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ANALYZING THE INFLUENCE OF COSTS AND DELAYS ON MODE CHOICE IN INTERMODAL TRANSPORTATION BY COMBINING SAMPLE AVERAGE APPROXIMATION AND DISCRETE EVENT SIMULATION

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ABSTRACT

Besides transportation costs the punctual delivery of the goods is a key factor for mode choice in intermodal transportation networks. However, only a limited number of studies have included stochastic transportation times in Service Network Design, which refers to decisions regarding transportation mode and services, so far. The paper on hand combines a Sample Average Approximation approach with Discrete Event Simulation for Service Network Design with stochastic transportation times, including the corresponding vehicle routing problem for road vehicles. The share of orders transported by intermodal road-rail vs. unimodal road transportation in dependence of costs and delays of the trains is evaluated for a generic transportation relation in Central Europe, backed by empirical data for transportation orders and delay distributions. The results show a strong effect of rail main haulage costs, whereas even for higher train delays road-rail transportation can still remain competitive.

1 INTRODUCTION

Intermodal transportation can be a decisive competitive edge for logistics service providers, since combining different transportation modes can reduce costs and ensure the timely delivery of goods (Crainic et al. 2018). Moreover, from the society's point of view intermodal transportation increases volumes of the environmentally-friendly modes rail and barge, and is therefore a main pillar for reaching emission reduction targets in the transportation sector. In Europe, especially combined transportation is promoted as an alternative to long-haul road transportation (European Commission 2015). Combined transportation is a special form of intermodal transportation, in which the main haulage is by rail, inland waterway, or sea, and pre/post haulage carried out by road is as short as possible (EUROSTAT et al. 2009).

However, the modal split of rail and barge with regard to inland freight transportation has not increased significantly over the last years in the EU-28 states. Around 18 % of total ton-kilometers has still been transported by rail in 2016, around 6 % by barge, and approximately 76 % by road. A crucial factor for increasing the shares of rail and barge is that decision makers for mode choice (freight forwarders, logistics service providers, shippers) are convinced that combined transportation is advantageous regarding costs and punctuality for their relations, compared to road transportation (Arencibia et al. 2015). In this context, investigations among such decision-makers have identified high transportation reliability as one of the most influential facilitators to modal shift, whereas low transportation flexibility can be a main barrier (Elbert and Seikowsky 2017). In consequence, decision makers rely on decision support systems, which incorporate not only a sole comparison of transportation costs and times, but moreover enable an evaluation of delays at the origin and destination of alternative transportation paths with different modes.

This decision support regarding transportation mode and services can be provided by solving the corresponding Service Network Design Problem (SND) (Steadieseifi et al. 2014). For incorporating delay into the SND, a stochastic version of the problem including uncertain transportation times must be studied (leading to a Stochastic Service Network Design, SSND). Additionally, more attention must be paid for road transportation in the models for SSND, which is not only the competing alternative for long-distance transportation, but also part of the intermodal paths in the form of pre/post haulage. Until now, the planning of the vehicle tours is neglected by assuming road transportation as always available and approximating its cost and transportation times by values only for the origin-destination paths of the orders (Hrusovsky et al. 2016). However, a precise estimation of costs and delays can only be achieved by planning the road vehicle tours, because costs depend on the overall travelled distance of a tour (including empty moves or detours for bundling several orders) and the delay of one order within a tour can result in secondary delays for the following orders. By neglecting the vehicle tours costs and delays for road transportation are systematically underestimated and therefore orders might be assigned to road transportation, even if there is no advantage compared to other modes. In consequence, the first research gap addressed by the paper on hand is the missing inclusion of the vehicle routing problem (VRP) into SSND and solving the resulting optimization problem (SSND-VRP) in an integrated manner.

As a second research gap, the impact of delays in main haulage on the transportation volumes of the intermodal legs has not been investigated by the means of a SSND-VRP model, which allows to evaluate an arbitrary range of costs and delays of different modes. On this basis, limits for costs and delays of rail and/or barge services can be determined for specific relations, so that those environmentally-friendly modes are an attractive alternative to road transportation.

According to those research gaps, the two main contributions of the paper are the following:

- A combined Sample Average Approximation (SAA) and Discrete Event Simulation (DES) approach is presented for solving the SSND-VRP with uncertain transportation times heuristically. SAA is a Monte Carlo-based sampling procedure for solving stochastic problems and well proven in the context of SSND (Demir et al. 2016).
- Backed by empirical data for transportation orders of a road freight forwarder and for delay distributions of intermodal trains of a railway company, the impact of train delays and costs on the share of road-rail combined transportation for a relation in Central Europe is analyzed by the means of Parameter Variation Experiments.

The remainder of the paper is structured as follows: In the second section, the relevant state of research for the SSND-VRP is summarized, including research streams relating to SSND and VRP with stochastic transportation times (travel times). In the third section, the combined SAA and DES approach for a SSND-VRP with full truckload transportation is introduced and a BR-GRASP (biased-randomized – greedy randomized adaptive search procedure) as a first solution algorithm is presented. Full truckload transportation is common for road and road-rail long-distance transportation in Europe (UIRR 2018) and therefore a relevant case for the integration of VRPs. BR-GRASP is a well-established metaheuristic for combinatorial optimization problems (including routing problems), because it combines a successful solution approach with low complexity in implementation (Festa et al. 2018). In Section 4, the Parameter Variation Experiments for a generic relation in Central Europe are conducted and the results are analyzed with regard to the influence of costs and delays on share of orders in road-rail transportation. The last section of the paper covers the conclusion and limitations of the presented research, as well as future research needs.

2 STATE OF RESEARCH

For evaluating costs and delays more accurately, vehicle routing for road transportation is integrated into the SSND presented in this paper. Hence, current research regarding SSND is as relevant as studies on VRP with stochastic travel times.

Research on SSND has focused on stochastic transportation demand rather than random transportation times. A few studies cover uncertain transportation times for static SSND. Static SSND, in contrast to dynamic SSND, refers to determining fixed transportation plans for given orders and/or commodities before the actual transportation process, without taking real-time data and adaption of transportation schedules into account (Hrusovsky et al. 2016). The existing studies deal with the operational planning level, in which the schedule of transportation services (e.g. rail, barge) is given and the objective is to find transportation paths for the commodities, which are feasible and optimize the expected value for cost, overall transportation times and delays with regard to possible travel time realizations out of stochastic distribution functions.

Demir et al. (2016) investigate a green intermodal SSND problem with a multi-criteria objective function including transportation and delay costs and also greenhouse gas emissions. Besides random travel times, demand uncertainty is also included in the model. A mixed integer formulation of the SSND problem is presented with decision variables for assigning the orders to given transportation services and continuous variables for the resulting commodity flow and transshipment volumes on the arcs and nodes of the network, respectively. The authors apply the SAA approach together with a commercial solver for determining the transportation plans. SAA is based on the Monte Carlo method, whereby a scenario sample for the stochastic parameters in the model (orders and travel times in this case) is generated. It consists of two stages: In the first stage a set of candidate solutions for the problem is determined by running the optimization model for a small subset of scenarios each time. In the second stage, those candidates are evaluated for a large sample and the candidate with the best objective function value is set as final solution (Verweij et al. 2003). Results for a real-world case study and larger generated instances show, that the stochastic solutions are superior to their deterministic counterparts, stressing the importance of accounting for random travel times in SND.

Hrusovsky et al. (2016) develop a hybrid simulation optimization approach. In contrast to the SAA approach, solving the optimization model and evaluating the solution by the means of a simulation experiment are repeated iteratively. After each iteration orders with high delays are sent back to the optimization and constraints are added for avoiding unreliable transportation paths. As a second paper, Layeb et al. (2018) also test an iterative simulation optimization approach. The analysis focusses on the value of the stochastic solution (VSS), which represents the expected value of using a stochastic model compared to the deterministic counterpart (Sun et al. 2017). For the network under study, a deterministic model cannot cope with the uncertainty caused by random demand and travel times, leading to statistical significant lower values for the OTIF factor (On Time and Full Delivery of orders). Further results demonstrate the importance of considering correct probability distributions, since for road travel times the shape of the distribution has a significant impact on the determined transportation paths. In consequence, random parameters in SSND should not only be covered by mean and variance, but by distribution functions fitting to empirical data for the network.

In summary, published work regarding SSND with random transportation times could prove the necessity of incorporating uncertainty into the models, as solutions can significantly differ in stochastic models and are superior to deterministic equivalents. However, stochastic vehicle routing for road transportation has not been incorporated yet, thus this research stream has developed independently from SND. Comparable to SSND, stochastic vehicle routing problems (SVRP) can be categorized into static (or a priori) and dynamic (or reoptimization) models, with the possibility to dynamically adapt routes for the latter part (Gendreau et al. 2014). As deterministic VRP, the stochastic approaches can be divided into several categories regarding network characteristics and considered constraints, among others: single/multiple vehicles, single/multiple depots, with/without vehicle capacity constraints, only pickup/only delivery/combined pickup and delivery, without time windows/soft time windows/hard time windows (Irnich et al. 2014). The full truckload case, which is considered in the model introduced in Section 3, results in the one-to-one Pickup-and-Delivery problem for multiple vehicles (PDPVRP). In this variant of the VRP, an order is always transported immediately and completely after pickup to its destination node. Full truckload is common for long-distance transportation and therefore has a high share in combined transportation road-rail (European Commission 2015), which is analyzed in the case study in Section 4.

For the PDPVRP, research has concentrated on the deterministic case yet. Large instances of the problem can only be solved by metaheuristics in acceptable time. It can be summarized that Large Neighborhood Searches, which analyze a high number of neighboring solutions in each iteration by destroying and repairing the current set of tours, are among the currently best performing metaheuristics. Ropke and Pisinger (2006) introduce an Adaptive Large Neighborhood Search, consisting of several removal and reinsert operators for the orders of the tours. During the exploration phase, operators that lead to larger improvements of the objective function in previous iterations, are preferably chosen.

Uncertain environments are mainly considered with regard to demand and/or customer locations in the form of dynamic (reoptimization) models for dynamically arriving requests during the tours. For this case, several approaches combine adaption of tours with prediction of further customer locations and/or demand (e.g., Sáez et al. 2008, Györgyi and Kis 2019). On contrary, approaches which consider random travel times for the PDPVRP are scarce. Wang and Regan (2001) contribute to the literature by formulating two different chance constraint models for local truckload trucking, where several orders must be transported in short distances (e.g. pre/post haulage for intermodal transportation). The chance constraints should ensure, that a minimum number of orders can be served within every tour in each scenario. Besides random travel times, uncertain service times at the nodes (customer and terminals) are additionally included into the model. The authors derive analytical expressions for the probabilities, that an order at a given position in a tour can be served within its time window in dependence of the orders in the previous positions of that tour. Li et al. (2016) study a Share-a-Ride Problem (also referred to as Dial-a-Ride Problem), which has a comparable model structure like the PDPVRP. Passengers and parcels must be transported between their origin and destination nodes by a given vehicle fleet. An Adaptive Large Neighborhood Search is tested with three sampling strategies: Fixed Sample Size Sampling, which determines the solution by a predefined number of travel time scenarios, and a SAA approach as well as a Sequential Sampling Procedure, which adapt the sample size for evaluating candidate solutions iteratively dependent on the estimated optimality gap. The results show a significant VSS compared to the deterministic model.

In summary, the papers of Wang and Regan (2001) and Li et al. (2016) represent first approaches of considering random travel times in PDPVRP. However, comparable to SSND uncertainty in transportation times have neither been studied extensively so far, nor have both research stream been integrated into a single model. Taking this research gap up, a combined SAA and DES approach for the SSND-VRP is presented in the following section.

3 METHODOLOGICAL APPROACH

In the following Section the setup for the SSND-VRP for full truckload orders and random transportation times is introduced in detail (Section 3.1). Following the problem description, the combined SAA and DES approach and the BR-GRASP are expounded (Section 3.2).

3.1 Stochastic Service Network Design with Integrated Vehicle Routing Problem (SSND-VRP) for Full Truckload Orders and Random Transportation Times

For the SSND-VRP a given set of full truckload orders $\mathrm{O} = \{\mathrm{o}_1, .., o_N\}$ is assumed. The transportation network represents the locations of shippers and consignees around intermodal terminals for given relations of intermodal services. It consists of the set of nodes $V = V_P \cup V_D \cup V_{TD} \cup V_{TA} \cup V_L$ with set of order pickup nodes V_P, set of order delivery nodes V_D (one node for each order $o \in O$, respectively), set of nodes for an order at an intermodal terminal for departure V_{TD} and arrival V_{TA} as well as the set of depots for the trucks V_L. Note that in general an arbitrary number of intermodal terminals can be considered. However, it is assumed that each order is assigned to one terminal for departure and arrival, respectively (the geographically closest terminal to the pickup and delivery nodes). Each order has a time-window with lower and upper bound $[t_{l,i}; t_{u,i}]$ at the respective pickup and delivery node $i \in V_P \cup V_D$. Moreover, a set of intermodal services $\mathrm{S} = \{s_1, .., s_N\}$ between the terminals and a two sets of truck tours (K_R for road transportation and K_{IM} for intermodal pre/post haulage) are given.

The overall objective is to minimize the transportation and delay costs. For the model, a two-stage approach is derived. The first stage consits of a (heuristic) optimization procedure. For each order $o \in O$ a transportation mode (road or intermodal) and, in case of intermodal transportation, a service $s \in S$ must be selected. Moreover, the tours for unimodal road transportation and pre/post haulage must be planned in dependence of the selected modes/services for the orders. In the second stage, a set of transportation and service time scenarios $N = \{n_1, .., n_N\}$ is considered in a DES. Each scenario n includes road transportation times t_{ijn} between nodes $i, j \in V$, service times s_{in} at nodes $i \in V_P \cup V_D \cup V_{TD} \cup V_{TA}$, departure time t_{dsn} and arrival time t_{asn} of intermodal service s. The values are drawn from predefined probability functions. The resulting model is a deterministic equivalent of the underlying stochastic problem consisting of one DES for each scenario n, which is a common approach in stochastic optimization (Birge and Louveaux 2011).

The transportation costs are independent of the stochastic transportation and service times and can be evaluated in the first stage. They include the distance-dependent cost for road transportation c_{ij} between two nodes $i, j \in V$, that are served in the tours of unimodal road transportation as well as tours for pre/post haulage in intermodal transportation. For unimodal road transportation, those costs comprise the loaded trips from a pickup node $i \in V_P$ to a delivery node $j \in V_D$ and the empty moves from a destination node to the pickup node of the next order (and additionally the first and last move from/to the depot). For pre/post haulage, the tours consist of the loaded moves from a pickup node $i \in V_P$ to a departure terminal node $j \in V_{TD}$ and from arrival terminal node $i \in V_{TA}$ to an order delivery node $j \in V_D$ as well as empty moves for connecting loaded trips and moves from/to terminal. If an order is transported intermodally, the fixed costs c_s for using intermodal service $s \in S$ (including main haulage and transshipment) are also taken into account.

The delay costs can be evaluated in the second stage by the DES, when the tours are known and the arrival times of each node in the tours can be calculated based on the transportation and service times in each scenario. Assuming a penalty cost factor c_d (money/time unit), the delay costs are assumed to be linear to the time window excesses for each pickup and delivery node. Of special importance for intermodal transportation is the fact, that only delays at the pickup and delivery nodes are relavant. In consequence, even high delays of the intermodal services do not automatically result in high delay costs. The delay costs depend much more on buffer times in the arrival terminal, which reflect the time span between arrival of the intermodal service and time window at order delivery node.

The overall costs of a solution, consisting of mode/intermodal service decision for each order and all road tours, include the overall transportation costs and the mean overall delay costs over all scenarios $n \in N$. Note that the objective of this model is to assign orders to transportation services and plan truck or vehicle tours before the actual transportation process starts. Recovery actions and dynamic adaptions during the transportation process are not integrated. Therefore, the transportation plan with minimal expected cost over all scenarios will be determined.

3.2 Solution Approach

For solving the SSND-VRP, two independent choices regarding sampling strategy on the one hand and algorithm for obtaining solutions regarding mode choice and vehicle tours (first stage of the two-stage approach) are necessary. A sampling strategy, which generates the set of scenarios by drawing concrete values out of the probabilty function for the uncertain parameters, must be defined, since there is not a given set of fixed scenarios as input for the model. The solution algorithm can then be applied to those generated instances of the optimization problem.

SAA is a commonly used sampling strategy for SND and VRP, based on Monte Carlo Simulation. Demir et al. (2016) apply SAA for a green intermodal SND. Li et al. (2016) test SAA, besides other sampling strategy, for solving a stochastic Share-a-Ride Problem.

SAA consist of two stages. In the first stage $|P|$ independent samples are generated, each of sample size Q. For each sample the optimization problem is solved and a respective candidate solution $\hat{x}_p$ is obtained. In the second stage, each candidate solution is tested with an independent sample of size $Q' \gg Q$.

The calculated objective function value $\hat{F}_{Q'}(\hat{x}_p)$ is an estimation for the upper bound of the optimal solution x^*. Therefore, it is usually assumed that the best solution $\hat{x}^*$ is $\hat{x}^* = \operatorname{argmin}_{\hat{x}_p} \hat{F}_{Q'}(\hat{x}_p)$ (Verweij et al. 2003). The number of candidate solutions P and the sample sizes Q and Q' must be defined beforehand.

Regarding the solution algorithm for the first stage a BR-GRASP is developed. In principle, the SSND-VRP can be formulated as a mixed integer linear program, which is NP-hard to solve, as SSND and VRP both are NP-hard (Layeb et al. (2018), Ropke and Pisinger (2006)). As commercial solvers are only capable of solving very small instances (see Section 4), a metaheuristic approach is necessary and a BR-GRASP is deemed to be adequate as a first solution approach for generating basic insights by the means of the case study presented in Section 4. GRASP consist of two phases: a construction phase in which a first feasible solution is obtained and a subsequent local search for improving the solution. In the opposite to a pure Greedy approach, which strictly selects the best solution of the current neighborhood for improving in the next iteration, a random component is incorporated (Feo and Resende 1995). In a biased-randomized GRASP (BR-GRASP) skewed probability functions are used, for which the probability of a solution of being selected increases with solution quality. In consequence, promising areas of the search space are explored more intensively, but without sticking in local optima (Festa et al. 2018).

The exact evaluation of the candidate solutions obtained by BR-GRASP in the second stage of the SAA approach is then achieved by DES for the large test sample. Figure 1 provides an overview of the solution approach.

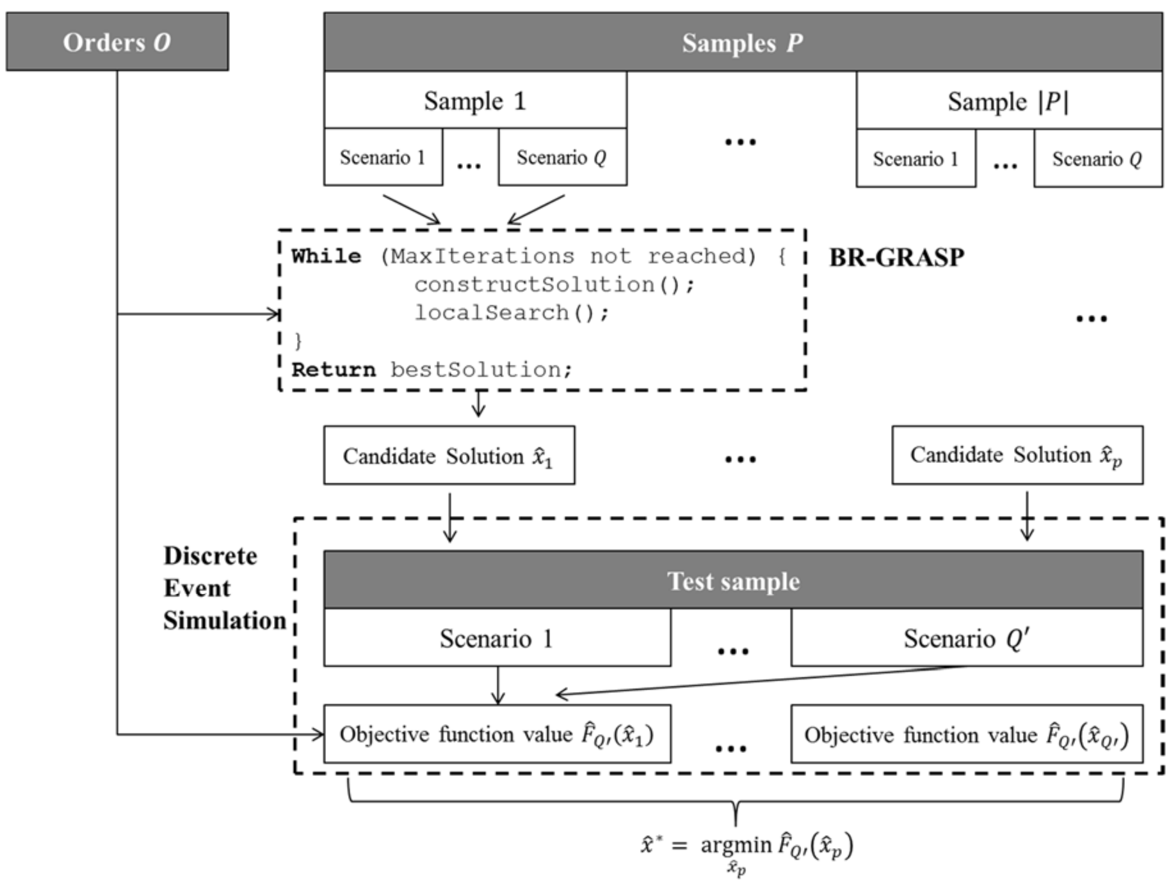

Figure 1: Solution approach with SAA, BR-GRASP, and DES.

The main idea of the BR-GRASP is to decompose the problem into a mode choice and a vehicle routing problem. For mode choice in the construction phase minimum possible costs for the different modes are estimated for each order separately without determining the exact vehicle tours. For road transportation, those costs consist of the distance-dependent and possible delay costs for the loaded trip from pickup to delivery node of the order. For intermodal transportation, the distance dependent costs for pre and post haulage as well as the costs for main haulage and possible delay costs at the delivery node are included. In the next step, the savings for intermodal transportation compared to road can be calculated as difference of both minimum costs. Based on those savings, the assignment to a mode in the construction phase is conducted. A skewed probability function is defined as presented in Figure 2. A probability of $p = 1$ is defined for the order with maximum savings and of $p = 0$ for the order with minimum savings. The probability values for all other orders are a linear function of the respective savings. Consequently, an order with equal minimum costs in both modes has equal probability to be transported by road or intermodal services. Finally, the exact vehicle tours for the generated sets of road and intermodal orders are calculated by a Greedy approach. The orders are sorted according to increasing start time at pickup node. Each order is then inserted into the vehicle tour (unimodal road, pre or post haulage) with minimum overall cost increase (transportation and delay costs).

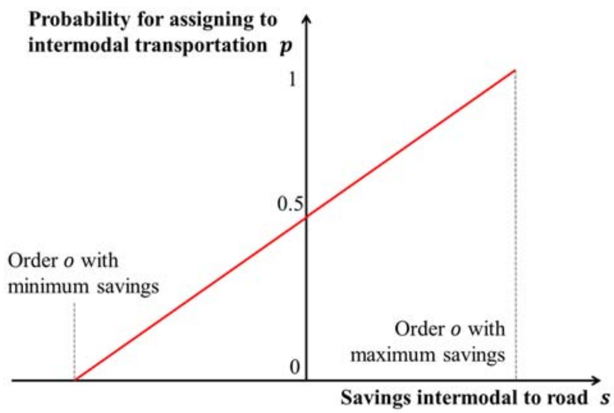

Figure 2: Skewed probability function for assigning orders to mode in construction phase.

The neighborhood for the following local search is defined by a swap operator, that switches the mode for every order separately. For each of the generated neighbors the exact vehicle tours are then calculated by the above-mentioned Greedy approach. The next move in the local search is also selected by a biased-random approach. In this case, a candidate list is created by sorting the neighbors according to increasing costs. From this list an element is chosen by a geometric distribution, which is commonly used for randomization in BR-GRASP (Festa et al. 2018). Pretest of the heuristic demonstrate that superior solutions can be obtained with this approach in contrast to a standard local search, in which the algorithm always terminates in a local optimum. The reason is a greater variety in solution candidates that are evaluated throughout the procedure.

4 RESULTS OF A CASE STUDY

Using the first solution approach for the SSND-VRP presented in Section 3, the second research gap discussed by the paper, regarding the influence of cost and delays in intermodal transportation on the market share compared to road transportation, can be addressed. Therefore, a representative relation for combined transportation road/rail in Central Europe is studied by the means of Parameter Variation Experiments, backed by empirical data for transportation order parameters and delay distributions. Two sets of experiments are conducted, using the software AnyLogic 8.0.5. In the first set with small instance size the BR-GRASP is evaluated against an exact solution approach for benchmarking the performance of the heuristic. The influence of cost and delays is on the market share is analyzed by the second set with large instance size. In Section 4.1 the basic parameters of the relation are described in detail. In Section 4.2 results are presented and practical implications can be derived.

4.1 Basic Parameters of The Relation

The objective of the case study is not to exactly map a specific real world relation, but rather analyzing a generic relation, for which the basic parameters are representative for several real-world relations of combined transportation road/rail in Central Europe. The relation consists of two transshipment terminals, with pickup and delivery nodes located around them. The transportation mode road/rail and the geographical area is chosen, because they represent an important market segment for continental intermodal transportation in Europe with a comparable high modal split of rail transportation (UIRR 2018). By this generic approach, it can be ensured to study a representative relation, in which intermodal and road transportation are both suitable in general, leading to a direct competition of the two modes.

In Table 1 the basic parameters for the representative relation are given. The number of train departures and their time schedules are based on data of a German intermodal operator (Kombiverkehr 2019). A time horizon of one week is considered in the model and the number of orders is set to 10 for the first set of experiments (benchmarking the heuristic) and 50 for the second set. Further data for order generation is provided by a German freight forwarder, from which the number of pickup and delivery nodes and their distance to the terminals are derived. The orders for the Parameter Variation Experiments are assigned to a pickup and delivery node according to the overall frequency of pickup-delivery-relations in the data of the freight forwarder. Therefore, a possible concentration of orders on certain pickup-delivery-relations is considered.

For determining a requested duration for each order (time span between order release and order due time), the minimum possible transportation time in unimodal road transportation between order pickup and delivery node is calculated based on the distance and an average velocity of 60 km/h. Hereby, driver resting times according to European law are also considered (European Parliament and Council 2006). The order duration is then drawn from a uniform distribution, ranging from 110% of minimum possible duration to 150% of minimum possible duration. The value for truck cost (distance-dependent) is taken from literature (Bicker 2014).

Table 1: Basic parameters for a representative relation for combined transportation road/rail in Central Europe.

Parameter	Value	Parameter	Value
Distance of intermodal main haulage	700km	Min./max. order duration compared to shortest possible duration in unimodal road transportation	110% to 150%
Number of train departures per week ($\|S\|$)	42	Road driving time distribution (compared to shortest possible driving time)	Min: 100% Max:150% Mean: 125% Stand. Dev.: 115%
Number of orders per week ($\|O\|$)	10, 50		
Number of pickup and delivery nodes ($\|V_P \cup V_D\|$)	120	Truck cost	0.75 €/km
Min./max. length of time windows	1h - 8h	Delay cost	100 €/h

Moreover, probability distributions for train delays, road transportation times and service times at pickup, delivery and terminal nodes must be specified. Distributions of train delays is given by a railway company for their intermodal trains on a relevant relation in Central Europe. As train delay is varied in the Parameter Variation systematically, the distribution is modified according to delay categories or maximum possible delay of a train as described in the next Section. However, the recourse to empirical data ensures that delay variation is conducted in a realistic range.

Road transportation time and service times are assumed to be truncated normal distributed, which is a common assumption for stochastic VRP (Li et al. 2010). The parameters for the distribution of road driving times (see Table 1) are given as relative excess compared to the shortest possible driving time, calculated as described above. The transportation time is then calculated as driving time plus driver resting times according to European law. The parameter values for distribution of road driving times are derived by a model calibration, in which average delays of orders transported by road are approximately equal to average delays for intermodal transported orders for the medium train delay category (see Section 4.2). Due to this procedure, the competitiveness of both transportation modes regarding delay costs is ensured.

4.2 Results

4.2.1 Benchmarking BR-GRASP against Exact Solution

For evaluating the performance of BR-GRASP, an exact solution is calculated by CPLEX 12.7.0 for a small instance with number of orders $|O| = 10$. Due to computational complexity, the exact solution can only be generated for the deterministic equivalent, which replaces the scenarios of the sample P for the candidate solutions by one deterministic problem instance using the expected values of the stochastic parameters. For BR-GRASP, $|P| = 5$ candidate solutions are determined with $|Q| = 10$ scenarios for each sample. Both solution approaches are evaluated by the same test sample with size $|Q'| = 100$.

The results in Table 2 demonstrate, that BR-GRASP clearly outperforms the exact solution in terms of quality and runtime. The higher objective value of the exact solution further indicates, that a deterministic equivalent cannot cover the stochastic nature of the problem sufficiently.

Table 2: Comparison of exact solution with deterministic equivalent to BR-GRASP.

Solution approach	Objective Function (€)	Runtime (seconds)
CPLEX with deterministic equivalent	6.348	43.200 (time limit)
BR-GRASP	5.791 (-8.8 %)	79

4.2.2 Evaluating the Influence of Cost and Delays on Market Share of Intermodal Transportation

For analyzing the influence of cost and delays on the market share of intermodal transportation, the share of orders assigned to intermodal transportation in the second set of experiments are shown in Table 3 (min., max. and mean value of the five solutions as well as the value of the best solution with minimum overall transportation and delay costs). The impact of varied parameters on the share of intermodal transported orders can be statistically assessed by conducting t-tests for difference in mean value for the share over the five candidate solutions for different parameter categories.

The first two experiments cover the influence of delays. In general, delay can be varied by shifting the whole delay distribution to lower or higher values without modifying its shape, resulting in changed mean delay. This is conducted in the first experiment with four delay categories (no delay to high delay), whereby the low delay category refers to approximately equally high delays compared to road transportation. Maximum possible delay is kept constant at 18 hours. A further possibility is to modify the shape of the distribution without changing mean delay as in the second experiment. In this case, maximum delay is varied in four categories (no delay, 13 hours, 18 hours and 24 hours). The mean value is kept constant at 4.23 hours (except for the no delay category), and therefore increasing maximum delay also results in a higher variance with higher probability for very high and very low delays. The distinction between varying mean and maximum delay enables to identify the "problematic" delays and the actual leverage for increasing modal split of intermodal transportation. It can be possible, that even when mean delay is high the modal split does not significantly decrease the share of intermodal transported orders, as long as maximum delay is in an acceptable range.

The results in Table 3 show that both forms of delays reduce the share of intermodally transported orders significantly. Whereas with no delay the share is comparably high (mean value of 0.38 over all candidate solutions), it is significantly reduced at 10% level even for low mean delay (mean share 0.32) and low max. delay of 13h (mean share 0.31). Further delay increase does not impact the share at a statistic significant level (significance levels in Table 3 are given for comparing subsequent delay categories). However, comparing the share for the best solution candidate a trend for further avoidance of intermodal transport can be assumed (varied mean delay: share is reduced to 0.28 for highest delay category; varied max. delay: share is reduced to 0.24 for highest delay category). As main insight it can be concluded that only a very high punctuality of intermodal transportation services can result in a competitive advantage over road transportation. In this case, orders with comparable transportation costs might be shifted from road. However, even for moderate delays, those orders are shifted back to road. Only the orders with clearly lower transportation costs (e.g. pickup and delivery nodes close to the terminals), which overcompensate even high delays, remain in intermodal transportation.

Table 3: Results for Parameter Variation Experiments with combined SAA and DES approach. Significance levels for share of intermodal orders are for two-tailed t-test for difference in mean of the candidate solutions between two subsequent parameter categories (e.g. between low delay and no delay).

Variation of delay distribution of intermodal trains		
Varied parameter	Share of orders in intermodal transportation [min, mean, max]	best
No delay	[0.32, 0.38, 0.46]	0.32
Low delay (mean 3.11h)	[0.26, 0.32, 0.40]*	0.40
Medium delay (mean 4.23h)	[0.22, 0.30, 0.34]	0.22
High delay (mean 5.00h)	[0.28, 0.30, 0.34]	0.28
Variation of maximum delay of intermodal trains		
No delay	[0.32, 0.38, 0.46]	0.32
Max. delay 13h	[0.26, 0.31, 0.34]*	0.30
Max. delay 18h	[0.22, 0.30, 0.34]	0.22
Max. delay 24h	[0.24, 0.30, 0.34]	0.24
Variation of cost for intermodal main haulage		
Low cost (300 €)	[0.36, 0.40, 0.44]	0.40
Medium cost (341.5 €)	[0.22, 0.30, 0.34]*	0.22
High cost (375 €)	[0.24, 0.27, 0.32]	0.24
Very high cost (400 €)	[0.16, 0.22, 0.26]*	0.24
*** $p < 0.001$; ** $p < 0.01$; * $p < 0.1$		

The third experiment analyze the impact of main haulage cost, the second relevant factor for the share of intermodal transported orders. For this experiment, the low delay category of the first experiment is assumed (comparable delays for intermodal and road transportation). The medium cost category (341.5 € main haulage of one order including transshipment) refers to the cost value based on literature (Janic 2008). The results show, that the share is more sensitive to higher costs than to higher delays. For medium costs

(341.5 €) compared to low costs (300 €) the mean share of all candidate solutions is strongly reduced from 0.40 to 0.30 at 10% level. Further cost lead to a more moderate decrease to 0.27 (for high cost of 375 €, not significant) and to 0.22 (for very high cost of 400 €, significant at 10% level), respectively. Therefore, a cost reduction from medium costs (which refer as benchmark for current cost level in intermodal transportation) to low cost could strengthen the competitive position of the environmentally-friendly mode. This relation could justify the need for higher subsidies, as the low cost level presented here might not be profitable for the intermodal operator.

In summary, the results for a generic relation in Central Europe stress the necessity for a high level of punctuality, if intermodal transportation should attract higher volumes. However, low cost levels might lead to a comparable modal shift, but may require external subsidies for the intermodal operator.

5 LIMITATIONS AND FURTHER RESEARCH

In this paper, the SSND-VRP was introduced and a first case study for a relation in Central Europe was solved by combining SAA with DES and a BR-GRASP. As main insight from the case study for establishing intermodal transportation as alternative to road transportation, it can be derived that only low costs and very low delays can shift further orders from road and in this way contribute to reducing greenhouse gas emissions. Further research could evaluate the extent to which higher delays can be compensated by reduced costs for intermodal transportation, as the results presented in this paper only analyze both factors independently.

When interpreting the results, several limitations of the study should be taken into account. Although a generic relation is analyzed for deriving more general insights, the implications might not be valid for every network. Especially the time criticality of the orders must be taken into account. For very narrow time spans between order release and due times, intermodal transportation could lose the advantage of providing a certain amount of buffer times in the destination terminal. Furthermore, the empirical data for the study should lead to implications oriented on a real-world case, but might also be not representative for every relation. Therefore, a more comprehensive study should be conducted with a broader range of varied parameters for identifying factors which influence the modal split for different types of networks.

A further limitation is the solution algorithm for the optimization. By solely applying one algorithm (BR-GRASP), the results could be biased by the algorithm and eventually differ for another heuristic, for example. Developing a more sophisticated meta-heuristic for solving the SSND-VRP can be seen as a main field for future research in this field, as a well performing solution approach can be an important contribution for efficiently combining different modes and increasing modal split of environmentally-friendly alternatives to road transportation.

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