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Development of a Multi-Step Approach for Continuous Planning and Forecasting of Required Transport Capacity for the Design of Sustainable Transport Chains

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Abstract

Logistics service providers deal with the challenge of estimating future freight transport demands due to the increasing volatility. Short-term planning horizons and planning uncertainties cause reduced capacity utilization and increasing empty mileage. Due to higher flexibility of road transportation, planning uncertainties in freight transport lead to using the road as a preferential mode of transport in most cases. Thus, more ecologically sustainable, but less flexible modes of transport as rail or waterway are omitted.
To overcome the aforementioned challenge, a multistep approach is proposed to continuously plan future transport capacity in order to redesign and adjust the intermodal fleet accordingly. The proposed multistep approach combines methods of forecasting, multi-period intermodal routing and decision support for capacity adjustments. Finally, we present first results on a use-case of outbound logistics in automotive industry and give an outlook on our future research.

Keywords: choice of transport modes; freight transport planning; multimodal fleet sizing.

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1. Introduction

Increasing volatility in transportation demand challenges logistics service providers and carriers to continuously utilize their transportation resources to a high extent (Handfield 2013), (Wittenbrink 2014). Short-term planning horizons and planning uncertainties lead to unfavorable mode choice and reduced capacity utilization (Lohre 2007), (Zesch et al. 2011), (Wittenbrink 2014). Nevertheless, mode choice and capacity utilization have significant influence on ecological efficiency of transport (Keller and Helmreich 2011). For logistics service providers, there is a need for an early detection of demand fluctuations to be able to react adequately to them (Hoff et al. 2010), (Bielli et al. 2011), (Bretzke and Barkawi 2012), (Corsten and Gössinger 2014). Advantageous fields of action are anticipatory capacity management measures as foresighted mode choice (Zesch et al. 2011), (Wittenbrink 2014), (International Union of Railways 2017), synchronization of order peaks and declines (Bretzke and Barkawi 2012), vertical and horizontal cooperation actions (Bretzke and Barkawi 2012), (Wittenbrink 2014), and the implementation of new pricing and business models (Stölzle 2010). We describe such a holistic model for multimodal fleet sizing, consideration of different transport modes and updates in forecasts over time. The model is described in chapter “Methodology”. In chapter “Evaluation” the model is applied to a certain use case, described in chapter “Use-Case Description”.

2. Literature Review

We have given a detailed state of the art analysis on the integrated forecasting, modal choice and fleet-sizing problem and summarized the most important research questions in a recent detailed review (Brunnthaller et al. 2017). As outlined, there exists no holistic model of the intermodal fleet sizing problem under consideration of continuously updated forecasts over time. Yet, the impact of forecasting of future transport demand on the quality of modal choice decisions and capacity adjustment measures has not been analyzed. Necessary forecasting quality to support logistics service providers’ decisions in a sufficient way has not been elaborated. The ecological and economic impact of horizontally integrated fleet sizing and transport mode choice has not been demonstrated. These findings go along with other literature reviews. One of them was conducted by SteadieSeifi et al. (SteadieSeifi et al. 2014), criticizing that there is no model concerning restricted transport capacity on strategic planning level as well as on tactical level. Moreover, the conclusion of the literature review by Hoff et al. (Hoff et al. 2010) also coincides as they insist on the necessity of an integration of future demand in fleet-sizing and mix issues.

3. Methodology

3.1. Continuous planning procedure

For the dynamic adjustment of fleet size and mix from a carrier’s perspective, we propose a continuous multi-step planning approach. In its core, the procedure consists of a forecasting procedure on future transportation demand in a specified network and future periods (Step 1), the derivation of possible fleet variants to fulfill given demand in future periods (Step 2), and the selection of preferred fleet variants for each future period (Step 3). The proposed procedure is schematically indicated in figure 1.

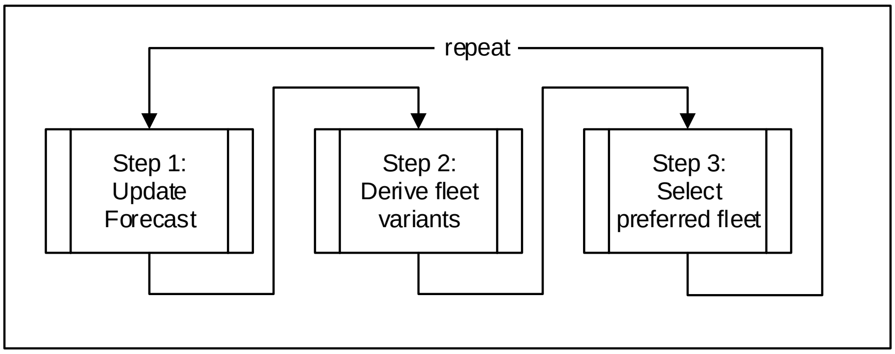

Fig. 1 Continuous pre-planning of required transport capacity

The planning circle is repeated continuously due to permanently updating the forecasting input dataset. Because of these updates in demand forecasts, fleet size and mix are adjusted accordingly by taking lead times and other constraints of adjustment measures into account (see table 3).

3.2. *Step 1: Forecast demand*

Objective of the forecasting procedure is to provide a basis for subsequent planning. For each Origin/Destination-relationship (O/D-relationship), the necessary transport volume for each specified period in the specified planning horizon is predicted. The procedure consists of multiple steps according to a series of different data sources available per O/D-relationship. On a first step, forecasts on future transport volumes from clients subjected to the O/D-relationships are integrated into the time series as soon as available. Since not all clients provide the necessary data, future transport demand is derived from past transport volumes and integrated into the time series. In case of no available forecasts from the clients and no past transportation data, estimations on the future transport volume are conducted and integrated into the time series. As soon as new forecasts of underlying clients, a new dataset of past transport data or any other information on changes to the transport volume is available, the forecasting-procedure is repeated. The procedure for each O/D-relationship and each period is indicated in figure 2.

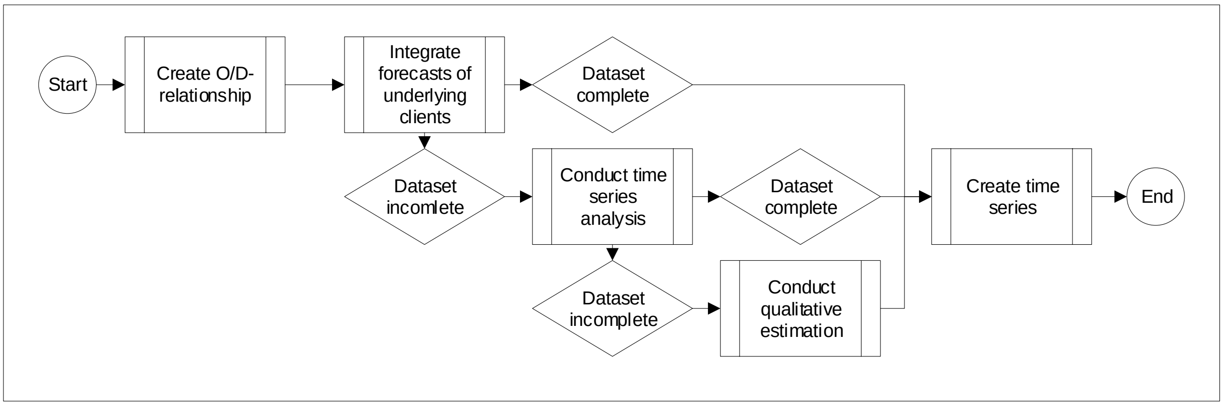

Fig. 2 Multi-step forecasting approach. Adopted from (Cowie 2009)

As indicated in Brunnthaller et al. (Brunnthaller et al. 2017) current multimodal planning procedures do not specify how input-data is derived. This is why we base our forecasts on a general concept of Cowie (Cowie 2009), integrating several data sources. We extend Cowie's model by the aspect of the integration of forecasts provided by clients. Additionally, the step "conduct time series analysis" is kept generic, due to life-cycles of the clients' businesses. Different models for time series analysis may fit, which is also indicated by Wang et al. (Wang et al. 2011) and further elaborated in chapter 4.1.

3.3. *Step 2: Derive fleet variants*

To get a proper estimation of necessary loaded and empty mileage according to the estimated transportation demand in future periods an aggregated circulation of a virtual fleet through the network is calculated. Therefore, a model of a multi depot vehicle routing problem with split deliveries (MDVRPSD) is developed considering several fleets according to the used means of transport. This procedure is repeated for each specified fleet variant and for every period within the planning horizon.

For each period in the planning horizon, the MDVRPSD is solved in the following way: Let $G = (V, E)$ be a directed graph, where V is the set of locations and E the set of routes between these locations. Let S be the set of all closed tours, which are composed of routes. For every $s \in S$ we define $R(s)$ as the set of all routes leading away from tour s. Additionally, K describes the set of pre-defined means of transportation for each fleet variant. On each route $(i, j) \in E$ the transportation demand $d_{i,j}$ has to be satisfied and every vehicle $k \in K$ has a transport capacity of $b_{i,j,k}$ on this route. Every vehicle k has a predefined maximal travel time T_k and it takes the vehicle $t_{i,j,k}$ time units to get from i to j. Finally, $a_{i,j,k}$ is an indicator variable that is 1 if vehicle k can take route (i, j) and 0 otherwise. The objective is to minimize the total cost while satisfying all transport demands. Furthermore, let $x_{i,j,k}$ be the number of times vehicle k travels from location i to j and let $c_{i,j,k}$ be the corresponding travel costs. Moreover, we define two indicator variables: $z_{i,j,k}$ equals 1 if and only if $x_{i,j,k} > 0$, which is due to constraints (5),(6) and (11) (with M sufficiently large).; $w_{s,k}$ equals 1 if vehicle k takes tour s, which is caused by constraints (8) and (12). Then the MDVRPSD can be formulated as follows:

$$\min_{x_{i,j,k}} \sum_{k \in K} \sum_{i \in V} \sum_{j \in V} x_{i,j,k} * c_{i,j,k} \tag{1}$$

subject to

$$\sum_{l} x_{i,l,k} = \sum_{l} x_{l,i,k} \qquad \forall i \in V, \forall k \in K \qquad (2)$$

$$\sum_{k} x_{i,j,k} * b_{i,j,k} \geq d_{i,j} \qquad \forall (i,j) \in E \qquad (3)$$

$$\sum_{i} \sum_{j} x_{i,j,k} * t_{i,j,k} \leq T_k \qquad \forall k \in K \qquad (4)$$

$$x_{i,j,k} \leq M * z_{i,j,k} \qquad \forall (i,j) \in E, \forall k \in K \qquad (5)$$

$$z_{i,j,k} \leq x_{i,j,k} \qquad \forall (i,j) \in E, \forall k \in K \qquad (6)$$

$$z_{i,j,k} \leq a_{i,j,k} \qquad \forall (i,j) \in E, \forall k \in K \qquad (7)$$

$$\sum_{(i,j)\in s} z_{i,j,k} - \sum_{(i,j)\in R(s)} z_{i,j,k} - w_{s,k} \leq |s| - 1 \qquad \forall k \in K, \forall s \in S \qquad (8)$$

$$\sum_{s\in S} w_{s,k} \leq 1 \qquad \forall k \in K \qquad (9)$$

$$x_{i,j,k} \in \mathbb{Z} \qquad \forall (i,j) \in E, \forall k \in K \qquad (10)$$

$$z_{i,j,k} \in \{0,1\} \qquad \forall (i,j) \in E, \forall k \in K \qquad (11)$$

$$w_{s,k} \in \{0,1\} \qquad \forall k \in K, \forall s \in S \qquad (12)$$

Equations (2) are the classical flow conservation constraints. Formulas (3) ensure that all demands are satisfied, while constrains (4) guarantee that no vehicle exceeds its maximal travel time. Inequalities (7) ensure that no vehicle uses a route, which is not available for this vehicle. Constraints (8) force $w_{s,k}$ to be equal to 1 if vehicle k takes tour s, where $|s|$ is the total number of routes belonging to s. Inequalities (9) guarantee that no vehicle takes more than one tour (i.e. takes no subtours).

The result of the procedure is the necessary distance and resulting GHG emissions for each mean of transportation, period and defined fleet variant.

3.4. *Step 3: Select preferred fleet*

Objective of the following procedure is to select a favorable fleet variant for each period within the planning horizon under consideration of costs and resulting GHG emissions. As means of transportation are not always owned, resulting mileage per transport means can be covered by subcontracted means or rented means. In case of demand fluctuations, means of transportations may also be put out of service.

To solve the multi-period decision problem a dynamic programming model is used. Therefore, the decision problem is defined by fleet-states y for each period $p \in (1, \dots, n)$. Each state $y = (y_1, \dots, y_n)$ consists of states y_p for each period $p \in (1, \dots, n)$, where $y_p = (y_{p,k})_{k\in K}$ and $y_{p,k}$is characterized by the following parameters:

$$y_{p,k} = \begin{pmatrix} Number\ of\ owned\ means\ of\ transportation\ k \\ Number\ of\ short-term\ rented\ means\ of\ transportation\ k \\ Number\ of\ long-term\ rented\ means\ k\ with\ 1\ month\ contract\ commitment \\ Number\ of\ long-term\ rented\ means\ k\ with\ 2\ month\ contract\ commitment \\ \vdots \\ Number\ of\ long-term\ rented\ means\ k\ with\ n\ month\ contracted\ commitment \end{pmatrix} \qquad (13)$$

The aim of the model is to find the optimal fleet variant y^* that minimizes the total transport costs. Let Γ_0 be the set of all valid states at period $p = 1$. Then y^* is given as

$$y^* = \underset{y \epsilon \Gamma_0}{\operatorname{argmin}} F_1(y), \tag{14}$$

where $F_p(y)$ is defined as the minimal total cost function from period p to n if state y is chosen. To determine $F_p(y)$, let $f_p(y)$ be the resulting costs in period p, if state y is chosen. Additionally, let $\Gamma_p(y)$ be the set of all valid states in period $p + 1$, if state y is chosen in period p. Then $F_p(y)$ can be written as

$$F_p(y) = f_p(y) + \min_{u \epsilon \Gamma_p(y)} F_{p+1}(u). \tag{15}$$

Since we only consider a finite time horizon, we define $R_n(y)$ as the value of the resulting fleet after period n. Therefore, $F_n(y)$ is given as

$$F_n(y) = f_n(y) - R_n(y) \tag{16}$$

4. Use-Case Description

The automotive industry is one of the most demanding client of logistics service providers. In particular challenging is the shipment of finished cars. The realization of paired transports is difficult because of specific means of transport (Klug 2010) and the high number of models and variants directly affects the logistics service operations (Stein et al. 2014). Therefore, the logistics operations of a Full Truck Load (FTL) logistics service provider for the automotive industry is in the focus of our considerations:

The regarded use-case is based on an extract of a real-life setting provided by an involved logistics service provider. It consists of 15 locations in Europe forming 11 contracted lines (O/D-relationships) Each line is subjected to a client. The planning horizon is specified with 24 months – each month forming a period in the planning horizon. In the simplified use-case scenario, forecasts are updated each month in two test periods of 12 months (test period 1: July 2015 to June 2016; test period 2: July 2017 to June 2017).

4.1. Forecast Demand

According to the presented procedure in chapter 3.2 a time series with estimated transporting demands of 24 months for each line and for each month in the test period is required. For each line, several long-term forecasts provided by the clients of the logistics service provider are available. Most of these forecasts are received sporadically during the test period. Some of the forecasts are available just once a year. Generally, they differ widely in the frequency of their availability, in the duration of the planning horizon and the granularity of the provided figures. Therefore, missing data points in the 24-month planning horizon are estimated by time series analysis.

For the application of the process “conduct time series analysis”, the logistics service provider makes a dataset of vehicles transported in the months from January 2013 to June 2017 per client and line available. For the time series analysis, we use different models to get along with different requirements regarding the current state of the product life cycle (PLC) on the regarded line for the automotive industry. Therefore, we integrate an autoregressive integrated moving average (ARIMA) model for the maturity state and a Holt-Winters model for stages of growth and face-off as described in Vogel (Vogel 2015) and Wang et al. (Wang et al. 2011). To guarantee the flexible application of the models we propose the sub-process “conduct time series analysis” as follows: The models are applied on past data, available at the current planning period. Predictions are made for the following 24 months. According to the evaluation of past errors, in the current period the model is applied with a minimum of earlier errors. The results are integrated into the dataset supplementing the missing data points of the planning horizon of 24 months.

As the contracts with the clients are subjected to a PLC, provision is made for manual changes of data. Additional O/D-relationships can be added and filled with data, if new contract volume over a longer period is conceivable or an existing contract is about to expire (Wang et al. 2011). Table 1 provides an overview of the available dataset and the resulting average mean absolute percentage error (MAPE) for the test period.

Table 1: Clients, lines and forecast quality

Clients	Origin	Destination	Maximum transportation duration in *months*	Type of transported vehicles	Average transport demand per month (07.2015-06.2017)	Standard deviation of transportation demand per months (07.2015-06.2017)	Average MAPE per forecast in test period (07.2015-06.2017)
Client 1	Location 1	Location 10	3	Executive car	226	226	0.27
Client 1	Location 1	Location 11	3	Executive car	175	172	0.22
Client 1	Location 1	Location 12	3	Executive car	835	225	0.68
Client 1	Location 2	Location 11	3	Mid-range car	393	121	0.28
Client 1	Location 3	Location 11	3	Mid-range car	735	190	0.42
Client 2	Location 4	Location 13	7	All-terrain vehicle	1203	412	0.23
Client 2	Location 4	Location 13	3	Mid-range car	865	234	3.89
Client 3	Location 6	Location 12	7	Mid-range car	157	168	0.55
Client 4	Location 7	Location 14	3	Compact car	1182	488	1.00
Client 4	Location 7	Location 12	3	Compact car	34	44	0.24
Client 1	Location 8	Location 15	3	Mid-range car	1317	315	0.73

4.2. *Derive fleet variants*

For the derivation of fleet variants, the MDVRPSD is solved in each month of the test period for each month of the planning horizon. For the presented use-case we define three types of transport means. A representative truck, a representative block train and a representative inland vessel. For each of these transport means and for every possible transport relation (loaded and unloaded), necessary input data for the MDVRPSD are estimated and integrated into the model. Distance, a loading factor (maximum capacity of vehicles per transport), transportation costs (loaded/unloaded), GHG emissions (loaded/unloaded) and duration (loaded/unloaded) are specified for each transport relation. For the use-case scenario, we assume precarriage and oncarriage by truck. Costs, GHG emissions and duration are estimated accordingly and surcharged on intermodal transportation. All cost and GHG emission data is calculated, depending on transport means, distances, durations, and loaded and unloaded weight.

4.3. *Select preferred fleet*

In order to meet the estimated transport demand and to derive an optimized fleet mix for each period we define several measures of capacity adjustment. Under consideration of those measures we solve the dynamic optimization problem described in chapter 3.4. The capacity adjustment measures specify the states y in equation 13. Additional constraints like lead time and minimal contract duration restrict the set of valid states Γ in future periods. For each line and capacity adjustment measure, costs are specified by a fixed and variable cost components. Considered capacity adjustment measures and their specifications are depicted in table 3.

Table 2: Considered capacity adjustment measures

Option for capacity adjustment	Means of transport	Fixed cost per period in *EUR**	Variable cost per km in *EUR**	Lead time of adjustment action in *months*	Maximum share of means of transport in *%*	Minimum contract duration in *months*
Own truck***	Truck	6.000	1.5	4	100	>24**
Put owned truck out of service	Truck	4.200	0	0	100	1
Subcontract trucks short-term	Truck	2.800	1.9	0	15	1
Subcontract trucks long-term	Truck	2.200	1.6	3	15	3
Rent blocktrain long-term	Blocktrain	36.000	9,5	6	100	>24**
Rent blocktrain short-term	Blocktrain	39.000	10,5	1	100	1
Own inland vessel	Inland vessel	66.000	9,5	6	100	>24**

*Depicted cost figures are exemplary estimations by the authors for the purpose of an evaluation of the methodology. There is no link to real-world data. Figures are in correct relations to each other.
**Minimum contract volume >24 indicates that the applied measure lasts until the end of the planning horizon.
***It is not intended to reduce the owned fleet in terms of selling trucks. However, trucks can be put out of service for single periods.

5. Evaluation

5.1. Continuous planning scenario:

For the evaluation of the added economic and ecologic value, we simulate a continuous application of the proposed planning models and compare the application to several static comparative scenarios. Therefore, we formulate a dynamic simulation model for the test periods in Matlab® and use the derived forecasts as deterministic input over time. We run the application twelve times during the two test periods. We start either in June 2015 or in June 2016 with a proper starting fleet. After forecasting 24 months and building fleet variants for the future periods, decisions are made on fleet adjustment measures according to their lead-time. The procedure is repeated in June and the following months of the planning period. The result is a continuously adjusted fleet over the test period.

5.2. Specified Key Figures

With an adjusted version of the MDVRPSD, the fit of the resulting fleet is tested on the actual observed transport demand in each period, as the available capacity in equation 3 is kept as a constraint. As a result of forecast errors, over- and undercapacities of the resulting fleet become obvious.

The cost evaluation is based on the resulting total cost of the applied fleet under consideration of occurring over- and undercapacities.

- Cost of overcapacities: Fixed cost according to table 3.
- Cost of undercapacities: Cost according to additional short term sub-contracted trucks given in table 3.

Occurring GHG Emissions are results of the application of the modified MDVRPSD.

5.3. Comparative planning scenarios

In the comparative planning scenarios, the fleet is specified in advance and is not adjusted during the test period. Based on common practice, we apply scenarios in which the owned fleet (own truck; rent blocktrain long-term) is adjusted to the minimum and the mean of the expected transportation demand on each line. Expected demand is derived according defined forecasts in June for the following year, as described in chapter 4.1. According to the minimum and mean demand on the regarded lines, the MDVRPSD is solved. The application of the MDVRPSD implies a simplified sample-routing procedure. In the next step, decision variables in the decision problem are limited to the long-term adjustment measures of renting a blocktrain and owning trucks and therefore the owned fleet for the test period is specified. According to specified principles in chapter 5.2., all additional demand is covered by short-term subcontracted trucks. Schematically, these scenarios are depicted in figure 3:

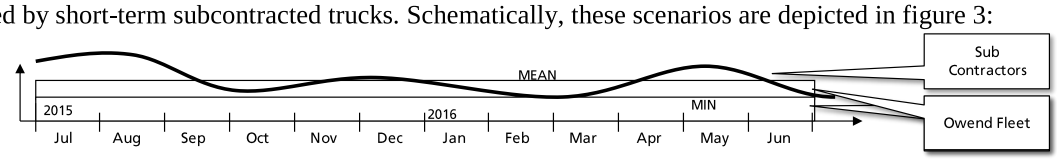

Fig. 3 Use-Case 1&2 (MIN&MEAN): Fleet adjusted to the min/mean and equally distributed with sample routing

In a third use-case, we do not implement sample routing of the fleet according to predicted transportation demand. We rather use indicators of the past period to make assumptions on the necessary fleet in the future test period. As indicators, we use the past modal split and the past mix of adjustment measures. To implement the procedure, we solve the MDVRPSD for observed transportation demand in the past period. The result of it is the share of loaded and empty mileage per line and means of transport as well as the fleet mix. According to these key figures and the predicted transportation demand, the future fleet mix is calculated. The procedure is depicted in figure 4.

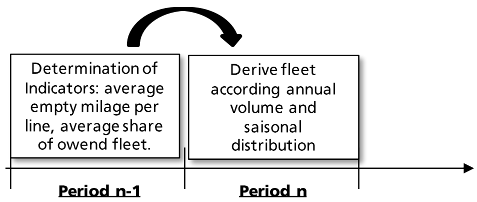

Fig. 4 Use-Case 3 (INDICATOR): Fleet adjusted to expected seasonal transportation demand according to past modal split and fleet mix

In a fourth and fifth planning scenario, we adjust the long-term fleet according to the expected demand fluctuation at the beginning and during the test period. In the single approach scenario, for each month, the MDVRPSD is solved and decisions for long-term fleet adjustment are derived. All additional demand is covered by short-term subcontracted trucks. Schematically, this scenario is depicted in figure 4. In the continuous approach scenario, in each month, the MDVRPSD is solved for the rest of the year. Decisions for long-term fleet adjustment are derived continuously. All additional demand is again covered by short-term subcontracted trucks. Schematically, this scenario is depicted in figure 5.

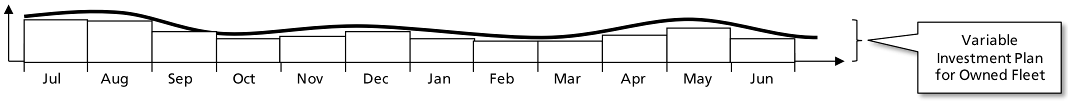

Fig. 5 Single and continuous approach: Fleet adjusted to expected seasons with sample routing in each period

All evaluation scenarios are subjected to the same constraints as the continuous approach. These constraints are depicted in table 3.

Table 3: Summary of Use-Cases

Scenario	Description	Specified transport volume	No. of planning procedures	Simulation of vehicle circulation	No. of simulations of circulation
Use-Case 1 (MIN)	Determination of fleet size and mix once a year on expected minimum of transport volume.	Minimum of exp. transport volume	1	Yes	1
Use-Case 2 (MEAN)	Determination of fleet size and mix once a year on expected mean of transport volume	Mean of expected transport volume	1	Yes	1
Use-Case 3 (INDICATOR)	Determination of fleet size and mix by the application of indicators of past periods.	Expected demand in once a year	1	No	-
Single approach	Determination of fleet size and mix by simulating fleet circulation for each period	Expected demand once a year	1	Yes	12
Continuous approach	Determination of fleet size and mix by updating fleet circulation in each period	Expected demand twelve times a year	12	Yes	144

6. Results of Evaluation

According to chapter 5.2, the result is the sum of costs and GHG emissions during the test periods of 2015 and 2016. An additional result is the applied fleet mix in the test period. Table 4 shows the sum of resulting costs and GHG emissions per planning variant for the test periods.

Table 4: Comparison of the continuous approach to the defined use-case scenarios

	Test period	Use-case 1 (MIN)	Use-case 2 (MEAN)	Use-case 3 (INDICATOR)	Single approach	Continuous approach
MIO	2015/16	24.4	16,3	16,6	15,9	15,3
EUR	2016/17	16,0	16,9	16,2	16,0	15,7
%	2015/16	145	103	105	100	
	2016/17	102	108	103	101	
tCO2e	2015/16	13.783	9.641	9.415	9.516	9.516
	2016/17	9.732	9.814	9.780	9.500	9.434
%	2015/16	145	101	99	100	
	2016/17	103	104	104	101	

In Use-case 1 (MIN scenario), the resulting fleet is adjusted to the minimum of predicted transportation demand on each line. Therefore, in 2015/16, there is no blocktrain integrated into the fleet mix. According to the predicted minimum demand, 46 trucks and 7 long-term subcontractors (max 15 %) are added to the fleet. A high share of additional short-term contractors has to be used during the year, to meet the observed demand resulting in a high share of costs and emissions. In Use-case 2 (MEAN scenario) a blocktrain can be utilized in the network. Additionally, 48 trucks and 8 long-term subcontractors are used to meet the predicted demand. Due to the use of a blocktrain, costs and GHG emissions are reduced significantly. In Use-case 3 (INDICATOR scenario) two blocktrains are used during the full test period. The high number of owned trucks is not used to the full extent, what leads to a high share of fixed costs. Therefore, almost no additional short-time subcontractors are needed.

In the single approach scenario, the fleet is adjusted to the predicted seasons as the described methodology of chapter 3 is applied at the beginning of the test period without repeating it. Therefore, the number of blocktrains fluctuates from 1-2 (long-term and short-term contracts) as well as the number of trucks fluctuates from 53-62. The number of additional short-term sub-contractors can be reduced to a maximum of 15. The applied fleet reduces costs and emissions. In the continuous approach in 2015/16, this result cannot be exceeded as forecasts seem to be of a high quality at the beginning of the test period. Fleet composition for the test period 2015/16 is depicted in Fig. 6.

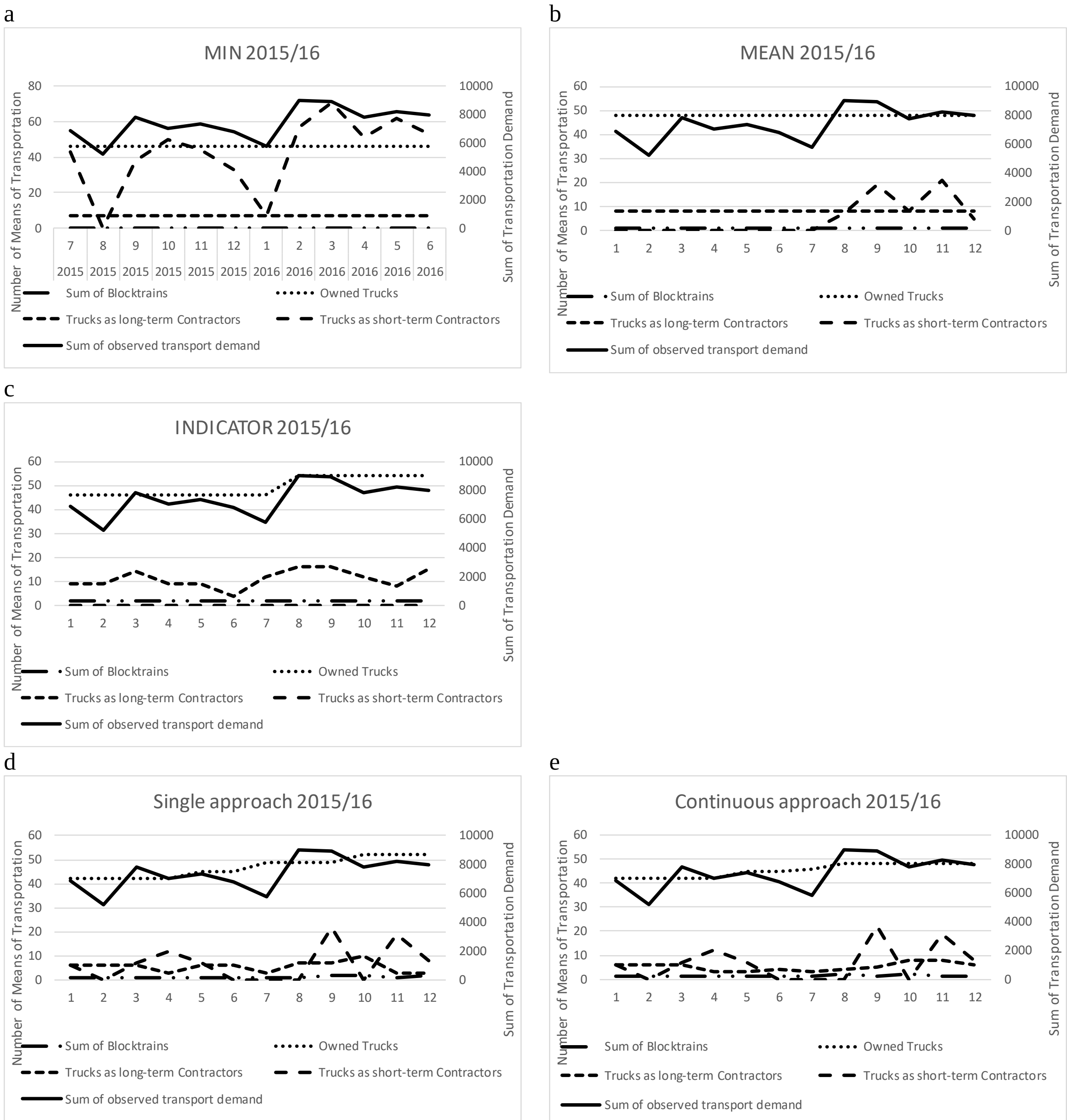

Fig. 6 Fleet composition per variant 2015/16

In test period 2016/17 figures are equivalent to Fig. 6. In period 2016/17, there is a blocktrain used already in the MIN scenario. Therefore, costs and emissions do not deviate as much as in the earlier test period. Compared to the MIN scenario, costs rise in the MEAN scenario, as the big fleet of trucks cannot be utilized due to demand fluctuations. The INDICATOR scenario high costs result from a high share of two blocktrains for the full period. In the single approach scenario, there is a rather low share of long-term sub-contractors compared to the continuous scenario. Additionally, the number of blocktrains in the single approach scenario varies from 1-2, as it varies from 1-3 in the continuous one.

7. Conclusion

As results show, proper planning leads to a reduction of costs and GHG emissions. For the described use-case, the integration of forecasts into the planning procedure adds value, as the high discrepancies in costs and GHG emissions of the MIN and MEAN scenarios clearly show. Whether continuous pre-planning gives additional value, cannot be answered unambiguously. As we have elaborated in chapters 3 and 4, predicted demands directly influence the routing of transport means and the choice of preferred variants. We see that the added value is highly dependant on the quality of forecasts. As the average MAPE in table 2 shows, we have integrated a wide range of forecast-qualities into the use-case. Despite a high average MAPE we see that results still are promising.

According to these results, the next research steps are to examine the dependencies on forecast qualities and the added-value to planning results. Additionally, shorter planning horizons could lead to different results. However, shorter planning horizon would also mean, to adapt the fleet adjustment measures. Moreover, our use-case refers to a rather simple network of FTL direct lines. We have solved an aggregated vehicle routing problem in order to evaluate distances between destinations of line *n* to the origin of line *m*. However, demands within the planning period are stochastically. These stochastics have additional influence on fleet size and composition, as other authors have shown. Complexity would increase if grouping and multi-deliveries are integrated. All these aspects give a wide field of research activities to apply forecasts in transportation planning.

Furthermore, the introduced use-case scenario refers to cost optimization. Thereby, we have shown interrelations of cost reduction and GHG emissions. However, these interrelations are rather complex and highly dependent on fleet composition and the utilization of the applied fleet. Another future research step will be the integration externalities into the cost function. This will show to what extent externalities have to be taxed in order to reduce GHG emissions and to what extent, they simply lead to higher costs without an impact on ecological aspects.

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