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Light electric vehicle sharing systems: Functional design of a comprehensive decision making solution

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ABSTRACT

The functional design of a decision support system for a state-of-the-art vehicle sharing system (VSS) inevitably includes the selection or definition of methodologies for planning and managing the observed VSS. In this paper, our focus is on an innovative VSS that utilizes light electric vehicles. Our goal is to specify the functions of a comprehensive decision making solution for such a VSS through a qualitative and systematic literature and system analysis. To achieve this goal, we rely on the holistic VSS management framework developed in our previous research. As a result of our study, we identify possible solution methodologies or algorithms for implementing functions of the designed decision making solution, and propose the necessary adjustments for their application in the case of light electric vehicles, or note any research gap. With these findings, we provide justified guidance to practitioners in creating these solutions, with the aim of reducing development time.

1. Introduction

Compared to the classical vehicle rental systems, vehicle sharing systems (VSSs) offer registered users the opportunity to rent vehicles for a short period of time, without explicit contract signing for each particular rental. This type of shared mobility is gaining popularity due to both financial and environmental benefits. However, they face many challenges, such as inventory management of vehicles and parking spots, system imbalance, determining pricing strategies, and demand forecasting. Currently, the majority of these services represent car sharing systems (CSSs), electric CSSs (eCSSs), and bike sharing systems (BSSs). More recently, moped sharing systems (MSSs) and kick scooter sharing systems (SSSs) have started to appear. Although vehicle types in the listed systems differ, the management and optimization challenges reappear in the same or similar forms, as we outline in Ataç et al. (2021).

In this paper, we concentrate on a new type of VSS that utilizes light electric vehicles (LEVs). These vehicles are larger than bikes but smaller than cars, and can even be driven in bike lanes (Fig. 1). They have space for a single person, i.e., the driver, and some luggage. Additionally, they offer a comfortable ride in rain or bad weather, since they possess a closed or covered cabin. For example, Swiss company ENUU operated such vehicles in several Swiss cities, as well as in Berlin, Germany, and Getaround (2019) offered a similar service in Rotterdam, The Netherlands. However, both companies discontinued this service in 2022 and we have not managed to obtain any further information about the reasons for such a decision. One reasonable assumption would be operational difficulties, which would make the presented study a valuable contribution to preventing such negative outcomes in future endeavours of this kind.

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(a) Side view   (b) Front view

Fig. 1. Light electric vehicle parked in the bike parking.

The purpose of this study is to identify planning and management challenges in an LEV sharing system (LEVSS), existing algorithms and solution methodologies which can be utilized for their solution, the necessary adaptations of the identified algorithms and methodologies for their utilization for LEVSSs, and methodological gaps that need to be overcome. This process is the main task of a functional design for any decision making solution. To perform this task in the context of an LEVSS, we rely on the general framework for management and optimization of the VSS operations and the comprehensive literature review, both presented in Ataç et al. (2021). By using the framework, one should be guided what planning and management challenges to expect and how to solve them. Additionally, we can determine the areas where research efforts should be focused in order to create a comprehensive decision making solution for an LEVSS.

The general framework is aimed to be applicable for any kind of VSS and allows detailed planning for a newly introduced VSS, which can use conventional or innovative vehicles. Hence, this paper presents also a conceptual and methodological application of the developed framework on an LEVSS. Nevertheless, the presented functional design approach is invariant towards the type of vehicle a VSS is using. Therefore, we argue that such an approach can also be utilized for the future types of VSSs. While applying the framework to an LEVSS, we have also identified an additional management task that was previously missing in the framework. It is about determining whether the system should impose obligatory parking reservation on its users and the reservation kind. The framework is now extended to accommodate this task, as presented in Section 2.3.

The specific features of the analyzed LEVs and the strong environmental and commercial potential of an LEVSS necessitate and justify a devoted analysis focusing on the optimization and management of a VSS using LEVs. Although there are similar studies conducted for electric vehicles (EVs) in general, we have not found any that corresponds entirely to the distinguishing characteristics of LEVs. For instance, the authors in Shen et al. (2019) analyze VSSs with EVs in general. However, they do not observe certain important aspects of an LEVSS: LEVs do not require any charging infrastructure, they can be driven on bicycle lanes, and the car pooling cannot be used to rebalance the fleet. On the other hand, Wu (2022) focuses on a novel model of EV sharing system maintenance based on the battery swapping stations. The LEVs in our work do not require such stations either as the batteries are replaced by the staff on the spot, possibly before or after performing a rebalancing operation. Similarly, Li and Jenn (2022) and Tang et al. (2022) deal with the optimization of EV charging infrastructure and activities. Additionally, the interaction between EVs and regular or micro energy grids has been a very active research topic recently, e.g., Barone et al. (2022), Singh and Dubey (2022), Vujasinović et al. (2022) and Li et al. (2022). However, these topics are not of interest for our study.

The proposed study aims to fill the revealed gap and make a valuable contribution to the current practices in management and decision making related to the LEVSSs. By having our study in hands, the designers and practitioners, i.e., business analysts, product managers, software architects, software engineers, etc., will have a curated selection of existing solution methodologies and recommendations for their application in LEVSSs. They will also be informed about the methodological gaps that need to be addressed in order to create a comprehensive decision making solution for LEVSSs. Therefore, the intention of this paper is to be a steering tool that guides practitioners' decisions when building a decision support system (DSS) for an LEVSS, ultimately enhancing efficiency and improving the overall development process.

The structure of the paper is as follows: The functional design of an LEVSS decision making solution is described in Section 2. In Section 3, we identify all works, to the best of our knowledge, which are applicable to the identified planning and management tasks of the envisioned decision making solution for LEVSSs. Finally, we provide final conclusions of our analysis in Section 4.

2. The design of a decision making solution for an LEVSS

In addition to the distinctions mentioned in the introduction, the LEVs are set apart from the other types of EVs by the fact that they are not charged at stations. Instead, the staff replaces the battery according to a selected strategy, e.g., when the battery falls below a certain charging level. Also, since LEVs are quite larger than bikes, it is not suitable to rebalance the system using trucks. Such distinctions between LEVs and other vehicle types necessitate certain adaptations of existing methodologies for their application to an LEVSS. Finally, we aim to apply our framework to a free-floating VSS, since this type of VSSs are becoming increasingly popular due to user convenience, e.g., Jacobs (2016) and Mobility (2019).

The required planning and management tasks for the designed decision making solution for an LEVSS are identified from the general framework (Ataç et al., 2021). Therefore, for the sake of paper self-containment, we repeat brief descriptions of the tasks, used terminology and framework notions in Section 2.1. In that way, we are able to present the design in the light of the previously developed framework. For a thorough description of the framework and VSS related notions, we refer the reader to the original work (Ataç et al., 2021).

The subsequent subsections, namely, 2.2, 2.3, and 2.4, provide the details about the planning and management tasks, along with their possible solutions, associated with each of the decision levels, respectively. In these three subsections, we analyze the applicable methodologies and offer discussion and recommendations for their application to an LEVSS, with respect to the specific features of LEVs and targeted sharing system.

2.1. Terminology and the framework

The framework is organized according to three dimensions: decision levels, actors, and layers. This structure provides an organized view of all VSS planning and management components, i.e., data obtained, models developed, and actions taken in general. The actions also represent the challenges encountered in VSS planning and management, as well as the required tasks for the corresponding DSS. Each component is placed within one framework's module, which represents an intersection of framework dimensions. The proposed framework is illustrated in Fig. 2, highlighting the dimensions, modules and their mutual relationships. The components are presented in the following subsections.

The first dimension, i.e., decision levels, captures the common planning time frames: strategic, tactical, and operational. The second dimension, i.e., actors, associates each component with either the supply or demand side of a VSS. Lastly, the third dimension, i.e., layers, represents the three layers of any decision making task: data, models, and actions. Modules at the data layer are not split among actors since the majority of the data is used by both sides.

We define two types of relations between the modules: intra-level interaction indicated by white arrows, and inter-level interaction represented by dashed arrows. The intra-level interaction appears as two-ways, i.e., the exchange of information between models of supply and demand actors, and one-way, the natural information flow from data, via models, to actions. On the other hand, the inter-level interaction passes the outputs of a higher decision level to the models layer of a lower level as inputs. With that, we present the influence of the higher level decisions to the possible choices at the lower level.

In the following subsections, we deep dive into the specifics of each decision level within the framework and present the respective tasks of a designed LEVSS management system, their potential solutions, and anticipated adjustments and modifications.

2.2. Strategic level

The strategic level encompasses various management and optimization tasks on both the supply and demand side of an LEVSS. They are depicted in the actions layer of the framework's strategic decision level (Fig. 3). These tasks can be tackled by the mathematical models and solution methodologies, presented further. The supply and demand models can also be utilized simultaneously and in conjunction. With that, the supply and demand actors act together and search for a mutual optimum.

2.2.1. Demand

Demand models primarily consist of mode- and destination-choice forecasting models, which are utilized to derive user segmentation, allocate advertisement budgets, and determine the market placement of the system. The user segmentation helps decision makers to better learn the users of the system. By determining the optimal budget for advertisement and market placement, the company enhances its visibility among potential users and targets the most promising user group, respectively.

There are many existing methodologies for mode choice estimation. In Campbell et al. (2016), the authors use a multinomial logit model to estimate the adoption of a new shared vehicle type. The data for the model parameters estimation is gathered through popular surveys. The surveys include both socio-economic inquiries as well as stated preferences towards transportation modes. An extension of this approach can be found in Narayanan and Antoniou (2023). Here, the authors create a generalized multinomial logit model which simultaneously accounts for multiple vehicle and ride sharing services, together with the conventional transportation modes. The methodologies used in Campbell et al. (2016) and Narayanan and Antoniou (2023) represent general discrete choice analysis. Therefore, they can be utilized for the estimation of adoption of new LEVSSs, even in the presence of other shared mobility services.

Similarly, Aguilera-García et al. (2020) develop a generalized ordered logit model to investigate the factors influencing the adoption and frequency of use of shared moped scooters for daily urban mobility. The authors employ socio-economic, travel-related, and personal-opinion data collected through a survey to build this model. It is important to notice that the independent model variables do not depend on the observed shared vehicle type, which makes the approach applicable to an LEVSS, too.

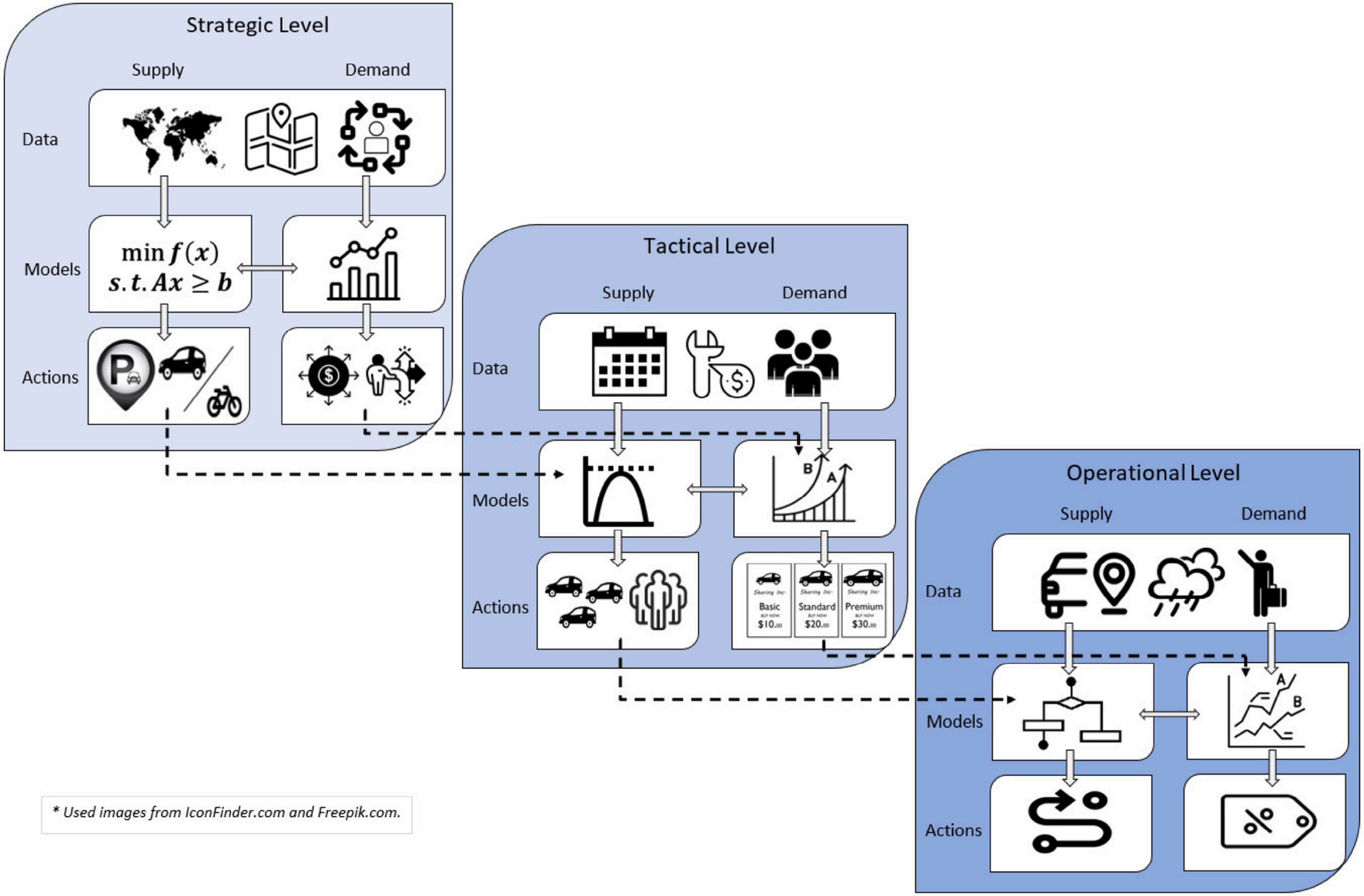

Fig. 2. Holistic decision making framework for vehicle sharing systems.

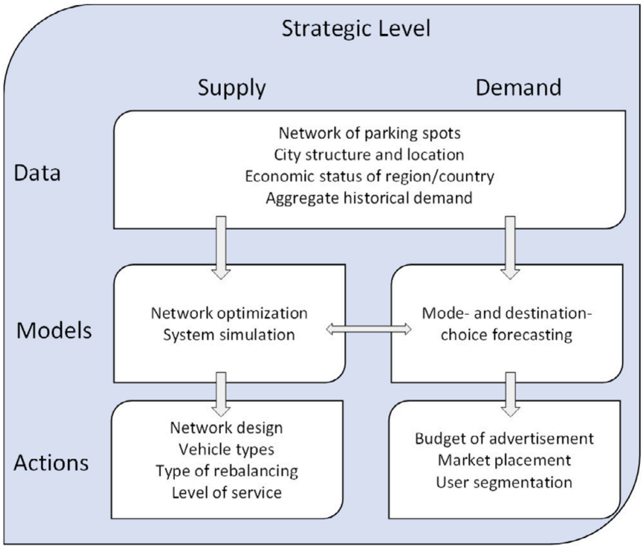

Fig. 3. Strategic decision level of the framework.

In addition to mode choice estimation, the user reactions to the introduction of a novel vehicle type or planned operation modes can be anticipated as suggested in Wu et al. (2019). For this purpose, a stated preference survey has been created wherein users are asked to choose between regular operation of a VSS, VSSs with additionally introduced rules, and conventional transportation means. By tailoring another survey which would include LEVs, the same models can be utilized for perceiving user reactions to the LEVSS introduction. The results can be used to design advertisements and determine the appropriate market share before introducing the new service and features.

Another approach for the analysis of demand market represents a user segmentation, which can be performed as demonstrated in Degele et al. (2018). In order to create segments, the authors combine hierarchical and partitioning clustering over users' demographic and trip data. The obtained clusters are further utilized to identify the characteristics of the obtained user segments and tailor the marketing strategies and offers accordingly. Although this analysis is applied to an electric scooter sharing system in Degele et al. (2018), the used data is independent of the used vehicle type in the sharing system. Therefore, the same approach can be applied to the case of an LEVSS.

2.2.2. Supply

The strategic level utilizes high-level models for optimizing the network and bringing the corresponding decisions.

The optimal location and size of parking facilities are crucial decisions to prevent both over- and understocking of the vehicles. Jointly, these decisions can be considered to be a part of the network design. They are made at the beginning of the system installment in the case of station-based configurations. The situation does not change for the free-floating configuration since each parking spot can be considered as a station with a capacity for only one vehicle. In this layer, the system simulation component assists operators in evaluating the system's state and taking appropriate actions.

The choice of rebalancing method is strongly related to the type of vehicles used in the system. For instance, the BSSs usually use big trucks to rebalance the vehicles, whereas in a CSS, the vehicles are generally rebalanced by the dedicated staff members. Moreover, user-based strategies can be used to improve the balance in the system or a combination of staff-based and user-based approaches might be applied.

Finally, the level of service (LoS) that the operator wants to provide to the users should be determined at this decision level. E.g., the operator may prioritize user satisfaction by increasing the number of vehicles and/or parking spots in the service area. On the other hand, if the operator is more capital-oriented, investment in the physical components of the system (vehicles, parking spot, etc.) is more crucial than the LoS, which makes it a secondary objective for the operator.

We argue that the network design algorithms for LEVs can be borrowed from other types of VSSs. For example, the authors in Boyacı et al. (2015) present an optimization problem and solution methodology for determining the optimal number and location of required stations, while taking into account the dynamic rebalancing of vehicles. In addition to that, the model is multi-objective, which allows the operator to examine the trade-off between the operator's profit and the offered LoS. As the problem is solved at the strategic level, the presented model requires service operating prices and aggregated demand data to be solved, without considering the specifics of utilized vehicles nor the details about rebalancing operations. Furthermore, the authors use origin and destination locations of the real demand to solve a maximal set covering problem and identify the candidate station locations for the aggregate model. We can then apply the inverse operation, as done in Weikl and Bogenberger (2015), and create a Voronoi tessellation from the obtained station locations. Then, each Voronoi cell becomes a future LEV parking zone, while the station capacity represents the needed number of parking slots within the zone. Therefore, the approach from Boyacı et al. (2015) can be used for designing the network of free-floating LEVSS, too, with appropriate adjustments of problem parameters.

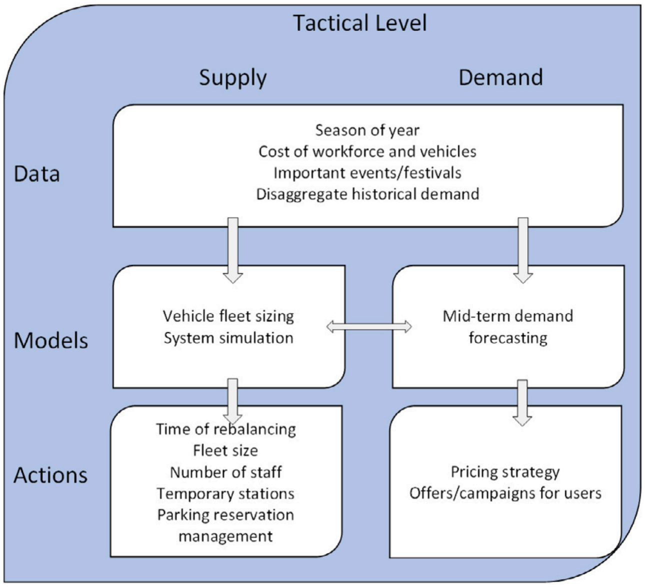

Fig. 4. Tactical decision level of the framework.

2.3. Tactical level

The outputs of the actions layer of the strategic level serve as inputs to the models layer of the corresponding actor, at this decision level. This relationship is denoted by one-way dashed arrows in Fig. 2. Further, we discuss the LEVSS management challenges and potential solution methodologies at the tactical level, first for the demand actor and then for the supply actor. These challenges are presented as the actions in the framework's tactical decision level, shown in Fig. 4.

2.3.1. Demand

Deciding the pricing strategy, i.e., to be fixed or dynamic, is an important component of this decision level. In the case of fixed pricing, the pricing values are also determined at this level. The offers and campaigns that will be presented to users are also determined within this decision level. The outcomes from the strategic level, such as the budget and target audience, can be used as attributes for the mid-term demand forecasting. The actions taken at this level, i.e., pricing strategy and campaigns, are passed on to the operational level.

The approach for determining pricing strategy, presented in Hansen and Pantuso (2018), does not contain any features that limit its application to CSSs only. Therefore, we can apply it to determine dynamic prices in an LEVSS as well. Similarly, midterm demand forecasting can be performed with the predictive models already used for the VSSs using other vehicle types, e.g., Faghih-Imani et al. (2017). Here, the authors build models that predict the need for rebalancing at each station and estimate the required number of vehicles. The models depend on variables describing the transport infrastructure, station locations, socio-demographic characteristics of the neighborhood, and day and time of the prediction. Since none of these variables depend on the specific vehicle type, the models can be applied to an LEVSS as well. Certainly, the models must be fine-tuned for the specific user share of the LEVSS.

The mode-choice ratio for an LEVSS can also be estimated using the approach presented in Li et al. (2018). Here, the authors model disutility functions for each transport mode, considering the characteristic multi-modal and multi-activity trips occurring in every day life. They employ a dynamic user equilibrium algorithm to estimate the mode of transport that will be chosen. To model the disutility function for a shared vehicle system, the authors use information on fleet size, parking locations, service fees, and estimated demand. Therefore, their approach can be used to reach the desired mode-choice ratio of an LEVSS by testing different values of the mentioned parameters.

2.3.2. Supply

The operator may increase or decrease the number of vehicles in the system once such a need is identified. Making changes to the fleet size at the operational level is impractical, and thus must be done here. The operator should be able to monitor and analyze such a need in a reasonable amount of time. Also, the operator might need to evaluate the current and potential future applications of strategies, such as rebalancing, reservations, and pricing. System simulations are often employed for this purpose.

The task of fleet sizing in LEVSSs can also be covered by the existing approaches and algorithms. Should the operator decide for a pure user-centric vehicle rebalancing strategy, the simulation-based optimization method proposed in Cepolina and Farina (2012) can be utilized. This is possible since the characteristics of the "personal intelligent city accessible vehicles", analyzed in

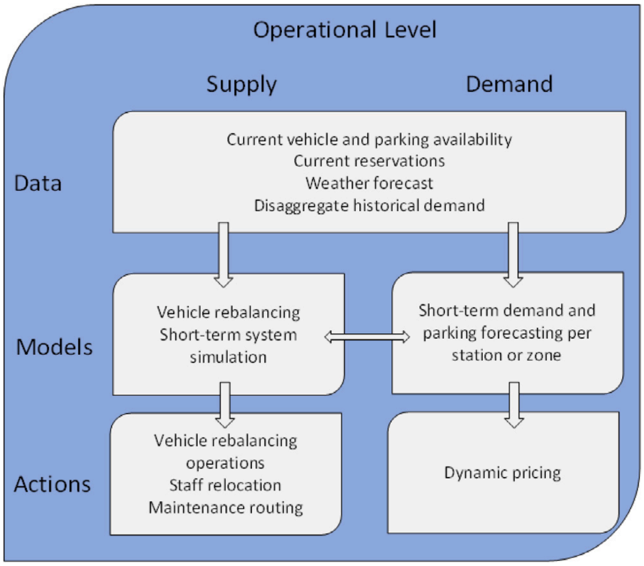

Fig. 5. Operational decision level of the framework.

their work, are highly similar to LEVs. The fleet size is determined to minimize the rebalancing cost and the waiting time for users to access an available vehicle. Each vehicle is represented by its initial position at the beginning of the planing horizon, the charging time, and the battery capacity and discharging law. To apply this approach, we need to replace the charging time with the battery replacement time. Also, in Cepolina and Farina (2012), the authors deal with station-based systems. To overcome this discrepancy, we can observe every zone as a station with the capacity equal to the number of parking spots in the zone. Furthermore, by utilizing the same approach for zone modeling, we can also adapt the queuing networks methodology for fleet sizing, proposed in George and Xia (2011), to the free-floating systems, including the targeted LEVSS.

Another decision at this level concerns whether a static or dynamic rebalancing should be applied. In the framework, we denote this decision as the time of rebalancing. In the case of static rebalancing, the operator should decide the specific time of day when rebalancing operations will be conducted. On the other hand, in the case of dynamic rebalancing, the operator needs to decide the frequency of rebalancing operations and whether they should be performed online or offline. Finally, for any form of rebalancing, the operator needs to hire staff dedicated to these activities. This decision is also made at the tactical level since ad-hoc hiring of workforce would not be feasible in practice. To address these questions, Boyacı et al. present a multi-objective optimization model that determines the optimal fleet size and staff number to maximize system profit when the vehicles are rebalanced by the operator's staff (Boyacı et al., 2015). Their model is built for electrical vehicles and takes into account the battery charging requirements. This makes it adaptable for our case of LEVs, again by scheduling battery replacement within the time slots planned for charging.

At this planning level, the operator can also decide whether to implement a parking reservation policy and, if so, what type of policy should be imposed. Users may be required to reserve a parking spot at their destination point before taking the vehicle. This can be mandatory for all trips or only for specific ones, such as shorter trips. Finally, the parking reservation can be optional or not available at all. A discrete event simulation methodology for deciding on the parking reservation policy is proposed in Kaspi et al. (2014). Their approach is not specific to a particular vehicle type or VSS configuration, and it can be adjusted to and used for an LEVSS as well. Notably, the task of determining the appropriate parking reservation policy is not present in the previous version of the holistic VSS framework (Ataç et al., 2021). Therefore, during this study, we have enhanced our framework by introducing it, as shown in Fig. 4.

Lastly, the tactical level should also be responsible for locating temporary stations for possible important events or festivals. However, we have failed to identify any work in the literature dealing with this particular problem.

2.4. Operational level

This section provides details at the operational level, designed to answer short-term questions in LEVSSs, for demand and supply actors, respectively. Similarly to the previous decision levels, these questions are represented by the actions layer of the framework's operational decision level, given in Fig. 5. The outputs from the actions layer of the tactical level are passed on as inputs to the models layer of the respective actors.

2.4.1. Demand

With short-term demand forecasting per station/zone, appropriate actions can be taken regarding dynamic pricing. Determining prices during the system operation has been presented in Pfrommer et al. (2014). We argue that the same approach can be applied in the LEVSSs in the following manner. In the referenced work, the model that determines whether a user accepts the incentive is based on the distance between the stations, additional walking time, and driving speed. The influence of vehicle type on the model is only through the driving speed, which can be easily adjusted for different vehicle types, including LEVs.

Similar to the other decision levels, demand forecasting can be performed with the predictive models already used for VSSs with other vehicle types. For example, we can use convolutional neural network models suggested in Lin et al. (2018). These models predict hourly demand per station based on the historical data of previous trips, with each trip described with duration, bike checkout and -in times, start and end stations, user, and user type. Furthermore, Ashqar et al. develop a method for predicting bike station counts that also includes weather conditions as predictors (Ashqar et al., 2019). They utilize the Random Forest algorithm to determine predictor significance and employ a regression model for the prediction itself, achieving promising results. Time of day, temperature, and humidity level are shown to be significant predictors for bike station counts in relation to weather conditions. The predictors used in this method, as well the predictors used in Lin et al. (2018), are not specific to vehicle types. Therefore, the proposed methods can be used in the case of LEVSSs, too.

2.4.2. Supply

By developing models for parking availability and vehicle locations in the next time window, the operator can make daily/hourly decisions regarding routing for rebalancing operations and maintenance. We can examine the former in three aspects: routing for vehicles relocation, routing for staff relocation, or both. We know the type of rebalancing from the strategic level and the time of rebalancing from the tactical level. Given these, we optimize routing for rebalancing operations both from the vehicle and staff perspectives, at this decision level. Routing for maintenance is also determined at the operational level. For a system operating an electric vehicle fleet, it is important to maintain sufficient battery levels for each subsequent trip. Therefore, regular checks should be conducted on the vehicles.

There are approaches for solving the abstracted rebalancing problem where the rebalancing operations are not accounted for in details, e.g., Jorge et al. (2014) and Faghih-Imani et al. (2017). While these approaches can be applied to LEVSSs, they only determine the number of vehicles to be rebalanced between specific stations. On the other hand, how the vehicles should be rebalanced and who should perform the rebalacing are the questions that the mentioned approaches do not answer.

To address those questions, the authors in Boyacı et al. (2017) optimize rebalancing operations of electric vehicles, where the staff is relocated between stations using bikes. The same approach can be used for the observed LEVSSs with one adaptation: the staff will need to use foldable bikes or scooters that can fit in the trunk of LEVs. The mentioned approach also accounts for the charging requirements of shared vehicles. In the case of LEVs, the batteries are not recharged but replaced by the relocation staff. However, this difference requires only minor adaptations of the proposed models, where the recharging time should be replaced with the battery replacement time, during which the vehicle cannot be used. The battery replacement can occur during a relocation or maintenance operation. In bike-unfriendly locations or seasons, public transport can be a preferable option for relocating staff. In such cases, the approach suggested in Boyacı et al. (2017) can still be used with adjusting the relocation time to the public transport.

Another relevant approach for rebalancing a free-floating electric CSS is presented in Weikl and Bogenberger (2015). This approach utilizes an optimization and rule-based method for rebalancing vehicles between zones, and even suggests GPS coordinates to which the vehicles should be moved based on actual and historical reservation data. The strength of this approach lies in its real-world testing in the CSS operations in Munich, which resulted in increased profits and decreased vehicle idle time. This indicates that the approach is a strong candidate for our observed LEVSS case. Still, the model approximates the cost of staff relocation between two vehicle rebalancing operations, which could be improved through further research.

In Febbraro et al. (2012), the authors deal with a free-floating CSS where the operator offers fee discounts to users who return vehicles to zones with a shortage of vehicles. The user's response is modeled with a utility function depending on the distance between the desired and proposed parking zones and the offered discount. However, the authors do not present a method for determining the optimal discount level with respect to system operation or profit, leaving room for future research to explore this aspect.

The authors in Clemente et al. (2017) go one step further and propose an optimization problem to determine the minimum number of vehicles within a parking area, below which the incentives should be offered. On the other hand, the probability of user accepting an alternative drop-off destination is arbitrarily defined, i.e., in a less precise manner compared to Febbraro et al. (2012). Despite the mentioned imperfections, the incentives for user-based rebalancing can be offered in an LEVSS as it is suggested in the two mentioned approaches, Febbraro et al. (2012) and Clemente et al. (2017), or a potentially an improved combination of them.

3. Recommendation summary for design and operations of LEVSSs

The analysis presented in the previous section demonstrates the effectiveness of the framework in mapping existing methodologies and algorithms to management challenges in a newly designed VSS. By utilizing the framework, we can also identify the gaps and direct the research in the appropriate way.

To complete our analysis, we use the thorough literature review from Ataç et al. (2021). From there, we select additional solution methodologies applicable to an LEVSS. We argue that these methodologies can be readily applied to LEVSSs without significant adaptations. The reviewed works and solution methodologies, whose adaptation to the specific characteristics of an

Table 1
Summary of the potential solution methodologies.

Decision level	Actor	Challenge	Potential solution methodologies
Strategic	Supply	Type of rebalancing	Queuing-based simulation (Barth and Todd, 1999)
		Network design	Simulation (Barth and Todd, 1999; Çelebi et al., 2018), Dynamic programming (Çelebi et al., 2018), MILP (Boyacı et al., 2015), Genetic algorithm (Miao et al., 2019)
		Vehicle types	Discrete event simulation (Illgen and Höck, 2018), Genetic algorithm (Miao et al., 2019)
		Level of service	–
	Demand	Budget of advertisement	Discrete choice models (Campbell et al., 2016; Narayanan and Antoniou, 2023; Aguilera-García et al., 2020), Probability models (Kutela and Teng, 2019), Game theory (Wu et al., 2019)
		Market placement	Discrete choice models (Campbell et al., 2016; Narayanan and Antoniou, 2023; Aguilera-García et al., 2020), Probability models (Kutela and Teng, 2019), Game theory (Wu et al., 2019), Discrete event simulation (Illgen and Höck, 2018)
		User segmentation	Hierarchical clustering (Degele et al., 2018)
Tactical	Supply	Time of rebalancing	Discrete-event simulation (Repoux et al., 2019; Nourinejad and Roorda, 2014), Particle swarm optimization (Nourinejad and Roorda, 2014)
		Fleet size	User equilibrium modeling (Li et al., 2018), Particle swarm optimization (Nourinejad and Roorda, 2014), Simulated annealing (Cepolina and Farina, 2012), Mean value analysis (George and Xia, 2011)
		Number of staff	MILP (Boyacı et al., 2015)
		Temporary stations	–
		Parking reservation management	Discrete-event simulation (Kaspi et al., 2014)
	Demand	Pricing strategy	MILP (Hansen and Pantuso, 2018), Discrete-event simulation (Clemente et al., 2017), Particle swarm heuristic (Clemente et al., 2017), User equilibrium modeling (Li et al., 2018)
		Offers and campaigns	Negative binomial distribution (Kutela and Teng, 2019)
Operational	Supply	Vehicle rebalancing	Matheuristic algorithm (Zhang et al., 2019), ALNS (Bruglieri et al., 2019), Binary logit and linear regression models (Faghih-Imani et al., 2017), Decomposition-based heuristic (Nourinejad et al., 2015; Weikl and Bogenberger, 2015), MILP (Boyacı et al., 2017), MIP (Jorge et al., 2014)
		Staff relocation	Decomposition heuristic (Nourinejad et al., 2015), MILP (Boyacı et al., 2017)
		Maintenance routing	Decomposition-based heuristic (Weikl and Bogenberger, 2015), MILP and black hole optimization heuristic (Masoud et al., 2019)
	Demand	Dynamic pricing	Quadratic programming (Pfrommer et al., 2014), MINLP (Jorge et al., 2015), Binary logit model (Febbraro et al., 2012)

LEVSS requires particular discussion, have been analyzed in Section 2. Finally, we associate all identified applicable methodologies, requiring adaptations or not, to the planning or management tasks, i.e., the actions, specified by the framework. This is summarized in Table 1.

The papers Ashqar et al. (2019) and Lin et al. (2018) are omitted from Table 1 since they focus only on short-term demand forecasting without mentioning which management task it is applied to. Nevertheless, the methodologies from those papers can be incorporated into solution methodologies for vehicle rebalancing or dynamic pricing.

Based on the analysis presented in Section 2 and Table 1, we conclude that the majority of management and planning tasks in LEVSSs can be effectively addressed using existing approaches, possibly with some adjustments. Therefore, designers and developers are recommended to utilize the listed approaches and potentially combine them to leverage the findings available at hand. Consequently, the building time of a DSS for LEVSSs is expected to be shortened as the time spent on the trial-and-error process is reduced. Although some of the analyzed methods have the potential to be further developed and improved, they represent a promising starting point for the efficient development of a DSS for LEVSSs.

Additionally, we have identified unanswered questions specific to LEVSSs that have not been addressed in the existing literature, to the best of our knowledge. These questions are:

- Determination of the desired level of service at the strategic level: The level of service at the strategic level influences lower decision level tasks, i.e., fleet and staff sizing, rebalancing operations, as well as pricing, by introducing additional constraints. Therefore, finding the most appropriate strategic level of service is significant for allowing the efficient and effective performance of an LEVSS in its daily operations.

- Optimization of temporary station locations at the tactical level: Temporary stations can accommodate varying demand characteristics during specific seasons or periods, such as holiday seasons or festivals. In such periods, passenger flows are usually different from the regular behavior. Hence, the usual operations might not satisfy the demand as expected.

In contrast to the other tasks from Table 1, finding solutions for the listed two would require dedicated research effort and time.

4. Conclusion

In this paper, we present the functional design of a decision making solution for a VSS utilizing a novel vehicle type, specifically the LEV. The design is guided by the holistic management framework for VSSs, crafted in our previous research (Ataç et al., 2021).

Through the presented analysis, we identify and present applicable methodologies and approaches for the management and optimization of a new LEVSS. Furthermore, we provide suggestions on how these methodologies can be adjusted to suit the specific characteristics of LEVSSs. As a result, potential designers or creators of an LEVSS management system are presented with justified and significant directions for the system implementation, with the ultimate goal of enhancing the development process. Additionally, we identify research gaps that need to be addressed in order to provide a comprehensive management and optimization solution for LEVSSs. The implementation directions and research gaps are summarized in Section 3.

The previously developed framework aims to address all vehicle types and settings of VSSs. With this work, our goal is also to demonstrate the framework's applicability and usefulness. Furthermore, we have identified another needed extension of the framework itself. The task of parking reservation management at the tactical level was previously missing and now it has been added to the framework.

The limitation of the presented study is a notable absence of works on the management and optimization of LEVSSs at all decision levels. This hinders our ability to compare our suggestions for adjusting methodologies with analytically proven models and algorithms. However, we intend to address this limitation in our future work through a planned collaboration with an industrial partner that specializes in developing decision making solutions for VSSs. This collaboration will provide us with valuable insights and access to real-world data and scenarios, enabling us to validate our suggestions and potentially tailor the selected methodologies specifically for LEVSSs.

Furthermore, we plan to work on the identified research gaps that debilitate creation of a comprehensive decision making solution for LEVSSs. Those are the strategic analysis of the level of service and the placement and sizing of temporary stations at the tactical level, as presented in Section 3. Given that these topics are not covered in the existing literature, to the best of our knowledge, for any kind of VSS, we believe that their solution will contribute to the management of other types of VSSs as well. Additionally, we will continue to further analyze other VSS types and potentially extend the framework to incorporate additional management and optimization tasks that have yet to be identified.

CRediT authorship contribution statement

Nikola Obrenović: Conceptualization, Methodology, Investigation, Writing – original draft, Supervision. **Selin Ataç:** Investigation, Writing – original draft, Writing – review & editing. **Michel Bierlaire:** Writing – review & editing, Supervision.

Data availability

No data was used for the research described in the article.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author(s) used the services of a professional technical writer who partially utilized OpenAI's ChatGPT in order to improve the readability of the manuscript and correct any grammatical or stylistic errors. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

References

Aguilera-García, Á., Gomez, J., Sobrino, N., 2020. Exploring the adoption of moped scooter-sharing systems in spanish urban areas. Cities 96, 102424. http://dx.doi.org/10.1016/j.cities.2019.102424.

Ashqar, H.I., Elhenawy, M., Rakha, H.A., 2019. Modeling bike counts in a bike-sharing system considering the effect of weather conditions. Case Stud. Transp. Policy 7 (2), 261–268. http://dx.doi.org/10.1016/j.cstp.2019.02.011.

Ataç, S., Obrenović, N., Bierlaire, M., 2021. Vehicle sharing systems: A review and a holistic management framework. EURO J. Transp. Logist. 100033. http://dx.doi.org/10.1016/j.ejtl.2021.100033.

Barone, G., Buonomano, A., Forzano, C., Giuzio, G.F., Palombo, A., Russo, G., 2022. Energy virtual networks based on electric vehicles for sustainable buildings: System modelling for comparative energy and economic analyses. Energy 242, 122931. http://dx.doi.org/10.1016/j.energy.2021.122931.

Barth, M., Todd, M., 1999. Simulation model performance analysis of a multiple station shared vehicle system. Transp. Res. C 7 (4), 237–259. http://dx.doi.org/10.1016/S0968-090X(99)00021-2.

Boyacı, B., Zografos, K.G., Geroliminis, N., 2015. An optimization framework for the development of efficient one-way car-sharing systems. European J. Oper. Res. 240 (3), 718–733. http://dx.doi.org/10.1016/j.ejor.2014.07.020.

Boyacı, B., Zografos, K.G., Geroliminis, N., 2017. An integrated optimization-simulation framework for vehicle and personnel relocations of electric carsharing systems with reservations. Transp. Res. B 95, 214–237. http://dx.doi.org/10.1016/j.trb.2016.10.007.

Bruglieri, M., Pezzella, F., Pisacane, O., 2019. An adaptive large neighborhood search for relocating vehicles in electric carsharing services. Discrete Appl. Math. 253, 185–200. http://dx.doi.org/10.1016/j.dam.2018.03.067, 14th Cologne-Twente Workshop on Graphs and Combinatorial Optimization (CTW 2016).

Campbell, A.A., Cherry, C.R., Ryerson, M.S., Yang, X., 2016. Factors influencing the choice of shared bicycles and shared electric bikes in Beijing. Transp. Res. C 67, 399–414. http://dx.doi.org/10.1016/j.trc.2016.03.004.

Çelebi, D., Yörüsün, A., Işık, H., 2018. Bicycle sharing system design with capacity allocations. Transp. Res. B 114, 86–98. http://dx.doi.org/10.1016/j.trb.2018.05.018.

Cepolina, E.M., Farina, A., 2012. A new shared vehicle system for urban areas. Transp. Res. C 21 (1), 230–243. http://dx.doi.org/10.1016/j.trc.2011.10.005.

Clemente, M., Fanti, M.P., Iacobellis, G., Nolich, M., Ukovich, W., 2017. A decision support system for user-based vehicle relocation in car sharing systems. IEEE Trans. Syst. Man Cybern.: Syst. PP, 1–14. http://dx.doi.org/10.1109/TSMC.2017.2665881.

Degele, J., Gorr, A., Haas, K., Kormann, D., Krauss, S., Lipinski, P., Tenbih, M., Koppenhoefer, C., Fauser, J., Hertweck, D., 2018. Identifying E-scooter sharing customer segments using clustering. In: 2018 IEEE International Conference on Engineering, Technology and Innovation. ICE/ITMC, pp. 1–8. http://dx.doi.org/10.1109/ICE.2018.8436288.

Faghih-Imani, A., Hampshire, R., Marla, L., Eluru, N., 2017. An empirical analysis of bike sharing usage and rebalancing: Evidence from Barcelona and Seville. Transp. Res. A 97, 177–191. http://dx.doi.org/10.1016/j.tra.2016.12.007.

Febbraro, A.D., Sacco, N., Saeednia, M., 2012. One-way carsharing: Solving the relocation problem. Transp. Res. Rec. 2319 (1), 113–120. http://dx.doi.org/10.3141/2319-13, arXiv:10.3141/2319-13.

George, D.K., Xia, C.H., 2011. Fleet-sizing and service availability for a vehicle rental system via closed queueing networks. European J. Oper. Res. 211 (1), 198–207. http://dx.doi.org/10.1016/j.ejor.2010.12.015.

Getaround, 2019. LEV - how it works? URL https://www.getlev.nl/en/how-it-works. Accessed: 2020-03-02.

Hansen, R., Pantuso, G., 2018. Pricing car-sharing services in multi-modal transportation systems: An analysis of the cases of Copenhagen and Milan. In: 9th International Conference on Computational Logistics. ICCL 2018, pp. 344–359. http://dx.doi.org/10.1007/978-3-030-00898-7.

Illgen, S., Höck, M., 2018. Electric vehicles in car sharing networks – challenges and simulation model analysis. Transp. Res. D 63, 377–387. http://dx.doi.org/10.1016/j.trd.2018.06.011.

Jacobs, F., 2016. Zipcar introduces free-floating car-sharing in Brussels. URL https://www.fleeteurope.com/en/smart-mobility//article/zipcar-introduces-free-floating-car-sharing-brussels?a=FJA05&t%5B0%5D=Zipcar&t%5B1%5D=Car%20sharing&t%5B2%5D=Belgium&curl=1. Accessed: 2021-05-19.

Jorge, D., Correia, G.H.A., Barnhart, C., 2014. Comparing optimal relocation operations with simulated relocation policies in one-way carsharing systems. IEEE Trans. Intell. Transp. Syst. 15 (4), 1667–1675. http://dx.doi.org/10.1109/TITS.2014.2304358.

Jorge, D., Molnar, G., de Almeida Correia, G.H., 2015. Trip pricing of one-way station-based carsharing networks with zone and time of day price variations. Transp. Res. B 81, 461–482. http://dx.doi.org/10.1016/j.trb.2015.06.003, Optimization of Urban Transportation Service Networks.

Kaspi, M., Raviv, T., Tzur, M., 2014. Parking reservation policies in one-way vehicle sharing systems. Transp. Res. B 62, 35–50. http://dx.doi.org/10.1016/j.trb.2014.01.006.

Kutela, B., Teng, H., 2019. The influence of campus characteristics, temporal factors, and weather events on campuses-related daily bike-share trips. J. Transp. Geogr. 78, 160–169. http://dx.doi.org/10.1016/j.jtrangeo.2019.06.002.

Li, X., Jenn, A., 2022. An integrated optimization platform for spatial-temporal modeling of electric vehicle charging infrastructure. Transp. Res. D 104, 103177. http://dx.doi.org/10.1016/j.trd.2022.103177.

Li, Q., Liao, F., Timmermans, H.J., Huang, H., Zhou, J., 2018. Incorporating free-floating car-sharing into an activity-based dynamic user equilibrium model: A demand-side model. Transp. Res. B 107, 102–123. http://dx.doi.org/10.1016/j.trb.2017.11.011.

Li, Q., Zhao, D., Li, X., Wang, X., 2022. Electric vehicle sharing based “energy sponge” service interfacing transportation and power systems. Clean. Logist. Supply Chain 3, 100022. http://dx.doi.org/10.1016/j.clscn.2021.100022.

Lin, L., He, Z., Peeta, S., 2018. Predicting station-level hourly demand in a large-scale bike-sharing network: A graph convolutional neural network approach. Transp. Res. C 97, 258–276. http://dx.doi.org/10.1016/j.trc.2018.10.011.

Masoud, M., Elhenawy, M., Almannaa, M., Liu, S.-Q.S., Glaser, S., Rakotonirainy, A., 2019. Heuristic approaches to solve E-scooter assignment problem. IEEE Access PP, http://dx.doi.org/10.1109/ACCESS.2019.2957303, 1–1.

Miao, H., Jia, H., Li, J., Qiu, T.Z., 2019. Autonomous connected electric vehicle (ACEV)-based car-sharing system modeling and optimal planning: A unified two-stage multi-objective optimization methodology. Energy 169, 797–818. http://dx.doi.org/10.1016/j.energy.2018.12.066.

Mobility, 2019. Catch a car is now mobility go. URL https://www.mobility.ch/fileadmin/files/about/media/media_releases/20190605-Media-release-Catch_a_Car-now-Mobility-Go.pdf. Accessed: 2021-05-30.

Narayanan, S., Antoniou, C., 2023. Shared mobility services towards mobility as a service (MaaS): What, who and when? Transp. Res. A 168, 103581. http://dx.doi.org/10.1016/j.tra.2023.103581.

Nourinejad, M., Roorda, M.J., 2014. A dynamic carsharing decision support system. Transp. Res. E 66, 36–50. http://dx.doi.org/10.1016/j.tre.2014.03.003.

Nourinejad, M., Zhu, S., Bahrami, S., Roorda, M.J., 2015. Vehicle relocation and staff rebalancing in one-way carsharing systems. Transp. Res. E 81, 98–113. http://dx.doi.org/10.1016/j.tre.2015.06.012.

Pfrommer, J., Warrington, J., Schildbach, G., Morari, M., 2014. Dynamic vehicle redistribution and online price incentives in shared mobility systems. IEEE Trans. Intell. Transp. Syst. 15 (4), 1567–1578. http://dx.doi.org/10.1109/TITS.2014.2303986.

Repoux, M., Kaspi, M., Boyacı, B., Geroliminis, N., 2019. Dynamic prediction-based relocation policies in one-way station-based carsharing systems with complete journey reservations. Transp. Res. B 130, 82–104. http://dx.doi.org/10.1016/j.trb.2019.10.004.

Shen, Z.-J.M., Feng, B., Mao, C., Ran, L., 2019. Optimization models for electric vehicle service operations: A literature review. Transp. Res. B 128, 462–477. http://dx.doi.org/10.1016/j.trb.2019.08.006.

Singh, B., Dubey, P.K., 2022. Distributed power generation planning for distribution networks using electric vehicles: Systematic attention to challenges and opportunities. J. Energy Storage 48, 104030. http://dx.doi.org/10.1016/j.est.2022.104030.

Tang, Y., Zhang, Q., Wen, Z., Bunn, D., Martin, J.N., 2022. Optimal analysis for facility configuration and energy management on electric light commercial vehicle charging. Energy 246, 123363. http://dx.doi.org/10.1016/j.energy.2022.123363.

Vujasinović, J., Savić, G., Željko V. Despotović, 2022. Architecture and sizing of system for remote control of renewable energy sources powered station for electric vehicles charging. In: 2022 IEEE 7th International Energy Conference. ENERGYCON, pp. 1–7. http://dx.doi.org/10.1109/ENERGYCON53164.2022.9830318.

Weikl, S., Bogenberger, K., 2015. A practice-ready relocation model for free-floating carsharing systems with electric vehicles – mesoscopic approach and field trial results. Transp. Res. C 57, 206–223. http://dx.doi.org/10.1016/j.trc.2015.06.024.

Wu, H., 2022. A survey of battery swapping stations for electric vehicles: Operation modes and decision scenarios. IEEE Trans. Intell. Transp. Syst. 23 (8), 10163–10185. http://dx.doi.org/10.1109/TITS.2021.3125861.

Wu, C., Vine, S.L., Sivakumar, A., Polak, J., 2019. Traveller preferences for free-floating carsharing vehicle allocation mechanisms. Transp. Res. C 102, 1–19. http://dx.doi.org/10.1016/j.trc.2019.02.019.

Zhang, D., Liu, Y., He, S., 2019. Vehicle assignment and relays for one-way electric car-sharing systems. Transp. Res. B 120, 125–146. http://dx.doi.org/10.1016/j.trb.2018.12.004.