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# Network planning and design in multimodal transportation under consideration of uncertainty

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**Abstract**

Uncertainty in terms of random transportation demand and random transportation times can significantly affect network planning and design as important fields of tactical planning in multimodal transportation. For providing an overview on the state of research, results of a systematic literature review are presented. The references are evaluated in terms of problem characteristics, model formulations and solution approaches. A clear focus on uncertain transportation demand can be observed. The dominant model formulation is two-stage stochastic programming. Various solution approaches exist, ranging from special procedures for stochastic programs (L-shaped method, scenario decomposition) to different metaheuristics. As solution quality can be enhanced, compared to deterministic planning, further improvements in computational efficiency for tackling large scale problem instances and the consideration of random transportation times are identified as major future research fields.



*Keywords:* Freight transportation planning; Service Network Design; Network Flow Planning; Multimodal; Intermodal; Stochastic Optimization

## 1. Introduction

Due to the ongoing trend towards specialization and internationalization of the members within supply chains the freight transportation plays a decisive role for efficiently fulfilling customer demand. Cost-effective and reliable transportation plans are a key pillar of successful supply chains (Sanchez-Rodrigues et al. 2010). Multimodal transportation, which refers to the transportation of goods by a sequence of at least two different modes of transportation (EUROSTAT et al. 2009), can be a beneficial approach for enhancing transportation operations by simultaneously exploiting the advantages of different modes (Crainic and Kim 2007). Furthermore, from the perspective of society as a whole, modal shift towards environmentally friendly transportation modes is a prerequisite for reducing the climate effects of the globalized economy. For the European Union (EU), road transportation is still the dominant mode in inland transportation, with a modal split of approximately 76% in 2016 (EUROSTAT 2018). In this context, multimodal transportation can contribute significantly for reducing greenhouse gas emissions of the EU member states by 40% in 2030 compared to 1990 (European Union 2016).

Despite those positive effects for economy and environment, in many cases unimodal transportation solutions remain the preferred option. Especially reservations concerning flexibility and reliability can motivate decision makers to rely on one transportation mode (Demir et al. 2016). In consequence, the consideration of uncertainty in the planning of multimodal transportation is a crucial factor for realizing its full potential and providing decision makers with adequate support for shifting transportation modes. Uncertainty includes unknown or stochastic transportation demand and stochastic transportation times (e.g. delays of transportation services). Stochastic demand is related to flexibility reservations, e.g. capacity shortages of transportation

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services in case of unforeseen demand peaks (Bai et al. 2014). Stochastic transportation times refer to reliability reservations and increased complexity due to coordinating different parts of the transportation chain, which are often executed by different actors (Elbert and Seikowsky 2017). An example is the prolongation of delays in one part of the transportation chain to the subsequent parts, which can require complex re-planning activities.

In general, multimodal transportation planning models can be categorized with regard to their decision horizon into strategic, tactical and operational planning (Steadieseifi et al. 2014). Strategic planning problems relate to investment decisions on the infrastructures (e.g. hub location problems). Tactical planning problems deal with network planning and design, which refers to optimally utilizing the given infrastructure by choosing services and associated transportation modes, allocating their capacities to orders, and planning their itineraries and frequency. A further field of tactical planning is the asset management, in which schedules for single vehicles are derived (Andersen et al. 2009). As third field the demand and capacity management aims to maximize revenue for the offered services or transportation capacities, respectively (Luo et al. 2016). Operational planning covers the same planning problems as tactical planning, but under consideration of real-time requirements. In contrast to tactical planning, the operational planning arises immediately before or during execution of the transportation services.

From the three decision horizons, network flow planning and design as field of tactical planning is of special interest to create incentives for a modal shift to environmentally-friendly transportation modes in the short and medium term. Sophisticated planning models, that incorporate uncertainty, can be a valuable aid for overcoming the flexibility and reliability reservations concerning modal shift as described above. Multimodal operators, which must plan schedules and capacities for their transportation services, as well as their customers (freight forwarders, shippers), which must chose a transportation mode and allocate orders to transportation services, can benefit. With regard to flexibility (stochastic demand), multimodal operators can ensure a trade-off between capacity utilization and providing sufficient capacity for covering peak demand. Analogously freight forwarders and shippers can determine capacity bookings in advance for fulfilling transportation orders and avoiding unused capacity. In terms of reliability (stochastic transportation times), for multimodal operators it become possible to analyze the punctuality of their services and plan measures for increasing reliability (e.g. buffer times between subsequent services). Freight forwarders and shippers can benefit from reliable estimates for transportation costs, transportation times and shares of on-time delivered orders. In sum, multimodal operators can plan transportation schedules, which fulfill market requirements regarding punctual services and covering peak demand, thus strengthen the competitive position vis-à-vis unimodal road service providers. On the other hand, mode choice behavior of freight forwarders and shippers can be transformed from a predefined selection of road transportation to a rationale selection of the most suitable transportation mode.

Whereas in past research has mainly focused on deterministic planning approaches, the importance of considering uncertainty gains increasing attention during the last years, resulting in several research streams and approaches for tactical planning in multimodal transportation. However, a systematic overview of regarded stochastic parameters, planning models and solution approaches is missing so far. For addressing this research gap, the objective of the paper at hand is to provide a comprehensive survey of network planning and design (as part of the tactical planning in multimodal transportation) under consideration of uncertainty. In detail, two research questions (RQs) should be answered by the means of a systematic literature review:

- RQ 1: How can research conducted on stochastic network planning and design in multimodal transportation be systematically classified with reference to problem characteristics (including stochastic parameters), model formulations and solution approaches?
- RQ 2: Which aspects (in terms of problem characteristics, models and solution approaches) are already considered and which fields for future research can be derived?

The remaining parts of the paper are structured as follows: Section two introduces an overview for tactical planning problems in multimodal transportation. The corresponding planning problems in the field of network planning and design are introduced and the research scope for the literature review is delimited. In section three we describe the methodological approach of the literature review and give an overview of publication data for the references contained in the content-related evaluation. In section four the literature is analyzed (RQ1) and further fields of research are identified (RQ2). Finally, section five summarizes limitations of the review and gives a conclusion.

## 2. Network planning and design as part of tactical planning in multimodal transportation

Tactical planning in multimodal transportation covers several planning problems, which can be categorized on a higher level in three planning fields (see Fig. 1): network planning or design, asset management as well as demand and capacity management. The classification scheme further shows actors in multimodal transportation facing the respective planning problems and the corresponding decisions of each planning problem.

Network planning/design covers the planning problems of service network design and network flow planning. According to Steadieseifi et al. (2014), service network design involves the service planning decisions including all decisions on choosing the transportation services and modes to move those commodities. Network flow planning relates to the flow planning decisions addressing the movement of orders (commodities) throughout the network. In consequence, service network design can include network flow planning decisions. In a first step, the corresponding decisions in service network design for multimodal transportation are schedules for offered services and capacities of transportation nodes and links (representing the capacities of the transportation vehicles or used storage capacities; strategic decisions define infrastructure capacities, which determine maximum capacities for the succeeding tactical planning). When schedules and or capacities are fixed, network flow planning decision including choice of transportation modes and services as well as commodity flow follow in the second step. The higher level decisions on schedules and capacities are solely taken by multimodal operators, whereas network flow planning can also be faced by shippers, freight forwarders or road carriers (depending on responsibilities for transportation planning in the individual case).

The field of asset management consists of the fleet management, which includes the vehicle routing problem. Within fleet management, the asset owner (multimodal operator, shipper, freight forwarder or road carrier) decides on vehicle paths or vehicle cycles (in case of schedules, which repeat periodically; Andersen et al. 2009). The vehicle routing problem can be understood as special case of fleet management for vehicles that start and end a closed tour at a predefined depot (usually the case for road transportation; Gendreau et al 2014). The demand and capacity management covers the revenue management, in which prices for the offered services a defined in order to maximize the revenue for given demand and capacities to sell (Gorman 2015). In the succeeding resource allocation booking requests (for defined prices) are assigned to services, which include the possibility of denying requests for the benefit of other requests that may generate higher revenues (Schönberger and Kopfer 2012).

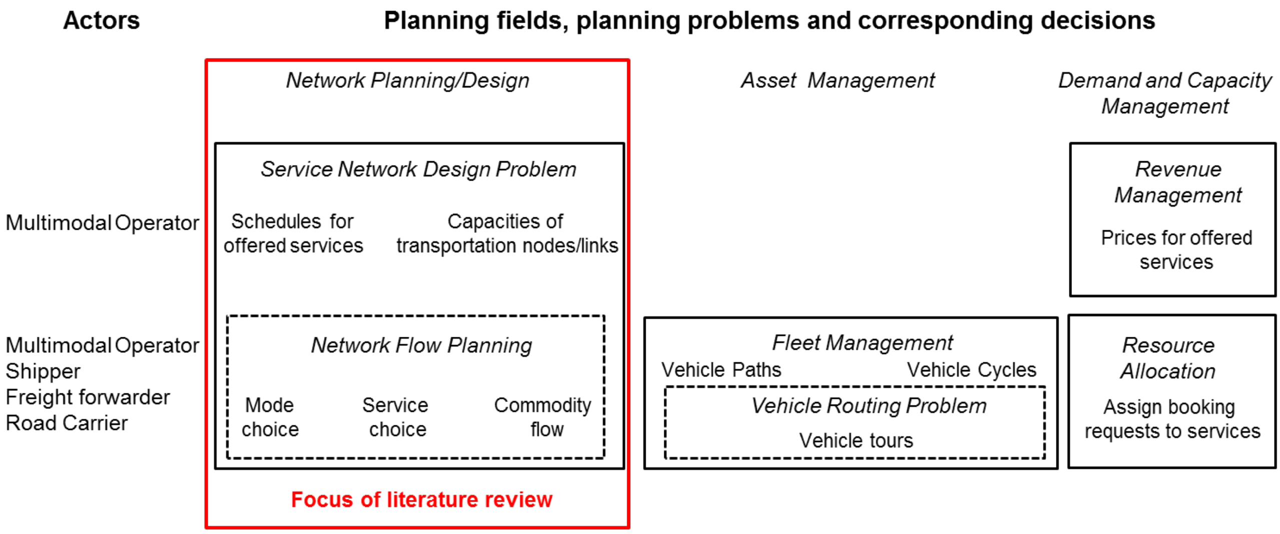


Fig. 1: Actors and planning fields (with planning problems and corresponding decisions) for tactical planning in multimodal transportation

The literature review, introduced in the next section, is limited to network flow planning and design, therefore including service network design and network flow planning with uncertainty. However, fleet management and vehicle routing problems could also be covered by the survey, since planning approaches could exist, which simultaneously cover network planning/design and asset management due to the intrinsic proximity (e.g. by defining a transportation schedule the fleet management can be integrated into the decisions). The review should point out which concrete uncertainty issues are already incorporated and which stochastic model and solution approaches exist. Moreover, open problems in the field of network planning/design bearing potential for future research become apparent.

## 3. Methodology

For identifying the relevant literature a systematic review according to the recommendations of Denyer and Tranfield (2009) was conducted. Three runs with different query strings for title, abstract and key words were carried out with the Scopus database. The query strings should ensure, that the two important types of multimodal transportation are included: intermodal transportation (where the load is transported from an origin to a destination in one and the same intermodal transportation unit without handling of the goods themselves when changing modes) and combined transport (intermodal transportation of goods where the major part of the journey is by rail, inland waterway or sea and any initial and/or final leg carried out by road is as short as possible) (EUROSTAT et al. 2009). Furthermore, the literature on service network design and network flow planning should explicitly be included in the survey. The following research queries result from those requirements:

- *(combined OR intermodal OR multimodal) AND transport* AND (stochastic OR uncertain* )*
- *"network design" AND transport* AND (stochastic OR uncertain*)*
- *"network flow" AND transport* AND (stochastic OR uncertain* )*

For giving an overview of the current state of research only references within the last ten years (publication year since 2008) were searched. In total 832 references could be found, for which in the next step the abstracts were screened for collecting relevant literature. Criteria for including papers in the evaluation are as follows:

- The paper explicitly tackles service network design and/or network flow planning with uncertainty in multimodal transportation
- The main focus is on multimodal transportation and not on other research fields (e.g. supply chain management, reverse logistics)
- Papers on disruption management and designing resilient transportation networks are excluded. Disruptions can be regarded as uncertainty. However, planning approaches can significantly differ compared to network planning/design and are therefore seen as an independent research topic.

Additionally, only papers in peer-reviewed journals with SCImago Journal Rank (as index based on the Scopus database) in the first and second quartile were included in the evaluation, to ensure a survey with relevant and high-quality research. Finally, further references fulfilling those criteria, that were cited among the considered papers, were integrated, too. Overall 15 references remain for content-based evaluation. The high number of excluded papers results from a large amount of literature dealing with network design in the context of supply chain networks, which was also covered by the research queries.

In the following section the results of the literature review are presented.

## 4. Results of the literature review

For systematizing the literature on service network design and network flow planning with uncertainty the references are evaluated with regard to problem characteristics, which concretize the tackled problem (transportation mode, time, commodity, actors and stochastic parameters), model formulations (basic approach and decision variables) and solution approach (basic procedure and scenario generation). For both basic planning problems, service network design and network flow planning, the references can be divided into seven categories, according to the specific problem under study, as shown in Fig. 2. The categories are further systematized with regard to actors facing the planning problem and covered uncertainty issue (stochastic demand, stochastic transportation times or both). In the following three subsections the content of the literature is expounded in detail (for problem characteristics, model formulations and solution approach). The fourth subsection gives a summary on general characteristics of stochastic solutions and the value of stochastic planning approaches, when they are compared to deterministic counterparts. In the last subsection fields for future research are identified.

| | **Stochastic Demand** | **Stochastic Transportation Times** | **Stochastic Demand and Transportation Times** |
|---|---|---|---|
| **Service Network Design** | Multimodal Operator<br>Minimum cost transportation schedule<br>*Lium et al (2009), Hoff et al (2010), Bai et al. (2014), Crainic et al. (2016)*<br>Minimum cost transportation capacity<br>*Crainic et al. (2011), Watson and Woodruff (2011), Crainic et al. (2014), Sun et al. (2017)*<br>Shipper<br>Minimum cost storage capacities<br>*Unnikrishnan et al. (2009)* | | |
| **Network Flow Planning** | Multiactor<br>Multiactor network flow<br>*Puettmann and Stadtler (2010)*<br>Shipper<br>Minimum cost network flow<br>*Meng et al. (2015)* | Multimodal Operator<br>Minimum cost network flow<br>*Hrusovsky et al. (2016)*<br>Freight forwarder<br>Minimum cost service choice<br>*Hui et al. (2014)* | Multimodal Operator<br>Minimum cost mode choice<br>*Zuidwijk and Veenstra (2015)*<br>Minimum cost network flow<br>*Demir et al. (2016)* |

Fig. 2: Classification of references to planning problems under consideration of actors and incorporated stochastic parameters.

### *4.1. Problem characteristics*

The first part of this subsection briefly explains the content of the included references within the nine categories of Fig. 2. In the second part, the references are systematically analyzed with regard to problem characteristics (regarded transportation mode, time, commodity, actors and stochastic parameters). For a further overview, the references are briefly summarized in Table 1 (service network design) and Table 2 (network flow planning), respectively.

The classification of the references in Fig. 2 shows, that for service network design only stochastic demand has been incorporated into planning so far. Moreover, the vast majority (eight out of nine references) develops planning approaches for multimodal operators. They can be divided into problems for finding minimum cost transportation schedules and minimum cost transportation capacities. In minimum cost transportation schedule problems (Lium et al. (2009), Hoff et al. (2010), Bai et al. (2014) and Crainic et al. (2016)) a fixed schedule for transportation services for a given set of origin-destination-relations over several time periods should be derived. Due to stochastic demand, an optimal trade-off must be found between low-cost, preplanned services with respective capacity (that could not be exploited in low-demand cases), and high-cost ad-hoc capacity for high-demand scenarios. Asset management is considered in a simplified manner by the means of conservation equations for vehicle flow. Only Crainic et al. (2016) derive a more advanced approach in this relation. They analyze a two-tier city logistics system, in which so called satellites function as cross-docking nodes for transshipping the commodities from large-capacity vehicles to city freighters, which execute the final delivery within the city center. Vehicle tours for road services are included within the network design, whereby vehicle tours and synchronization times for the cross-docking operations are determined.

Minimum cost transportation capacity problems (Crainic et al. (2011), Watson and Woodruff (2011), Crainic et al. (2014) and Sun et al. (2017)) deal with a single-period planning, in which capacity of transportation links and network flows must be determined with regard to stochastic demand volumes. Within the optimization procedure fixed costs for installing capacity on the transportation links and variable commodity flow costs must be considered. Overall, a commodity flow with lowest expected costs throughout different demand scenarios must be ensured. Since the problem is limited to a single period and vehicle flow is not explicitly considered, this approach can be seen as a simplified method for stochastic service network design in multimodal transportation for providing a first estimate of transportation links that should be operated with high capacity. Due to simplification larger networks can be analyzed.

Unnikrishnan et al. (2009) study more special cases of stochastic service network design, a minimum cost storage capacity problem from the perspective of a shipper. The shipper decides on storage capacities to be installed in his network and corresponding network flows and inventories in each period. For transportation services he can chose among a leader carrier and secondary competitive carriers. Assuming stochastic supply and demand volumes, the demand should be fulfilled at minimum overall costs. Storage capacities must be dimensioned accordingly, guaranteeing enough buffers and simultaneously avoiding unused capacity.

Compared to stochastic service network design, for specific problems in stochastic network flow planning are more diversified, leading to six categories, which only contain one reference, respectively. Additionally, a broader range of actors is covered (besides multimodal operators and shippers also freight forwarders and a multiactor approach) and the references include stochastic transportation times, too.

Puettmann and Stadtler (2010) investigate a multiactor network flow planning problem with uncertain demand release times. An intermodal operator must plan the commodity flow for a maritime transportation network, including decisions for pre- and post-haulage, executed by external road carriers, in the hinterland. The road carriers plan their drayage operations under consideration of transportation orders from further customers (orders exogenously given). The pre- and post-haulage costs of the intermodal operator depend on the tour planning of the road carriers. The intermodal operator books all services for the whole chain in advance. Due to the long transportation durations of the maritime main haulage, the road carriers in the export region must anticipate future stochastic demand release times of the orders from the other customers, for estimating their transportation costs. The authors develop an iterative information exchange procedure between the actors, where proposed transportation plans are exchanged and coordination among the actors is reached. In effect, each actor can reduce his own transportation costs.

Meng et al. (2015), Demir et al. (2016) and Hrusovsky et al. (2016) analyze minimum cost network flow planning problems, in which optimal transportation services must be chosen for each order from a set of available services. Therefore, the decision making scope includes all three aspects of network flow planning (mode choice, service choice and the commodity flow within the chosen transportation services). Meng et al. (2015) consider stochastic demand volumes from the perspective of a shipper (in this case “demand” equals transportation of finished goods). Within the planning, fixed transportation capacities must be booked in advanced for delivering the goods. Demand exceeding the capacities can be transported by costly ad-hoc services. Hrusovsky et al. (2016) and Demir et al. (2016) refer to intermodal operators. Hrusovsky et al. (2016) take stochastic transportation times into account. For a set of given orders an optimal trade-off between minimum transportation costs and minimum delay costs, caused by unpunctual delivery at the final destination, must be determined when selecting transportation services and deriving commodity-flow. Demir et al. (2016) study a similar approach, but take additionally stochastic demand into account. In this case, not only delay costs must be incorporated, but also sufficient booking of fixed capacity for avoiding excessive use of costly ad-hoc capacity.

Hui et al. (2014) and Zuidwijk and Veenstra (2015) limit the decisions to service choice or mode choice, respectively. Hui et al. (2014) model an air freight forwarder shipment planning with stochastic processing times by the means of a job assignment problem (minimum cost service choice). Jobs or activities reflect the single transportation services along the chain (multi-stage road transportation from/to the airport, air transportation in the main haulage). By assigning shipments with the share the same activity within a stage of the chain to one actor, cost savings from consolidation can be reached. On the other side, by assigning subsequent activities of a shipment to one actor, cost savings from integration can be reached. The objective is to define a minimum cost job assignment to actors with regard to consolidation and integration, which further accounts for delay costs and reliability penalty costs resulting from stochastic processing times. In this case, high integration and consolidation can reduce activity costs, but increases the impact of delayed activities, since more shipments are affected by deviations occurring at one actor.

Table 1. Problem characteristics, model formulations and solution approaches for service network design problems with uncertainty

| **Reference** | **Problem characteristics** | | | **Model Formulation** | | **Solution Approach** | |
|---|---|---|---|---|---|---|---|
| | **Mode** | **Time, commodity and actors** | **Stochastic parameters** | **Basic Approach** | **Decision Variables** | **Basic Procedure** | **Scenario Generation** |
| **Minimum cost transportation schedule problems** | | | | | | | |
| Lium et al. (2009) | not specified | Multi-period<br>Multi-commodity<br>Single-actor | Demand Volume | Two stage stochastic programming | <u>First stage</u><br>- Vehicle flow (integer)<br><u>Second stage</u><br>- Commodity Flow (continuous)<br>- Additional capacity (continuous) | Standard Solver | Moment Matching |
| Hoff et al. (2010) | not specified | Multi-period<br>Multi-Commodity<br>Single-Actor | Demand Volume | Two stage stochastic programming | <u>First stage</u><br>- Vehicle flow (integer)<br><u>Second stage</u><br>- Commodity Flow (continuous)<br>- Additional capacity (continuous) | Neighbour-hood-based metaheuristic | Random |
| Bai et al. (2014) | not specified | Multi-period<br>Multi-Commodity<br>Single-Actor | Demand Volume | Two stage stochastic programming | <u>First stage</u><br>- Vehicle flow (integer)<br><u>Second stage</u><br>- Commodity flow (continuous)<br>- Increase/decrease in vehicle flow (integer)<br>- Additional capacity (continuous) | Standard Solver and heuristic with sequential solving of first stage and second stage (for large instances) | Moment Matching |
| Crainic et al. (2016) | Road | Multi-period<br>Multi-Commodity<br>Multi-Actor with centralized planning | Demand Volume | Two stage stochastic programming | <u>First stage</u><br>- Selected transportation services (binary)<br>- Selected tours (binary)<br><u>Second stage</u><br>- Selected additional tours (binary) | Standard solver (first stage) and heuristic approach (second stage) | Random |
| **Minimum cost transportation capacity problems** | | | | | | | |
| Crainic et al. (2011) | not specified | Single-period<br>Multi-Commodity<br>Single-Actor | Demand Volume | Two stage stochastic programming | <u>First stage</u><br>- Installed transportation links (binary)<br><u>Second stage</u><br>- Commodity flow (continuous)<br>- Additional capacity (continuous) | Progressive-hedging based metaheuristic (based on Scenario decomposition/ Lagrangian relaxation) | Random |
| Watson and Woodruff (2011) | not specified | Single-period<br>Single-Commodity<br>Single-Actor | Demand Volume | Two stage stochastic programming | <u>First stage</u><br>- Installed transportation links (binary)<br>- Transportation link capacity (continuous)<br><u>Second stage</u><br>- Activated transportation links (binary)<br>- Commodity flow (continuous) | Progressive-hedging based metaheuristic (based on Scenario decomposition/ Lagrangian relaxation) | Random |
| Crainic et al. (2014) | not specified | Single-period<br>Multi-Commodity<br>Single-Actor | Demand Volume | Two stage stochastic programming | <u>First stage</u><br>- Installed transportation links (binary)<br><u>Second stage</u><br>- Commodity flow (continuous) | Progressive-hedging based metaheuristic<br>(from Crainic et al 2011) | Scenario Grouping |
| Sun et al. (2017) | not specified | Single-period<br>Multi-Commodity<br>Single-Actor | Demand Volume | Two stage stochastic programming | <u>First stage</u><br>- Selected transportation links (binary)<br>- Capacity of transportation links (continuous)<br><u>Second stage</u><br>- Commodity flow (continuous)<br>- Unsatisfied demand (continuous) | Standard solver | Random |
| **Minimum cost storage capacity problems** | | | | | | | |
| Unnikrishnan et al. (2009) | not specified | Multi-period<br>Single-commodity<br>Multi-actor with centralized planning | Supply and demand Volume | Two stage stochastic programming | <u>First stage</u><br>- Storage capacities (continuous)<br><u>Second stage</u><br>- Commodity Flow (continuous)<br>- Inventories (continuous) | Stochastic L shaped method with regularized decomposition | Random |

Zuidwijk and Veenstra (2015) analyze a minimum cost mode choice problem of an intermodal operator with regard to stochastic demand release times and transportation times. They determine the value of information in container transportation with regard to efficiency and reliability. Efficiency refers to the expected overall transportation costs and reliability is defined by the share of containers arriving on time. An intermodal operator can decide on the fraction of containers transported by barge and road and the barge departure time. A late barge departure and a high number of containers transported by barge maximize the efficiency, but bear the risk of a low reliability due to a possible late arrival of the barge. On the opposite, road transportation is more flexible at the expense of higher transportation costs. Within this context, several scenarios regarding container release times (no information about release times, known probability distributions, known actual release times) are compared.

Table 2. Problem characteristics, model formulations and solution approaches for network flow planning with uncertainty

| **Reference** | **Problem characteristics** | | | **Model Formulation** | | **Solution Approach** | |
|---|---|---|---|---|---|---|---|
| | **Mode** | **Time, commodity and actors** | **Stochastic parameters** | **Basic Approach** | **Decision Variables** | **Basic Procedure** | **Scenario Generation** |
| **Multiactor network flow problems** | | | | | | | |
| Puettmann and Stadtler (2010) | Maritime transportation with road transportation in hinterland | Multi-period Multi-Commodity Multi-Actor with decentralized planning | Demand release time | MIP | Intermodal operator<br>-Commodity flows (Assignment of orders to liner-services and carriers, binary)<br>- Additional capacity (continuous)<br>- Inventories (continuous)<br>Road carrier<br>- Commodity flows (Assignment of orders to tours, binary)<br>- Additional capacity (Assignment of orders to additional capacity, binary) | Standard Solver and heuristic with priority values for tour planning of road carriers | Random |
| **Minimum cost network flow problems** | | | | | | | |
| Meng et al. (2015) | Road, rail and short-sea shipping | Multi-period Single-Commodity Single-Actor | Demand Volume | Two stage stochastic programming | First stage<br>Fixed capacity booking (integer)<br>Second stage<br>Commodity flow (integer) | Scenario decomposition/ Lagrangian relaxation | SAA |
| Hrusovsky et al. (2016) | Road, rail and barge | Continous Multi-Commodity Single-Actor | Transport-ation time | MILP with discrete-event and agent-based simulation | - Selected transportation services (binary)<br>- Commodity flow (continuous) | Standard Solver | Random |
| Demir et al. (2016) | Road, rail and barge | Continous Multi-Commodity Single-Actor | - Demand volume<br>-Transpor-tation time | MILP | - Selected transportation services (binary)<br>- Commodity flow (continuous) | Standard Solver | SAA |
| **Minimum cost service choice problems** | | | | | | | |
| Hui et al. (2014) | Road-Air | Continuous Multi-Commodity Multi-Actor with centralized planning | Processing Times | Two stage stochastic programming | First stage<br>- Initial Agent-activity-assignment (binary)<br><br>Second stage<br>- Adjusted Agent-activity-assignment (binary) | Tabu search with assignment-rules from practice for second stage decisions | Moment Matching |
| **Minimum cost mode choice problems** | | | | | | | |
| Zuidwijk and Veenstra (2015) | Road and Barge | Continuous Single-Commodity Single-Actor | Demand release time and transport-tation time | Analytical | - Fraction of containers planned for barge transportation (continuous)<br>- Barge departure time (continuous) | Analytical expressions for Pareto-frontiers | Analytical (no scenarios) |

In summarizing the problem characteristics with regard to stochastic parameters, considered mode, time, commodity and actors, several conclusions can be derived. For stochastic parameters, the main emphasis is on random demand. Only four references within network flow planning incorporate random transportation times and only two references (Demir et al. (2016) and Zuidwijk and Veenstra (2015)) simultaneously consider uncertainty in demand and transportation times.

Most of the references do not specify a specific transportation mode, so that the approach can be seen as general suitable for different modes. Regarding the references with explicitly named modes, all of them include road transportation, either for pre- or post- haulage in the transportation chain or as alternative for the origin-to-destination transportation. Only one reference analyzed road-air transportation (Hui et al. 2014) and only one paper analyzes the maritime transportation chain, including the main haulage with deep-sea liner services (Puettmann and Stadtler 2010).

Time is included in most of the references by a multi-period approach (defining discrete time-intervals for the planning horizon) or as continuous dimension. By using the multi-period approach, cyclic schedules for transportation modes with fixed departure and arriving times can be represented (by defining decision variables for number of departing vehicles/transportation services on a link for each time-interval). Furthermore, multi-commodity planning models dominate as well as models for a single-actor or for multi-actors with centralized planning. The difference between those categories is that in the first case, it can be assumed that all assets belong to the same actor and information exchange only takes place within a company. In the latter case, the perspective of a centralized organizing actor is taken, who dispatches his own transportation services along with services of secondary further actors (e.g. road carriers for ad-hoc transportation of orders exceeding the own capacity). Only Puettmann and Stadtler (2010) analyze a decentralized planning of multiple actors.

After giving an overview on the planning problems and their basic characteristics, the next subsection summarizes the modelling approaches for tackling planning under uncertainty.

### *4.2. Model formulations*

The model formulations can be classified into four main categories: two stage stochastic programming, linear/nonlinear programming, combined linear programming with simulation and analytical solutions. First, the planning models of each category are further described and the corresponding decision variables are outlined. Afterwards, a brief overview is given on the formulation of the objective functions, reflecting the basic aims of tactical planning under uncertainty.

The clear dominant model formulation is two stage stochastic programming (eleven out of 15 references, including all references relating to service network design, apply this method). In two stage stochastic programming, the first-stage decision variables are taken before random scenario realization. Therefore, they represent fixed decisions throughout all scenarios. The second stage refers to disclosed uncertainty, whereby recourse actions can be taken (Birge and Louveaux 2011). Optimization problems are solved for the first stage and for all scenarios in the second stage. The objective function for the first stage consists of deterministic terms for the first-stage decisions and the expected value of the second stage objective function.

Applied in the context of service network design, for minimum cost transportation schedule problems in the first stage the decision variables include fixed vehicle flow (representing cyclic transportation schedules) in form of integer variables (Lium et al. 2009, Hoff et al. (2010) and Bai et al. 2014). Crainic et al. (2016) integrates the vehicle routing planning by the means of binary variables for transportation services and vehicle tours to be selected (out from an enumeration of possible tours generated beforehand). For the minimum cost transportation capacity problems (simplified single-period network design problems), in the first stage selected transportation links with given capacity are represented by binary variables (Crainic et al. (2011) and Crainic et al. (2014)). Watson and Woodruff (2011) as well as Sun et al. (2017) additionally incorporate continuous variables for capacity decisions on each link. In the minimum cost storage capacity problem (Unnikrishnan et al. (2009)), storage capacity decisions (continuous) are taken in the first stage without deciding on transportation services.

The recourse actions in the second stage of service network design problems contain the commodity flow within the defined network schedules and/or capacities as well as ad-hoc decisions for capacity adaptions (usually ad-hoc capacity increase) by the means of continuous variables. It is assumed that ad-hoc transportation services are immediately available (e.g. outsourcing to external partners), so that the commodity flow utilizing those capacities can directly be derived. Within minimum cost transportation schedule problems, only Bai et al. (2014) also includes integer decisions on increasing/decreasing vehicle flow for a scenario-specific adaptation of the periodic transportation schedule. Since Crainic et al. (2016) consider the vehicle routing planning, second-stage decisions are on additional tours to select (binary).

With regard to network flow planning, Hui et al. (2014) and Meng et al. (2015) use a two stage stochastic programming formulation as well. Hui et al. (2014) formulates the service choice decisions (activity-agent-assignment) with binary variables in the first stage. For the second stage an adaption of all activity-agent-assignments as recourse actions is allowed. Meng et al. (2015) decide on integer capacity booking for different transportation modes within the minimum cost network flow problem. In the second stage, the commodity flow is represented by integer variables, referring to single loading units.

Besides two stage stochastic programming, linear programs without distinguishing a first and a second stage are formulated for the network flow planning, too. For multiactor flow planning, Puettmann and Stadtler (2010) derive separate mixed-integer programs for the intermodal operator and the road carrier, which form the basis for coordinating the transportation plans among each other. The intermodal operator determines the commodity flow in form of binary decisions on selected transportation services (for maritime main haulage and pre-/post-haulage by road carriers). Furthermore, continuous variables are used for inventory in the terminals and additional capacities for orders exceeding the given capacities of the road carriers. The road carrier takes decisions on commodity flow in the form of assigning orders to a set of enumerated tours (binary) and to additional external capacity. Since uncertainty only affects release times of transportation orders of the road carrier, it can be considered in the enumerated tours (in principle all possible tours for all possible sets of order release times are enumerated; only a subset of tours must then be considered for a specific order release time scenario).

Demir et al. (2016) formulate a mixed-integer linear program for the minimum cost network flow problem with random demand and transportation times. Selection of transportation services is included by binary variables and commodity flow within each service by continuous variables. Additional capacity bookings or cancellations of transportation services as reaction to realized demand are incorporated within commodity flow.

Hrusovsky et al. (2016) is the only reference that combines a mixed-integer linear program with a combined discrete-event and agent-based simulation for minimum cost network flow with stochastic transportation times. In an iterative manner, selected transportation services (binary) and commodity flow (continuous) is determined by optimization and simulated in the next step for determining delays due to stochastic transportation times. Additional constraints are added in the optimization problem for shipments with high expected delays after each simulation run for reducing the probability that the respective transportation paths are chosen again. The optimization-simulation-iteration is repeated until no significant improvements of the objective value are reached.

Zuidwijk and Veenstra (2015) is the only reference deriving analytical expressions (value of information for a minimum cost mode choice problem). The aim of the paper is to analyze the general impact of knowing certain information regarding demand distributions on efficiency and reliability by the means of a simplified transportation chain, consisting of one barge service and road transportation. Under those assumptions, Pareto optimal decisions can be calculated analytically.

With regard to formulation of objective functions, a focus on cost minimization can be concluded. Nine references accounting for transportation service costs, capacity costs, commodity flow costs or inventory costs, respectively (corresponding to the decision variables, see Table 1 and Table 2). Stochasticity in form of uncertain demand affects the overall costs in form of additional transportation capacity, which must be acquired, since the models assume that demand is fulfilled in every scenario. Only Sun et al. (2017) cover costs for unfulfilled demand, allowing the decision to reject transportation demands. When uncertain transportation times are included, penalty costs for delays or unreliability are incorporated in the objective function (Hui et al. 2014, Demir et al. 2016, Hrusovsky et al. (2016)). Demir et al. (2016) add chance constraints, which excludes unfeasible transportation plans from the solution space. Moreover, Demir et al. (2016) and Hrusovsky et al. (2016) are the only two references that integrate emission costs of transportation and transshipment activities. The resulting multi-criteria optimization problem consist of minimizing the weighted sum of commodity flow and transshipment costs, delay costs and emission costs.

For summarizing the review of model formulations, it can be stated that all service network design problems are formulated as two stage stochastic programming models. Whereas in the first stage binary or integer variables on selected services, installed transportation links, vehicle flows and capacities of nodes and transportation links are incorporated, the second stage variables are usually continuous decisions on commodity flow on regular transportation links and flows covered by additional capacity. Asset management is only fully incorporated by Crainic et al. (2016) in form of binary decisions on selecting out of enumerated vehicle tours. For the network flow planning, also MI(L)P formulations and simulation approaches are present besides stochastic programming. Decisions often cover the binary assignment of orders to services (or, more generally spoken, of activities to agents). Commodity flows are modelled as continuous or integer variables (referring to loading units) or as binary decisions for order-specific service/tour selection.

In the next subsection the solution approaches for solving the presented models are described in detail.

### *4.3. Solution approaches*

A commonly used approach for solving stochastic optimization problems is based on scenario generation, where a defined number of scenarios with realizations of the uncertain parameters are generated and the optimization is conducted for those instances. In the context of stochastic programming the expected value of the second stage in the objective function is approximated by the mean value over the scenarios, resulting in the so called extensive form (Birge and Louveaux 2011). The scenario set is also referred to as scenario tree (Kaut and Wallace 2007). Therefore, on the one hand the solution approaches can be differentiated by the basic procedure used to solve the optimization problem (e.g. standard solver, metaheuristic). On the other hand they are characterized by the applied scenario generation method. The latter terms are expounded first, followed by an overview on the basic solution procedures.

For scenario generation four methods are applied within the survey references (see Table 1 and Table 2): random scenario generation (eight references), moment matching (three references), sample average approximation (SAA, two references) and scenario grouping (one reference). Random scenario generation represents a Monte Carlo approach, whereby scenarios are randomly generated by drawing a subsample based on assumed distribution functions for the stochastic parameters. Applying pure random generation does not necessarily ensure in-sample and out-of-sample stability (Kaut and Wallace 2007). In-sample stability describes, that for different scenario trees (different subsamples of scenarios) an (approximately) equal objective function value is reached. Under out-of-sample stability it is understood that the solutions determined by the scenario trees are also equal to the true objective function value. When both conditions are satisfied, the scenario generation procedure guarantees that a representative sample (with regard to the underlying distribution functions) is selected. Based on the method introduced by Høyland et al. (2003) a moment matching scenario generation procedure is introduced in multimodal transportation planning by Lium et al. (2009). The authors show that by controlling marginal distributions of stochastic parameters (in this case random demand volumes) and their correlations, in- and out-of-sample-distribution is achieved. Therefore, applying the moment-matching scenario generation of Høyland et al. (2003), which produces a discrete joint distribution consistent with specified values of the first four marginal moments (mean, variance, skewness and kurtosis) and correlations of the stochastic parameters, is sufficient for generating a representative sample. Hui et al. (2014) and Bai et al. (2014) are further references using moment matching.

Sample average approximation (SAA) is another method of generating random samples, but ensuring convergence of the objective function value to the true value within a predefined confidence interval. In general, a number of independent samples with a fixed number of realizations of the stochastic parameters are generated. Each sample is solved for creating a set of candidate solutions. Those are evaluated by a further sample (with very high sample size) and the best solution with regard to this test sample is selected as optimal solution to the problem. A last approach for reducing computational time is scenario grouping, introduced by Crainic et al. (2014). In their procedure generated scenarios are assigned to groups and the multi-scenario subproblems for each group are solved. The grouping is performed by a k-means clustering algorithm, using a distance measure for assessing similarity of scenarios. Grouping can then be undertaken by combining similar scenarios, by combining dissimilar scenarios or by a mixed approach (combining similar scenarios, but adding a dissimilar scenario in each group). Groups of similar scenarios bear the advantage of lower computational times for calculating a group-specific solution, but higher computational times for reaching a consensus on first stage decision variables (that must be equal throughout the scenarios). The authors conduct computational experiments and show that the highest solution quality can be reached by the mixed approach, whereas the best compromise between computational time and solution quality is ensured by similar scenario grouping.

After generating the scenarios, four basic solution procedures can be distinguished for solving the instances (see Table 1 and Table 2): using standard solvers (seven references), scenario decomposition approaches (one reference), Benders decomposition (also referred to as L-Shaped method, one reference) and metaheuristics (eight references). In general, the computational effort for solving the stochastic models is high, because the problems are (in most cases) NP-hard and due to scenario generation multiple instances must be solved. Consequently, the application scope for standard solver is limited to rather small network sizes or relatively simple problems (like Sun et al. 2017) when two stage stochastic programming models are formulated. However, for MIP or MILP formulations, foregoing to differentiate into a first and second stage, standard solvers can still handle the stochastic planning problems. Puettmann and Stadtler (2010) as well as Demir et al. (2016) rely on standard solvers for the network flow planning (the former reference incorporates a simplified heuristic based on priority values for tour planning of the road carrier). When stochasticity is included by combining simulation and optimization in the model formulation (Hrusovsky et al. 2016), standard solvers can be applied for the associated MILP, too. The authors compare the achieved solutions for the same problem instances as in Demir et al. (2016), who use standard solvers for MILP with an SAA approach. Comparable solution quality is achieved and in addition even larger instances can be tackled by combined optimization-simulation.

Two stage stochastic programming models with high computational effort require different solution approaches. Benders decomposition (or L-shaped method) is a general procedure for solving stochastic programs in the extensive form, applied by Unnikrishnan et al. (2009). The original problem is decomposed into a master-problem and multiple sub-problems. The sub-problems represent the scenarios with fixed first stage decisions. The objective value for the second stage is a piecewise linear function of the first stage decisions. Therefore, it is possible to solve the master problem iteratively and to add feasibility and optimality cuts with regard to the second stage problems in every iteration. The stochastic program can be solved to optimality or the procedure can terminate prematurely if no significant improvements for the objective function value are observed. Unnikrishnan et al. (2009) investigate computational improvements by applying regularized decomposition. In every iteration, a term for the distance of a new solution to the current upper bound is additionally included in the objective function, avoiding that solution spaces with low probability of improving the objective function are exploited extensively. In their computational experiments for networks with up to 250 nodes a significant improvement in solution quality and a reduction in iteration size could be achieved by combining the L-shaped method with regularized decomposition.

Meng et al. (2015) conduct scenario decomposition in form of a dual decomposition and Lagrangian relaxation. Each scenario is solved independently, whereby non-anticipativity constraints are added for the first stage decision variables of the two stage stochastic program. They ensure equality of the first stage decisions throughout the scenarios. These non-anticipativity constraints are incorporated in the objective function of the first stage by Lagrangian relaxation, resulting in a term that is separable in scenarios. For this problem the Lagrangian dual model can be solved by a subgradient method based optimization iterative procedure (iteratively solve all small-scale scenario specific sub-problems and update the Lagrangian multipliers by the subgradient, which results from the currently found optimal solution). As case study a network in China with 19 nodes, 17 train routes and eight ship routes can be solved to optimality using a SAA scenario generation procedure.

Within the field of metaheuristics for solving two stage stochastic programs, three basic approaches can be distinguished within this survey: neighborhood-based metaheuristics, progressive-hedging and tabu search. Hoff et al. (2010) create a neighborhood-based metaheuristic for service network design. The basic principle is to create different transportation schedules for first stage decisions by swapping vehicle positions in the nodes and adding vehicle paths for arcs with high ad-hoc capacity costs. The second stage recourse problem is then solved by a Greedy heuristic. Computational experiments for test instances with up to 30 terminals and 90 demand scenarios demonstrate that especially large instances can be solved with good solution quality, whereas standard solver cannot find approximately good solutions within a week.

Crainic et al. (2011) (also applied in Watson and Woodruff (2011) and Crainic et al. (2014)) develop a progressive-hedging based metaheuristic, which bases on the scenario decomposition/Lagrangian relaxation approach described above. Analogously, the scenario-separable first stage objective function is formulated with Lagrangian relaxation of the non-anticipativity constraints. This objective function has the structure of a commodity network flow problem for each scenario with modified fixed cost terms (for installed capacity on transportation links as first stage decisions). The authors show, that by iteratively adapting these fixed costs a solution with unified first stage decisions throughout all scenarios can be found. Instances up to 100 commodities and 90 scenarios can be solved, for which standard solvers exceed the predefined time limit. Watson and Woodruff (2011) further investigate measures to improve computational times of progressive-hedging. By computational experiments the authors demonstrate that (among others) variable fixing in early iterations and termination criteria, which detect cyclic behavior of the variable values, can reduce computational times effectively.

Hui et al. (2014) use a tabu search for their agent-activity-assignment problem formulation. The second stage decisions are taken by rule-based assignment (myopic rules from practice). The first stage decisions result from tabu search. The algorithm iteratively repeats the first and second stage until the maximum number of iteration steps is reached. The authors solve agent-activity-assignments with instance sizes up to eight activities for eight agents.

For summarizing the solution approaches, due to the high number of scenarios and NP-hardness of the problems, standard solvers will not (or not in all cases) provide solutions for real-world problem instances within acceptable computational times, especially in case of the service network design problem. As first measure reducing the scenario number should be taken into account by moment matching or scenario grouping. In a second step, heuristic approaches should be preferred. From current research a strictly superior heuristic approach cannot be identified (yet). Metaheuristics, Benders decomposition or scenario decomposition all bear the potential for generating acceptable solutions with moderate computational effort.

Due to the increased computational complexity for stochastic models, the question arises, if significant improvements compared to deterministic planning approaches are reachable. Therefore, in the next subsection, general characteristics of stochastic solutions are compared to their deterministic counterparts. The value of stochastic approaches in network planning and design is discussed afterwards.

### *4.4. General characteristics of stochastic solutions and value of stochastic planning approaches*

Six references of the survey compare their stochastic approach with a deterministic one and work out differences in the solution characteristics. For the minimum cost transportation schedule problem with stochastic demand (service network design), Lium et al. (2009) and Bai et al. (2014) conduct computational experiments to compare a deterministic solution with expected values to the solution derived by two stage stochastic programming. The benefits of the stochastic solution depend on correlation of the demand volumes. Lium et al. (2009) work out that the more uncorrelated or negatively correlated the demand volumes are, the higher is the solution quality gain compared to the deterministic approach. Those advantages are achieved by higher consolidation and higher flexibility. Consolidation relates to tendency of the stochastic solution to route commodity flows over transshipment nodes for bundling them, although expected demand values would justify direct transportation. Flexibility is achieved by creating more different paths (in the transportation schedule) between origin-destination-pairs.

However, Bai et al. (2014) show that savings of the stochastic solution are the highest for very uncertain and also for positively correlated demand, and not that significant for uncorrelated demand. The deterministic solution tends to pair up positively correlated demand in commodity flow, leading to high outsourcing and/or rerouting (changes in transportation schedules of vehicles) as recourse action. Therefore, a stochastic solution approach is especially useful for environments with highly uncertain demand and high outsourcing and/or rerouting costs.

Sun et al. (2017) compare three solution approaches (two stage stochastic programming, skeleton and upgrade) for the minimum cost transportation capacity problem with stochastic demand, incorporating stochasticity at different degrees, to a deterministic approach. The stochastic solution can be compared to the deterministic one by the value of stochastic solution (VSS), a commonly used measure introduced by Birge (1982), which calculates the expected value of using a stochastic model (or the expected losses of using a deterministic model, respectively). A pure deterministic approach can lead to losses up to 12% in the objective function value in the computed scenarios, compared to the two stage stochastic programming approach. The authors confirm the results of Bai et al. (2014) in terms of a higher VSS for positively correlated demand, because the stochastic provides more (fixed) capacity in the first stage. However, it could be sufficient to solve the mixed deterministic-stochastic models (skeleton and upgrade) for achieving comparable solution qualities as achieved by two stage stochastic programming. In the skeleton approach, binary decisions on transportation arcs to open are determined by the deterministic model. Afterwards, the stochastic program (with fixed binary variables) is solved for determining capacity of the arcs (first stage) and commodity flows (second stage). In the upgrade approach the deterministic model is solved and the solution is taken as lower bound on the variables in the stochastic model. By the skeleton approach 97% of loss in the VSS can be recovered, by the upgrade 94%. From the results, two conclusions can be derived. First, skeleton can be a promising heuristic approach for stochastic service network design. Second, upgrade indicates that an installed deterministic solution has the potential to function well even for varying demand volumes by increasing capacity to cover peaks in commodity flows. However, the last result contradicts the statements of Bai et al. (2014), who stress the importance of providing sufficient fixed capacity.

Two further references analyze the stochastic solution characteristics for the minimum cost network flow planning problem. Meng et al. (2015) compare the solution of the two stage stochastic programming solved by SAA to the deterministic solution with expected values for the random demand volumes. Their computational experiments show, that for high enough sample size in the SAA, the stochastic solution outperforms the deterministic one throughout all scenarios. Demir et al. (2016) is the only reference in the survey, which compares the solutions additionally for stochastic transportation times (and not only for stochastic demand volumes). The conducted computational study, based on a real-world case study, shows that considering uncertain transportation times leads to a higher value of the stochastic approach than considering uncertain demand volumes. The deterministic solution especially tends to produce infeasible routes, in which the commodities cannot reach their final destination (or must then be transported by ad-hoc trucking, for example).

Zuidwijk and Veenstra (2015) analyze a minimum cost mode choice problem with a special focus on the value of information. They compare four scenarios with regard to available information on stochastic release times of containers, which can be transported either by barge or by road. The intermodal operator can have no information about release times, the probability distributions of the release times can be known, the probability distributions can further be specified for a number of specific categories of containers and the actual release times can be known beforehand (deterministic scenario). By analyzing a single-stage transportation chain (just including the barge or road transportation on a single link) Pareto-optimal solutions (regarding reliability and efficiency) in the four information scenarios can be compared. The largest improvements can be achieved, when probability distributions are known (compared to no information on release times). This result indicates that the general approach of incorporating distribution functions into the stochastic model may be sufficient for deriving transportation plans, whereas further information would not contribute that much in tactical planning.

In summary, all references stress the value of incorporating uncertainty into the planning models. Significant gains compared to a deterministic approach could already be achieved (at least in some cases) by heuristic solutions, that combine stochastic and deterministic approaches. The references in this survey indicate that for limiting computational effort to an acceptable level, it may be more valuable to generate a high number of scenarios and apply heuristic solution procedures than solving fewer instances to optimality. The most important feature of stochastic solutions with regard to demand volumes is the information on their correlations. The majority of the sources analyzing service network design point out that for highly correlated demand (positively or negatively) stochastic models provide superior solutions for the (first stage) decisions on transportation capacities/fixed schedules. Finally, the consideration of uncertain transportation times into stochastic models can (at least in some cases) be higher than incorporating uncertain demand volumes.

After presenting problem characteristics, model formulations and solution approaches with their characteristics for stochastic service network design and network flow planning, in the last subsection an outlook to fields for future research is given.

### *4.5. Fields for future research*

With reference to problem characteristics (section 4.1), literature has focused strongly on stochastic demand so far. For service network design there is even no single reference dealing with stochastic transportation times. Future research should cover this uncertain factor with higher priority. Demir et al. (2016) show in a first approach, that the value of stochastic planning for uncertain transportation times can even be higher than for uncertain demand. The importance of this conclusion is additionally emphasized by empirical surveys among decision makers within the transportation chain, which identify more reservations about reliability of multimodal transportation than of flexibility with regard to demand fluctuations (Elbert and Seikowsky 2017). Moreover, a common approach in practice is to preselect relations with a high basic level of transportation demand for multimodal transportation and absorb peak demand with more flexible road transportation. By this rule-based mode choice strategy, stochastic demand can be easier to handle in practice compared to stochastic transportation times, where delays in one stage of the network impact the succeeding stages. Since only two references include uncertain demand and transportation times simultaneously, more effort in this direction can also provide new results on stochastic solutions covering both aspects.

Relating to analyzed transportation modes, only one reference explicitly covers air and maritime transportation, respectively. For those modes, further research especially considering stochastic transport times/delays can be valuable, since in air transportation the punctual delivery is a decisive competitive factor due to time-critical shipments. In maritime transportation delays of the liner services can be difficult to handle, because due to the high capacity of container vessels a large number of shipments arrives delayed at the port simultaneously. This cannot only cause congestion within the port, but may also force to shift to road transportation because of capacity shortages of the barge and railway services. Deriving transportation schedules for those environmentally-friendly modes that provide a certain amount of reserve capacity could be an approach for increasing their modal shares.

In addition, only one reference (Puettmann and Stadtler 2010) considers multiple actors by the means of a decentralized coordinated planning. This aspect is a further potentially high interesting research stream, because a single actor planning approach can only cover the situation of a (large) operator owning all required transportation assets. However, a main characteristic of multimodal transportation in real-world is the interdependence between several actors with responsibility for one specific part in the transportation chain.

From the perspective of model formulations, a research gap lies in the inclusion of integer variables for commodity flow in the service network design problems, since in real-world situations the decision can be on single loading units to transport, and not on continuous flows. Assuming continuous variables can be a justified simplification in this case, when the number of loading units is high and rounding does not affect the overall solution quality, but might be not adequate when deciding separately on loading units of specific orders.

Furthermore, Crainic et al. (2016) is the only reference including asset management in service network design and Puettmann and Stadtler (2010) the only one for network flow planning. Both references demonstrate that, in principle, this additional aspect can simultaneously be covered even in stochastic planning, which comes along with higher computational effort per se. Deterministic approaches within this research stream show the possibility for significant improvements (Andersen et al. 2009), so that developing further heuristics for stochastic planning with asset management may contribute to improved transportation planning in multimodal transportation.

Another field that can be combined with network design and planning is revenue management and resource allocation (see also Fig. 1). Current research focusses on cost minimization under the prerequisite of fulfilling all occurring transportation requests. In an approach combining the two planning fields the objective function would be profit maximization, considering revenues of accepted transportation orders and costs of the transportation plan. As additional (recourse) decision the selection of fulfilled orders can be incorporated or prices for transportation services can be adapted, hence reflecting additional costs for ad-hoc capacities. However, it should be mentioned that the scope of the literature review explicitly excludes revenue management and resource allocation and therefore it cannot be ensured that no such approaches already exist. Additionally, only two references (Demir et al. 2016 and Hrusovsky et al. 2016) include emission costs in the objective function. Since reducing environmental impacts of transportation is a main driver for promoting multimodal transportation, future research could cover this aspect for further developing decision support towards robust and environmentally-friendly transportation plans.

In terms of solution approaches, research on integrating simulation and/or combining optimization and simulation can enhance the stochastic network design and planning. Hrusovsky et al. (2016) demonstrate that an iterative optimization-simulation procedure can achieve comparable solution quality as optimization combined with an SAA approach and even larger instances can be covered. As one main advantage of simulation is the possibility of dealing with stochastic environments, it is somehow surprising that only one reference rely on simulation so far.

## 5. Limitations and Conclusion

The paper at hand summarizes the state of research in stochastic network planning and design as part of the tactical planning of multimodal transportation. Overall, existing approaches demonstrate the value of including uncertain demand and transportation times into the planning. Significant improvements with regard to transportation costs as well as delay costs (or avoiding unfeasible transportation plans) can be achieved. However, the state of research for this precise topic can be classified as still in its beginnings. Further efforts to achieve computational improvements for dealing with large-scale real-world problem instances should be made, so that a benefit for the actors in multimodal transportation (operators, freight forwarders, shippers and road carriers) in everyday practice is possible. Moreover, a stronger consideration of uncertain transportation times should be strived.

In terms of limitations of the survey, the sample of references is limited to publication not earlier than 2008, indexed in the Scopus database and to journals in the first two quartiles of the SCImago Journal Rank. Although the relevant current literature should be included, the entire spectrum of research is not covered. In addition, the narrow scope of the review must be considered. Only references with explicit focus on stochastic network planning and design were evaluated. Therefore, possibilities of transforming approaches from other research fields (especially in terms of model formulation and solution procedures) are not investigated (e.g. supply chain network design, stochastic vehicle routing planning). Furthermore, deterministic approaches are excluded and in consequence possible adaptions of deterministic models for covering stochasticity are not analyzed as well. In a next step, reviews on stochastic planning in multimodal transportation can be expanded to those areas, along with further fields of tactical planning (asset, demand and capacity management) and further decision horizons (strategical and operational).

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