Invited Review

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Multimodal Freight Transportation Planning: A Literature review

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Abstract

Multimodal transportation offers an advanced platform for more efficient, reliable, flexible, and sustainable freight transportation. Planning such a complicated system provides interesting areas in Operations Research. This paper presents a structured overview of the multimodal transportation literature from 2005 onward. We focus on the traditional strategic, tactical, and operational levels of planning, where we present the relevant models and their developed solution techniques. We conclude our review paper with an outlook to future research directions.

Keywords: Freight Transportation Planning, Multimodal, Intermodal, Co-modal, Synchromodal, Review

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1. Introduction

Freight transportation is a key supply chain component to ensure the efficient movement and timely availability of raw materials and finished products (Crainic, 2003). Demand for freight transportation results from producers and consumers who are geographically apart from each other. Following trade globalization, the conventional road mode is no longer an all-time feasible solution, necessitating other means of transportation (and their combinations). In this regard, in 2010 about 45.8% of total freight transportation in European union countries were transported via road, 36.9% via sea, around 10.2% via rail, and 3.8% via inland waterways (EUROSTAT, 2012).

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The freight transportation market has witnessed several trends. In many parts of the world, new markets are rising and the customer base is growing. Furthermore, several trade regulations encourage easier and smoother international trade. Following the economic crisis in 2008, many industries browsed their business processes in order to decrease their costs and increase performance. As a consequence, shippers, carriers, and Logistics Service Providers (LSP) were urged to work at lower cost, while still maintaining high quality. Companies saw the solution in more cooperation and integration, as such utilizing resources more efficiently.

Besides economic factors, environmental concerns are high on the agenda. New regulations and taxes were raised to encourage companies to shift to more sustainable solutions. Clearly, in this context, efficient and effective transportation is needed, as the transportation cost share in the supply chain is significant (Ghiani et al., 2013).

A transportation chain is basically partitioned in three segments: *pre-haul* (or first mile for the pickup process), *long-haul* (door-to-door transit of containers), and *end-haul* (or last mile for the delivery process). In most cases, the pre-haul and end-haul transportation is carried out via road, but for the long-haul transportation, road, rail, air and water modes can be considered. As pointed out, long-haul transportation usually involves combining different modes, but also in pre- and end-haul transportation, more and more multimodal systems are observed (using a combination of trucks and bicycles in city logistics, for instance).

All literature discussed in this review paper focuses on multimodal freight transportation, most of which is containerized (growing around 15% annually). Key reasons for containerization are an increase in the safety of cargo, reduction of handling costs, standardization, and accessibility to multiple modes of transportation (Crainic and Kim, 2007).

The research in the area of multimodal transportation planning accelerated during the last decade, urging for an update. The chapter of Crainic and Kim (2007) on intermodal transportation, the review papers of Christiansen et al. (2007) and Bektaş and Crainic (2008), are the most recent review papers on multimodal transportation planning problems. These reviews cover the literature up to 2005. Therefore, this review paper includes research from 2005 onwards. Public transportation, the ‘pure’ pre-haul and end-haul transportation problems and city distribution planning are out of scope. The interested reader is referred to Laporte (2009) for an overview on vehicle routing solution developments and Parragh et al. (2008) for a review on pickup and delivery problems. To keep the length of this paper reasonable, the operational planning of multimodal terminals is also out of scope. The review paper by Stahlbock and Voß (2008) gives a nice overview in this field.

Over the years, different terminologies circulate in the literature and in the industry: *multimodal*, *intermodal*, *co-modal*, and more recently, *synchromodal* transportation. We give a definition for each here.

Multimodal transportation: Multimodal freight transportation is defined as the transportation of goods by a sequence of at least two different modes of transportation (UNECE, 2009). The unit of transportation can be a box, a container, a swap body, a road/rail vehicle, or a vessel. As such, the regular and express delivery system on a regional or national scale, and long-distance pickup and delivery services are also examples of multimodal transportation.

Intermodal transportation: Intermodal freight transportation is defined as a particular type of multimodal transportation where the load is transported from an origin to a destination in one and the same intermodal transportation unit (e.g. a TEU[1] container) without handling of the goods themselves when changing modes (Crainic and Kim, 2007). Intermodal terminals around the globe give companies the flexibility and the economies of scale of using multiple modes.

Co-modal transportation: This type of transportation focuses on the efficient use of different modes on their own and in combination. Co-modality is defined by the Commission of the European Communities (CEC, 2006) as the use of two or more modes of transportation, but with two particular differences from multimodality: i) it is used by a group or consortium of shippers in the chain, and ii) transportation modes are used in a smarter way to maximize the benefits of all modes, in terms of overall sustainability (Verweij, 2011).

Synchromodal transportation: Synchromodal freight transportation is positioned as the next step after intermodal and co-modal transportation, and involves a structured, efficient and synchronized combination of two or more transportation modes. Through synchromodal transportation, the carriers or customers select independently at any time the best mode based on the operational circumstances and/or customer requirements (Verweij, 2011).

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[1] Twenty-foot Equivalent Unit

It is striking to see the common aspects in all definitions: the use of more than one transportation mode. Of course, the devil is in the details and some definitions put more emphasis on certain aspects of the transportation process. Synchromodal emphasizes the (real-time) flexibility aspect, intermodal focuses on the same loading unit, and co-modal adds resource utilization. Note, however, that the basic definition of multimodal transportation does not exclude any of the other definitions. In our view, the definition of multimodal transportation is still valid and should be used rather than developing new definitions and/or new words. Multimodal is the broadest definition and includes the other notions. Additionally, the relevant Operations Research (OR) literature does not provide any additional explanations on the characteristics and (conceptual) formulations. Our review reveals that in the literature, multimodal and intermodal are used interchangeable. No OR literature is found where co-modal or synchromodal is used. In what follows, we use *multimodal* consistently.

The structure of our paper is similar to the previous review papers and is based on the decision horizon of the planning problems: *strategic*, *tactical*, and *operational* planning. In Section 2, we cover the recent literature on strategic planning problems. Section 3 presents the recent developments on tactical planning problems and Section 4 gives an overview on recent papers about operational planning problems. Finally, in Section 5 we provide overall conclusions and a fundamental prospective for future research. In total, we reviewed 78 papers, of which 28 papers are on strategic planning, 37 papers on tactical planning, and 13 papers on operational planning problems. We approached the different papers by looking at their motivations, the characteristics of the different encountered problems, and their respective solution methods. Every section then was built around more or less the same structure: (1) a description of the conceptual and mathematical models (2) the solution methods used and (3) the opportunities for future research based on the identified gaps.

2. Strategic Planning Problems

In this section, strategic planning issues encountered in multimodal freight transportation and the future development directions are presented. Strategic planning problems relate to investment decisions on the present infrastructures (networks). Table 1 and Figure 1 provide a structured view of the recent literature.

Table 1: Practical aspects of strategic planning problems

Reference	Mode	Multi-commodity	Allocation [1]	Direct Shipment	Capacitated	Transshipment	Scheduling Issues	Uncertainty Issues	Decentralized Decision Making	Additional objective components
Alumur et al. (2012b)	Road, Air	✓	S	✓			delivery due-date constraints			
Elhedhli and Hu (2005)			S							congestion costs
Elhedhli and Hu (2010)			S							congestion costs
Lei and Church (2011)	Road		S	✓					✓	total distance
Limbourg and Jourquin (2009)	Road, Rail		S	✓						transshipment costs
Lin and Lee (2010)	Road	✓	S		✓		delivery due-date constraints		competition	maximizing marginal profit
Meng and Wang (2011a)	Road, Rail, Ship	✓	S		✓	✓			✓	transshipment costs in maximizing marginal profits of carriers
Meyer et al. (2009)			S							longest transportation path
Rodríguez et al. (2007)			S				minimizing incurred delays			delay costs
Sim et al. (2009)			S					travel times		longest transportation path
Tan and Kara (2007)			S				delivery due-date constraints			number of opened hubs
Camargo et al. (2009)			M							
Gelareh and Nickel (2011)			M	✓						
Gelareh et al. (2010)	Ship		M	✓		✓	fixed-schedule services		✓	maximizing market share
Ishfaq and Sox (2010)	Road, Rail, Air		M	✓		✓	fixed-schedule services			setup costs (including fixed location and modal shift costs)
Ishfaq and Sox (2011)	Road, Rail		M	✓		✓	delivery due-date constraints and waiting times			fixed location setup and modal shift costs
Ishfaq and Sox (2012)	Road, Rail, Air		M	✓		✓	delivery due-date constraints and waiting times	operating times at hubs		fixed location setup and modal shift costs
Marín et al. (2006)			M	✓						
Racunica and Wynter (2005)	Road, Rail	✓	M	✓						
Rodríguez-Martín and Salazar-González (2008)		✓	M		✓					
Smilowitz and Daganzo (2007)	Road, Air		M	✓	✓		service level constraints	demand		operating and repositioning costs
Sörensen et al. (2012)	Road, Rail		M	✓	✓					
Vasconcelos et al. (2011)	Road, Ship		M	✓					✓	
Wagner (2008)			M				service level constraints			number of opened hubs
Yoon and Current (2008)		✓	M	✓						
Yaman (2011)			*r*	✓						
Yaman (2009)	Road, Air		H & S				delivery due-date constraints			
Alumur et al. (2012a)	Road, Air		H & M			✓	delivery due-date constraints			operating costs on links and hubs

[1] S: Single allocation, M: Multi-allocation, *r*:*r*-allocation, H: Hierarchical allocation

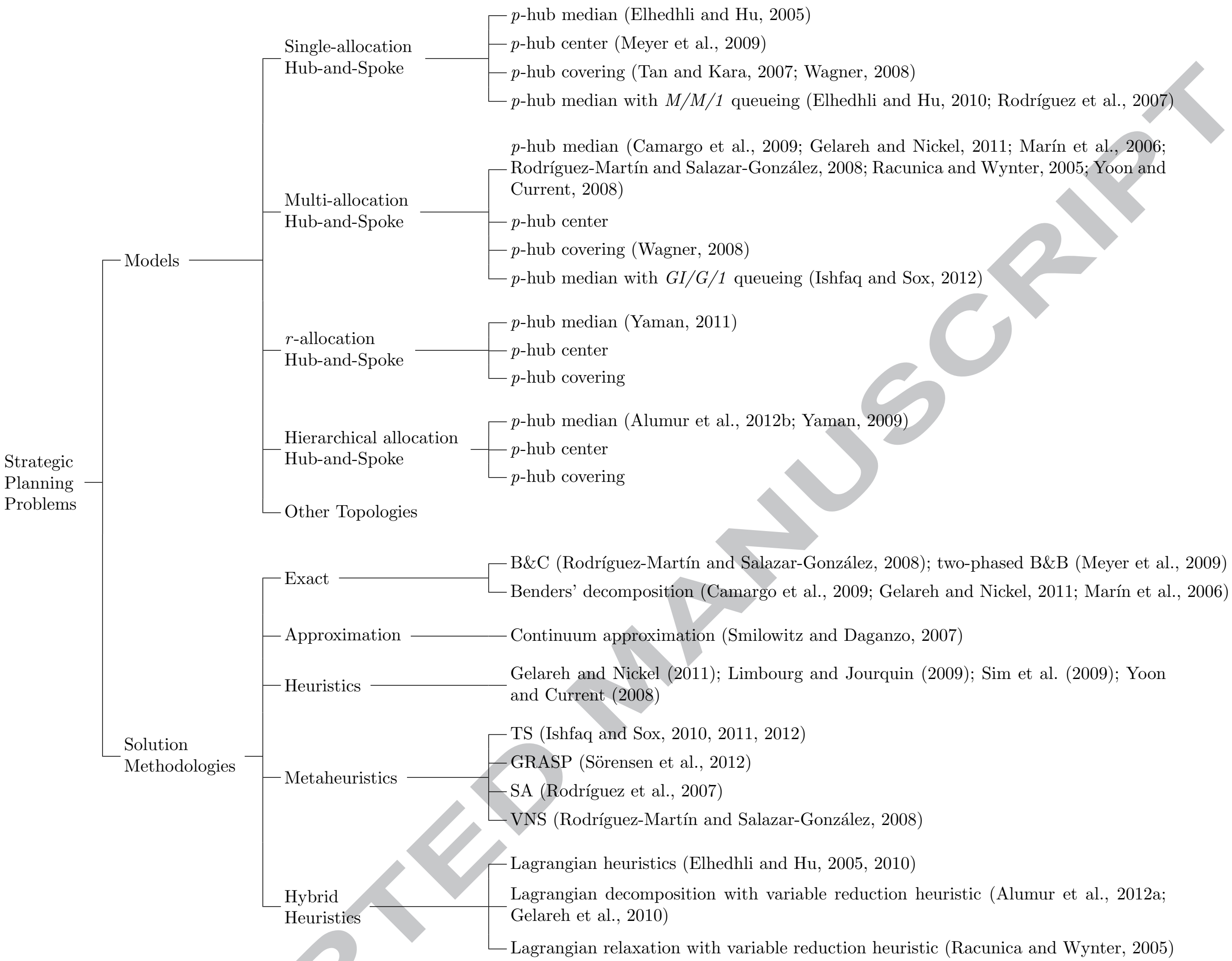

Figure 1: OR aspects of strategic planning problems

In order to maximize the utilization of multimodal transportation, consolidation is essential. In a *consolidation system*, instead of direct shipment of every cargo, low volume cargo is moved to a consolidation center and bundled into larger flows, transported by high-frequency and high-capacity multimodal services. These services have lower prices, expressed by *discount factors* per load unit, compared to other links.

Figure 1 shows the variety of **models** being used. In practice, there are various transportation network topologies: direct link, corridor, hub-and-spoke, connected hubs, static routes, and dynamic routes (Woxenius, 2007). In the literature, consolidation systems are mostly configured as *hub-and-spoke* networks, with *hub* being a freight handling (consolidation) facility. Locations of hubs are determined and *spoke* nodes are allocated to the hubs. These problems are called *hub location problems*. Figure 1 clearly reveals that the literature is concentrated on studying hub-and-spoke types of networks. No work is found on other network topologies. Depending on the real-world application, studying and comparing the various network topologies is interesting (Figure 2), both from theory and an application point of view. For instance, in transportation systems with waterways, the corridor topology seems promising.

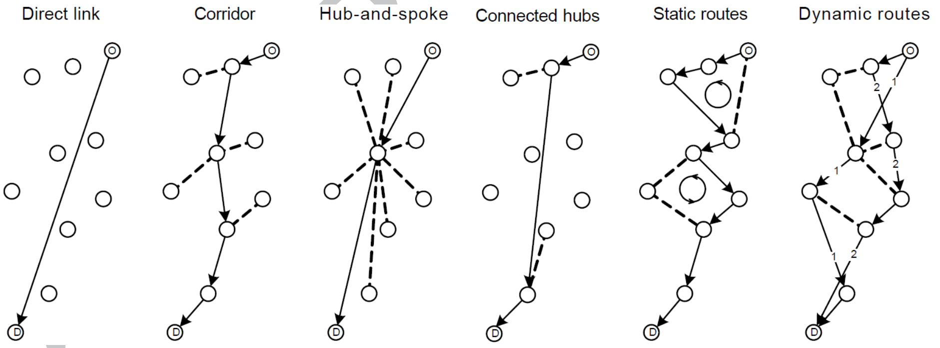

Figure 2: Six options for O/D transportation in a network of ten nodes. Dotted lines show operationally related links in the network design. In 'Dynamic routes', two alternative routes are shown. In all other designs, the routing is predefined (Woxenius, 2007)

In the literature, the hub location problem is commonly modeled as *hub median* or *hub center* problems (Meyer et al., 2009). The main objective of hub median problems is to minimize total transportation cost. If there is a maximum limit on the number of hubs, it is called the p-hub median problem. In hub center problems on the other hand, the objective is to minimize maximum distance (cost) between Origin-Destination (O/D) pairs. Next to these two formulations, hub location problems are sometimes modeled as *hub covering* problems where the objective function is to maximize the total number of served spoke nodes. For an extensive study on hub location problems, we refer to Alumur and Kara (2008).

Figure 1 shows that there are relatively few papers studying hub covering and hub center problems, compared to hub median problems. Where maximizing market share and customer recognition is the prime goal, hub covering problems offer the best approach to model them. In comparison, hub center problems are suitable for designs where immense worst-case O/D distance is not desirable, especially in time-sensitive delivery systems. These problems are interesting to study.

One of the assumptions generally made in hub location problems is that the interhub network is a complete graph, but the spoke nodes are not always interconnected. Direct shipment between spoke pairs is also not allowed and the flow of cargo traverses at most two hubs. In practice, especially on an international scale, such a rigid structure is unlikely. Direct shipment by trucks is commonly used, and complete multimodal networks are not feasible. These facts bring many modeling and methodological challenges which need more investigation. A considerable part of the literature has a direct shipment option in their model. However, only Rodríguez-Martín and Salazar-González (2008) and Alumur et al. (2012a) assume an incomplete underlying network.

The nature of products plays an important role in choosing the suitable hub location model, particularly in multi-commodity freight transportation. The hub median problem is widely used but the hub center problem is usually more suitable for planning huge networks, or planning delivery of perishable or time-sensitive cargos. Multi-commodity is critical in the distribution of sensitive cargo such as perishable and hazardous products. In practice, there are some preservation or safety restrictions in consolidating such cargo that affects their flow and might affect the design of the network. Our investigation (in Table 1) reviews few papers studying multi-commodity transportation which implies potential future research opportunities.

In addition to the topology discussions, the allocation of the spoke nodes to hubs plays a major role in hub location problems. There are different allocation policies of spoke nodes to the located hubs: single, multi-, r-, and hierarchical allocation. In *single allocation* problems, flow of spoke nodes can be assigned to only one hub, while in *multi-allocation* problems, flow of spoke nodes is allowed to be assigned to more than one hub node. In *r-allocation* problems, spoke nodes are allocated to at most r hubs. In *hierarchical allocation*, the interhub network, connecting only pairs of hubs has two levels. Spoke nodes are allocated to the first level hubs and these hubs are allocated to second level larger hubs.

The r-allocation hub median problem is a generalization of single and multi-allocation formulations where each spoke node is allocated to at most r hub nodes. This problem, introduced by Yaman (2011), aims to reduce the size of multi-allocation problems. Yaman (2011) proposes an uncapacitated r-allocation p-hub median problem where there are delivery deadlines, and direct shipment is permitted. She furthermore proposes several variations on this model and analyzes them for different values of r. For instance, one variation is the model where nodes with high demand values are allocated to more hubs, and nodes with low demand values are allocated to fewer hubs, resulting in distinct r values per hub. Other variations include service quality restrictions and delivery time restrictions, or considering the possibility of non-stop service between O/D pairs. Yaman (2011) analyzes these models based on the value of r and concludes that single allocation solutions may be more expensive than multi-allocation solutions, but allowing one or two more hubs may result in considerable savings in terms of the routing cost. Moreover, the resulting networks are likely to be much easier to operate and manage.

Hierarchical allocation hub median problems have a special structure of interhub network where there is a multi-level network of hubs, and each spoke node is allocated to one first level hub and each of these hubs is allocated to only one second level hub. Motivated by a cargo transportation system in Turkey, Yaman (2009) introduces a hierarchical hub median problem where traffic from an origin to a destination visit up to four hubs on its way. She also models a time restricted version of this problem where all cargo is required to be delivered to destinations within a given time bound and total routing costs is minimized. Later, Alumur et al. (2012b) propose a linear Mixed Integer Programming (MIP) formulation with some variable fixing rules and valid inequalities for the same problem, but with the difference that the objective function is to minimize total transportation and location costs per unit of time.

The r-allocation and hierarchical allocation hub median problems merit more research. The r-allocation reduces the problem size, interesting for solving larger sizes of instances. Solving the standard instances, r-allocation hub location problems spend less time reaching the optimal solution than a counterpart multi-allocation problem. On the other hand, hierarchical allocation problems are most suitable for large international networks with multi-level network of hubs.

The described models are solved using a variety of **solution methodologies**. To evaluate the performance of the solution algorithms designed in the literature (Figure 1), mostly the standard Australian Post (AP) and Civil Aeronautics Board (CAB) data sets are used. The CAB data set is relatively small and the majority of the literature is able to solve them to optimality in less than one hour. The AP data set on the other hand is larger (includes 200 nodes). Decomposition and relaxation approaches have been widely used and show promising results. However, the literature is able to find the optimal solution of instances with up to 30 nodes (Marín et al., 2006), or to reach a 9% optimality gap (Gelareh and Pisinger, 2011). Besides, the majority of the literature ignores capacity on the hubs and fixed costs of establishing the hubs. These elements make the problem even more difficult to solve. Rodríguez-Martín and Salazar-González (2008) propose a Branch-and-Cut (B&C) algorithm based on double decomposition, to solve a generated data set including up to 20 spoke nodes and 50 hubs. Their proposed algorithm is still not able to efficiently solve the instances of the capacitated hub median problem, but performs much better than a standard B&C algorithm with a Bender's decomposition. In practice, in a multimodal package delivery system for example, the number of served nodes and hubs are much more than the standard AP instances. Therefore, designing more powerful and efficient solution algorithms is needed.

Observing the literature, still many opportunities for **future research** exist. Capacity limitation on links and hubs is a first example. Capacity in consolidation systems causes significant congestion at hubs. Inclusion of congestion in hub location problems leads to more balanced distribution of flows throughout the network and decrease the operational costs of the crowded hubs. Elhedhli and Hu (2010), Rodríguez et al. (2007), and Ishfaq and Sox (2012) model the service at a given hub as queueing networks and include the congestion as the flow beyond the capacity. These are the few cases explicitly considering congestion leading to an interesting research direction in studying high-volume capacitated systems.

Another example of future research area is transshipment and its associated costs. Ignoring transshipment might result in suboptimal or infeasible solutions. In multimodal network design, transshipment are these operations at a multimodal terminal to shift flow from one mode to the next (Vis and de Koster, 2003). It fundamentally depends on technology and the equipment used to transfer operations. Studying feasibility, capacity, operation time and cost of transshipment in network design problems play a crucial role in multimodal transportation problems, especially with more than two modes. Ishfaq and Sox (2010, 2012) include both transshipment costs and a fixed cost to reflect modal choice in multimodal hub network design. They call this *modal connectivity cost*. The authors show in both papers that in comparison to over-the-road structure, design of multimodal networks is sensitive to the network parameters, especially to the cost ratio of transportation modes and this modal connectivity cost. Better insight in the cost structure of intermodal transport chains is one way to find necessary and effective policy actions for realising modal shift, which needs more research attention.

There has been limited attention on locating empty unit storage facilities. In consolidated systems, especially in containerized transportation, locating storage facilities for these resources are as important as locating the hubs. Consolidation operations are easier, faster and smoother, if the required empty units are available on time. Lei and Church (2011) seems to be the only recent work on this type of problems. They deal with locating empty container storage yard away from ports. Studying the performance efficiency and cost reduction resulting from integrating their location in conventional hub location problems is another interesting area of research.

In addition to all these issues, in strategic level planning, competition and cooperation considerations affect the market study. As a result, based on the market and the shares of individual companies, the design of the network, location and number of hubs alters. Lei and Church (2011) incorporate the greedy-like behavior of drayage companies in designing their network. Meng and Wang (2011a) include different stakeholders and investment budget limits, and suggest a joint U-shaped transportation cost function. Vasconcelos et al. (2011) study the cost reduction of adding a hub to the existing network, which they calculate by the percentage of loads moving through the new hub. Lin and Lee (2010) incorporate competition in their hub location problem, and maximize profit of all carriers. Gelareh et al. (2010) address the competition between an existing dominating operator and a newcomer liner service provider which tries to locate their hub in a way to maximize the number of attracted customers. Inclusion of cooperation and competition, and studying the role of individual decision makers merit more attention in the network design and its cost calculations.

Last, but not least, environmental issues and requirements bring challenges. It is generally accepted that multimodal transportation itself has environmental privilege compared to unimodal truck transportation systems. Still, this issue has not yet been studied in hub-and-spoke network design problems.

3. Tactical Planning Problems

Tactical planning problems deal with optimally utilizing the given infrastructure by choosing services and associated transportation modes, allocating their capacities to orders, and planning their itineraries and frequency. Table 2 and Figure 3 provide an overview of the literature discussed on tactical planning problems.

Deciding whether to send cargo direct or through a consolidation system entails a tradeoff influenced by system costs, operation times, network structure, and customer requirements. In the literature on tactical planning problems, mostly hub-and-spoke structures are regarded. Freight on hub-and-spoke networks is transported by a single service, or a sequence of services where the loads are transferred from one service to the next at intermediate terminals. A *service* is characterized by its origin, destination, and intermediate terminals, its transportation mode, route, and its service capacity. Likewise, a *mode* is characterized by its loading capacity, speed, and price. Usually, these services and modes have fixed costs.

Following Figure 3, there are two groups of **models**. The first group, *Network Flow Planning* (NFP), relates to the flow planning decisions addressing the movement of orders (commodities) throughout the network. The second group, *Service Network Design* (SND), involves the service planning decisions including all decisions on choosing the transportation services and modes to move those commodities.

SND problems are furthermore partitioned into *static* and *dynamic* problems. While in both groups one determines the frequency of the service, the capacity allocation, the equipment planning, and the routing and flow of commodities, in the former it is assumed that all problem aspects are static over the time horizon, and in the latter, at least one feature (e.g. demand) varies over time. Table 2 shows a growing body of literature in SND problems compared to NFP problems. This trend indicates that decision makers take the fixed cost of employing services into account and look for cost-efficient solutions.

Table 2: Practical aspects of tactical planning problems

Reference	Mode	Category [1]	Fixed Schedules	Assets [2]	Empty Flows	Elastic demand	Split delivery	Additional Scheduling Issues [3]	Transshipment	Uncertainty Issues	Decentralized Decision Making	Additional objective components
Chen and Miller-Hooks (2012)		F								disruption		maximizing resilience
Cohn et al. (2008)	Road, Air	F										cost based on modal price
Croxton et al. (2007)		F										
Huang et al. (2011)		F								disruption		
Meng and Wang (2011b)	Ship	F	✓		✓				✓			empty unit transport costs
Meng et al. (2012)	Ship	F	✓						✓	demand		maximizing net profit
Miller-Hooks et al. (2012)		F								disruption		maximizing resilience
Verma and Verter (2010)	Rail	F					✓	DD				bi-obj. incl. total exposure
Verma et al. (2012)	Rail	F					✓	DD				bi-obj. incl. total exposure
Anghinolfi et al. (2011)	Rail	S	✓			✓		DD	✓			transshipment costs plus penalty for not served demands
Ayar and Yaman (2012)	Road, Ship	S	✓					DD				penalty for waiting at terminals
Bektaş et al. (2010)		S										capacity violation penalty
Caris et al. (2012)	Barge	S	✓		✓						✓	arc fixed costs, terminal waiting costs, penalty for empty capacity, and cooperation costs
Crainic et al. (2006)		S										
Chang (2008)	Road, Air, Ship	S	✓						✓			bi-obj.: travel cost; travel time
Cho et al. (2012)	Rail, Air, Ship	S						DD				bi-obj. incl. total travel times
Chouman and Crainic (2011)		S										
Gelareh and Pisinger (2011)	Ship	S	✓			✓			✓			maximizing net profit
Hsu and Hsieh (2007)	Ship	S	✓						✓			bi-obj. incl. fuel costs, transshipment costs and inventory costs
Lin and Chen (2008)	Road, Air	S	✓		✓			DD	✓			transshipment costs
Minh et al. (2012)		S		S	✓							
Pazour et al. (2010)	Road, Rail	S										bi-level: min. time, max. benefit
Shintani et al. (2007)	Ship	S	✓		✓				✓			maximizing net profit
Agarwal and Ergun (2008)	Ship	D	✓						✓			maximizing net profit
Andersen and Christiansen (2009)	Rail	D	✓		✓			VT	✓	travel times		maximizing net profit
Andersen et al. (2009a)		D	✓	S	✓							
Andersen et al. (2009b)	Rail	D	✓	S	✓			Synch				waiting times
Andersen et al. (2011)		D	✓	S	✓							
Bai et al. (2012)		D	✓	S								
Bauer et al. (2010)		D	✓		✓							emission costs
Hoff et al. (2010)	Road	D	✓				✓			demand		system costs, ad hoc capacity increase cost, handling and storing costs
Lium et al. (2009)	Road	D	✓		✓		✓			demand		system costs, ad hoc capacity increase cost
Moccia et al. (2011)	Road, Rail	D	✓				✓	FS	✓			
Pedersen et al. (2009)	Rail	D	✓	S	✓							
Puettmann and Stadtler (2010)		D	✓		✓			DD		demand	✓	outsourcing costs for drayage carriers, transshipment costs for intermodal operator
Teypaz et al. (2010)		D		S		✓		1D	✓			maximizing net profit
Zhu et al. (2011)	Rail	D	✓	M	✓				✓			

[1] F: Flow network planning, S: Static SNDs, D: Dynamic SNDs
[2] S: Single asset, M: Multi-asset
[3] DD: Delivery Deadline, FS: Flexible Schedules, VT: estimating Value of Time, 1D: one-period Delivery, Synch: Synchronization

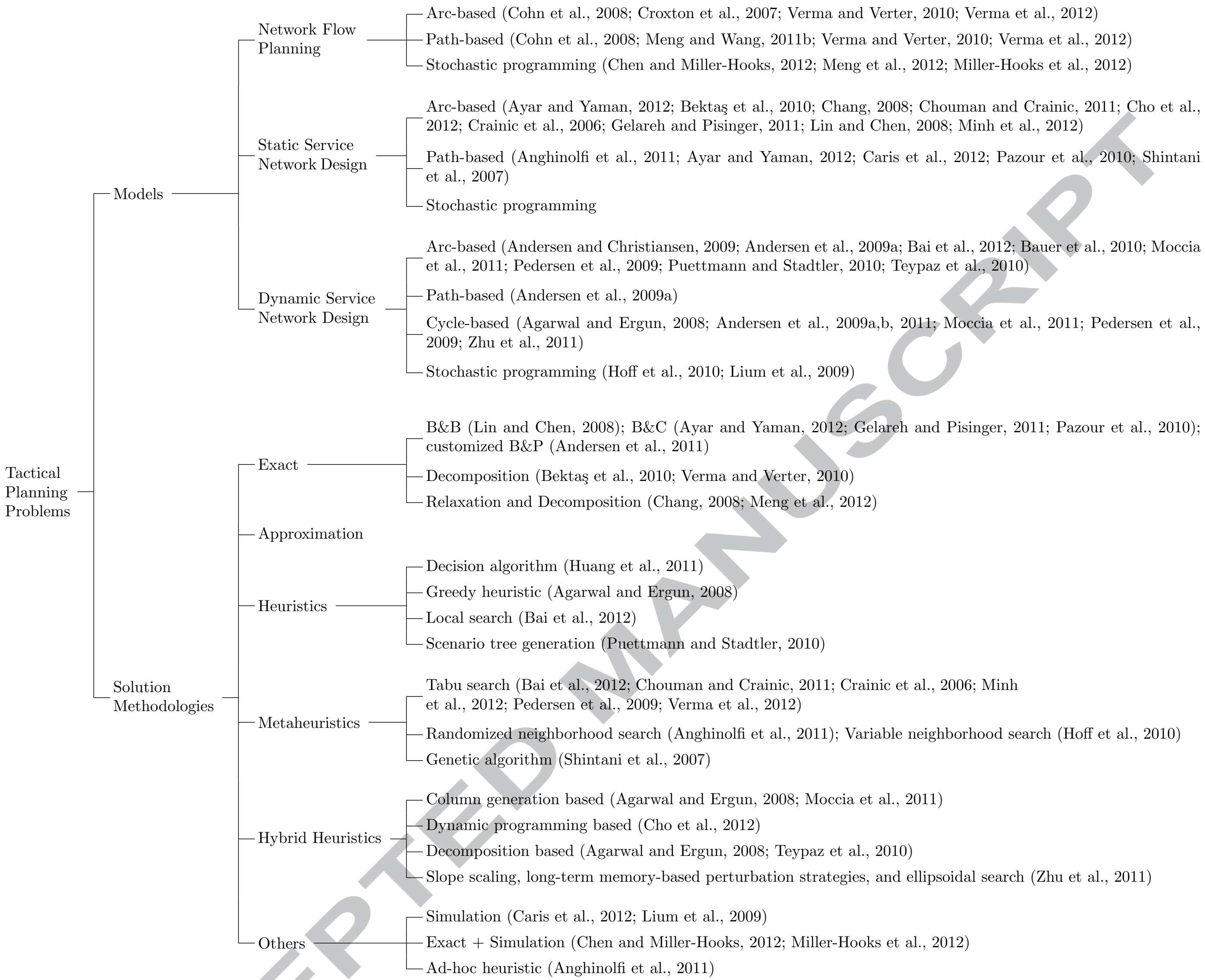

Figure 3: OR aspects of tactical planning problems

In both NFP and SND problems, continuous variables are used to represent commodity flows throughout the network, but in SND problems, binary variables are included for selection of services. The variables can be *arc-based* representing flow on an arc or *path-based* representing flow on a path (a series of arcs). SND problems are then modeled as Fixed-Cost Capacitated Multicommodity Network Design (CMND) problems.

Dynamic SND problems have a time dimension in the CMND formulation, making it a discrete multi-period model. Therefore, the SND problem is mapped both in time and space, and each node in the new network represents a terminal at a time period. This *space-time* network has the potential to accommodate many real-life properties of SND problems. An example is waiting or transfer operations at a terminal, represented by arcs connecting different time periods with the same locations. Another example is different transportation modes, represented by additional arcs. Such arcs can therefore accommodate different costs for terminal operations and modal costs. For an overview on dynamic SND problems, we refer to Wieberneit (2008).

In addition to planning flows of commodities, routing, and scheduling of services, managing limited available resources (assets) are also integrated with SND problems. *Assets* can be containers, vehicles, crews, power units, engines, etc. Positioning, balancing, repositioning, and rotation of assets are the subject of asset management. Assets follow a "full-asset-utilization" policy ensuring that the composition, capacity, and other characteristics do not change over the planning horizon. *cycle-based* variables can be used to integrate the mode or vehicle rotation over the planning horizon into SND models. In this order, backward arcs connecting later time periods to earlier ones are used to represent cycles and rolling horizons. Figure 4 gives an illustration of a space-time network with cycle arcs.

In NFP and SND problems, arc-based variables are mostly used (Figure 3), while path-based and cycle-based formulations, particularly in dynamic SNDs where the physical network is multiplied by the number of time periods, are computationally interesting to study. A cycle-based formulation as soon as the cycles are enumerated, outperforms the arc-based formulation in both time and solution quality (Andersen et al., 2009a). Andersen et al. (2009a) show that compared to the arc-based formulation which yield 5% to 20% gap, the cycle-based formulation exhibit gaps from 1% to 5%. However, the drawback is that by increasing the number of periods in the planning horizon, the number of cycles to be generated grows exponentially and generating them needs smart enumeration algorithms. To cope with this problem, Andersen

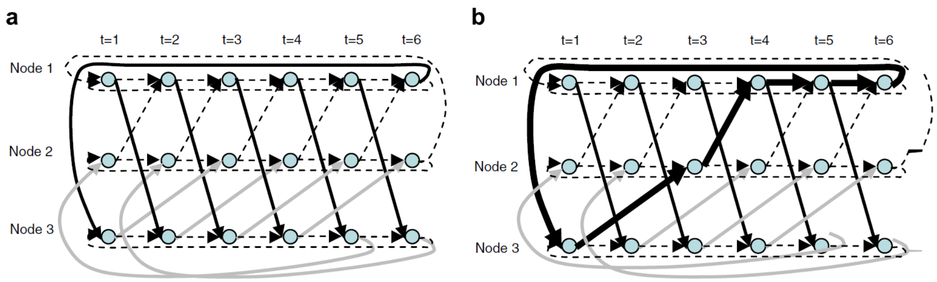

Figure 4: (a) Space-time network with three nodes and six time periods. (b) Example of a feasible service plan. (Andersen et al., 2009b)

et al. (2011) design a customized Branch-and-Price (B&P) algorithm for the problem presented Andersen et al. (2009a) and show its superiority to the other common exact algorithms. In their proposed algorithm, they integrate two column generation subproblems for integer cycle design and continuous flow-path variables. They also use a combination of branching strategies, a mechanism to dynamically add violated strong linear relaxation cuts, and an acceleration technique based on depth-first search to speed up finding integer solutions.

Solving NFP and SND problems due to their large set of variables is difficult. Figure 3 presents the **solution methdologies** used, and clearly shows that due to complexity of these problems, heuristic and metaheuristic solution methods are the prime choice. Among them, Tabu Search (TS) seems to be a popular metaheuristic algorithm (Bai et al., 2012; Chouman and Crainic, 2011; Crainic et al., 2006; Minh et al., 2012; Pedersen et al., 2009; Verma et al., 2012). However, we found no paper applying approximation techniques, which is an interesting research opportunity.

In order to evaluate the performance of the proposed algorithms, good benchmark sets are needed. The majority of the research on tactical planning level address specific real-world problems and the algorithms designed for those problems. Thus, a solid analysis on the efficiency of different algorithms, due to the lack of general benchmark sets, is not attainable. We can only mention some of the interesting results obtained by the researchers. For instance, Bektaş et al. (2010) compare arc-based and flow-based decomposition methods in solving small sizes of their nonlinear problem, and show that despite the fact that the arc decomposition has a better convergence, it takes more time compared to flow-based decomposition. In overall, both techniques handle the nonlinearity efficiently.

Zhu et al. (2011) compare the performance of their hybrid algorithm with a state-of-the-art solver for small to medium sizes of a randomly generated data set. They show that their algorithm outperforms in computational time and even solution quality when instance size grows. For instance, the combination of slope scaling and long-term memory-based perturbation achieves on average 21% improvement in solution gap in 10 hours compared to the solver. Inclusion of ellipsoidal search even improves the solution gap by 2% more. For small instance, this hybrid algorithm finds the optimal solution of 5 out of 7 instances and reaches a gap of 0.13% for the others.

Ayar and Yaman (2012) use a real world data set with 34 nodes and 167 services, and generate a random network of 66 nodes and 1200 arcs, and test them for 400 up to 1000 commodities. Their first conclusion is that by increasing the number of commodities, the optimality gap decreases. Moreover, adding valid inequalities and variable fixing strategies result in significant improvements both in time and solution quality. All their instances are solved to optimality within 6 minutes. Ayar and Yaman (2012) also investigate variable fixing based on capacity restrictions, but in overall, it does not bring much improvement to their previous valid inequalities and variable fixing strategies.

The work of Pedersen et al. (2009) is one of the examples of using TS as the base of solution algorithm. They use the instance sets of Crainic et al. (2000) and Ghamlouche et al. (2003). In comparison to a MIP solver, their algorithm shows robustness, and even outperforms the solver in 33 cases of the 78 instances they tested. Although the tuning of TS is dependent to the instance characteristics, in instances with particular structures like high fixed-variable cost ratio and/or loose capacity, TS outperforms the MIP solver. With the use of an independent multisearch strategy, Pedersen et al. (2009) could furthermore improve the results to 2% more. However, their TS still stands as a powerful algorithm.

Adding to the aforementioned discussions, we see many other opportunities for **future research**. Overall, Table 2 shows that little work has been carried out on integrating asset management in SND problems, while in multimodal transportation, especially in containerized shipment, more than one type of loading units are involved, and repositioning their empties is costly. Furthermore, these assets require simultaneous allocation planning. As an example, crew scheduling is usually studied independently, but it also depends on the service schedules, and embedding it in SND problems is expected to provide higher performance efficiency. In recent literature, Zhu et al. (2011) extend the conventional SND and include car classification and blocking, and train make-up in a railway system. Their space-time modeling includes three layers for service, block, and car. They design a hybrid metaheuristic algorithm combining slope scaling, long-term memory-based perturbation strategies, and ellipsoidal search method, which can solve problems with up to 10 yards, 60 tracks and 3050 services. In solving small sized instances, in case their model cannot find the optimal solution in 10 hours, it reaches an optimality gap of 0.13%. Moreover, in solving bigger sizes, it outperforms a commercial solver both in time and solution quality.

Another capital aspect of multimodal transportation systems worth more consideration is the transshipment of loads at terminals and its effects on the performance of the whole system. *Transshipment* is usually implicit in multimodal transportation tactical planning, though feasibility of operations, especially in the presence of fixed timetables depends on explicit study of transshipment operations and their related costs. Meng and Wang (2011b) only impose a constraint on maximum berth occupancy time for each ship deployment plan, and Anghinolfi et al. (2011) also include a restriction on maximum handling operations for each train at a given terminal. Still, these research works do not assess any explicit costs to these operations. Gelareh and Pisinger (2011) subtract a general transshipment costs (per container at a given port) from the revenue in their objective function. Hamzaoui and Ben-Ayed (2011) integrate transshipment costs into a handling cost per container, which also includes loading and unloading costs. Andersen and Christiansen (2009) study the issues of border crossing and embed the handling costs in terminals into unit flow cost.

Some papers include detailed transshipment operations and their costs. Hsu and Hsieh (2007), in addition to servicing costs such as ship pilotage and berth occupancy, consider cargo handling, equipment charges, and inventory costs into their cost function. Shintani et al. (2007) have port related costs and cargo handling costs which are subtracted from revenue in their objective function. Hoff et al. (2010) explicitly include inventory holding costs at terminals into their objective function, and Zhu et al. (2011) include restrictions on maximum track occupation of trains at terminals and maximum number of block-building workload at each period, along with costs related to these operations into their model.

Transshipment becomes more critical in the presence of cut-off times and when synchronization of the system plays an important role in on-time delivery of time-sensitive products. Andersen et al. (2009b) seem to be the only one taking synchronization into account. They extend the work of Andersen and Christiansen (2009) by including the synchronization within the system and with the neighboring systems. They conclude that by more collaboration and integration of transportation systems, significant improvement in performance can be achieved. In order to have a synchronized transportation system, studying transshipment, its conditions, and costs offers another interesting future research direction.

However, synchronization of operations might fail if uncertainty is ignored. Assuming the planning elements such as coming demand as deterministic generates suboptimal solutions, redundant costs and less efficiency. Among various types of uncertain factors, stochastic demands are studied mostly, and modeled as multi-stage stochastic programs (Hoff et al., 2010; Lium et al., 2009; Meng et al., 2012; Puettmann and Stadtler, 2010). Stochastic demand is not the only source of uncertainty. Andersen and Christiansen (2009) study the variability of travel times in their service network design, but with a different modeling approach. They add a slack variable that represents this variability, set a penalty cost for it in their objective function, and analyze the utilization of their fleet based on positive values of this variable.

Moreover, a reliable transportation network is a network that can recover from any disruption by preventing, absorbing, or mitigating its effects. Unexpected incidents like traffic jam, accidents, storms, hurricane, etc. can cause disruption on a link or in a terminal. In multimodal transportation planning, providing reliable but cost-efficient services is a hard task. If the designed network is flexible enough, disruption might be absorbed by the normal plans, but if this flexibility has not been deliberated, recovery plans are required to revive the system and keep the promised service levels. In multimodal transportation, such recovery plans usually involve service and modal change. In the recent literature, Huang et al. (2011), Chen and Miller-Hooks (2012), and Miller-Hooks et al. (2012) take disruption and required recovery and preparedness actions into account. Huang et al. (2011) compare the forecasted delay on a distressed link to the tolerance threshold of the next link, and if the delay crosses the threshold, a re-routing with the smallest deviation and least cost is made. Chen and Miller-Hooks (2012) define an indicator of network resilience to assess the vulnerability of a time-definite network and make a priori investment decisions for recovery action with a given budget. *Resilience* is defined as the ability of a network to cope with disruption via its topological and operational attributes. Miller-Hooks et al. (2012) extend this work by including *preparedness* actions that can provide increased recovery capability and increased coping capacity. Chen and Miller-Hooks (2012) omitted preparedness actions in order to decompose the problem into independent deterministic subproblems.

Huang et al. (2011) comprise forecasting decisions, propose a decision model based on an optimization model and an improved depth-first search method. Chen and Miller-Hooks (2012) design a framework employing Benders' decomposition, column generation, and Monte Carlo simulation, and Miller-Hooks et al. (2012) present an integer L-shaped method and Monte Carlo simulation to solve this problem. Although all these three groups test their models on small instances, they provide interesting results. For instance, both Chen and Miller-Hooks (2012) and Miller-Hooks et al. (2012) indicate that competing measures such as reliability and flexibility that do not consider recovery actions may underestimate the network's ability to cope with unexpected events. In fact, a network may not be very reliable or flexible, but may be resilient or may be reliable or flexible, but not sufficiently resilient. Moreover, the maximum resilience is obtained from taking both preparedness and recovery options, and the more the budget is spent on preparedness options, the greater the benefits would be.

Disruptions are usually dealt with at the operational level, treated by the costly last minute solutions. However, the impact of a disruptive event and its aftermaths on the performance of a multimodal transportation system is dramatic and might result in the complete failure, especially in a large-scale international scope. Reflecting reliability and resilience into the tactical planning shows great improvement in the operations, implying that designing suitable pre-disaster and post-disaster actions requires further attention.

In Section 2, we give an argument on the importance of the role of decision makers in the planning. On tactical level planning, the collaboration or competition of carriers influence the service level, the synchronization, and the system performance. In practice, an independent party manages each hub and leg of a multimodal transportation network. In the presence of their cooperation, for instance, a terminal operating company receives the information on the arrival of a ship or trains early enough to plan the necessary unloading, transshipment and loading tasks. In addition, the cooperating carriers can react to disruptions faster, using vehicles, modes, and resources of each other. Puettmann and Stadtler (2010) test the idea that collaboration reduces the operational costs on a chain with one multimodal operator and two carriers responsible for pre-haul and end-haul drayage. In their scheme, the three parties do not exchange any information and plan their own operations, however they iteratively exchange proposals and their cost effects are compared to the solution without coordination. Due to the time lag between the departure and arrival of orders, they include stochastic demand in their scheme, which calls for adaptation of plans. The authors present three models for the proposal generation for the involved parties and use a scenario tree generation to quantify the expected gain of coordination. At the end, they conclude that transportation parties can significantly reduce in operational costs by collaboration.

From a different point of view and motivated by a Belgian barge transportation network, Caris et al. (2012) study a SND problem focusing on cooperation of inland terminals and line bundling. They define different cooperation scenarios and analyze them by means of simulation. The authors conclude that given the current transport volumes, more bundling opportunities may be created by reducing the number of departures or setting up a truck collection/distribution network. However, reducing the number of departures may lead to less service offered to customers. This can be solved by more cooperation between inland terminals to attain economies of scale and to reduce maximum waiting times for inland barges at sea terminals.

In SND problems, the individual role of the stakeholders is usually ignored and it is assumed that the whole transportation system is managed by a central party (namely multimodal operator). While in practice, each company has its own goal and policies, and shares limited data with others. Furthermore, these companies are competing with each other, keeping the market dynamic and vibrant. Inclusion of cooperation and competition in tactical planning problems merit more research.

Multimodal transportation service network design is in practice a complex problem with thousands of variables and constraints. With better study of the problem structure and design of smarter solution algorithms, it should be possible to derive more accurate solutions in less computational time.

4. Operational Planning Problems

On operational planning level, we still look for the best choice of services and associated transportation modes, best itineraries and allocation of resources to the demand. However, we need to answer the real-time requirements of all multimodal operators, carriers and shippers. Operational

Table 3: Practical aspects of operational planning problems

Reference	Mode	Problem Type [1]	Assets [2]	Transshipment	Synchronization	Additional Scheduling Issues	Multiobjective	Uncertainty Issues	Decentralized Decision Making	Additional objective components
Bandeira et al. (2009)	Road, Rail	FMRA	S							all costs related to transportation of empty units
Chang et al. (2008)		FMRA	S							
Erera et al. (2005)	Road, Rail, Ship	FMRA	S			plus unscheduled services				repositioning and cleaning costs of containers
Di Francesco et al. (2013)	Ship	FMRA	S			one-day earlier scheduling		disruption		shortage costs
Lam et al. (2007)	Ship	FMRA	S					demand		
Song and Dong (2012)	Ship	FMRA	S	✓						terminal and replenishment costs
Topaloglu (2006)		FMRA	S					demand and travel times	✓	
Topaloglu (2007)		FMRA	S					demand and travel times	✓	
Topaloglu and Powell (2005)		FMRA	S					demand	✓	
Topaloglu and Powell (2006)		FMRA	S					demand		
Topaloglu and Powell (2007)		FMRA	S							
Bock (2010)		IRP		✓	✓	Driver's rest time		travel times	✓	transportation costs of owned and outsourced, loading and unloading costs, tardiness costs incurred due to late deliveries and late pickups, and vehicle fixed costs
Goel (2010)	Road, Rail	IRP		✓				travel times	✓	costs arising if customer demands cannot be satisfied in time (stockout costs)

[1] FMRA: Fleet Management and Resource Allocation, IRP: Itinerary Re-Planning

[2] S: Single asset, M: Multi-asset

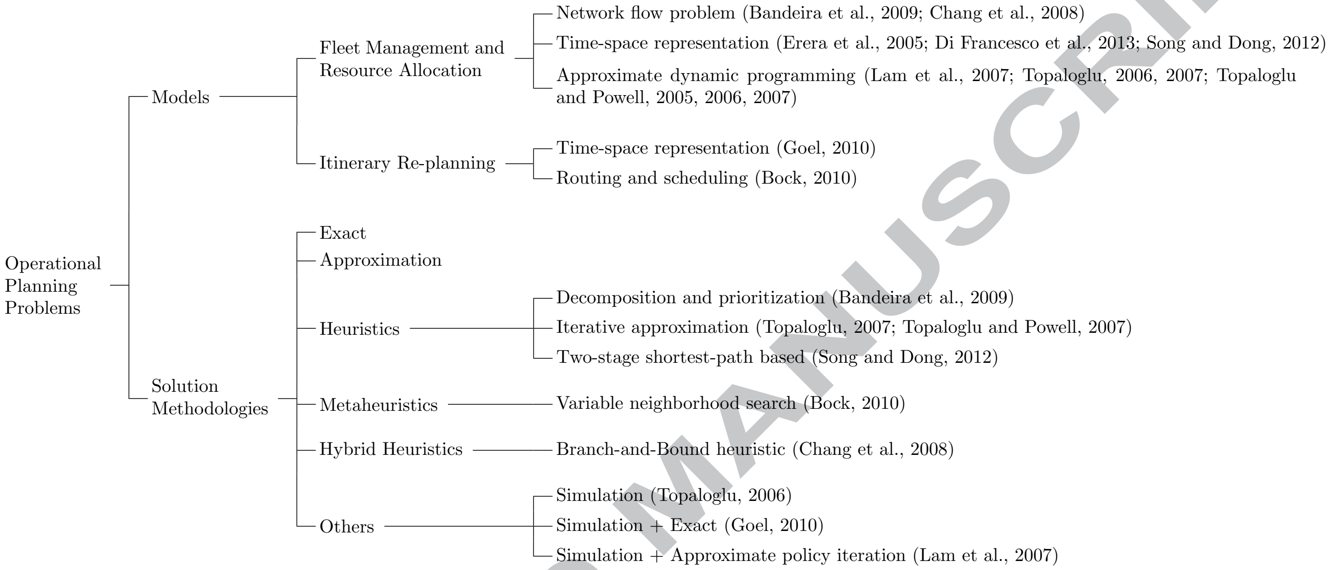

Figure 5: OR aspects of operational planning problems

planning deals with dynamicity and stochasticity that are not explicitly addressed at strategic and tactical levels. These characteristics make operational planning problems remarkably complex. Hence, designing accurate and fast solution algorithms is then essential. Table 3 and Figure 5 provide a structured view of the literature addressing operational planning problems.

These problems relate to real-time planning for orders, and reaction and adjustment to any kind of disturbance (e.g. accidents, weather changes, or equipment breakdowns). Most of these system elements vary with time and show a non-deterministic behavior. Current decisions depend on both the present information and an estimation of the future, and the objective is not only to minimize the costs, but also to maximize reliability of the system. Table 3 and Figure 5 reviews the relating little work that has been carried out on operational planning problems.

In order to discuss the different problems, models and solution methodologies, we group the operational planning literature under two main topics: resource management and itinerary replanning. *Resource Management* problems deal with the distribution of all resources throughout the network: positioning, repositioning, storing, and allocating them to customer orders. *Itinerary Replanning* problems are focused on real-time optimization of schedules, modal routes, and relevant response to operational disturbance. Resource management and itinerary replanning problems are in practice intertwined and act as two components of a bigger operational planning problem. In the followings, for each group, we discuss the recent developments on modeling and solution methods.

Resource management are problems on how and when to optimally utilize the limited available resources. Some examples of these resources are vehicles (e.g. planes and trucks), trailers, rail cars, locomotives, containers, equipments, crew, power, etc. Once a resource is allocated to an activity, it is no longer available for certain duration. Moreover, when it becomes available again, it is often at a different location where it is not needed (Crainic, 2003). Empty loading unit repositioning and fleet management problems are more specific variants of resource management problems.

In *empty loading unit repositioning*, there is a set of empty and reusable loading units that should be shipped back from the location they are emptied to the locations they are needed. These loading units do not directly incorporate in the profit of transportation, but guarantee requested service level. In empty repositioning problem, future customer demand is unknown and the objective function is to minimize empty transportation plus storage costs, stockout costs, and in some cases, substitution costs. These problems are usually **modeled** as NFP problems with continuous variables to represent the movement of the loading units. In the literature, Erera et al. (2005) compare a base repositioning strategy (a current state-of-the-practice) with three alternative strategies which integrate the repositioning and routing of the containers simultaneously. These three strategies are weekly, bounded daily, and unbounded daily repositioning. Erera et al. (2005) compare these strategies on a network with 10 ports and 900 orders and up to 1000 containers. They show that the proper timing of repositioning is more important than deciding on the number of containers to be repositioned, and unbounded daily repositioning in overall is the best strategy.

Chang et al. (2008) investigate the substitution between containers of different types and its interchange cost reduction. *Container substitution* is defined as fulfilling the requests of one type of container with another type. In their paper, street-turn and depot-direct movement are allowed; therefore, empty containers can directly be transported among customers without passing through the terminals. They show that with substitution, port trips can be reduced by 70% and transportation costs from 4% to 47%.

These papers exclusively study empty repositioning of loading units. However, none of them includes uncertainty or disruption (at locations or on the routes) into account. Di Francesco et al. (2013) study the effect of partial or complete port disruption in empty container repositioning in a liner shipping system. They model it as a time-space representation and consider a set of different disruption scenarios. They also include some non-anticipativity conditions to equalize the here-and-now decision variables over all scenarios. Di Francesco et al. (2013) test all combinations of a problem including 5 locations (2 hubs), a 50 period rolling horizon scheme, 2 (normal and disrupted) scenarios, and 2000 customer orders. They show that in case of a normal scenario, the optimal deterministic solutions are the best, but in case of a disruption, the multi-scenario model produces the most effective results. Di Francesco et al. (2013) show their model is able to handle 12 disruption scenarios with up to 20 location in less than one hour.

In order to solve empty repositioning problems, different heuristics have been applied as the **solution methodologies**. Chang et al. (2008) test their Branch-and-Bound (B&B) heuristic on a transportation systems with 12 consignees and 8 shippers, 2 local container depots and 1 container terminal, and up to 985 containers. Bandeira et al. (2009) implement decomposition and prioritization approaches on a 4 depot case with 4 to 8 clients. They test and analyze the performance for different sizes of container fleet from 48 to 216 containers. Their computational time ranges from 9 to 8800 CPU seconds. Bandeira et al. (2009) show that the suitable number of containers is highly dependent on the system parameters, and uncertainty makes the decision more difficult. For an integrated forward and backward planning of container fleet, Song and Dong (2012) analyze their shortest-path algorithm on two small and medium sized instances with 8 and 24 locations, 24 vessels, and 80000 containers. Their solution method in both cases provides better performance compared to the state-of-the-practice method, and the heuristic is only 3.3% worse than the exact algorithm in solving the small sized case. Even though it takes almost triple of computational time compared to the practice, in less than one hour the proposed heuristic provides a solution 89% better than the state-of-the-practice.

In addition to planning the allocation and positioning of empty loading units, the allocation and positioning of the operating fleet is also important but hard. In *Fleet Management*, there is a limited set of vehicles with limited capacity and the problem is to optimally allocate the capacity of this fleet to the random future orders, or allocating the vehicles to defined services, in order to maximize net profit. These problems also include decisions of repositioning empty vehicles, transshipment, and many others. Overall, in both variants of resource management problems, balancing the distribution of resources is the core of these highly dynamic problems.

The early well-known approaches **modeling** dynamicity were the space-time representations where the stochastic and time-dependent version is decomposed into with space and time indexed subproblems, and the impact of the current decision on the future is assessed by value functions. Due to the high number of possible load realizations, realistic problem sizes, and integrality requirements, Benders' decomposition and general stochastic techniques such as scenario-based methods or dynamic programming seem not feasible for computing the value functions arising from practice. Therefore, most of the stochastic fleet management models revolve around the idea of approximating the value function in a tractable manner. This class of problems has been well studied but is still under further developments.

Topaloglu and Powell (2005, 2006, 2007) are some of the recent examples of fleet management problems modeled as *Approximate Dynamic Programming* (ADP). Figure 6 gives an illustration of the essence of ADP problems. These studies offer a nice framework for modeling and solving a variety of real world problems, especially those including time windows or labor restric-

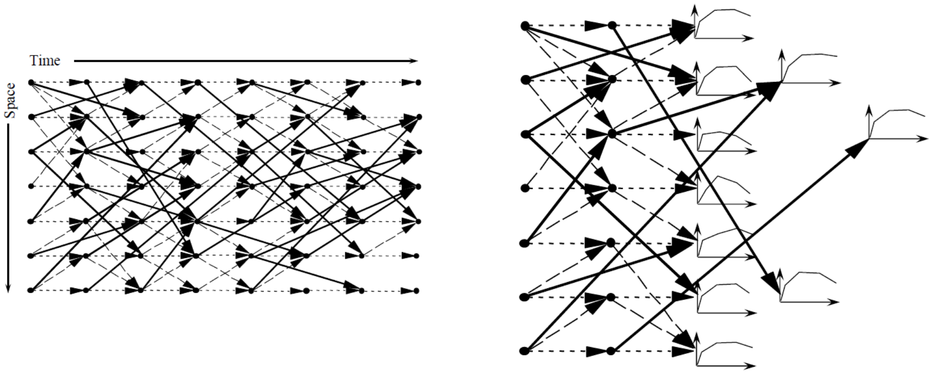

Figure 6: ADP solves sequences of smaller subproblems. (Left) A typical space-time network used in dynamic resource allocation; (Right) Some smaller subproblems. We need an approximation to capture the impact of present decisions on the future. (Powell, 2008)

tions, by addressing them at the level of the local subproblem. Topaloglu and Powell (2006) extend previous works on ADP models for fleet management to include heterogeneous resources and substitution among them. Their method uses a hybrid of linear and piecewise-linear approximations of the value function. Topaloglu and Powell (2007) develop sensitivity analysis methods for a stochastic dynamic fleet management model to compute the change in the objective value in response to changes in fleet size and load availability. Topaloglu and Powell (2005) extend the dynamic resource allocation problem to a distributed decision-making case. They use nonlinear functional approximation to model the coordination of actions of different agents.

Basically, simulation and approximation are used as **solution methodologies**. Topaloglu and Powell (2005) solve instances with 20 locations, 200 vehicle, and up to 6000 orders, and claim that in the deterministic version of the problem, the solutions are near-optimal, but in the stochastic version with random demands, centralized decision making is slightly more effective than distributed decision making. Topaloglu and Powell (2006) model and solve the problem with up to 60 locations, 600 vehicles, and 4000 orders. The hybrid value function seems to perform the best in the deterministic case, while piecewise linear value function provides the best solutions in the stochastic case. Topaloglu and Powell (2007) propose an approach which does not need multiple simulations with different values of the model parameter which is an important advantage. They decompose their dynamic program into time-staged sub-problems and by using an iterative improvement scheme; the value function is obtained with approximation. These test are done on problem sets with 40 locations, 200 vehicles, and up to 3000 orders during their planning horizon. Topaloglu and Powell (2007) implement this procedure first for single vehicle type and then extend it to the multiple vehicle type problem. Overall, ADP with good approximation of value function stands strong in solving fleet management problems with realistic sizes.

The *itinerary replanning problems* form our second group of operational planning problems. They are concerned with optimally responding to real-time system evolution, to maximize the service quality and therefore the marginal profit. Here, the notion of a planned solution does not make sense and the whole operation should continuously react and adapt in real-time (Crainic, 2003). The updating procedure, its accuracy and speed have a major influence on the efficient performance. Moreover, a single model or a solution approach no longer is capable of handling these complex problems. As such, there is a need to employ combinations of approaches, not only from the OR area, but also decision-making and computational sciences.

There is no doubt that ICT as well as tracking technologies such as RFID opened up many opportunities for carriers and shippers for a better trade. Crainic et al. (2009) gives an overview of different developments and current technological challenges in Intelligent Transportation Systems (ITS), both in hardware and software platforms. ITS delivers precise information in matter of seconds, hence significantly reduces the uncertainty at the terminals and for the next carriers of the loads (Crainic et al., 2009). Most of the developments in this regard have been hardware-driven, and more efforts are still needed to model and solve multimodal transportation planning problems under real-time information in an integrated chain (Crainic et al., 2009).

In the recent literature, Bock (2010) and Goel (2010) address the real-time issues into their **models**. Bock (2010) introduces a real-time-oriented control approach for efficient consolidation, transshipment, and dynamic handling of disturbances such as vehicle breakdown and accidents. Partial or total outsourcing of transportation services is also allowed and rest times for truck drivers are enforced. There are two different plans for dynamic update handling, namely, the relevant and the theoretical plans. When the execution of the *relevant plan* takes place, at an adaptation phase, generated future modifications are tested with the *theoretical plan* and based on future decisions.

This approach works in a rolling horizon fashion. The simulation produces a future temporary optimization problem which solutions determine the next transportation paths of each request and vehicle at the end of current time interval.

From a different perspective, Goel (2010) studies the value of utilizing RFID technology and visibility over shipments throughout a multimodal transportation network of road and fixed-scheduled rail, with variable transit times. In this network, there are two decision-makers: a transport manager responsible for planning the shipments, and a terminal operator responsible for dealing with unforeseen deviations. If the manager does not see the deviations in time and adjust accordingly, the terminal operator must then decide upon the shipment flows. Goel (2010) analyzes four levels of visibility, namely, *no visibility*, *daily snapshot*, *departure/arrival*, and *checkpoint*.

In order to **solve** these itinerary planning problems, Bock (2010) designs a variable neighborhood search algorithm and solves generated instances with up to 5600 locations, 372 orders, 399 transshipment locations, and 55 vehicles. He shows that the exact solutions are outperformed in a real-time environment and a continuous improvement results in substantial cost reductions. Goel (2010) designs a simulation heuristic which at each iteration solves a multi-commodity network flow problem based on the updated information. He compare the defined visibility levels on a small real-world network of 1 supplier, 3 rail operators with up to 40 trains per operator, and 3 factories. Goel (2010) concludes that on-time delivery performance can be significantly improved by increasing the level of visibility.

The number of papers on operational planning is remarkably lower than on the tactical and the strategic planning problems, opening many opportunities for **future research**. We presented the highlights of the recent research. Operational planning problems are huge, complex and heavily time consuming to solve. Huge sets of data should be processed and new plans must be produced in matter of minutes or even seconds. Better approximation, better decomposition of the problem, and tighter formulations can improve the performance of the DSS. Parallel computation and algorithms also promise significant improvements in solving huge problems in matter of both time and efficiency. Moreover, the decision process and its timing might be also interesting. Usually the decisions are made when the input data has arrived to the system. For example, it is assumed that the arrival of a ship is announced right when it arrives to a terminal. Planning the required operations beforehand might save both computational and execution times.

Moreover, in the operational planning literature, the modal switch is ignored. Assume that for example, at some point a large volume order arrives, or there is a modal breakdown. In such a situation, the choice of transportation mode and its operational costs are worth studying. In addition, no paper has discussed the dynamic allocation of multi-asset resources. In an international containerized transportation chain, usually more than one type of loading unit is used. For instance, reusable boxes or cages are allocated to customer orders, while the containers are allocated to move these smaller units. Not only repositioning of empty containers is important, but returning and positioning of empty smaller units is also important. Furthermore, incorporating transshipment time and capacity in terminals are interesting subjects in resource management. Regarding empty loading units, it would be interesting to incorporate inventory and replenishment techniques to the ordering process of these resources.

5. Prospectives

Multimodal transportation has become the key platform for containerized transportation solutions. In this review paper, we presented the recent developments and efforts on multimodal transportation planning from 2005 onward. Tactical level issues have been studied the most and strategic level problems rank second, followed by the operational level problems. Still, many challenges remain.

First of all, a better study of various physical topologies needs to be done. We observed that mostly the network is assumed to have a hub-and-spoke topology, while a corridor network is for example more appealing in a region with waterway transportation. Moreover, transportation of time-sensitive (e.g. express delivery and perishable) or even hazardous products (e.g. LNG) might require different transportation structures, policies, and objectives. These objectives might be furthermore conflicting with each other requiring multi-objective methodologies. In the recent literature, only Chang (2008), and Hsu and Hsieh (2007) study the trade-off between different objectives, e.g. costs and time. Multi-objective transportation planning thus merits more research.

Regarding transportation resources, there is a big gap in incorporating the backward flows into the planning of forward flows. The literature shows that by integrating the repositioning decisions in the network design, solutions are significantly more cost efficient and time saving. Moreover, due to the limited number and capacity, and additional regulations (e.g. working hour regulations for drivers), simultaneous planning of multiple resources (e.g. vehicles plus drivers) should be incorporated. Taking dynamicity and stochasticity of the data into account also remains a major research challenge.

In most papers, it is assumed that the transportation system is centrally managed and only the requirements of the multimodal operator are taken into account. Obviously, the interactions and competitions among the carriers influence the execution of the plans. Their collaboration for example ensures the on-time delivery. Furthermore, integrating different levels of planning might provide more reliability, flexibility, and more important sustainability, generating more efficient solutions for the industry.

For all three planning levels, due to the complexity of the problems, solving them is still a challenge in itself. Decomposition and relaxation techniques are used extensively. Branch-and-Cut algorithms provide a flexible platform to include many properties of network design problems, and with smart exploitation of the problem structure, finding stronger bounds and cuts, it is possible to push the size limits and solve more realistic problems. Among the metaheuristic algorithms, the family of Tabu search heuristics was used most. This fact leaves a great opportunity to study other families of metaheuristic algorithms, especially population-based algorithms, and compare their performance. In addition, parallel computing offers a capability to handle time and memory consuming solution algorithms especially for large and decentralized planning problems.

In this paper, we also discussed the different terminologies used in practice: multimodality, intermodality, co-modality, and synchromodality. The latter two have not received any attention from the OR community. However by looking at their definition, synchromodality seems to be very appealing for the flexibility and efficiency it envisions. It offers a better utilization of transportation modes and resources, a better consolidation of loads, flexibility and freedom to switch modes, and synchronization of the services. These terms are in fact the essence of optimized multimodal transportation planning which needs to take many practical aspects into account such as the collaboration of the administrative bodies, uncertainty, traffic at terminals or en route, resource limitations and modal capacities. To conclude, despite the fact that the research in the area of multimodal transportation planning has accelerated, we believe that this outline and review gives ample new research directions for future study.

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Highlights:

- We give an overview of the multimodal transportation literature from 2005 onward.
- We approach the papers on strategic, tactical, and operational levels of planning.
- We discuss multimodal, intermodal, co-modal, and synchromodal transportation.
- We conclude our review paper with future research directions.