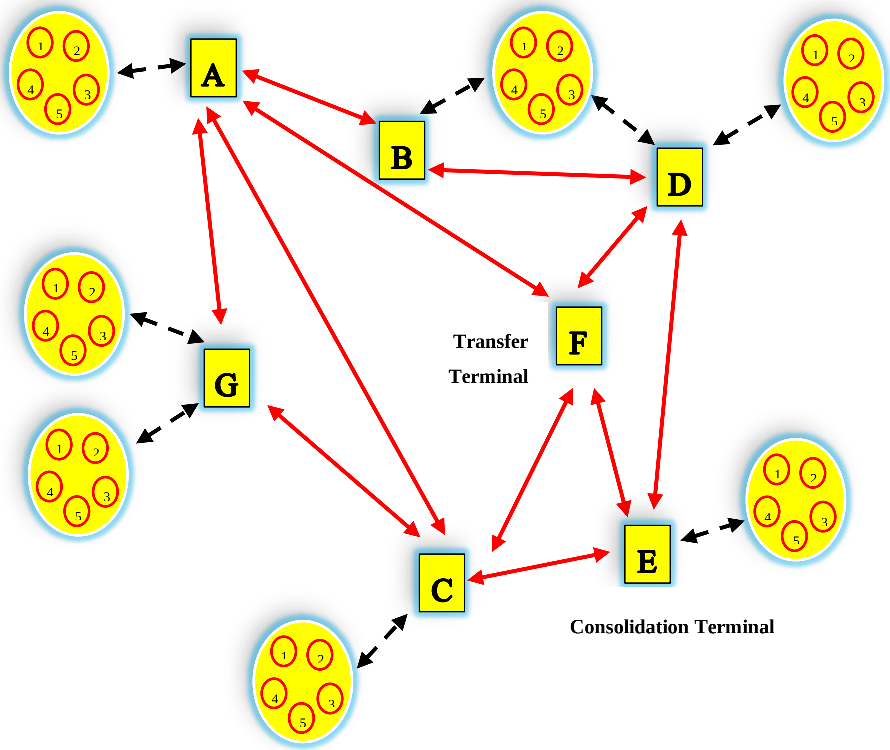

Figure 2.2 Hyper-corridor network [3]

The arcs connect two nodes and they are shown in different ways. Generally, there are three types of arcs that may make up the physical network. The first ones are the long-haul arcs that connect two terminals. The second ones are the feeder arcs (dash-lines in the Figure 2.2) that indicate the connection between terminals and zones. The last ones are the pickup-and-delivery arcs that deliver inbound shipments to customers within defined zones, as well as collect outbound shipments from shippers' locations. Note that a combination of feeder and pickup-and-delivery arcs and long-haul arcs are called a segment [3, 6].

There are three particular network structures in M1M system:

1. Single-segment corridor made up of one long-haul that links two terminals and two feeder segments for connecting zones to a terminal illustrated in Figure 2.3 [3].

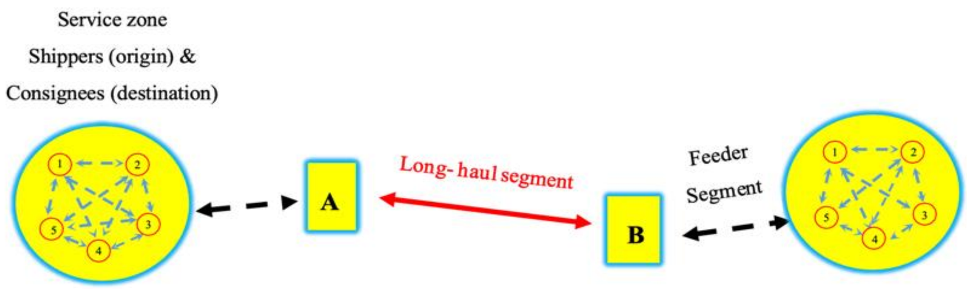

Figure 2.3 Single-segment network [3]

2. Multi-segment corridors where all zones and terminals are on a unique physical path and there are more than two of them [3], as illustrated in Figure 2.4.

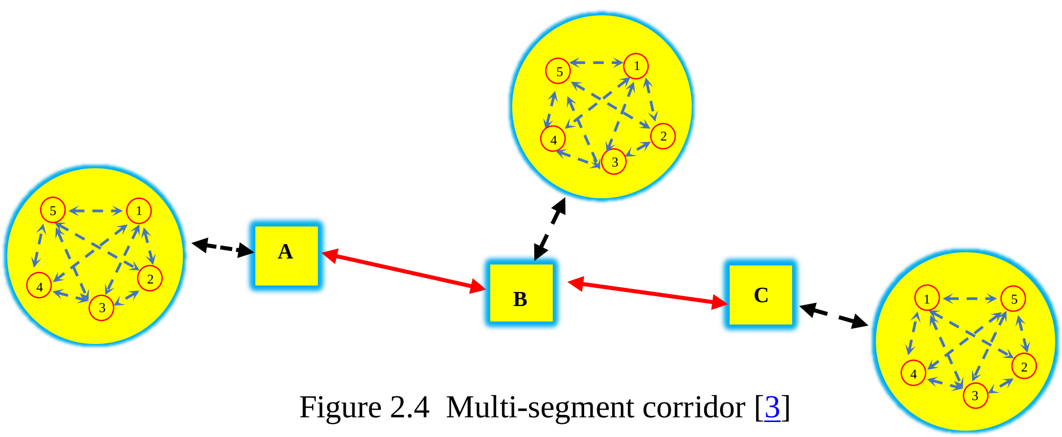

Figure 2.4 Multi-segment corridor [3]

3. Hyper corridors network in which long-haul segments and feeder arcs link a limited number of zones and terminals, as shown in Figure 2.2 [3].

Transportation activities at the operational level in M1M system are consolidation of requests, transfer operations, and requests delivery as are described in the following [7]:

1- A request is picked up at a shipper facility (initial consolidation);
2- The request is carried to one of the terminals related to the zone (nearest one);
3- The requests delivered to the terminals can be a single product. In this case, transfer operations are unloading, cross-docking and then loading it to an outgoing vehicle. In the case of multi-product, with particular logistic characteristics, the requests should be unloaded, re-classified, sorted, and finally loaded into the outgoing vehicle (second consolidation) [7].
4- The outgoing vehicle could go either to the customer's door or intermediary terminals.

2.3 Shipper-demand requests for transportation

Shippers are the demand side of M1M system that require their requests to be transported to the final destination [2]. Each request has its physical, time, and economic attributes.

2.3.1 Basic attributes

Basic attributes define the descriptive features of each request. The basic attributes of the requests are as follows:

- Origin: the node of the shipper facility in a particular zone;
- Destination: the node of the consignee facility within a particular zone;
- Volume: the number of standard loading units.

2.3.2 Time attributes

Based on the problem's assumption, all or some of these time characteristics could be considered for a request. The time attributes of the requests are as follows.

- Acceptance time window: the time interval during which the platform must decide to accept or not the request, and transmit the decision to the shipper;

- Availability time: when the request emerges in the system and is available for shipping;
- Earliest delivery: when the request can be delivered earlier, with a penalty cost;
- Latest delivery: the time moment that after that delivery is no longer acceptable;
- Delivery due date: the target, delivery time of the request to the consignee.

2.3.3 Economic attributes

Economic features are composed of the revenue for the IDSP because of taking care of the requests. Yet, sometimes, the IDSP is penalized because all requests might not be delivered within their specified time window. The requests could be delivered earlier or later than their preferred time intervals. Consequently, IDSP has to pay penalties to the shippers for handling their requests outside the delivery time window [2, 3].

2.4 Carrier-capacity offers

Apart from shippers, the M1M system also includes many carriers. As the supply side of M1M system, they provide capacities by proposing service offers [3].

Each offer has their physical, time, and economic attributes.

2.4.1 Basic attributes

Basic attributes define the descriptive features of each offer. They are as follows.

- Origin: we assume that offers start working at a shipper location or terminal;
- Destination: which may be a consignee location or terminal;
- Capacity: the maximum volume that an offer may carry;
- Mode: the type of a vehicle that is associated with the service offer [5].

2.4.2 Time attributes

Similar to the time characteristics of the requests, the time attributes of offers can be classified as follows.

- Acceptance time window: the time interval within which the platform must accept or reject the offer, and submit the decision to the carriers.
- Time schedule: showing the departure and arrival times of an offer at each stop; in this study, there are not any intermediate terminals because we are focusing on a single-segment corridor network.
- Availability interval: the time window within which the offer is available in the system and can be used.
- Travel time: total needed time for an offer to move from origin to destination that is depended on the distance between origin and destination and general speed.
- Return time: the time when an offer is released from duty at its destination node.

2.4.3 Economic attributes

If the IDSP decides to use an offer, it will have to pay the fixed and variable costs related to this offer. The fixed cost is for using the offer and depends on the service type (i.e., regular and spot market) while the variable cost gives the cost per unit of volume and distance that is applied [2, 3].

2.5 Summary

In this chapter, we first described the M1M decision-making structure and its interactions. Then, different types of physical networks were stated. It is worth mentioning that in the next chapters, we will focus on single segment corridors. We also introduced three components of this system which are supply as well as demand sides of the system, and the IDSP as the decision-maker. Then, basic, time, and economic attributes of requests and offers have been discussed in this chapter.

CHAPTER 3 PROBLEM DEFINITION

This study focuses on the operational planning of a consolidation-based transportation system that is relevant in the context of M1M. As we already mentioned in Section 2.1, the M1M system consists of three main components; many shippers that define the demand side, many carriers that define the supply side, and the IDSP, in the middle as the central decision-making platform. In all generality, the IDSP seeks to plan the overall system to achieve maximum efficiency for all involved stakeholders. Among three particular network structures in M1M system defined in the previous chapter, we are working on the special case of an M1M system which is the single-segment network. This network consists of a single long-haul segment and two feeder segments, each of the latter connecting a terminal and a node representing the entire zone [3]. This research does not consider pick-up and delivery operations conducted in the service zones, so the requests (demand) will be aggregated in a single node and assigned to the nearest terminal associated to them [10]. Therefore, what we are planning at the operational level is the services required to move the demand from terminals A to B, or from B to A, see Figure 3.1.

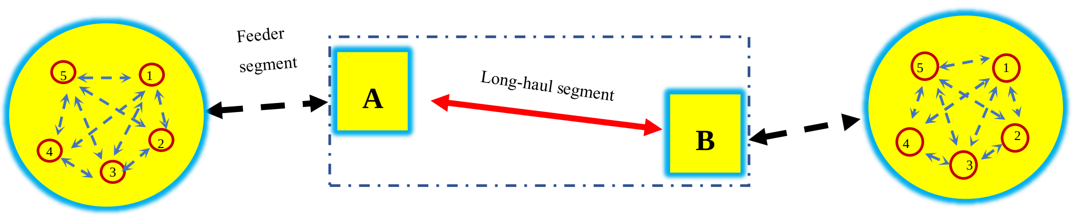

Figure 3.1 Single-segment network [3]

In this study, the operational planning of the M1M system, which is guided by the tactical planning, aims to adapt the tactical transportation plan to the short-term activities considering the received shipper-requests and carrier-offers with their various basic, time, and economic features. These requests and offers correspond to those selected in the tactical transportation plan and are the only ones considered. Therefore, no additional ad-hoc carrier-offers and shipper-requests are received while performing the operational planning in this system.

We select the offers and then assign the requests to the available offers in a way that minimizes the costs and meet the needs of both shippers and carriers. In this study, we assume that all the requests must be shipped through the regular offers or the spot market.

The IDSP can make decisions at different times: when a request or an offer arrive to the system; once a number of requests and offers appear; or based on predefined schedule (e.g., every 5 hours) [3, 7]. In this study, we assume the IDSP makes decisions on a daily basis and a discrete-time representation is considered. Therefore, in optimization terms, we build a multi-period model for the Operational Planning Horizon (OPH), which is defined for a number of consecutive periods, with equal length, starting at time t and finishing at time instant T, see Figure 3.2 [7].

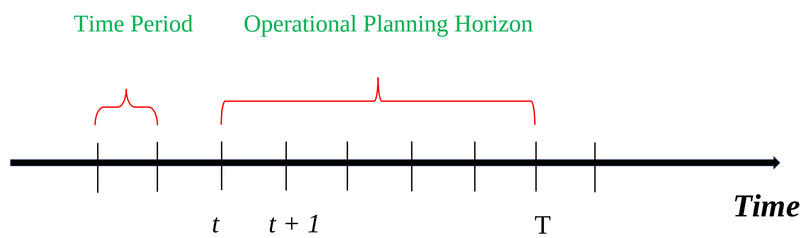

Figure 3.2 Operational Planning Horizon [7]

There are two strategies to formulate the optimization model at each decision time in this thesis: look-ahead and myopic strategies. These two strategies differ in terms of the information that is considered to make the decisions.

When the decisions are made based exclusively on known information; the requests and offers received in the past and now, and the decisions made in the past, it is called a myopic decision-making strategy [3, 5].

Based on [3, 5], in the look-ahead approach, the required information for the IDSP to make the decisions at the current time are new information of requests and offers, past time periods decisions' information, and predicted requests and offers information related to the following periods, as illustrated in Figure 3.3.

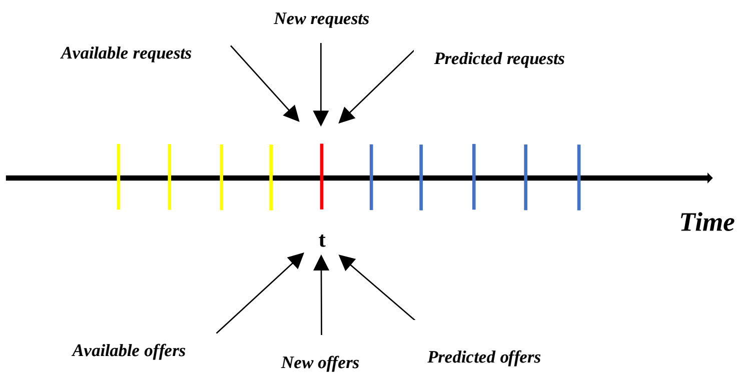

Figure 3.3 Available information under the look-ahead strategy at time t

To assess the two approaches within the dynamic informational environment of the considered system, we develop a simulation that reproduces how the system could be working eventually. We are simulating the operations day by day, where the sequential operational decisions are made via the use of a rolling-horizon framework. The rolling-horizon framework enables the current, predicted and past contextual information to be iteratively updated.

The process of decision-making in the rolling-horizon framework requires some rules to define the degree of flexibility that a decision maker can consider. These rules are used to define policies that show how much the decision maker is allowed to change the previously made decisions that are still active given the new information (the information that is available at the current period). In this thesis, we define a single policy that only implements the decisions related to the current period. Specifically, any decisions which were not executed in the past are reoptimized considering the new information.

The objective of this thesis is to assess the impacts of using either a myopic or a look-ahead strategy to solve the sequential decision making problem that naturally occurs when performing the operational planning that is faced by the IDSP in the considered system.

CHAPTER 4 LITERATURE REVIEW

This thesis deals with the application of the rolling-horizon approach to the operational planning of M1M systems. Therefore, in this chapter, we review the relevant literature on the operational planning in Section 4.1, and the rolling-horizon approach in time-structured problems in Section 4.2. Then, the research gap is presented in Section 4.3.

4.1. The operational planning of M1M systems

At the operational planning level of consolidation-based freight transportation , daily decisions are primarily concerned with managing resources, monitoring the operations, and updating plans [6]. According to [9], operational planning is related to "what" and "when" issues. For example,

- when decisions are made;
- what information these decisions are based on;
- when the decisions are implemented;
- for how long they are applied;
- what interactions in time exist among these decisions and their consequences.

According to [8], profitability and maintaining a competitive position are among the ultimate targets of any transportation firms. In this regard, the firm's operations are guided by strategic and tactical plans, but the overall performance of a company is determined by its operational capabilities. The operational planning happens in a highly dynamic environment in which detailed representations of facilities, vehicles, activities, and the time factor play a key role. Moreover, at the operational level, there are various issues including the selection of offers, best itineraries, and assignment of resources to demand that must be addressed in order to ensure that demand is met, and cost is minimized.

In paper [14], the authors provide an overview of the multimodal transportation literature since 2005 in a systematic manner. As well as the strategic, tactical, and operational levels of planning, they also focus on the appropriate models for each of these levels and the solution methods that were developed for each model.

In paper [15], the authors investigate how to select services for delivering shipments with diverse features over a multi-period horizon. Under uncertain demand, the decision maker maintains a balance between current and future costs at every point in time to minimize the total costs over the entire period that is considered. A Markov Decision Process (MDP) for modeling the trade-off between postponing and transporting the shipments is presented. In order to avoid the complexity of the computation of solving the MDP while keeping its modeling functionalities, they present an Approximate Dynamic Programming (ADP) approach. They explore the benefit of look-ahead in their planning problem and on ADP designs. Moreover, they observe that there is a connection between the look-ahead method performance and flexibility in time window and number of freights. Finally, a series of numerical experiments are conducted, which show that their look-ahead approach has more benefit than a benchmark heuristic.

In paper [20], the authors study in depth the state-of-the-art synchromodal and Physical Internet models with an emphasis on their methodologies, designs, and findings that have been published in scientific publications. There are no thorough links between PI and synchromodality in the scientific literature. Therefore, it is important to assess and explore the correlation between these two concepts in order to understand how they can strengthen each other.

Paper [4] proposes a novel Bin Packing problem setting that allows the Bin Packing model and solution methods to be applied to a wide range of practical applications, including both logistics capacity planning and several other applications. The Multi-period Variable Cost and Size Bin Packing Problem with Assignment Costs (MVCSBPP-AC) considers not only the physical attributes of items and bins, the economic features of bins, and the time attributes of items and bins, but also the time-dependent cost of assigning the items to specific bins. This cost is calculated based on any penalties for the early or late delivery of the items. The Variable Cost and Size Bin Packing Problem with Assignment Costs (VCSBPP-AC) is a sub-variant of MVCSBBPP-AV which is considered in this paper as well. The authors present mathematical formulations for the Single-period Variable Cost and Size Bin Packing Problem with Assignment Costs and Multi-period Variable Cost and Size Bin Packing Problem with Assignment Costs.

In addition to the mathematical formulations of these new variants of BPP, they propose seven constructive heuristics for addressing the single-period and multi-period models. A comprehensive computational experimentation is performed that indicates a high level of performance both in terms of the CPU time and the quality of the solutions provided by the proposed heuristics.

4.2. The rolling-horizon approach in time-structured problems

A rolling-horizon framework is able to control the implementation and re-optimization of decisions by dividing the time horizon into smaller ones and solving one subproblem for each smaller time horizon.

According to [12], time-structured problems like logistics, process optimization and production planning tasks are often big and modern solvers are usually unable to achieve global optimality for these problems in a reasonable time. Therefore, the rolling-horizon approach is used, but according to the authors, this approach has deficiencies, which they attempt to analyze in order to develop an algorithm to compensate for them. As a result, the new rolling-horizon decomposition approach is modified to tackle large-scale optimization issues effectively. In addition, the authors propose the conditions under which the rolling-horizon algorithm provides near-optimal high-quality solutions. Computational studies show that the new rolling-horizon approach can be applied to various challenging optimization problems such as lot-sizing and tail-assignment, and the obtained results are very close to a global optimal solution.

In paper [13], a multi-stage stochastic program is developed to optimize strategic and tactical decisions simultaneously. In addition, a data-driven rolling-horizon approach is presented in which, by observing stochastic parameters over the past time horizon, decision makers can update their scenario tree for the subsequent period(s) and adjust the corresponding decisions in a rolling-horizon manner. Then, for creating an efficient scenario tree, they employ a forward scenario tree construction technique. Finally, a comprehensive numerical analysis is conducted to confirm the efficiency of the proposed model, rolling-horizon procedure, and the performance of the scenario tree construction technique.

In paper [16], the authors introduce an online synchromodal matching problem in which a centralized platform aims to provide the best matches between carriers and shippers. Since new shipments arrive in the system over time, they propose a rolling-horizon approach to take care of them. They also develop a preprocessing-based heuristic to solve the dynamic shipment matching effectively and reduce the computational complexity. This heuristic algorithm has three steps: preprocessing of path generation with single or multiple services, preprocessing of feasible matches in which combination of shipments and path are defined, and a binary integer programming (BIP) model to generate optimal solutions. They validate their proposed heuristic algorithm and rolling-horizon approach on an intermodal network in Europe. In large instances and in a dynamic context, the results demonstrate that this algorithm generates timely solutions in an efficient and accurate way.

In multimodal transportation, paper [22] introduces a dynamic and stochastic shipment matching problem (DSSM). In this paper, a multi-stage stochastic programming is used to describe the DSSM problem. Because of the curse of dimensionality, an anticipatory optimization approach (AOA) and a myopic optimization approach (MOA) were developed. The first approach combines the utilization of the rolling-horizon framework (for handling dynamic events) and a sample average approximation method (for including stochastic information). Then, AOA is compared with a myopic approach, which is based on deterministic information; the results show that the performance of anticipatory optimization approach is better because it decreases the cost of matching shipments under different scenarios and it reserves capacity for the future requests.

4.3. Research gaps

We present our work, which is based on reference [4] at the operational level. Notice that, in this paper, the capacity planning optimization is based on bin packing idea. Thus, items turn into the requests and bins represent offers in our study. In this paper [4], the problem is solved over a given horizon once. We propose a rolling-horizon framework to handle sequentially making decisions in this thesis.

To the best of our knowledge, there have not been papers performing an empirical study of rolling-horizon procedures based on optimization models for the operational planning of freight transportation in the context of an M1M system.

CHAPTER 5 METHODOLOGY

This chapter starts with the formulation of the mathematical models for the look-ahead and myopic strategies of the operational planning in Section 5.1. Then, it continues with the definition of the simulation study in Section 5.2. Finally, the considered policy and the proposed rolling-horizon approach are discussed in Section 5.3.

5.1 Operational planning models

Two optimization models proposed by reference [4] are represented in the following. The multi-period and single-period models are used to define the look-ahead and myopic strategies, respectively. The research paper [4] focuses on a system in which a set of items being owned by different stakeholders must be moved by a set of carriers at a given time period. In this system [4], the items and bins are available to the system at different time periods. The decision maker aims to minimize the total cost by selecting a subset of bins and determining which item should be loaded into each bin for every time period. In this problem, each item is characterized by its volume and the availability time window, the delivery time window, and the delivery due date. These time characteristics related to the requests are illustrated in the Figure below.

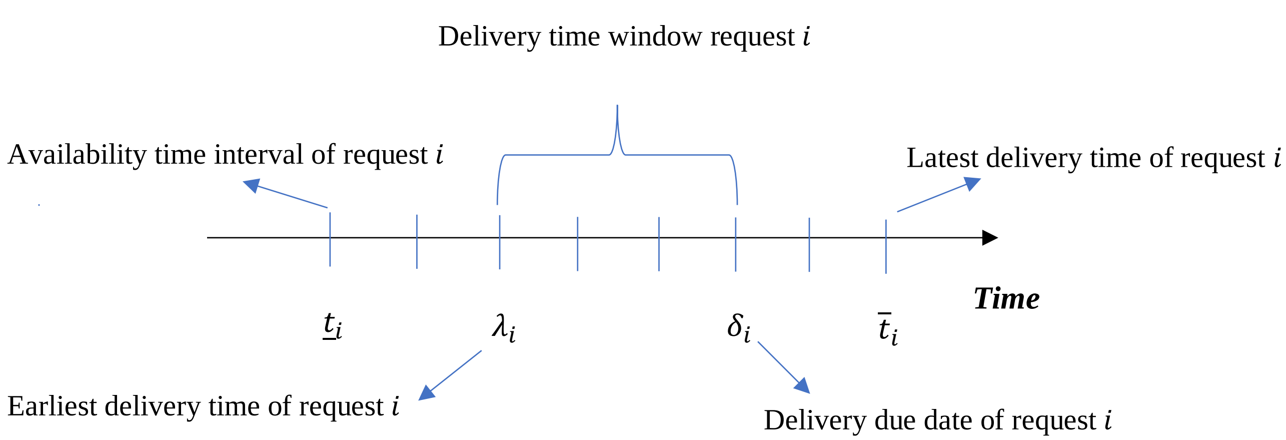

Figure 5.1 Request’s time characteristics

When the item is made available to the system, it can be loaded onto a bin that leaves the system immediately, or it can also be loaded onto a bin that departs the system in subsequent periods. When there is not enough capacity in the selected bins to ship the items at a specific time period, a non-participating transportation service provider delivers the items via the spot market with higher costs. Similarly, each bin is characterized by the time window in which they are available, capacity, and fixed cost.

The main objective of the problem presented in this thesis is minimizing the total cost including the fixed cost of selecting the bins, the cost of shipping the item by the spot market, and the cost of assigning an item to a bin. The cost of assigning a request to an offer may involve transportation cost and any penalties associated with early or late delivery of an item. It is important to note that, as capacity-planning optimization is based on Bin Packing ideas [4,18], items turn into shipper-requests while bins represent the carrier-offers for their transport. Note that in Chapter 2, we presented the general characteristics of the demand (shipper-requests) and supply (carrier-offers) at the operational level.

5.1.1 Formulation of the multi-period model

We first define below a multi-period mathematical model with new notations:

<u>Sets and Parameters</u>	
$\mathcal{I}$	Set of requests indexed by i
$\mathcal{J}$	Set of offers indexed by j
$\mathcal{T}$	Total time indexed by t
$\mathcal{T}_i = [\underline{t}_i, \overline{t}_i] \subset \mathcal{T}$	Availability time interval of request i
δ_i	Delivery due date of request i
λ_i	Earliest delivery time of request i
$\overline{t}_i$	Latest delivery time of request i
$\Upsilon_j = [\underline{\Upsilon}_j, \overline{\Upsilon}_j] \subset \mathcal{T}$	Availability time interval of offer j

$(\underline{\Upsilon}_j \geq 1, \overline{\Upsilon}_j \geq \underline{\Upsilon}_j)$ & $\left(\underline{t}_i \leq \lambda_i \leq \delta_i \leq \overline{t}_i\right)$

$\mathcal{T}_{ij} = \left[\underline{t}_i, \overline{t}_i - \alpha_j\right] \cap \Upsilon_j$	Feasible time for request-to-offer assignment (α_j = traveling time of offer j)
ϕ_j	Fixed cost of selecting and using offer j
V_i	Volume of request i
θ_{ijt}	The request-to-offer assignment cost of the request $i \in \mathcal{I}$ to offer $j \in \mathcal{J}$ at period $t \in \mathcal{T}_{ij}$
ϑ_{it}	Assignment cost of request i to the spot market at period $t \in \mathcal{T}_i$
C_j	Capacity of offer j

Decision Variables

x_{ijt}	Equals 1, if request i is assigned to offer j at period $t \in \mathcal{T}_{ij}$; 0, otherwise.
s_{jt}	Equals 1, if offer j is selected at period $t \in \Upsilon_j$; 0, otherwise.
u_{it}	Equals1, if request i is assigned to the spot market at period $t \in \mathcal{T}_i$; 0, otherwise.

■ Objective Function

$$\textbf{MIN} \quad \mathcal{Z} = \sum_{j\in\mathcal{J}} \sum_{t\in\Upsilon_j} \phi_j s_{jt} + \sum_{i\in\mathcal{I}} \sum_{j\in\mathcal{J}} \sum_{t\in\mathcal{T}_{ij}} \theta_{ijt} x_{ijt} + \sum_{i\in\mathcal{I}} \sum_{t\in\mathcal{T}_i} \vartheta_{it} u_{it} \tag{5.1}$$

■ Constraints

$$\sum_{t\in\Upsilon_j} s_{jt} \leq 1 \qquad \forall\, j \in \mathcal{J} \tag{5.2}$$

$$\sum_{i \in \mathcal{I}} V_i x_{ijt} \leq C_j\, s_{jt} \qquad \forall\, j \in \mathcal{J}, t \in \Upsilon_j \tag{5.3}$$

$$\sum_{j \in \mathcal{J}} \sum_{t \in \mathcal{T}_{ij}} x_{ijt} + \sum_{t \in \mathcal{T}_i} u_{it} = 1 \qquad \forall\, i \in \mathcal{I} \tag{5.4}$$

$$x_{ijt} \in \{1,0\} \qquad \forall\, i \in \mathcal{I}, j \in \mathcal{J}, t \in \mathcal{T}_{ij} \tag{5.5}$$

$$s_{jt} \in \{0,1\} \qquad \forall\, j \in \mathcal{J}, t \in \Upsilon_j \tag{5.6}$$

$$u_{it} \in \{0,1\} \qquad \forall\, i \in \mathcal{I}, t \in \mathcal{T}_i \tag{5.7}$$

The three terms in the objective function correspond to the total cost of assigning the requests to the offers during their feasible time intervals, the total cost of selecting the offers, and the total cost of using the spot market. The constraints (5.2) ensure that each offer can only be selected one time during its availability time interval. Constraints (5.3) guarantee the capacity of selected offers. Constraints (5.4) enforce the satisfaction of request, i.e., each request has to be shipped by a regular offer or the spot market. Constraints (5.5)- (5.7) indicate the domain of decision variables.

5.1.2 Formulation of the single-period model

The formulation of the single-period model is presented here, which is similar to the multi-period model except for the time index on decision variables and parameters [4].

- **Objective Function**

$$\textbf{MIN} \quad \mathcal{Z} = \sum_{j \in \mathcal{J}} \phi_j s_j + \sum_{i \in \mathcal{I}} \sum_{j \in \mathcal{J}} \theta_{ij} x_{ij} + \sum_{i \in \mathcal{I}} \vartheta_i u_i \tag{5.8}$$

- **Constraints**

$$\sum_{i \in \mathcal{I}} V_i x_{ij} \leq C_j\, s_j \qquad \forall\, j \in \mathcal{J} \tag{5.9}$$

$$\sum_{j \in \mathcal{J}} x_{ij} + u_i = 1 \qquad \forall\, i \in \mathcal{I} \tag{5.10}$$

$$x_{ij} \in \{0,1\} \qquad \forall\, i \in \mathcal{I}, j \in \mathcal{J} \tag{5.11}$$

$$s_j \in \{0,1\} \qquad \forall\, j \in \mathcal{J} \qquad (5.12)$$

$$u_i \in \{0,1\} \qquad \forall\, i \in \mathcal{I} \qquad (5.13)$$

The objective function minimizes the cost of selecting the offers, assigning the requests to the offers, and using the spot market. Constraints (5.9) enforce the offer capacity. Constraints (5.10) guarantee that each request must be delivered either through the regular offers or a spot market . Finally, constraint (5-11) to (5-13) enforce the domain of variables.

5.2 Simulation study

Since we cannot implement the models and observe the real system, we need to create an artificial environment on a computer, which can be done through a numerical simulation model. By designing such an environment, we are able to see how the system works eventually and monitor it. The goal is to simulate daily operations where the optimization models are used to make decisions as we proceed.

To implement the simulation study, we assume a background file is used in which the sets of randomly generated requests and offers with their characteristics have been specified. The structure $P^0 = \left[\mathcal{T}_i\, ;\, V_i;\, \Upsilon_j\right]_{i\in\mathcal{I}, j\in\mathcal{J}}$ shows each request availability interval ($\mathcal{T}_i$), its volume (V_i), and the offer's availability time (Υ_j).

In order to solve the model, we need the information related to carrier-offers and shipper-requests. Yet, in practice, there is a possibility that the information we have generated randomly is different from the current realization of requests and offers. Note that requests and offers, as originally listed in the background file, corresponds to forecasts, not realized events. Thus, through the simulation, we update the periodic realized requests and offers, as explained in the following. Then, we can see how the actual present information can be applied in the operational decision-making models based on the rolling-horizon framework.

Let us assume that we are in the period t; we sort all the requests in the initial prediction P^0 based on their arrival time and put them in list L_t. In addition, we consider that each request in this list might be postponed with the probability $\pi_i^{\mathcal{P}}$to the next period (in spite of the prediction of its availability for current period). It might also be cancelled with probability $\pi_i^{\mathcal{C}}$. Therefore, if it is not cancelled or postponed, it can be processed and the probability of being available in the current period for the request is $1-(\pi_i^{\mathcal{P}}+\pi_i^{\mathcal{C}})$.

We generate a random variable ε with uniform distribution between 0 and 1. For each request $i \in L_t$, if $\varepsilon \le \pi_i^{\mathcal{P}}$, the request is postponed to the next period. If $\varepsilon > 1-\left(\pi_i^{\mathcal{P}}+\pi_i^{\mathcal{C}}\right)$, the request is available for the current period and we put it in L_t^A, which is the *List of available requests* ($L_t^A \in L_t$), otherwise ($\pi_i^{\mathcal{P}} < \varepsilon \le 1-\left(\pi_i^{\mathcal{P}}+\pi_i^{\mathcal{C}}\right)$), it is cancelled.

Moreover, we need to check the feature (volume) of each request in the list L_t^A. To do so, the actual volume of each request (V_i^A) is randomly generated in the interval $\left((1-\Delta_i)\,V_i\,,(1+\Delta_i)\,V_i\right)$, where Δ_i and V_i are the fluctuation rate and request volume in the set of randomly generated requests, respectively.

For realizing the offers availability, we first define L'_t as the list of available offers in period t. For each offer ($j \in L'_t$), if $\varepsilon \le \pi_j^{\mathcal{C}'}$, the offer is cancelled. Otherwise, the offer is available for the current period. Then, the list of available offers is $L_t^{A'}$. Note that the capacity of the offers does not change; and they appear with the same capacity that was predicted for them. Therefore, we can define $R_t = \left[\, L_t^A;\ V_i^A;\ L_t^{A'}\right]$ representing the list of available requests, the actual volume of these requests, and available offers. We use the structure R_t as an input of the optimization models.

5.3 A rolling-horizon framework for multi-period optimization problem

According to [3, 5], at any time t, not all decisions should be implemented. The planning horizon is divided into two components, the current implementation and the look-ahead. The decisions related to the current period t are not to be changed in the subsequent periods. The IDSP sends these decisions to the appropriate departments and stakeholders for execution. The following periods, from period $t+1$ to period t + T, are in the look-ahead component. The majority of decisions taken during these periods are temporary in nature, not intended for implementation.

We need to define a policy as a rule that applies in the operational planning and allows the decision maker to fix some decisions. In this thesis, we use a specific policy as described below.

Three different situations in terms of request's and offer's availability might take place:

1- Request and offer are both available in the current period:

  - If we select the offer and the request is assigned to it during the current period, this decision will be fixed and will not change because this information is actual.

2- Request is available in the current period while the offer is available in subsequent periods:

  - If we assign this request to the offer, this decision is not fixed, and we can update this decision in the next periods based on the new realized information.

3- Request and offer are both available at future periods:

  - Obviously, the offer selection and request assignment decisions can be updated.

Based on Table 5.1, the decisions related to the current period are implemented. However, decisions related to the future periods should be revisited. To clarify, let us consider the current period in which both request and offer are available. If the request is assigned to the offer and the offer leaves the system in this period, this decision will be fixed. However, if the request is assigned to the offer and the offer departs in a subsequent period, this decision can be revisited.

Table 5.1 Policies

Request Availability	**Offer Selection**	**Assignment**	**Policy**
Current Period	Current Period	Current Period	Fixed decisions
Current Period	Next Periods	Next Periods	Not Fixed decisions
Next Periods	Next Periods	Next Periods	Not Fixed decisions

To optimize the daily operational decisions by a look-ahead approach, we apply the rolling-horizon policy mentioned above in which the length of rolling-horizon is finite. The length of rolling-horizon is 7 days.

Suppose we start on Monday. First, using the realized information related to the received requests and offers for Monday, as well as future predictions for Tuesday to Sunday, we optimize the decisions of selecting the offers and assigning requests to the selected offers. Based on our proposed rolling-horizon policy, that part of decisions which are related to Monday’s request-to-offer assignment must be fixed and the remainder of decisions for the next days, (i.e., those for

Tuesday to Sunday), are not fixed and can be updated by re-optimizing decisions, which will use new information in the future.

Our weekly horizon then advances to Tuesday as illustrated in Figure 5.1. To keep the length of rolling-horizon fixed, we add Monday at the end of new horizon. Similar to the decision-making process on Monday, we optimize the decisions of selecting offers and assigning requests to selected offers for the current day, i.e., Tuesday, using: 1) its realized information; 2) future predictions for Wednesday to Monday; 3) fixed decisions related to Monday.

In general, through the proposed rolling-horizon approach, we are able to optimize the daily offer selection and the request assignment decisions considering a 7-day look-ahead based on the current information and future prediction of the next 6 periods.

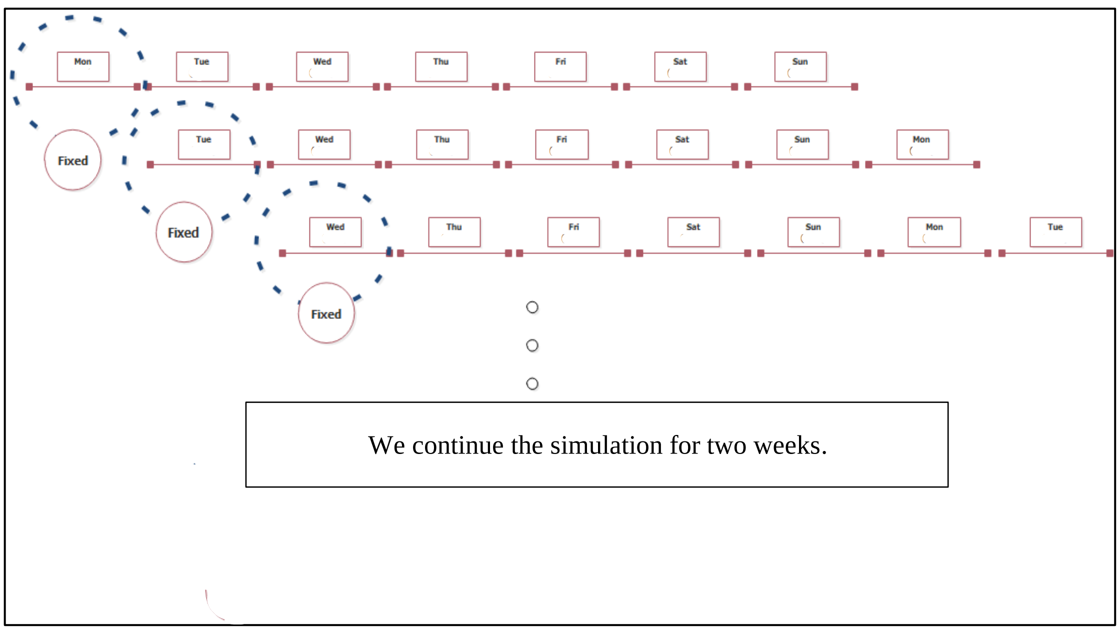

Figure 5.2 Illustration of a 7-day look-ahead horizon

5.4 Summary

In this chapter, two operational planning models proposed by Crainic et al.[4], with new notations, were presented to be applied for the single-segment corridor network. These are look-ahead model that considers past, new and predicted information simultaneously, and the myopic model that just takes into account present and past information.

Compared to reference [4], we are simulating the operations day by day, where the sequential operational decisions are made via the use of a rolling-horizon framework (implemented using either the myopic or look-ahead strategy). The rolling horizon procedure is used in the context of performing the considered sequential decision making process that appears at the operational level of the considered system. The bin packing model which was presented in this chapter, is used to solve the multi-period problem that goes into the policy that we are implementing. Based on this policy, the decisions related to the current period are implemented. However, decisions related to the future periods should be revisited.

In the next chapter, we will test two approaches and analyze their solutions. We will also answer to the raised question about the value of look-ahead versus the myopic model.

CHAPTER 6 EXPERIMENTAL ANALYSIS AND RESULTS

In this chapter, we present a series of computational experiments to evaluate the performance of the multi-period and single-period models. This chapter is organized as follows: in Section 6.1, we propose a general procedure to carry out the experimental analysis; we present the data generated by MATLAB for the experimental phase in Section 6.2; and Section 6.3 presents the computational results and analysis.

All computational experiments were conducted on a laptop with an Intel (R) Core (TM) i7-7500U 2.70 GHz CPU and 8.00 GB of RAM. For data generation, we used MATLAB language version 3.10.4, and the mathematical models were solved by IBM ILOG CPLEX Version: 20.1.

6.1 General procedure

We present a procedure for conducting the computational experiments and evaluating the proposed rolling-horizon approach.

The general procedure can be defined as follows:

1- Generating the data randomly for the operational planning by MATLAB;

2- Realizing the available requests and offers related to the current period;

3- Solving the look-ahead model and obtaining results;

4- Fixing the current period’s decisions and removing the related requests and offers from the list;

5- Repeating the steps 2 to 5 for the next periods;

6- Analyzing the results.

6.2 Description of the instance

We are generating the instance for the problem described in Chapter 3, where the operational planning involves exclusively the specific requests and offers, with their characteristics, chosen by the tactical planning process. Therefore, no additional ad-hoc requests and offers are received. Note that the considered requests might not show up or might be late and their volume might be different from the one determined in the tactical plan. Similarly, the offers also might be canceled, otherwise they are available in the system with the defined capacity. As the demand must be satisfied, the IDSP has the possibility to call upon ad-hoc capacity (e.g., spot market) when needed. In the computational experiments, we assume that we are provided with exogeneous predictions for requests and offers. These predictions are randomly generated in the initialization phase of our simulations. The number of requests and offers is considered 500 and 200, respectively. The instance is generated using the following parameters:

- Availability time windows for requests and offers ($\mathcal{T}_i$ and Υ_j) are randomly chosen between 0 and T, with their length randomly varying between 1 and 5 time periods.
- Request-to-offer assignment cost $\left(\theta_{ijt}\right)$ $=\beta_1 + \beta_2 \times \left(t - \underline{t}_i\right) + \beta_3 \times max\{(\lambda_i - t), 0\} + \beta_4 \times max\{(t - \delta_i), 0\}$, for request $i \in \mathcal{I}$, offer $j \in \mathcal{J}$, and time period $t \in \mathcal{T}_{ij}$, where β_k, $k = 1, 2, 3, 4$ are random numbers in these intervals $[20, 30], [3, 5], [1, 2]$, and $[3, 5]$, respectively.
- Spot market cost (ϑ_{it}) = $\vartheta_1 + \beta_2 \times \left(t - \underline{t}_i\right)$, where ϑ_1 is a random number between $[100, 200]$.
- The probability of postponement of each request ($\pi_i^{\mathcal{P}}$) = 10%
- The probability of cancelation of each request ($\pi_i^{\mathcal{C}}$) = 15%

Furthermore, V_i (request's volume), C_j (offer's capacity), and ϕ_j (offer's fixed cost) are randomly generated parameters based on uniform distributions, shown in Table 6.1.

Table 6.1 Parameters for the random generation of data based on uniform distributions

ϕ_j	V_i	C_j
U (80,120)	U (10,20)	U (50,150)

6.3 Computational results and analysis

We solve the operational planning models with data generated using the parameters defined in Section 6.2. This section is organized as follows:

In Section 6.3.1, we compare the behaviour of the multi-period model with the single-period model with respect to five defined Key Performance Indicators and the standard deviations. In Section 6.3.2, we observe the advantage of multi-period model compare to the single-period one in terms of cost reduction. The effect of the length of look-ahead on the cost, run time, and cost reduction is discussed in Section 6.3.3. Finally, the interplay between prediction variability and the length of the look-ahead is presented, in Section 6.3.4.

6.3.1 Comparing the multi-period models with the myopic model

The aim of this section is to analyze the solution of the multi-period model solved by the proposed rolling-horizon approach with length of three and seven days, in comparison with the single-period model when the number of days for the simulations considered is 14. To do so, we define five key performance indicators: total cost, consolidation rate which is total requests shipping per selected offers, percentage of requests assigned to the spot market, the number of selected offers, and use of the selected offer capacity (as a ratio to total capacity). In order to compare these KPIs, we perform 10 replications of the simulation for the instance and report average values. These ten replications correspond to runs performed with different seeds for the random number generators, thus with different realizations of the requests and offers.

- *Models*
    - Rolling-horizon ($\ell_{RH} = 7$)
    - Rolling-horizon ($\ell_{RH} = 3$)
    - Single-period

- *Key Performance Indicators (KPI)*

    1) Total cost

2) Consolidation rate, i.e., total requests shipping per selected offers

3) Percentage of requests assigned to the spot-market

4) The number of selected offers

5) Use of the selected offer capacity (as a ratio to total capacity)

Table 6.2 presents the results for the five KPIs. The cost of solving the model for two weeks, with the myopic model is higher compared to a multi-period model with rolling-horizon of different lengths. We also observe that the consolidation rate, the second KPI, is higher in the multi-period model because the IDSP is able to use the capacity of offers in subsequent periods. The percentage of requests assigned to the spot market, the third KPI, is higher when the myopic model is used due to the fact that this model does not consider future periods and if there is not enough capacity to ship the requests by the regular offers, they are assigned to the spot market with higher cost. In addition, the number of offers used in a specific interval (average in one week), the fourth indicator, shows that the multi-period model takes advantage of regular available offers more effectively and provides more efficient capacity usage. Finally, the last KPI, the use of the selected offer capacity, is higher in multi-period models since it offers more flexibility in shipping the requests

Table 6.2 Comparing RH method with myopic model with respect to KPIs (10 replications)

KPI	Rolling-horizon ($\ell_{RH} = 7$)		Rolling-horizon ($\ell_{RH} = 3$)		Single-period (Myopic)	
	Average	std. dev.	Average	std. dev.	Average	std. dev.
Total cost	15537.45	1840.31	16108.17	2110.48	21798.07	2974.20
Consolidation rate	4.38	0.37	4.11	0.40	3.39	0.42
Percentage of requests assigned to the spot-market	10.06	1.81	11.97	2.06	25.98	4.78
The number of selected offers	27.00	3.00	34.00	4.00	42.00	7.00
Use of the selected offer capacity	0.90	0.05	0.88	0.65	0.57	0.09

The standard deviation measures the variability of the distributions. Table 6.2 shows how the variability increases when we are comparing the runs of different methods. For example, the standard deviations (for all considered KPIs) increase when the length of the rolling-horizon decreases.

The spider plot in Figure 6.1 shows the performance of each method across the different KPIs. Analysing this figure gives us insights into the weakness of single-period model in consolidation of requests and reducing the total cost. It also shows that using the multi-period models results in more profitable operations.

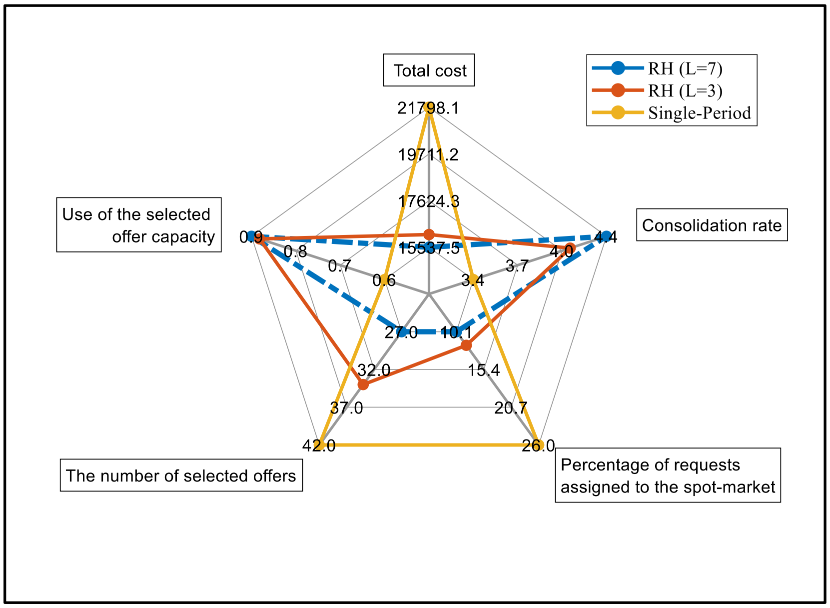

Figure 6.1 Spider plot to compare the multi-period and single-period models

In Figure 6.2, we use a box-plot, which serves as a visual aid to identify the changes in total cost in 10 replications of each method. It shows the median and dispersion of the total cost in the single-period model and the multi-period models solved by rolling-horizon with the length of three and seven days. In 10 replications of each method, it can be observed that the median in the multi-period model solved by rolling-horizon ($\ell_{RH} = 7$) is less than in the multi-period model solved by rolling-horizon ($\ell_{RH} = 3$) and the myopic model. This indicates that, over 10 replications, the total cost in multi-period models (with the lower median) has lower values or a smaller central tendency. Moreover, the dispersion of the total cost for the multi-period model ($\ell_{RH} = 7$) indicates that the total cost does not vary significantly in multiple simulation runs (10 runs) and consequently solving our problem with the look-ahead approach can improve the system performance.

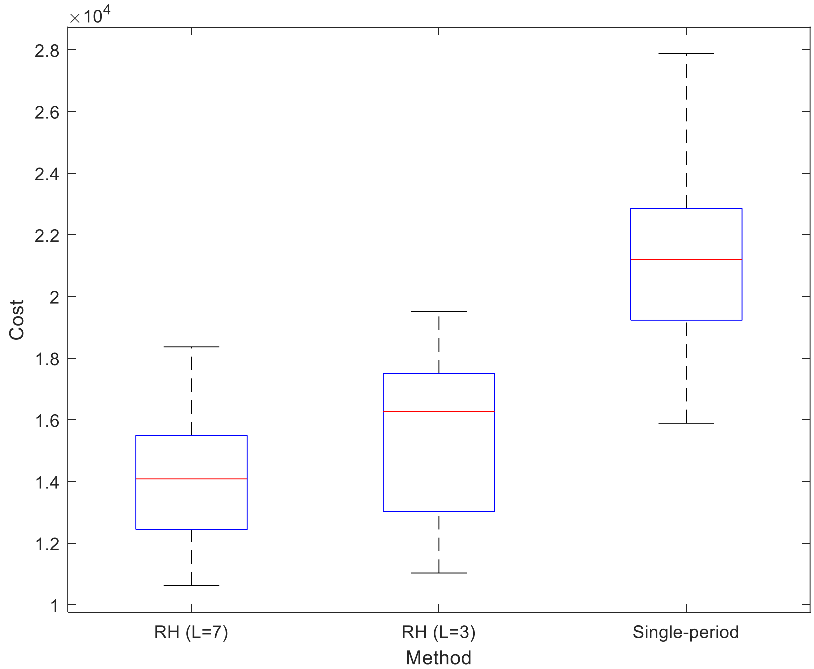

Figure 6.2 Box-plot to illustrate the deviation of cost in different methods [10 replications]

6.3.2 The value of the rolling-horizon approach

Table 6.3 shows the total cost for the single-period and the multi-period models when the number of days for the simulation varies. Initially, when the number of days is small, cost reduction using the multi-period model (L=7) is around 20%. However, when the number of days increases, the multi-period model clearly outperforms the single-period model in total cost. When the number of days is set to 23, the multi-period model solved by rolling-horizon approach dominates the single-period model very significantly by improving the cost around 50%.

Table 6.3 The value of the RH method in reducing the cost vs single-period model

No of days	Cost of Single-period	Cost of Rolling-horizon ($\boldsymbol{\ell_{RH} = 3}$)	Cost of Rolling-horizon ($\boldsymbol{\ell_{RH} = 7}$)	Cost Reduction (%) using RH ($\boldsymbol{\ell_{RH} = 7}$) vs. Single-period
7	10899.43	8466.40	8064.65	20.106
8	12456.04	9573.83	8874.34	22.755
9	14013.05	10536.96	9746.34	25.880
10	15570.54	11508.25	10557.01	29.197
11	17127.85	12427.14	11399.46	33.442
12	18684.46	13545.67	12405.16	33.606
13	20241.87	14611.33	13346.10	34.064
14	21798.64	16074.65	14161.44	35.034
15	23355.08	16518.84	14917.58	36.127
16	24912.65	17109.11	15439.87	38.023
17	26469.09	18143.28	16115.85	39.114
18	28026.65	19123.57	16878.08	39.777
19	29583.05	20082.94	17565.35	40.624
20	31140.28	21048.00	18305.27	41.216
21	32697.11	22025.77	19142.20	41.456
22	34254.54	22251.01	19219.23	43.892
23	35811.52	23677.98	19372.34	50.386

6.3.3 Analysis of the length of look-ahead

In this section, we study the impact of the length of the look-ahead period on the performance of the system. Table 6.4 depicts the impacts of length of look-ahead on both cost and cost reduction and run time when the number of days is set to 30. As it can be observed, initially, when the length of look-ahead is 0, there is a high cost of 46710.15 and 0% cost reduction. By increasing the length of look-ahead (0 to <11), the cost monotonically decreases and the cost reduction grows. Thus, this allows for more consolidation opportunities that enable the costs to be reduced.

Moreover, in Figure 6.3, it can be observed that both criteria, the cost and the percentage of cost reduction, hit a plateau for a length of look-ahead (>11), which means that, although increasing the length of the look-ahead improves the overall performance of the system, numerical experiments show that this improvement can be neglected after a certain value. Further increases in the length of look-ahead only increase the computational time.

Regarding the run time, it is noteworthy that the maximum run-time is 600 sec (10 min) for solving each iteration of the rolling-horizon (i.e., $t = 1,2,..,30$).

Table 6.4 The impact of the length of the look-ahead periods on Cost and time

Length of Look-ahead	Cost	Run-Time (sec)	Cost Reduction using Look-ahead vs. Single-period (%)
(Single-period)	46710.15	13.64	0
1	31673.81	35.95	32.191
2	29874.12	57.12	36.044
3	26094.54	112.48	44.135
4	25844.84	179.42	44.670
5	23585.84	234.54	49.506
6	21968.35	307.40	52.969
7	20649.04	389.54	55.793
8	19541.84	498.16	58.164
9	19047.12	560.38	59.223
10	18894.75	589.04	59.549
11	18794.85	+600	59.763
12	18107.36	+600	61.235
13	18107.36	+600	61.235
14	18107.36	+600	61.235
15	18107.36	+600	61.235

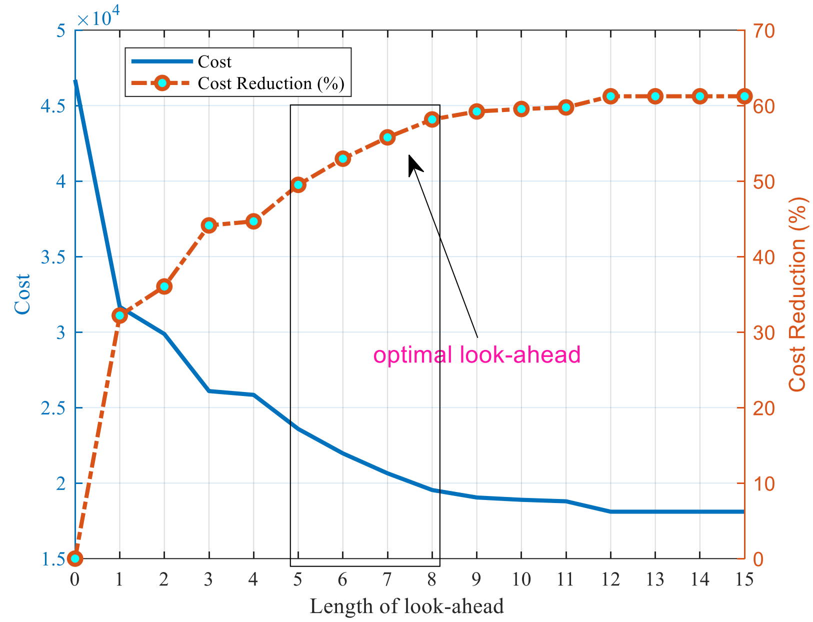

Figure 6.3 Analyzing the impact of the length of the look-ahead on performance of the system

6.3.4 The impact of the prediction variation on the cost and standard deviation

As it was discussed in the previous sections, looking-ahead when we are making decisions results in reducing costs and better capacity usage. In this section, the interplay between prediction variability and the length of the look-ahead is presented. Note that the number of days for the simulations considered is 14.

In order to assess the impacts that varying levels of prediction accuracy have on the results obtained, we conduct experimental tests using varying levels for the delta parameter (i.e., Δ_i = 0.1, 0.2, 0.3, 0.4, and 0.5). As we discussed in Chapter 5, in the initial the phase of simulation, we randomly generate sets of requests with their characteristics and then create the periodic realized requests and offers from these sets. For each request, the actual volume (V_i^A) is randomly generated in $\big((1-\Delta_i)\, V_i\,, (1+\Delta_i)\, V_i\big)$ interval, where Δ_i and V_i are the fluctuation rate and request volume in the set of randomly generated requests, respectively.

Tables 6.5 and 6.6 illustrate how the reliability of prediction influences the average cost and standard deviation of cost while solving the myopic and look-ahead models with different lengths. In these tables, multiple simulation runs (10 runs) show that increasing the delta parameters increases the average and standard deviation of the cost in all methods due to the fact that when our predictions about the volume of the requests are not precise enough, the costs of the system might increase because of lower capacity utilization and inefficient consolidation of the offers.

Moreover, the accuracy of predictions affects the added efficiency that is possible via use of the look-ahead. In Tables 6.5 and 6.6, by comparing the results obtained when the length of look-ahead is 3 and 7, it can be observed that for small value of delta (variation prediction), using the look-ahead method is advantageous and the standard deviation of cost with increasing the length of look-ahead decreases. However, when delta is set to a larger value, using a longer look-ahead becomes less advantageous due to the fact that our predictions were less accurate with respect to the original predictions. Regarding the standard deviation of the cost, in Table 6.6, when delta is set to 0.5, the variability of the results, in multi-period models, are significant and increasing the length of the look-ahead from 3 to 7 results in increasing the standard deviation of the cost.

Table 6.5 Sensitivity analysis of the impact of prediction variation (Δ) on average cost obtained by different look-ahead

Length of Look-ahead	Average Cost (10 replications)				
	Δ= 0.1	Δ= 0.2	Δ= 0.3	Δ= 0.4	Δ= 0.5
Single-period	20155.35	22582.39	23508.63	26110.85	28253.03
3	16644.40	17194.81	19606.69	20466.91	22453.12
7	15612.13	16387.10	18143.76	19355.71	22576.05

Table 6.6 Sensitivity analysis of the impact of prediction variation (Δ) on standard deviation of the cost obtained by different look-ahead

Length of Look-ahead	std. dev. of Cost (10 replications)				
	Δ= 0.1	Δ= 0.2	Δ= 0.3	Δ= 0.4	Δ= 0.5
Single-period	2106.78	2960.20	4148.90	5120.42	7135.65
3	1860.65	2115.86	3493.15	4894.85	5545.61
7	1556.90	1710.40	3291.28	4708.94	5668.87

CHAPTER 7 CONCLUSION AND RECOMMENDATIONS

In this study, we focused on the operational planning level of an integrated multi-stakeholder consolidation-based transportation system called M1M that consists of three main components; many shippers (demand side), many carriers (supply side), and the IDSP, in the middle as the central decision-making platform. The main information for an M1M system is made up of shipper requests and carriers capacity offers that arrive to the system dynamically with various basic, time, and economic characteristics. Regarding the requests, we considered a decisional process where all the requests must be delivered. However, the decisions on the selection of capacity offers (regular and spot market for the requests that cannot fit into the selected offers), and shipment-to-service assignments should be made.

We considered two strategies for decision-making in this problem; 1) a myopic approach in which decisions are made based exclusively on the known information available now without taking into account what might happen afterwards; 2) a second strategy, look-ahead, where the decisions made now may have an impact on the follow up periods, and what happens in the near future may also influence the decisions we make now. Thus, look-ahead strategy integrates past, new, and predicted requests into decision processes. We represented the single-period and multi-period mathematical models proposed by reference [4]. The multi-period and single-period models were used to define the look-ahead and myopic strategies, respectively.

Due to the fact that we need to see how the system works, we are simulating the operations daily using the optimization models. The decision maker makes decision sequentially and several aspects of this process can be uncertain. For example, the decision maker can assume that the quantity and time feature of the requests are approximations of the real values. Regarding time characteristics, in general, the time availability of a request can be estimated, and it might arrive in the same time as it was predicted, or it might be postponed or cancelled. On the other hand, the offers might not appear in the system exactly as they were predicted as well. A change in some requests and offer characteristics could lead to an increase of the costs as well as delays and decreasing capacity utilization rate. Therefore, in each period, we specified the actual value of the current requests and offers through a simulation.

The rules are used to define policies in the process of sequentially making decisions. So, a policy shows how much a decision-maker is allowed to change his previously made decisions. In this study, we used a specific policy that just implements the decisions of the current period and, therefore, the decisions that have not been executed in the past and decisions made for future periods can be updated.

We further analyzed the results of the performed computational experiments in terms of the value of considering the look-ahead approach in this context. The experimental results showed that solving a multi- period model would be more beneficial because it allows for better consolidation and more efficient utilization of the offers. In the multi-period formulation, requests can be assigned to regular offers in the subsequent periods rather than shipped through the spot market at higher cost in the current period, which shows the advantage of the look-ahead decision-making strategy.

Several directions can be suggested for future research:

This study can be extended to a hyper-corridor network with intermediate terminals instead of focusing on a single-segment network with two terminals, origin and destination. Considering such a system, which involves additional consolidations, would be interesting and practical in different applications.

Moreover, the current study focused on one specific policy, while the performance of different policies in terms of the cost, time, and consolidation rate can be analyzed in future research. A possible extension to our implemented policy is to consider fixed decisions (for both offers selection and assignments) that can be extended beyond the current period (occurring in the subsequent periods). Such policies would be interesting to study in the context of a setting where the cost can vary greatly and a certain lead time might be required to implement operational decisions.

Additionally, in practice, different types of requests and offers are frequently encountered. As an example, perishable loads that require different humidity and temperature for storing could be considered, and consequently multipurpose capacity offers are also needed to carry these requests. Thus, various type of requests and offers could be taken in to account in a further study.

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