Flexible Services and Manufacturing Journal
https://doi.org/10.1007/s10696-024-09556-8

Integrated planning approach for fleet sizing and fleet management of freight railcars

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Accepted: 14 June 2024

Abstract
Despite the general support for rail as sustainable and efficient transport mode, its share on modal split remains rather low. One of the reasons for this is the low flexibility and adaptability of rail system to changes in, e.g., demand due to the complex multi-stage planning processes that are partly done manually. In our paper we focus on the fleet planning process for freight railcars and we propose an integrated planning approach consisting of two parts. Firstly, a fleet sizing optimization model is applied to obtain the optimal assignment of railcars to customers' orders. Within this model, we consider a heterogeneous fleet and take into account substitution between clusters and customers' preferences. The optimal fleet size is computed on a monthly basis for a planning horizon of multiple years, accounting also for railcar flows between months and years. Secondly, a fleet management model in form of knowledge-based decision support system is applied to help the planner to make changes in the fleet mix by investing into or leasing new railcars, performing revisions and decommissioning of old or unutilized railcars. As also illustrated in the designed real-world case study, the integrated planning approach is able to provide the planner with an overview of possible actions including their direct impact on the fleet mix for a mid-term planning horizon.

Keywords Rail transport planning · Fleet management · Fleet sizing · Optimization · Decision support

1 Introduction

Rail freight transport is often considered as a sustainable and efficient alternative for transporting goods, either on its own or combined with other modes in multimodal transport networks. This is not only stressed in the academic literature (Dekker et al. 2012; Islam and Eidhammer 2016; Agamez-Arias and Moyano-Fuentes 2017), but also strongly supported by the European Union (EU) with its initiatives (e.g., EC

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Published online: 24 July 2024

2011, 2019; Rail Freight Forward 2018; Shift2Rail 2021) that should contribute to shift of transports from road to rail. Moreover, the importance of rail should increase in the future since it is a central part of synchromodal planning concepts (Van Riessen et al. 2015; Prandtstetter et al. 2016) and the railcar is seen as one of the core elements of the physical internet (Sternberg and Norrman 2017).

Despite all these initiatives, statistics show that the usage of rail transport within the EU has a rather stagnating or even decreasing trend. As an example, the share of rail on the modal split of inland freight transport within the EU decreased by 1.5% between 2012 and 2019 and reached 17.6%, whereas truck transport grew by 2.8% and reached 76.3% (Eurostat 2021). This development might be caused by multiple reasons. One of them are changing market conditions, where supply chains are getting more responsive and flexible and therefore demand more frequent deliveries with smaller transport quantities (Manders et al. 2016). This situation favors the road transport with its possibility of door-to-door connections and flexible routes on the dense road network (Chopra and Meindl 2013). Another aspect is the lacking interoperability in the EU railway system with different technical, infrastructural and operational standards that lead to operational inefficiencies, for instance requiring driver and engine changes at the border (ERA 2022). Finally, the currently used transport planning processes can be also perceived as potential obstacles in increasing the competitiveness of rail in comparison to road.

When looking at rail transport planning in Europe, the tasks are performed on strategic, tactical and operational level. Whereas strategic tasks take several years and include infrastructure planning and construction as well as vehicle procurement (Breugem 2019), the tactical planning process starts with rail timetables, which are created up to one year in advance. Based on that, each train receives a reserved time slot to follow its route. Following these timetables, the available railcars need to be assigned to the planned demand and locomotive and crew schedules need to be coordinated with the already existing train timetables (Cacchiani 2009). Moreover, there are freight trains scheduled at short notice. Since these steps are performed by different units within a company or even by different companies and their support with software and optimization models is not sufficient, creating such yearly plans might take several weeks. Only then tactical plans are translated into operational daily plans.

Moreover, tactical rail freight demand forecasting on a yearly basis is very uncertain and hard to forecast due to the fact that only part of the demand is based on long-term contracts with customers and another part is based on spot market with short-term notice. Thus, the real demand is usually known only few days or weeks in advance and fluctuations in demand might be high (Bojovic 2002). Therefore an efficient planning model for assigning railcars to demand and determining the optimal fleet size is needed in order to be able to react to demand changes and adapt the created plans accordingly.

Besides complex planning processes, the availability of appropriate railcars is another factor that influences the ability of railway companies to fulfill the demand for their services. As stated by Bojovic (2002), railcars are very expensive and important capital resource of railway companies. Therefore, fleet planners need to find the optimal fleet size in order to avoid high costs if the railcar inventory is too high, but also to prevent situations where they are not able to satisfy demand due to missing railcars.

In general, railway companies in Europe are responsible for the movement and allocation of railcars located on their territory (Bojovic 2002). These railcars consist of their own cars, also called system cars, and foreign cars, which are railcars owned by other companies that can be temporarily used by the respective railway company on its territory under stated rules (GCU 2020). Since the costs of foreign cars are usually higher and their availability is uncertain, the focus lies on the planning of system cars. System cars can be either owned by the company or leased for certain time (e.g., months or years) from an external railcar keeper, whereby leasing is usually more expensive than buying an own railcar when the usage period is sufficiently large (Klosterhalfen et al. 2014). Another aspect is the time needed to obtain new railcars. Whereas leasing existing railcars can take several months, the procurement process for new railcars can take up to two years, starting with a tender and ending with the delivery of the railcars (Papatolios 2021). Besides that, leasing of railcars is usually used to cover a temporary increase in demand whereas new railcars usually have a lifetime of more than 10 years (Klosterhalfen et al. 2014). System cars can be either freely assigned to the demand or there exist also dedicated railcars that are only used for a certain customer during a longer time period (Kallrath et al. 2017).

In order to address the described challenges in railcar planning, we present an integrated planning approach combining a fleet sizing mixed-integer linear programming (MILP) model with a fleet management decision support model. By combining these two models, our approach covers both the demand side, represented by the assignment of railcars to the forecasted demand, and the supply side, represented by the management of the available railcar fleet and decisions about its expansion or the usage planning of old or unused railcars. The presented approach will be applied to a case study illustrating typical challenges connected to fleet planning. Thus, the contributions of this paper are fourfold:

- We propose an integrated planning approach that covers the process of fleet planning combining tactical assignment of railcars to the demand with strategic decisions about the fleet mix. The plans are created for multiple years in order to get an overview about required changes in fleet mix in advance so that the railway company has enough time to react to these changes. To the best of our knowledge, such integrated approach does not exist in the available literature.
- Coordination of both models enables feedback loops and adaptions leading to the best solution in both assignment of railcars and fleet mix. Moreover, although the demand considered within one model run is assumed to be deterministic, the model can be solved quickly multiple times with different scenarios and allows reactions to demand changes in a relatively short time.
- The presented optimization model takes into account specific aspects that need to be considered when assigning railcars in practice, including compatibility of railcar types with different goods, substitution of railcar types between each other, dedicated railcars and customers' preferences for certain railcars. The objective is on one hand to reach high customer satisfaction by optimizing their preferences and, on the other hand, to minimize total costs and the number of

required railcars. The model identifies potential missing railcars using hypothetical dummy railcars and assigns automatically the railcars from each type to the customers' orders based on selected criteria. Although many of these aspects and objectives have been considered individually before, as shown later in the literature review, to the best of our knowledge there does not exist a model that would combine all of them together.

- A case study was developed for testing the proposed planning approach, which is based on a real-world example and illustrates the influence of changes in input factors (e.g., demand) and potential changes in fleet mix on the optimal fleet size. The considered scenarios can serve as a decision support for fleet planners in a railway company.

The structure of the paper is as follows: Sect. 2 gives an overview about the available literature regarding the fleet sizing, fleet management and decision support models in general. Sect. 3 starts with a summary of the specific requirements considered in our planning approach and then presents the coordination of both models and describes each model in detail. In Sect. 4 the case study is introduced and results for changes in demand and fleet mix are presented. Section 5 concludes the paper and gives outlook for possible future research directions.

2 Literature review

In order to be able to respond to customers' demand and transport their goods, each railway company needs to maintain a fleet consisting of different types of railcars. In order to effectively manage this fleet, a variety of decisions need to be taken such as decisions regarding the fleet composition, including fleet mix and fleet size (Klosterhalfen et al. 2014; Kallrath et al. 2017). The latter is often combined with the assignment of railcars to customers and allocation of empty freight cars that need to be decided on the operational level. For a recent exhaustive literature review and classification of tactical/strategic and operational problems related to fleet management and fleet sizing we refer to Milenkovic and Bojovic (2019). Dejax and Crainic (1987) provide an overview and a classification of empty vehicle flow problems for different transport modes. In the next paragraphs we first review the fleet sizing problem and the methods used to model this problem, afterwards we look at the factors that are considered by different authors in the context of fleet sizing and finally we discuss the combination of fleet sizing with fleet management and the use of decision support systems (DSS) in the related areas.

The goal of fleet sizing is to determine the optimal number of railcars used for transporting the goods. This number should not be too high to avoid high costs neither too low to avoid shortages in demand satisfaction (Turnquist and Jordan 1986). As pointed out by Sayarshad and Marler (2010), the problem is not only relevant for rail transport, but can be applied to a variety of areas including, among others, trucking industry, airlines or material handling. According to the taxonomy developed by Turnquist (1985), the models can be classified based on their traffic pattern, shipment size relative to vehicle and deterministic or stochastic analysis. In case of traffic pattern we can distinguish one-to-one problems with one origin and one destination (Sim and Templeton 1982), one-to-many problems with one origin and multiple destinations (e.g., vehicle routing problems) (Parikh 1977) and many-to-many problems used in transport networks (Bojovic 2002). Shipment size differentiates between shipments with full-vehicle load and shipments that are smaller than the vehicle capacity. Demand and travel times are important factors for distinguishing between deterministic (Sayarshad and Ghoseiri 2009; Yaghini and Khandaghabadi 2013) and stochastic models (List et al. 2003; Milenković et al. 2015).

Multiple approaches are used to model the fleet sizing problem. Often the network flow models are used that model transport flows in a time-space network, where the position of the individual railcars is visible in each period and thus it can be checked whether the number of railcars in each node meets the expected demand (e.g., Sherali and Maguire 2000). Another approach is taken by Klosterhalfen et al. (2014) that combine a deterministic MILP model with a stochastic inventory model. They study a problem from the chemical industry that deals with finding the optimal fleet mix, i.e. types of railcars, and fleet size, i.e. the quantity per type, from the perspective of a railcar owner. The objective is to minimize the direct railcar costs and the number of railcar types. They use a two-step process. First, the fleet mix is set based on a deterministic MILP. Then, the fleet size is determined by an approximation from inventory theory. In queuing models the transport requests in each node are mapped in form of a queue, whereby the model calculates the optimal number of railcars needed to minimize waiting times (e.g., Koenigsberg and Lam 1976; Parikh 1977; Papier and Thonemann 2008). List et al. (2003) propose a robust optimization approach for fleet sizing with the options to delay and defer shipments. Milenković and Bojović (2013) study a problem of rail freight car fleet size and allocation based on optimal control theory.

The considered fleet sizing aspects also vary between the available papers. As an example, Klosterhalfen et al. (2014) consider uncertainty in demand and travel times and include substitution possibilities. Substitution of railcars is also considered by Milenković et al. (2015) who study a fleet sizing problem for heterogeneous fleet under demand and travel time uncertainty. In contrast to that, Heydari and Melachrinoudis (2017) do not allow the substitution between different railcar types, but take into consideration preferences of the customers in railcar type assignment. Kallrath et al. (2017) consider multiple railcar types that differ in their size and volume and address the problem of finding the optimal number of railcars for each size. The first step of their fleet design problem is based on the approach used by Klosterhalfen et al. (2014).

Related to fleet sizing is the problem of empty car allocation, which is an operational task dealing with the optimal assignment of empty railcars to individual nodes in the network, so that empty runs are minimized and sufficient railcars are available in each node to cover demand and avoid waiting times (Gorman et al. 2010; Upadhyay and Bolia 2014; Gorman 2015; Heydari and Melachrinoudis 2017). One possible method to tackle this problem is inventory control approach used by, e.g., Philip and Sussman (1977), Mendiratta and Turnquist (1982) or Milenković and Bojović (2013). Whereas most of the mentioned papers consider a homogeneous fleet and hence no substitution possibilities are explored, Engels and Schrader (2015) deal with railway freight car dispatching where substitutions at different exchange rates are possible. Because of its interdependencies, the fleet sizing and empty car allocation problem should be solved together (e.g., Beaujon and Turnquist 1991; Cheung and Powell 1996; Wu et al. 2005; Sayarshad and Ghoseiri 2009).

Whereas the integration of fleet sizing models with operational planning activities, such as empty car allocation, is very common, the combination of fleet sizing and decisions about fleet mix is rather scarce in the literature. Recently, Baykasoglu and Subulan (2019) recognized the need for integrating the fleet mix decisions into intermodal transport planning and Milenkovic et al. (2023) emphasized that railcars as expensive assets need to be highly utilized. Baykasoglu et al. (2019) reviewed the literature on fleet planning problems and developed a framework which categorizes the different types of fleet problems into long-term, medium-term, and short-term. They conclude that fleet planning is not an isolated topic but links multiple problems, like, e.g., fleet size and mix, fleet deployment, vehicle inventory management, empty vehicle repositioning, etc., and therefore requires a simultaneous optimization of interactive planning problems. Also, Baykasoglu et al. (2019) conclude that research should focus on optimization-based DSS for practical intermodal fleet planning applications. A DSS should cover multiple planning horizons and be able to address the requirements of multiple decision makers. The authors further stress the importance of the DSS to cover multiple decisions, i.e, long, medium, and short-term decisions and to provide several feasible solutions to the decision makers.

Despite these facts, we did not find any papers explicitly combining fleet sizing with fleet management decisions that focus on the acquisition and management of railcars that are used for a longer period of time (Cordeau et al. 1998). One of the reasons for this might be that these measures often require a domain-specific knowledge about the state of the railcars and possibilities to make changes in the current fleet mix, which can be supported by using DSS. The domain knowledge can be depicted as rule-based expert systems, which define knowledge by if-then rules (Power 2002). The *if* part of the rule describes a specific situation, whereas the *then* part describes a certain action (Kurfess 2003). Power (2002) simplifies the pioneering research of Alter (1980) into three main types of DSS, namely data-driven, model-driven, and knowledge-driven. In our context, mainly the knowledge-driven DSS are relevant, where problems of a specific domain are grasped by the system and recommendations given to managers are, among others, used for investment optimization (Power 2002).

In the logistics domain, Lau and Tsui (2007) propose an expert system including rule-based reasoning for shipment consolidation in the airfreight industry. Tekin Temur et al. (2014) and Pourjavad and Mayorga (2018) use fuzzy rule-based expert systems for forecasting and prioritizing reverse logistics operations. Couillard (1993) proposes a DSS for vehicle fleet planning offering a step-to-step approach to managers. DSS in fleet management use dynamic approaches, e.g., in airline planning and ambulance dispatch and relocation (Andersson 2005; Andersson and Värbrand 2007, 2016). Optimization-based DSS including rolling horizon principles are used in maritime transportation (Fagerholt et al. 2010), strategic decisions in the food producing industry supply chain (Kostin et al. 2011), or in the disruption management for railway rolling stock (Nielsen et al. 2012). Other domains using expert systems are for example the financial sector (Nikolopoulos and Fellrath 1994; Shiue et al. 2008), construction industry (Amiruddin and Atiq 2009; Ooshaksaraie et al. 2012), environmental management (Reffat and Harkness 2001), and medical diagnosis (Prasad et al. 1996).

In the work at hand, the fleet sizing and fleet management problem under the consideration of various railcar types are integrated into the DSS. The importance of considering investment decisions in the rolling stock market, which is characterized by long lead times and major investments, was also confirmed by Murillo-Hoyos et al. (2016), who address the challenge of rolling stock purchase to include major capital expenditure and therefore propose a purchase cost modeling approach for a better cost estimation. Therefore, decisions on investments are considered, given different possible scenarios for future demand development.

3 Integrated planning approach

As shown in Sect. 2, the fleet sizing problem is widely discussed in the literature. Nevertheless, in practice it is often necessary to identify possible future changes and potential over- and understocking situations in the railcar inventory due to the changing demand or customer preferences and to react to these situations in advance due to the long delivery times of new railcars, as described in Sect. 1. In order to achieve this, our integrated planning approach combines a fleet sizing optimization model with a fleet management decision support model that gives an overview about the development of the railcar inventory for multiple years and helps the fleet planner to identify and perform necessary adaptions. Additionally, both models include specific factors that enable the planner to take into account the preferences of customers as well as the strategic decisions of the railway company.

The integrated approach and the coordination of the two models is depicted in Fig. 1. In general, the planning starts with the fleet sizing model (Part 3 in Fig. 1), which takes the data about available railcars from fleet input data (Part 2) and about demand from demand input data (Part 1) and calculates the optimal fleet size for each month. In this step, railcars of similar types are grouped into clusters which are assumed to have the same characteristics and capacities. Planning is done in yearly cycles for the following years, giving a mid-term overview about the required number of railcars for all clusters on an aggregated level. The aim is to have an aggregate plan which shows potential discrepancies between the available and the required railcars in the different periods instead of getting a detailed assignment plan of the individual railcars to the individual orders. The model is described in detail in Sect. 3.2.

Once the fleet sizing plan is ready, it shows the number of railcars needed from each cluster to satisfy the planned demand in each month. These results serve as an input for the fleet management model (Part 4). Here the aggregated plan is disaggregated in order to identify the individual railcars from each cluster which will be assigned to the demand, based on different characteristics, such as type, age, technical condition, etc. Afterwards necessary adjustments in the fleet mix are planned—leasing or investing in new required railcars, exploitation possibilities for railcars

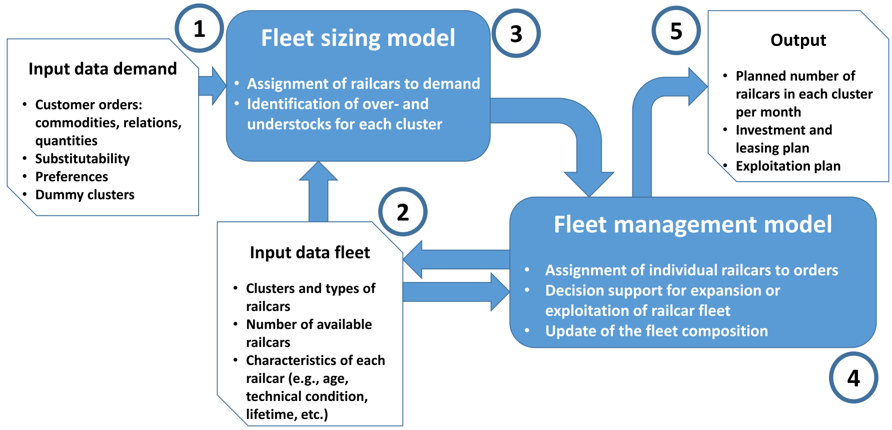


Fig. 1 Overview of the integrated planning approach

which are too old, in bad technical condition or not needed anymore. Once this is finished, the list of available railcars is updated and sent back to the fleet sizing model, where a new fleet sizing plan can be created based on the new fleet mix. This can be repeated multiple times, depending on the considered adjustments, until the final plan is reached. The process ends with an output (Part 5) that summarizes the planned number of railcars in each month and the measures which need to be taken to reach the planned fleet mix.

Besides the consideration of different measures in the fleet management model, the approach also allows to consider variations in input data, e.g., in form of different expected demand scenarios. In this way the planner gets an overview about the influence of demand and supply factors on the fleet mix in a relatively short time, so that qualified decisions about necessary measures can be made.

The fleet management model is described in Sect. 3.3 whereas the fleet sizing model is discussed in Sect. 3.2. Before the detailed description of both models, Sect. 3.1 gives an overview about the required input data and considered factors.

3.1 Input data and considered factors

Before solving the models, two types of input data are needed: on one hand, there is data regarding the fleet mix (Part 2 in Fig. 1) and, on the other hand, the data about the demanded transport quantities and the planned routes is needed (Part 1).

The fleet mix data includes the types of railcars, the number of available railcars per type and the characteristics of each individual railcar, such as costs, age, technical condition, etc. Whereas the fleet management model considers each railcar individually, for the fleet sizing model similar types of railcars are grouped to clusters. One cluster can include multiple types of railcars that might have small differences between each other in the type of equipment that they have available (e.g. due to a newer generation of the railcar), but for the purpose of our planning can be considered as similar with regard to the capacities or type of commodities they can carry.

The reason for defining clusters is the reduction of model complexity since the fleet sizing model requires only the aggregated number of available railcars per cluster whereas the fleet management model is responsible for assigning concrete railcars to the individual orders.

For assigning the demanded transport quantity to the railcars, the fleet sizing model looks separately at each node, from which the commodities have to be transported, calculates how many full railcar loads are necessary to transport the demanded quantity per month and makes sure that there are enough railcars available every day. Based on input from practice, the model assumes that once the railcars are loaded, they leave the node, transport the goods to the final destination and return back to the origin (Kallrath et al. 2017). This roundtrip is called a relation and besides the origin and destination it is characterized by additional factors, such as the specific route, maximum carrying capacity of the bridges or loading gauge of the track. The time needed to complete the roundtrip on a certain relation is assumed to be equal for all railcars of the same cluster transporting a certain type of commodity. This roundtrip time is needed to calculate the number of railcars returning back to the origin node every day, which can then be used again for transporting the next load. If these railcars are not sufficient to cover the demand, additional railcars are needed that increase the total number of railcars assigned to a transport order. Furthermore, the capacity of a railcar in tons has to be defined for each combination of cluster, type of commodity and relation as model input. In this respect, we consider the transports on a one-to-one basis and we assume deterministic demand and travel times (see Sect. 2).

Customers usually define order quantities in tons on a yearly basis, which are then in the pre-processing phase divided into monthly quantities. The yearly quantity can be either divided evenly or seasonal variations between months can be considered. The monthly quantities are divided evenly to individual days of the month within the model to calculate the number of required railcars per day.

Besides defining the yearly and monthly transport quantities, the type of commodity and the relation, there are additional aspects integrated in the fleet sizing model which are based on inputs from practice and enable to take into account specific requirements of the customers and planners:

- *Substitution and cluster preferences:* Railcars in each cluster have technical limitations regarding the types of commodities which they can transport, e.g., coil cars cannot be used to transport bulk goods or containers require special flatcars with appropriate mounting. Therefore, it has to be specified which clusters can be used to transport the commodity from the order. In addition to specifying the allowed clusters, the customer can also state preferences for the individual clusters, whereby the highest preference gets the preference number one and the next clusters with lower preferences get higher preference numbers in the order in which they are preferred. These preference numbers are taken into account in the objective function of the fleet sizing model, where the model minimizes the total sum of preference numbers and in this way tries to assign the highest preference to each order if sufficient railcars are available. If there are no railcars left from the highest preference, they can be substituted by the clusters with lower preferences. Each customer has to specify at least one preference and each chosen cluster should have a different preference number.

- *Minimal share of order quantity transported by a cluster:* Although the model tries to assign the cluster with the highest preference to each order, it can happen that an order only gets the clusters with lower preferences due to insufficient number of railcars in the preferred cluster. However, the model enables the customer to specify the minimal share of the total transport quantity which has to be transported by the cluster with the highest preference. In this way it is guaranteed that at least some part of the ordered quantity will be carried by the preferred cluster. This share can be between 0–100%.
- *Orders with dedicated railcars:* Besides the standard orders, which define the transport quantity that is assigned by the fleet sizing model to the required number of railcars, the model also takes into account special type of orders in which the customer directly defines the type and number of railcars that have to be used for his/her order in each month. Since for these orders the number of railcars is already defined, the dedicated railcars are just added to the total number of needed railcars. Still, they have to be considered in the model since they can be used for another order in months where they are not needed for the order with dedicated railcars.

In addition to these assumptions based on inputs from practice, we also consider modelling assumptions that give an overview about the number of required railcars and decrease the planning complexity:

- *Dummy clusters:* One input of the fleet sizing model is the number of currently available railcars. However, considering only the available railcars could lead to infeasible solutions if they are not sufficient to satisfy the demand. Moreover, the fleet sizing model should also indicate potential needs for increasing the number of railcars in clusters with increasing demand. As a solution, we introduce dummy clusters. A dummy cluster is a complementary cluster to the cluster with the highest preference for each given order, i.e. the cluster with preference number one. Simultaneously, the preference number of a dummy cluster is higher than the preference numbers of all other clusters. Therefore, the model tries to assign all available railcars first and chooses railcars belonging to a dummy cluster only when no other railcars are available. In this way it is ensured that the model prefers the currently available railcars and still indicates through the dummy clusters how many railcars and which types should be procured. This information is then given to the fleet management model which helps the planner to decide how and when the railcars will be supplied.
- *Transitions between months and average number of railcars:* Whereas the daily number of railcars used for each order is calculated separately in each month, the roundtrips of railcars are tracked across multiple months. This means that railcars leaving the origin at the end of a month only return back in the first days of the next month (depending on their roundtrip time) and therefore still influence the railcar inventory at the beginning of that month. In this way we can reuse the returning railcars in the next month or indicate to the planner that they still need

to be considered at the beginning of the month even if they are not needed in that month due to, e.g., lower demand. This is important for calculating the number of railcars needed in each month: since we create the plan on a monthly basis, but we measure the railcar inventory in each node per day, the model takes the average number of railcars needed per day over the whole month and reports it as the optimal fleet size.

- *Transitions between years:* In order to reduce the computational complexity and enable changes in rolling planning process, the fleet sizing model is solved separately for each year. In the first step, the fleet size is optimized for the first year and the results for the last days of that year are used as initial input parameters for planning the second year in the next step. This is repeated every year.

3.2 Fleet sizing model

In the fleet sizing model, an assignment of orders to railcar clusters is determined. Given is a set A of orders, which is partitioned into two subsets, $A = \hat{A} \cup A'$. Set A' contains the orders with dedicated railcars and the number of dedicated railcars for each order is given in h_{ig}. The orders in set $\hat{A}$ are standard orders for which the type and number of railcars is decided in the model. For these orders parameter d_i denotes the quantity in tons that has to be transported.

Every order $i \in A$ consists of a specific type of commodity $\iota(i)$ for a given relation $\rho(i)$ and month $\mu(i)$. Moreover, for every order $i \in A$, a set of feasible clusters is given. This is specified in parameter a_{ig} that is 1 if cluster g is a feasible type of transport for order i. Besides that, a priority number p_{ig} is given that reflects the wish that this order is transported with a railcar of cluster g. Furthermore, for each order $i \in A$ a minimum quantity, α_{ig}, that has to be transported by railcars of cluster g can be specified. This quantity can be transported either by railcars of the standard cluster g or railcars of the corresponding dummy cluster $\tau(g)$.

Let G denote the set of all clusters, including also dummy clusters, whereas set $G' \subseteq G$ denotes only standard clusters without dummy clusters. For every cluster $g \in G$, the number of available railcars is specified in c_{gm} for every month m. For dummy clusters this parameter gets a high value (e.g., 10,000) to represent virtually unlimited number of available dummy railcars. The use of each railcar causes cost k_{gm} defined for each cluster g and each month m. The total cost is limited by the maximal budget BO.

N is the set of months in the current planning horizon and $\tilde{N}$, $N \subseteq \tilde{N}$, extends N by the last month of the previous planning period. T denotes the set of days in the planning period. The number of days per month m is given by q_m and each day t can be associated to its respective month using parameter $\nu(t)$. The set of days included in each month m is denoted by T^m.

R is the set of relations and set J contains the types of commodities that need to be transported. These sets are important for determining the capacities and roundtrip times. To compute the number of necessary railcars, parameter b_{rgj} specifies the number of tons that fit into one railcar of cluster g on relation r for commodity j. The relation r is used as an index, since different relations have different restrictions concerning the maximum load per railcar that depends on the maximal allowed axle load which is restricted by the lowest allowed axle load from all bridges and track categories used on that relation. Roundtrip times in days s_{rgj} are given for relation r in cluster g and commodity j, since also the unloading time influences the total roundtrip time.

As mentioned in Sect. 3.1, we solve the problem on yearly basis and results from the previous year are considered in the planning of the current year. For this we need the information about the planned orders and quantities for all days at the end of previous year that are closer to the end of the year than the maximal roundtrip time included in the input data (due to monthly transitions). Therefore, we define the set $\hat{T}$ that contains the days smaller than the maximal roundtrip time. A^0 denotes the set of orders from the previous planning period, $\widetilde{V_{ig}}$ the full railcar loads of order i and cluster g from the previous planning period and $\widetilde{I_{grj}}$ the inventory of railcars of cluster g for relation r and commodity j for the previous planning period.

Furthermore, for calculating the daily inventory of railcars the following sets are defined: The set F_{rj} contains all orders with relation r and commodity j, i.e., $F_{rj} = \{i \in A | \rho(i) = r \wedge \imath(i) = j\}$ and the set F^0_{rjt} contains all orders with relation r, good j and days t at the beginning of the year that are smaller than the corresponding roundtrip time s_{rgj}, i.e. $F^0_{rjt} = \{i \in A^0 | \rho(i) = r \wedge \imath(i) = j \wedge t <= s_{rgj}\}$.

Table 1 shows the sets and parameters of the model and the decision variables are given in Table 2.

The mathematical model is defined as follows:

$$lexmin(F1, F2)$$

subject to:

$$F1 = \sum_{i \in A} \sum_{g \in G} y_{ig} p_{ig} \tag{1}$$

$$F2 = \sum_{g \in G} \sum_{m \in N} E_{gm} k_{gm} \tag{2}$$

$$E_{gm} \leq c_{gm}, \forall g \in G, m \in N \tag{3}$$

$$E_{gm} = \sum_{r \in R} \sum_{j \in J} W_{gmrj}, \forall g \in G, m \in N \tag{4}$$

$$\sum_{g \in G} y_{ig} a_{ig} = 1, \forall i \in A \tag{5}$$

$$y_{ig} a_{ig} \frac{d_i}{b_{\rho(i),g,\imath(i)}} = B_{ig}, \forall i \in \hat{A}, g \in G \tag{6}$$

Table 1 Sets and parameters

A	Set of orders, $A = \hat{A} \cup A'$
$\hat{A}$	Set of standard orders
A'	Set of orders with dedicated railcars
A^0	Set of orders from the previous planning period
F_{rj}	Set of all orders with relation r and commodity j
F^0_{rjt}	Set of all orders with relation r, commodity j and days t smaller than the corresponding Roundtrip time s_{rgj}
G	Set of clusters (including dummy cluster)
G'	Set of standard clusters without dummy clusters
J	Set of commodities
N	Set of months
$\tilde{N}$	Set of months including previous planning period
R	Set of relations
T	Set of days in the planning period
T^m	Set of days included in month m
$\hat{T}$	Set of days at the beginning of the year smaller than maximal roundtrip time
α_{ig}	Minimum quantity of order $i \in \hat{A}$ that has to be transported by railcars of cluster $g \in G$
a_{ig}	Parameter a_{ig} is 1 if order $i \in \hat{A}$ can be feasibly transported by railcars of cluster $g \in G$, 0 otherwise
b_{rgj}	Capacity of railcar of cluster $g \in G$ in tons per load for relation $r \in R$ and commodity $j \in J$
BO	Budget limit in the planning period
c_{gm}	Number of currently available railcars of cluster $g \in G$ in month $m \in N$
d_i	Demand of order $i \in \hat{A}$ in tons
h_{ig}	Number of dedicated railcars of cluster $g \in G'$ for order $i \in A'$
k_{gm}	Costs per railcar of cluster $g \in G$ in month $m \in N$
p_{ig}	Priority number of cluster $g \in G$ for order $i \in A$
q_m	Number of days in month $m \in N$
s_{rgj}	Roundtrip time in days for relation $r \in R$ of cluster $g \in G$ for commodity $j \in J$
$\widetilde{I_{grj}}$	Demand for railcars of cluster $g \in G$ for relation $r \in R$ and commodity $j \in J$ for previous planning period
$\widetilde{V_{ig}}$	Full railcar loads of order $i \in A$ and cluster $g \in G$ from previous planning period
$\iota(i)$	Commodity of order $i \in A$
$\mu(i)$	Month of order $i \in A$
$\rho(i)$	Relation of order $i \in A$
$\nu(t)$	Month of day $t \in T$
$\tau(g)$	Dummy cluster associated to cluster $g \in G'$

$$V_{ig\mu(i)} = \frac{B_{ig}}{q_{\mu(i)}}, \forall i \in \hat{A}, g \in G \tag{7}$$

Table 2 Decision variables

B_{ig}	Number of monthly full railcar loads of order $i \in \hat{A}$ on railcars of cluster $g \in G$
I_{gtrj}	Inventory of railcars of cluster $g \in G$ on day $t \in T \cup \{0\}$ for relation $r \in R$ and commodity $j \in J$
E_{gm}	Demand for railcars of cluster $g \in G$ in month $m \in N$
V_{igm}	Number of daily full railcar loads of order $i \in A$ on railcars of cluster $g \in G$ in month $m \in \tilde{N}$
W_{gmrj}	Demand for railcars of cluster $g \in G$ in month $m \in N$ for relation $r \in R$ and commodity $j \in J$
y_{ig}	Portion of order $i \in A$ that is transported in a railcar of cluster $g \in G$

$$V_{ig\mu(i)} = y_{ig} a_{ig} \frac{h_{ig}}{s_{\rho(i),g,\iota(i)}}, \forall i \in A', g \in G \tag{8}$$

$$\begin{aligned} I_{gtrj} = I_{g,t-1,r,j} + \sum_{i \in F_{rj}} V_{ig\nu(t)} \\ - \sum_{i \in F_{rj}} V_{ig\nu(t-s_{\rho(i),g,\iota(i)})}, \forall g \in G, t \in T \setminus \hat{T}, r \in R, j \in J \end{aligned} \tag{9}$$

$$\begin{aligned} I_{gtrj} = I_{g,t-1,r,j} + \sum_{i \in F_{rj}} V_{ig\nu(t)} - \sum_{i \in F_{rj}} V_{ig\nu(t-s_{\rho(i),g,\iota(i)})} \\ - \sum_{i \in F^0_{rjt}} \widetilde{V_{ig}}, \forall g \in G, t \in \hat{T}, r \in R, j \in J \end{aligned} \tag{10}$$

$$W_{gmrj} \geq \frac{\sum_{t \in T^m} I_{gtrj}}{q_m}, \forall g \in G, m \in N, r \in R, j \in J \tag{11}$$

$$y_{ig} + y_{i,\tau(g)} \geq \alpha_{ig}, \forall i \in \hat{A}, g \in G' \tag{12}$$

$$\sum_{g \in G} \sum_{m \in N} E_{gm} k_{gm} \leq BO \tag{13}$$

$$I_{g0rj} = \widetilde{I_{grj}}, \forall g \in G, r \in R, j \in J \tag{14}$$

$$V_{igm} = 0, \forall i \in A, g \in G, m \in \tilde{N} \setminus \{\mu(i)\} \tag{15}$$

$$B_{ig} \geq 0, \forall i \in \hat{A}, g \in G \tag{16}$$

$$I_{gtrj} \geq 0, \forall g \in G, t \in T \cup \{0\}, r \in R, j \in J \tag{17}$$

$$V_{igm} \geq 0, \forall i \in A, g \in G, m \in \tilde{N} \tag{18}$$

$$E_{gm} \geq 0 \text{ and integer}, g \in G, m \in N \tag{19}$$

$$W_{gmrj} \geq 0 \text{ and integer}, \forall g \in G, m \in N, r \in R, j \in J \tag{20}$$

$$y_{ig} \geq 0, \forall i \in A, g \in G \tag{21}$$

We consider a bi-objective optimization problem solved by a lexicographic approach. In the first step, the objective $F1$ is optimized and a budget limit is used to constrain total costs specified in Constraint (13). $F1$ minimizes the sum of priority numbers defined by the customers for each order for all feasible clusters (priority number 1 is the highest priority). Afterwards, the objective $F2$ is optimized among the set of solutions with minimal sum of priority numbers. $F2$ minimizes total costs of railcars assigned by the model. Costs of unassigned railcars are not considered since they could be used elsewhere.

Constraints (3) make sure that the number of assigned railcars does not exceed the number of available railcars. The number of assigned railcars per cluster is calculated in Constraints (4) as a sum of assigned railcars for all relations and commodities. Although Constraints (3) and (4) could be integrated into one constraint, we divide them and we explicitly define E_{gm} since this variable is needed for the fleet management model. Constraints (5) guarantee that every order is assigned to a feasible railcar cluster.

For the standard orders, for which the number of required railcars is to be planned by the model, the number of full railcar loads per month is calculated in (6) and broken down into individual days in (7). For orders with dedicated railcars, the number of dedicated railcars is divided by the corresponding roundtrip time to calculate the required daily number of railcars in (8).

Constraints (9) calculate the daily inventory of railcars that are required for each cluster, relation and commodity. This condition applies to all days that are longer than the maximum roundtrip time from the beginning of the year (e.g., if the maximum roundtrip time is 28 days, this secondary condition will be used from January 29th). For the first days of the year (up to the maximum roundtrip time) Constraints (10) are used, since they also take the daily shipments from the previous period, i.e. December of the previous year, into account. Based on the daily inventory, the average number of needed railcars for each cluster, relation and commodity is calculated for every month in Constraints (11) and this average serves as a lower bound for the reported number of needed railcars.

Constraints (12) ensure that the minimum transport quantity specified in α_{ig} is transported by railcars of the desired cluster, either by the currently available railcars or by the dummy railcars. In Constraint (13), the total costs are limited by the upper budget limit. Constraints (14) define the daily inventories of the previous periods and Constraints (15) make sure that the daily full railcar loads are assigned to an order only in its respective month. Finally, non-negativity or integer conditions are given in (16)–(21).

3.3 Fleet management model

The goal of the fleet management model is a user-centered decision support for the management of the current and future railcar portfolio. Decisions concerning the increase or decrease of the railcar stock should be rule-based as far as possible. The user should thus be provided with a basis for strategic considerations by having the system suggest measures for increasing or decreasing railcar inventory.

Whereas in the fleet sizing model the railcar portfolio size required in the future was determined, in the fleet management model the future requirements are first allocated at the individual railcar level, i.e., the model granularity is changed. The second step deals with the problem of railcars that will not be used in the future and the resulting railcar portfolio that will actually be available. The third part covers the set of rules for meeting demand with newly purchased or leased railcars, and the fourth part covers the recycling of railcars that are no longer needed.

The intended results are a valid decision support that sufficiently and accurately reflects the decision rules in railcar capacity planning. Due to the strong strategic considerations in railcar portfolio management, a DSS based on expert rules was selected as a suitable method. On the one hand, it enables rule-based decisions to be made as automatically as possible and, on the other hand, it provides sufficient flexibility to allow the user decision-making freedom.

The overarching processes of the decision model are shown in Fig. 2. The processes for strategic railcar capacity planning were jointly discussed, modelled, and adapted in regular meetings with partners from practice. Although the applied rules cannot be described in detail due to confidentiality reasons, the following paragraphs illustrate the processes applied in the model.

The process at the highest level of abstraction describes the essential steps to perform strategic railcar capacity planning which consist of four sub-processes:

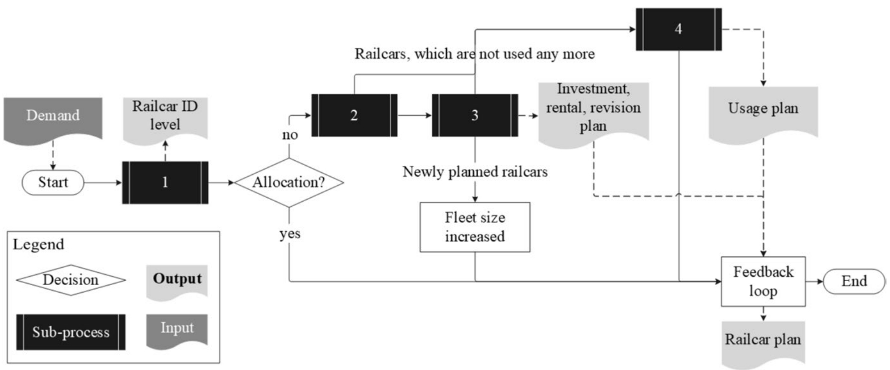


Fig. 2 Overview of the fleet management model

- *Sub-process 1—Assignment to single railcar level:* In this process, the aggregated monthly demand for railcars of each cluster resulting from the fleet sizing model (E_{gm}) is broken down to the individual railcar level and assigned to the actual railcar stock. The calculated demand is increased by a safety margin to account for unexpected railcar failures and covered by the physically available railcars. In the process, the allocation is performed as follows: First, externally leased railcars are allocated as they constitute a direct monthly cost factor. Second, priority is given to the company's own railcars, where the residual book value (RBV) is an important decision criterion. RBV shows the value of the railcar in the balance sheet of the company based on its useful life and depreciation. For planning purposes, railcars with positive RBV are preferred to those without RBV. In this way, a specific physical railcar is assigned to the calculated total monthly requirement. A detailed description of the railcar assignment is shown in the pseudocode in Algorithm 1.
- *Sub-process 2—Assignment of available railcars:* Due to the dynamically considered time horizon of multiple years, broken down to a monthly level, railcars drop out of the fleet due to their revision due date (every 6 years), the end of their leasing period, or the end of their technical service life (30 years). Essentially, the four process strands *End of technical service life, Revision, End of rental* and *Overstock* can be distinguished:

  – *End of technical service life:* Railcars that reach the end of their technical service life defined for their cluster go directly to *Sub-process 4*. Those railcars are labelled as "end of technical service life reached" and are shown to the user in the final usage plan for further processing.
  – *Revision*: Railcars that have reached their revision due date enter this process line. The decision about revision depends on the criteria of future demand and RBV. If there is future demand for this railcar for at least 50% of the future periods within the planning horizon and the RBV is positive, the railcar is scheduled for a revision. The 50%-restriction was added to consider revision costs since those are not taken into account by the fleet sizing model. We assume that a revised car has to be used at least half of the time so that a revision is cost effective. If future demand exists within the planning horizon and the RBV is zero, a user decision is required and the railcar enters *Sub-process 3*. If there is no future demand for the railcar, it enters the *Sub-process 4*.
  – *End of leasing:* The criteria for a leasing extension are the future demand and the leasing costs of a railcar. A leasing extension is designed for four years, whereas revisions are the preferred choice before extending a leasing contract. If there exists a short-term need within the next 12 months, the railcar qualifies for a leasing extension, otherwise the leasing contract expires.
  – *Overstock* : If railcars are not allocated in certain periods, it is determined whether there is future demand for that railcar. If the railcar is not used within the planning horizon, it enters *Sub-process 4*. If it is used at least once within the planning horizon, a distinction is made between short-term

and long-term demand. If there is long-term demand (later than 12 months from now), the railcar qualifies for leasing or decommissioning. If there is short-term demand within the next 12 months, the railcar is labelled as "theoretically usable".

- *Sub-process 3—Investment, rental, revision and conversion planning:* In this sub-process those railcars are allocated, for which no clear decision could be made and for which user input is required. The DSS provides the user with relevant information for the decision and the previously assigned labels per railcar. Relevant information is, for example, the amount of unmet demand over the time horizon per railcar cluster, the number of railcars with expiring leasing contract, number of revisions with a RBV of zero, cost information, or the target lease rate per railcar cluster. The information provided helps the user to make decisions to fill unmet demand in the planning horizon. The user input can be entered at the individual railcar level. The investment in new versus the leasing of railcars can be decided by, e.g., comparing the monthly depreciation rate with the leasing rate and by considering future demand and the target leasing rate for the specific railcar cluster. Here, considerations on the strategic level can be included.
- *Sub-process 4—Usage planning:* This sub-process is used for railcars that have reached the end of their technical service life or for which there is no short-term or long-term demand within the planning horizon. Here, the user is provided with relevant information and recommendations regarding scrapping, selling, leasing or decommissioning of a railcar. In this process, too, the user can influence the result on the basis of strategic considerations.

Algorithm 1 Pseudocode for Sub-process 1

input : E_{gm} - number of demanded railcars of cluster $g \in G$ and month $m \in N$ from fleet sizing model
sm - safety margin accounting for unexpected railcar failures
TD_{gm} - total number of required railcars of cluster $g \in G$ and month $m \in N$
L_{gm} - number of externally leased railcars of cluster $g \in G$ and month $m \in N$
O^{+}_{gm} - number of own railcars with positive RBV of cluster $g \in G$ and month $m \in N$
O^{-}_{gm} - number of railcars without RBV of cluster $g \in G$ and month $m \in N$
output: List of assigned railcars for each cluster $g \in G$ and month $m \in N$

```
                                        // Update number of railcars by safety margin
for g ∈ G do
    for m ∈ N do
        TD_gm = E_gm * sm
                                        // Assign leased railcars
        if TD_gm ≤ L_gm then
            Assign TD_gm railcars from the pool of leased railcars
        else
            Assign all leased railcars
            TD_gm = TD_gm − L_gm
                                        // Assign railcars with positive RBV
            if TD_gm ≤ O+_gm then
                Assign TD_gm railcars from the pool of railcars with positive RBV
            else
                Assign all railcars with positive RBV
                TD_gm = TD_gm − O+_gm
            end

                                        // Assign railcars without RBV
            if TD_gm ≤ O−_gm then
                Assign TD_gm railcars from the pool of railcars without RBV
            else
                Assign all railcars without RBV
                TD_gm = TD_gm − O−_gm
            end
        end
    end
end
```

4 Case study

In order to test the performance of the proposed model and its applicability in practice, we created a case study based on realistic assumptions that illustrates different situations in which the integrated planning approach could support the fleet planning activities. Although the data was adapted for the testing purposes, due to confidentiality reasons it is not possible to reveal detailed fleet data. Nevertheless, the description of the situation using anonymized data will be provided in the next paragraphs.

All tests are performed for a planning horizon of seven years in order to have a mid-term overview about the number of assigned railcars that serve as a basis for decisions in the fleet management model. Within this planning horizon, the fleet sizing model is run for every year separately and the resulting inventories and daily loads from the previous year are taken as inputs for planning in the current year. The fleet sizing model was implemented in PuLP modeler in Python and solved using CPLEX 12.10 on an Intel(R) Core(TM) i5-5300U CPU with 2.3 GHz and 8 GB of memory. The total solution time per presented scenario is less than 10 min. The fleet management model was implemented in R.

This chapter is divided into four parts: Sect. 4.1 introduces the case study and describes the input data and considered assumptions. Sect. 4.2 represents a short computational study showing the impact of the growing number of orders on the computational times of the fleet sizing model. Sect. 4.3 presents results of the base case scenario and discusses different scenarios including investment in new railcars, reductions in the railcar inventory as well as changes in demand and their influence on the fleet. The results are summarized in Sect. 4.4.

4.1 Case study introduction

The case study is based on transports between different European countries and regions, including Austria, Germany, Italy and Hungary. The starting point for planning is the demand forecast prepared on a yearly basis for each customer and then aggregated to a certain type of commodity and relation on which this commodity has to be transported. Each relation represents flows either between two different countries or transports within the same country, without specifying the exact origin and destination. In total, we consider 12 different relations with roundtrip times ranging from 5 to 22 days depending on the relation and cluster.

Commodities can be transported by five different clusters of railcars that differ by the type of commodity which they can be used for, the daily costs as well as their capacity in tons based on the type of commodity and relation since there exist weight limitations for different railway track classes (UIC 2022). The considered railcar clusters included open railcars as well as different types of flat railcars. The daily costs per railcar are assumed to be between 20–40 EUR and they have to be multiplied by the number of days per month to obtain the monthly costs per railcar. Within the case study, we only take into account the costs of assigned railcars. The clusters are for the purpose of this case study named C1–C5 and their characteristics are summarized in Table 3.

Differences between clusters are related to their usage in transport operations. Cluster C1 can be used for many types of commodities and it is also often used for transports within the same country, therefore the minimal roundtrip time is lower in comparison to the other clusters. Since it can be used for various types of commodities, it also has a relatively high range of capacities, including lighter goods with higher volume as well as heavy goods. This cluster has the highest number of available railcars and we assume here that there is a seasonal pattern with the number of railcars fluctuating between 1,300 and 1,700 per month. Monthly costs for C1 are in the medium range among the clusters. Cost savings can be achieved by using clusters C2-C4 that have similar costs and belong to the cheapest clusters, but they also have more specific equipment and therefore also limitations in types of commodities that can be transported by them. The availability of C2 and C3 is rather limited whereas C4 has a higher number of available railcars. C2, as an older type, has a bit lower capacity whereas C3 can transport the highest quantities at once. C5 is assumed to be a relatively new cluster with flexible transport possibilities for different types of commodities. However, due to this flexibility it has the highest costs and it is not so much known by the customers yet. Since each cluster also has its corresponding dummy cluster, we consider 10 clusters in total.

With regard to commodities, we distinguish between six different types of commodities, for the purpose of this case study named G1-G6, that are summarized in Table 4. They consist of different materials including raw materials, agricultural products or construction materials and differ also in transport quantities and number of orders. The number of yearly orders shows also the number of relations on which the commodities are transported (one order per relation) and the monthly orders show the number of months in which an order has been placed. As an example, there have been orders for all 12 months and all five orders of G3 whereas there were four months in which there was no quantity ordered for one of the yearly orders of G4. This is related to seasonal fluctuations in many of the orders, the most prominent example being G1 that is only transported in four months of the year, namely during autumn and winter. However, these seasonalities balance each other out so that the total transported quantity per month is relatively stable between 300,000–360,000 tons, increasing only in the last three months of the year to more than 500,000 tons. The column with preferred clusters shows which clusters can be used for transporting each commodity

Table 3 Considered clusters and their characteristics

Cluster	Capacity in tons	Roundtrip time in days	Number of available railcars per month
C1	40–62	5–20	1300–1700
C2	46–58	8–22	70
C3	50–65	8–21	90
C4	49–57	8–21	950
C5	48–62	8–20	270

where each order includes preferences for 1–4 clusters. The clusters are ordered according to their importance and it can be observed that C1 is the most preferred cluster (included in 19 orders, in 14 of them as a first preference) whereas cluster C4 is preferred only for G2 and G6 and cluster C5 can be used for transport of G2. The demand plan also includes two orders with dedicated railcars, with 30 C3 railcars assigned to one G4 order and seven C3 railcars assigned to a G5 order. Another six orders have specified the minimal share of goods transported with the preferred cluster in range of 50–80%.

4.2 Computational study

In order to analyze influence of the model complexity on the computational times of the MILP fleet sizing model, we performed tests with multiple instances that differ in the size of yearly orders and the corresponding number of relations. For all instances we use 10 clusters and 6 commodities as described in Sect. 4.1. Also the base case instance with 21 orders is the one described in the same section. In addition to that we added instances with 10, 50, 93 and 218 orders. The two biggest instances are based on the base case instance and represent a more detailed version of transport flows showing flows between smaller regions than those defined in the base case instance, therefore also the average volumes of yearly orders are decreasing with the size of the instance. Although finding the solution for these instances is possible, it is not relevant yet from the practical point of view since the accuracy of demand forecasts on such detailed level is very low. Therefore further tests in Sect. 4.3 were done using the base case instance. The solution times are summarized in Table 5 where it can be seen that it is possible to obtain the solution for the base case instance in about 8 min and for the biggest instance in less than 3 h. This is much shorter than multiple days or weeks needed for the current process in practice.

4.3 Case study scenarios and results

When optimizing the plan for the next seven years, we at first assumed that the demand and available railcars will not change during the planning horizon. An

Table 4 Considered commodities and their characteristics

Commodity	Demand in tons	Yearly orders	Monthly orders	Preferred clusters	Orders with dedicated railcars	Dedicated railcars cluster and number
G1	600,000	1	4	C1		
G2	1,970,645	6	67	C1,C4,C5		
G3	1,387,630	5	60	C1,C2,C3		
G4	306,000	2	20	C1,C3,C2	1	C3–30
G5	56,400	3	32	C1,C3,C2	1	C1–7
G6	185,250	4	44	C1,C3,C2,C4		
Total	4,505,925	21	227			

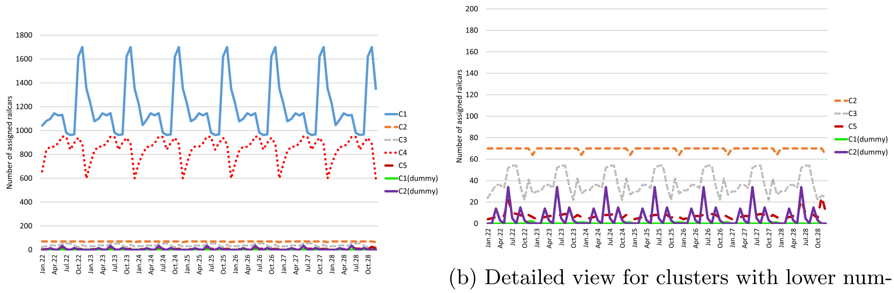
exception is that starting with the second year we gradually increased the number of orders for which also cluster C5 is available as the lowest preference. With this we account for the fact that the flexible C5 railcars could be used more in the future if they are better known by the customers. We define this as the base case scenario.

The results of the fleet sizing model for the base case scenario are depicted in Fig. 3, where the left side shows the overall picture and the right side gives a detailed view of clusters with lower numbers of railcars for a better overview. As it can be observed, clusters C1 and C4 are highly utilized with seasonal peaks for C1 in winter due to the transports of G1. The very low utilization of C5 is only marginally increasing in the later years where the C5 railcars replace missing C1 railcars due to their availability for a higher number of orders. Cluster C3 also has a seasonal pattern with higher demand in summer, but there are sufficient railcars to cover the demand. This is not the case for cluster C2 where it can be observed that all 70 railcars are fully utilized and additional C2 railcars are needed in the majority of the months. The results for costs and preferences summarized in Table 6 in Sect. 4.4 show that in the base case scenario more than 97% of the order quantity is transported by a cluster with the highest preference, more than 2% receive the second preference and only 0.11% of the goods use the third preference. The sum of preferences is 1,630.52, which is by 2.6% higher than the theoretically minimal sum of 1,589 that would be reached if all monthly orders would get the cluster with the highest preference.

As Fig. 3 shows, if the preferences of the customers have to be met, it is necessary to increase the number of C2 railcars whereas the utilization of the C3 and C5 railcars might be rather low. As a consequence, in the next sections we take these results into account and present two cases showing the increase in C2 railcars and decrease of C3 railcars to demonstrate the value of the proposed DSS for the planner. In addition to that, we also investigate the influence of demand changes and the required measures to effectively react to these changes. All presented scenarios are calculated independently of each other and based on the base case scenario with the exception of the C4 reduction scenario presented in Sect. 4.3.4 that is based on the demand decrease scenario from Sect. 4.3.3.

Table 5 Computational times for instances with different sizes

Instance	Number of yearly orders	Number of relations	Average volume of yearly orders in tons	Time needed to obtain the optimal solution (min)
1	10	7	385,150	3.01
2	21	12	214,570	7.73
3	50	32	72,040	25.42
4	93	67	48,450	52.10
5	218	177	20,670	160.50



(a) Overall results

(b) Detailed view for clusters with lower numbers of railcars

Fig. 3 Results of the fleet sizing model for the base case scenario

4.3.1 Investment in new railcars

The occurrence of C2(dummy) railcars in the results of the fleet sizing model in Fig. 3 shows that there might be a permanent need for increase in this cluster and therefore investing in these railcars might be meaningful. Therefore, the fleet management model is applied on these results to support the planner in making decisions regarding the development of the fleet mix.

In our scenario, the 70 available C2 railcars consist of 27 leased railcars with a long-term contract and 43 owned railcars. The latter would have to be gradually withdrawn from the operation due to missing technical revision that is due every six years. Furthermore, the owned railcars are a rather old fleet with no RBV. Based on the underlying rule set of *Sub-process 1* of the fleet management model, first the leased railcars and afterwards the owned railcars are assigned to cover the demand. Even though the owned railcars would be needed throughout the whole planning horizon, they are not automatically assigned for revision in *Sub-process 2*. The reason is that with no RBV they have theoretically reached the end of their service life. Now, the planner has two options in *Sub-process 3*: Either these old railcars will be manually assigned for revision (which prolongs their service life for another six years) or new railcars will be purchased. The old railcars would then be presented to the planner in *Sub-process 4* to be sold or scrapped.

In this case of purchasing new railcars, the fleet management model would suggest to invest into 80 new C2 railcars. This number is derived by rerunning the fleet sizing model without any restrictions on the number of available railcars per cluster. Based on this idealized fleet composition, 80 railcars would be the maximum number of additional railcars, so that the old owned ones are still used for at least 50% of the periods.

Another option to invest in new railcars would be leasing them for a limited period of time. Since the demand forecast shows that there might be a long-term need for these railcars, we assume that the planner decided to purchase the suggested 80 C2 railcars. However, the procurement of new railcars takes about 12 months and therefore these railcars will only be available from one year's time on. The resulting fleet mix together with the theoretical demand for C2 railcars is presented in Fig. 4. Note that because of the investment in new railcars, all the old owned railcars are

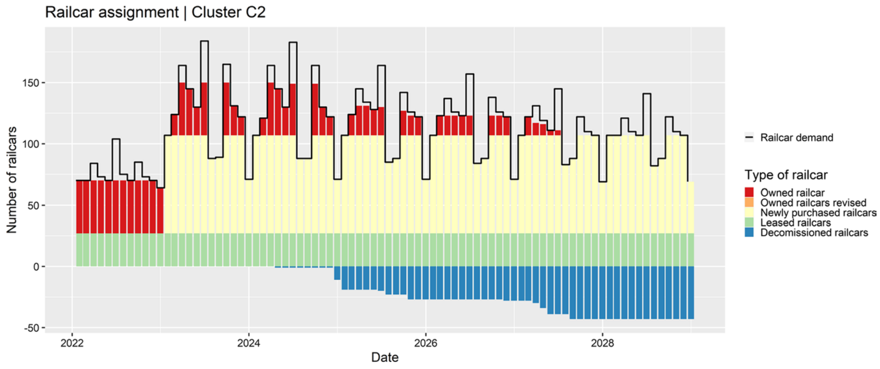


Fig. 4 Assignment of C2 railcars from the fleet management model

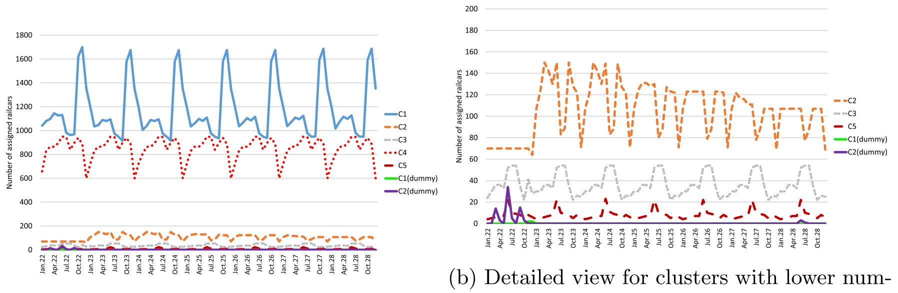
automatically assigned for decommissioning as soon as their next revision would be due.

After making the investment decision, the change in the fleet mix will directly influence the assignment of railcars to the orders. As a consequence, the fleet sizing model is run again with the additional 80 railcars and the results are shown in Fig. 5. Here it can be seen that there are still some C2(dummy) railcars in the results for the first year (that could be covered by, e.g., short-time usage of foreign cars), but starting with year 2023 the total number of C2 railcars increases to 150 and their amount decreases gradually to 107 railcars in year 2028 due to decommissioning of the old railcars. All available C2 railcars are highly utilized during the majority of time with the exception of short periods with temporarily lower demand in summer or winter. These periods could be used for doing repairs or revisions of the unused railcars. The decommissioned railcars are mainly replaced by C1 railcars which are the second preference of customers that cannot get C2 railcars. Since the demand for C2 railcars is still quite high, the planner could in the next iteration think about revising the old railcars instead of their decommissioning or buying additional railcars. However, this is beyond the scope of this scenario that should illustrate the impact of the first investment decision.

The investment decision has positive impact on the preferences and costs, since the sum of preferences decreases by 1.76%, the share of demand transported with the highest preference increases to 99.14% and there is a reduction of the original costs to 99.82% due to higher use of cheaper C2 railcars (see Table 6).

4.3.2 Decrease of railcar inventory due to the end of the leasing contract

In the next scenario we return to the base case results from Fig. 3 and consider the low utilization of the 90 available C3 railcars. Having a closer look at the railcar fleet, it can be observed that 39 out of these railcars were actually only leased and the leasing ends at the end of month 16 of the planning horizon. The 51 owned railcars consist of 39 railcars with a remaining RBV and 12 older railcars with no RBV. Most of the owned railcars have to undergo a technical revision within the first 18



(a) Overall results

(b) Detailed view for clusters with lower numbers of railcars

Fig. 5 Results of the fleet sizing model after investment in 80 new C2 railcars

months of the planning horizon. Assuming that the planner's goal is to increase the utilization of the C3 railcars, they, therefore, have two options: Either to not prolong the leasing contract or to decommission a large portion of the owned railcars. Since the RBV of the newer railcars is still quite high, the planner might decide to not prolong the leasing contract. In that case the fleet management model suggests to gradually revise the owned railcars and use these to cover the demand. The results of the model are shown in Fig. 6.

Note that there are still temporary demand peaks for 2–3 months per year that cannot be met with the revised newer railcars. This is due to the 50%-restriction to account for revision costs in *Sub-process 2*. To close the gap, the planner could either manually revise some of the older railcars that are currently selected to be decommissioned or try to cover the demand with substitute railcars of a different cluster. Running the fleet sizing model again with the reduced number of available railcars, the new solution shows that the missing railcars during the peak can be replaced by unutilized C1 railcars and there is only a slight decrease in the share of demand transported by the clusters with the highest preference from 97.71 to 97.63% and an increase in operating costs of 0.06% due to the utilization of the more expensive C1 railcars (see Table 6).

4.3.3 Increase and decrease in demand

Demand uncertainty is one of the most important causes for inaccurate planning of railcar quantities. As stated by Milenković et al. (2015), demand variations are significant in case of freight railcars. Whereas this is especially true for short-term demand, mid-term forecasts also tend to show changes in demand. As an example, Bärmann and Liers (2018) state that German railways expect a mean increase of 2% per year for rail freight traffic until 2030. Based on this, we take the forecast for the first year of the planning horizon and illustrate potential changes in demand on three different cases: firstly, we assume an optimistic case with an increase in the quantities in the next years by 2% per year, which leads to an increase in demand of approximately 12.5% until the end of the planning horizon. Secondly, a more realistic case considers a combination of increase and decrease, where a 2% increase is assumed in the first two years and then a 2% decrease in the third year and this is

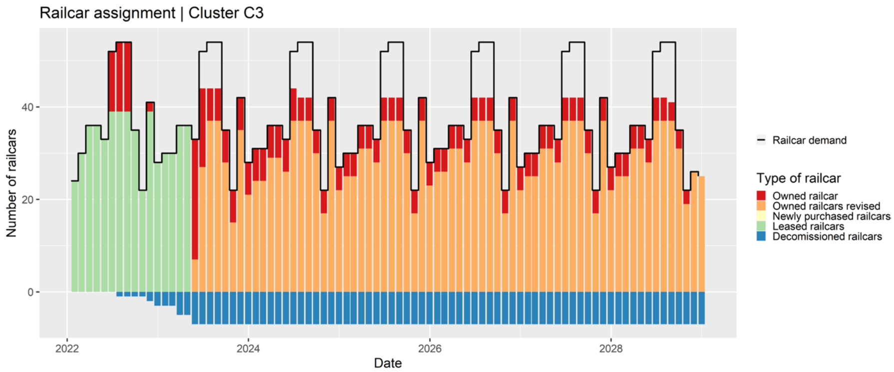
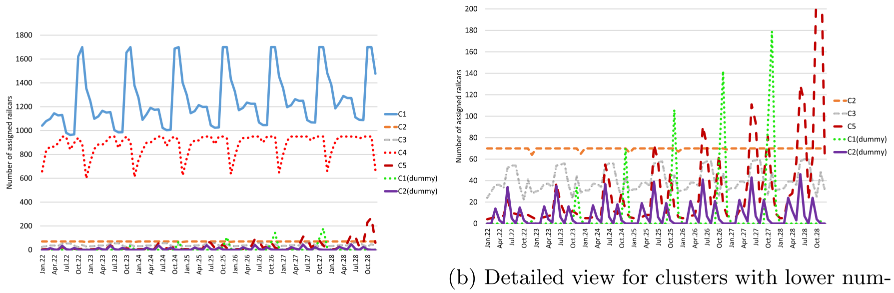


Fig. 6 Composition of C3 railcars from the fleet management model

repeated in two cycles for the planning horizon. However, railway companies might also face decrease in demand due to various reasons, such as economic crisis, pandemic situation etc. Therefore, in the third pesimistic case, analogously to the first case, we also model a decrease in demand by 2% per year to illustrate its potential effects on the fleet. The results for all three cases are depicted in Figs. 7, 8 and 9.

In case of increasing demand, there is a clear trend of higher utilization of the available railcars that can be observed for C4 as well as for C1. In the second year, 13 additional C4 railcars and 20 additional C1 railcars are needed on average and this number continuously increases to 60 C4 railcars and 121 C1 railcars in the last year of the planning horizon. Moreover, the need for new C2 railcars is persisting as it was also in the base case scenario and there is an additional trend of using C5 railcars that is mainly visible later in the planning horizon where they replace C1 railcars due to their availability for higher number of orders with the time. In the initial years, where C5 railcars are only available for a limited number of orders, the model suggests to increase the inventory of C1 railcars instead of them, which leads to the suggestion to increase the inventory by up to 179 C1 railcars in Year 6. Therefore, it could be advisable to try to increase the use of C5 railcars earlier instead of buying new C1 railcars. Since the original fleet is used for transporting higher quantities, the limited number of available railcars decreases the share of demand transported by clusters with the highest preference to 96.69% and the total costs of the used railcars increase by 6.76% in comparison to the base case scenario (see Table 6).

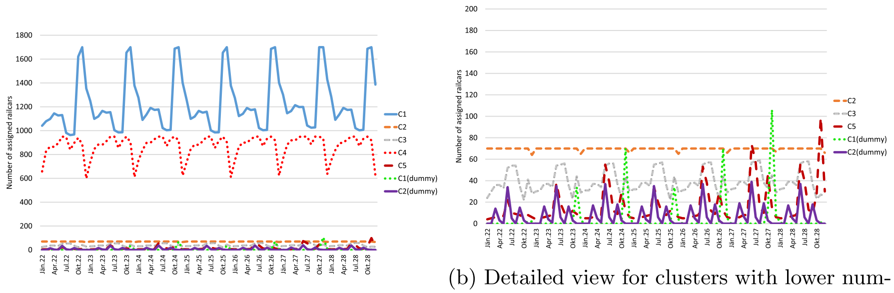
If the combination of increases and decreases in demand is considered, it can be observed that the need for C1 and C4 railcars is slightly lower in the months with lower demand in comparison to demand increase case, but the whole fleet is still used in the peak months. To make it more concrete, the difference in the number of C1 railcars needed in off-peak months is between 39 in Year 4 up to 102 in Year 7, for C4 railcars the differences fluctuate between 15 and 71. Moreover, the needs for additional C1 railcars and for C5 railcars are also lower in this case. Still, it could be advisable to try to use more C5 railcars instead of additional C1 railcars as it was suggested before. In terms of preferences and costs, this demand pattern increases



(a) Overall results

(b) Detailed view for clusters with lower numbers of railcars

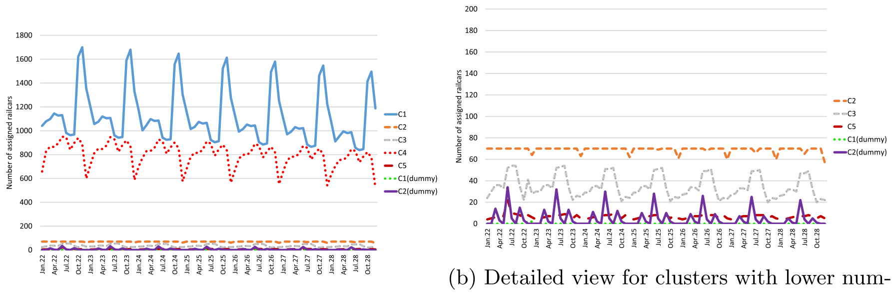
Fig. 7 Results of the fleet sizing model for 12.5% demand increase



(a) Overall results

(b) Detailed view for clusters with lower numbers of railcars

Fig. 8 Results of the fleet sizing model for the combination of demand increase and decrease



(a) Overall results

(b) Detailed view for clusters with lower numbers of railcars

Fig. 9 Results of the fleet sizing model for 12.5% demand decrease

the sum of preferences by 0.32% and the costs by 3.64 % in comparison to the base case scenario.

The decrease in demand shows impact on all clusters, but the highest effects can be observed for the biggest clusters C1 and C4. The maximal needed number of railcars in Year 7 for these clusters is by 105 (cluster C4) to 204 (cluster C1) railcars lower than in the base case scenario. This has also positive influence on the costs that decrease to 94.07% of the base case value, but the share of demand transported by the cluster with the highest preference improves only slightly by 0.26–97.97% since there are still missing C2 railcars that would improve the situation (see Sect. 4.3.1). Although this might seem as a positive result at the first sight, it actually leads to worse results of the railway company since costs of utilizing the railcars decrease by approximately 6% whereas the demand (and thus potential income) decreases by more than 12%. Moreover, it also results in a higher number of unutilized railcars for which it is necessary to find another use (e.g., leasing them to other company or decommissioning them). The influence of these measures is discussed in the next section.

4.3.4 Decreasing the number of railcars

As shown in Fig. 9, the number of required C4 railcars is expected to decrease if the demand decreases. Consequently, the maximum need for C4 railcars will decrease to 845 out of the currently 950 available railcars. Therefore, the fleet planner could consider decreasing the number of C4 railcars and based on their technical and economic status decide whether they are suitable for offering them to other railway undertakings or they need to be scrapped. When looking into the fleet mix of the C4 railcars using the fleet management model, it can be observed that the fleet consists of 275 rented railcars with a long-term contract, 493 owned railcars with a remaining RBV and 182 owned older railcars with no RBV. The results of the railcar assignment by the fleet management model are illustrated in Fig. 10.

While externally leased railcars are preferably used to cover the demand, owned railcars are gradually revised, if economically viable, or selected to be decommissioned, if they reached their end of service life. Out of the 182 old railcars, 134 are automatically assigned for decommissioning. For the other 48 railcars the decision is left to the planner whether it is meaningful to revise them once again or decommission them as well. Since in this scenario the demand decreases quite substantially, there are even 33 railcars with a remaining RBV that are not automatically selected to be revised. For those railcars the planner has to evaluate whether it is economically viable to pay for the revision and then lease or sell them to other railway undertakings.

After implementing this measure, the fleet sizing model is solved again and Table 6 shows that this reduction of the fleet slightly increases the costs and the share of demand transported by a cluster with the highest preference drops to 97.47%. Now it again depends on the planner to evaluate whether this increase in costs is acceptable in exchange for not investing in the revision of the railcars.

4.4 Summary of results

The six discussed scenarios illustrate the high uncertainty and variety of factors which need to be considered by the fleet planner when making decisions about changes in the fleet mix. Whereas an anticipated demand increase would result in higher utilization of the currently available railcars, it would also require effort to

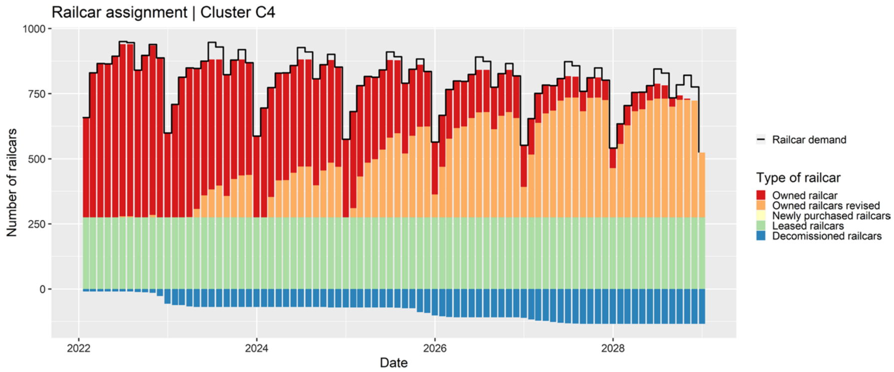


Fig. 10 Composition of C4 railcars from the fleet management model

Table 6 Comparison of presented scenarios in terms of costs and preferences

Scenario	Preferences		Costs (%)	Demand served with preference		
	Total sum	Change to base case (%)		One (%)	Two (%)	Three (%)
Base case	1630.52		100.00	97.71	2.18	0.11
Invest in C2	1601.78	−1.76	99.82	99.14	0.85	0.01
End of leasing C3	1639.38	0.54	100.06	97.63	2.31	0.06
Demand increase	1641.70	0.69	106.76	96.69	3.23	0.08
Demand increase+decrease	1635.72	0.32	103.64	97.94	2.04	0.02
Demand decrease	1625.57	−0.30	94.07	97.97	2.02	0.01
Reduction of C4	1626.56	−0.24	94.34	97.47	2.51	0.02

improve the utilization of C5 railcars in the next years and additional investments if the company wants to ensure a high service level in terms of satisfying the preferences of the customers. As a first step, investing in C2 railcars would be recommended since these railcars do not only improve the performance for the base case scenario but will be also needed in case of demand increase and partly also if the demand decreases. In contrast to that, if additional demand cannot be found for clusters C3 and C4, reductions of their fleet size would be necessary. However, this should be done carefully since decommissioning too many railcars could temporarily decrease the service level for customers as shown in Table 6. Still, it is necessary to observe signals to be able to react adequately to changes in demand and to adapt the fleet size and mix, which can be done relatively quickly using the proposed integrated planning approach.

5 Conclusions and future research directions

Planning of railway operations requires coordination of multiple activities which takes a lot of time due to missing digitalization and adequate software support of the processes. As a consequence, the flexibility of railway system and its ability to react to changes is very limited. This results in a relatively low usage of rail in Europe in comparison to road transport.

In order to tackle this problem, we proposed an integrated planning approach that combines two problems: defining the optimal fleet size for the coming years and making decisions about the changes in the fleet mix. Whereas the first task was solved by implementing a MILP optimization model, fleet management is dependent on specific expert knowledge and case-dependent information. Therefore, a DSS was found to be more suitable for this part of the planning approach. The presented model considers a heterogeneous fleet and introduced dummy clusters to highlight the need for additional railcars. Moreover, the focus is put on the preferences of the customers, who can specify their preferred clusters and the minimal share of order quantity that has to be transported by the most preferred cluster. Only after minimizing the sum of preference numbers the total costs of assigned railcars are taken into account. Besides that, we account for differences with regard to relations, commodities and roundtrips. Transitions between months and years are also part of the model.

The application of the planning approach to a case study based on real-world scenarios has illustrated the possibilities which the fleet planner can use to derive decisions about changes in the fleet mix. This is not only helpful in good times, when demand is increasing and new investments are necessary, but also in cases where decisions about extending or ending the leasing contract and reducing the number of available railcars have to be made.

Although the used demand and roundtrip time data is deterministic, the planning approach still enables the fleet planner to model different situations and get a picture about possible outcomes before the final decision is made. This is possible due to its ability to derive the results in a relatively short time, the possibility to test multiple scenarios, and the direct interaction between the fleet sizing and the fleet management model in form of feedback loops. Nevertheless, the integrated planning approach could be still improved in the future by taking into account uncertainty (e.g., in roundtrip times) and replacing the deterministic demand data with stochastic demand distributions, minimizing the fluctuations between the number of assigned railcars in the different months and considering also the costs of railcars that are not directly utilized in the optimal fleet sizing plan. Moreover, possible connections to the next planning steps (e.g., railcar allocation) could be also added.

Acknowledgements The paper is based on the results of the Backbone PI: Rail project (FFG 2021) conducted by multiple partners from academia and practice. The authors gratefully acknowledge funding provided by the Austrian Research Promotion Agency (FFG) within the scope of the research project Backbone PI: Rail - Digital transformation of railcar planning for establishing the rail as the backbone of the physical internet.

Funding Open access funding provided by Vienna University of Economics and Business (WU). Openaccess funding provided by Vienna University of Economics and Business (WU).

Declarations

Conflict of interest The authors declare that they have no conflict of interest.

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