Available online at www.sciencedirect.com

ScienceDirect

Transportation Research Procedia 00 (2022) 000–000

Transportation Research Procedia

www.elsevier.com/locate/procedia

Transport Research Arena (TRA) Conference

Fleet optimization in shared mobility services: Theoretical and findings and future steps

Chrysostomos Mylonas[a]*, Maria Stavara[a], Dimitris Tzanis[a], Evangelos Mitsakis[a]

[a]*Centre for Research and Technology Hellas, 6th km Charilaou-Thermis, Thessaloniki, 57001, Greece*

Abstract

The rise of innovative mobility services provides new alternatives to existing transport modes complying with the vision of sustainable urban mobility. However, this rise implies a series of challenges for the transport sector associated with the need for adapting the yearlong planning processes to the specific needs of these services. The current paper, by focusing on shared-mobility services, provides a brief overview of relevant strategic planning frameworks and considerations discussed so far in the scientific community. This is done by emphasizing on the assessment of the optimal fleet size of these services. Finally, it presents the conceptual framework and the computational flow of a tool oriented to support such a strategic planning purpose.

Peer-review under responsibility of the scientific committee of the Transport Research Arena (TRA) Conference
Keywords: Shared-mobility services; Optimal fleet size; Sharing and pooling; Urban planning and transport

1. Introduction

In recent years, shared mobility services are gaining more and more ground constituting an appealing alternative to conventional modes of transport enabling a wide range of benefits. A prominent example constitutes cost savings given that many persons can collectively fulfil their mobility needs without using their personal vehicle. On top of that, the reduced use of private vehicles relieves the adverse impacts of mobility to the environment and improves the quality of life within European urban spaces. Furthermore, shared mobility services can be used for first- and last-mile trip purposes (Shaheen & Cohen, 2018), enabling synergies with existing, within a city, public transport services.

However, the extent to which these benefits will be realized relies on the effective planning of these services. According to Shui and Szeto (2020), planning of shared mobility can be divided into strategic, tactical, and operational.

* Corresponding author. Tel.: +30-231-125-7623.
E-mail address: chmylonas@certh.gr

Peer-review under responsibility of the scientific committee of the Transport Research Arena (TRA) Conference

Strategic planning revolves around long-term decisions, such as the determination of required fleet and the location of dispatching stations (if any). On the other hand, tactical planning revolves around medium-term decisions oriented to ameliorate the performance of provided services through, for instance, static fleet relocation and demand management. Finally, operational planning involves short-term decisions responding in a dynamic manner to time specific needs and conditions.

This paper has its focus on strategic planning and in particular on the determination of the optimal fleet size of shared mobility services. It does so by analyzing a relevant use case targeting one of the pilot cities of a currently on-going Horizon 2020 project, titled nuMIDAS (New Mobility Data and Solutions Toolkit), namely the city of Milan. This use case responds to the need of the city to streamline tenders for shared mobility services by including a rational value for the required fleet and, thus, to orchestrate service provision in line with equity principles understood from both travelers and service operators' perspective.

Before the analysis of the use case, this paper provides a brief, yet inclusive, discussion of the relevant literature with the aim of identifying the crucial parameters that need to be considered during the assessment of the optimal fleet size of shared mobility services. This is the scope of Section 2. Subsequently, in Section 3, a technical description of the use case is provided by highlighting its goals, key actors, required inputs, and target outputs. Finally, in Section 4, the operational prototype of the tool associated with this use case is presented, including its conceptual framework and computational flow.

2. Literature review

The determination of the optimal fleet size of shared-mobility services responding successfully to existing or forecasted demand constitutes a critical concern for several stakeholders involved in the value chain of shared-mobility services. Building upon the related literature (Shui & Szeto, 2020; Zhai et al., 2019), the fleet size of these services should fulfil the objectives of both operators and travelers. The main interest of service operators is to maximize their profit or profit margin, while the main interest of travelers is to minimize their generalized trip costs (e.g., travel time from an origin to a destination). In this respect, transport planning authorities are typically called to find a balance between the perception of operators and travelers, thus enabling the sustainability and viability of provided services. Despite the importance of this topic, research endeavors providing a concrete solution to the optimal fleet sizing of shared-mobility services from both perspectives are limited. The main purpose of the current subsection is to provide an overview of existing research endeavors with the aim of paving the ground for the identification of the critical factors that need to be considered.

Wallar et al. (2019) presents a four-stage methodology for optimizing the fleet size of shared mobility services, complying to the concept of Mobility-as-a-Service (MaaS), along with fleet composition. The first stage involves the identification of the number of vehicle deposits that are needed to efficiently dispatch the vehicles of which a fleet is comprised through a linear integer programming algorithm that seeks to optimize service rate based on maximum waiting time and maximum delay. The second stage includes the identification of the set of vehicle trips that serve transport demand expressed through service requests. The third stage involves the computation of the minimum number of trips so that each request is served exactly once. The final stage includes the estimation of the number and type of vehicles needed to carry out these trips in a manner compliant to the minimum desired service quality (e.g., each trip has one outgoing and incoming transition).

Narayan et al. (2020) present a model for determining the fleet size of an on-demand system offering private (e.g., taxi-like) and pooled (e.g., ridesharing) services assuming demand elasticity. Such an assumption is made on the premise that the fleet size affects the level of provided service that, in turn, affects the attractiveness of the provided service. It is assumed that each user owns a set of travel plans, assigns an evaluation score to the executed plan, and replan his/her travel strategy (e.g., selected route, selected mode, departure time), thus forming a computational sequence that continues in time until a convergence criterion (i.e., equilibrium) is achieved. Demand constitutes an input to a supply determination module the purpose of which is to identify the optimal fleet size of the on-demand system. The interim results of this module affect the day-to-day travel strategy of users, including potential demand-side variations. The whole process terminates when an optimal solution, i.e., equilibrium state, is identified. Optimality is judged from two perspectives. The first one is the so-called "agency's perspective" based on which a transport planning authority wishes to minimize the generalized travel cost of users and the costs induced by service operators.

The second one is the so-called "operator's perspective" based on which a service operator wishes to maximize its profit. The mathematical formulation of the first perspective includes the minimization of the Total Agency Cost (TAC) discerned into the users' travel cost and the operator's operating cost. Users' travel cost includes several individual components, such as walking time, in-vehicle time, and waiting time, which are all affected by the decision variable (i.e., fleet size). Similarly, the operator's operating cost is a function of the distance travelled by the vehicles of which the fleet is comprised, which is also affected by the size of the fleet. The mathematical formulation of the second perspective includes the maximization of the operator's profit, which is the difference between the operator's revenue and expenditure. Other parameters that are involved in the mathematical relationships the value of which needs to be provided as input include value of time, cost of vehicles' maintenance, cost of fuel, and fare or distance-based fare of provided services.

Li and Tao (2010) suggest that the determination of the optimal fleet size of a shared-vehicle service, operated by a car rental company within two cities, can be analyzed appropriately as a multi-criteria problem. Special attention is paid on the identification of a cost-effective way of transferring vehicles from one city to another aiming to serve both cities as well. A dual-stage model, based on dynamic programming and heuristics, is suggested to address both the problem of the optimal fleet size and vehicle transfer policy. Such a model considers several factors, including lost sales, transfer costs between cities, and the extent of the demand for the shared-vehicle service that corresponds to round trips versus single trips. Round trips are made by local travelers, who pick a vehicle from one city and return it in the same city, while single trips are made by inter-city travelers, who pick up a vehicle at City A and drop it off at City B. Given the unbalanced fleet that may be caused by inter-city travelers and the inability to know in advance the ratio of local to inter-city travelers, the authors deal with several variations of the original problem, involving a finite and an infinite planning horizon as well as zero and non-zero transfer costs. Moreover, they provide extensions of the adopted model into which involve: a) the relaxation of several assumptions (lost sales, lack of information about demand composition, and in-day vehicle transfers), b) the analysis of a network comprised of more than two cities, and c) the analysis of a fleet comprised of multi-type vehicles with each type fitting the needs of specific customers. The relaxation of the lost-sales assumption is made on the premise that a car-rental company has access to a B2B leasing market and is, by that means, able to satisfy a certain portion of demand through non-owned vehicles that should be returned by customers at the end of the planning horizon. The relaxation of the uncertainty related to demand composition is based on the premise that a car-rental company can analyze historical demand-side data and estimate the ratio of local to inter-city travelers. Finally, the relaxation of the in-day vehicle transfer is made on the premise that a car-rental company may decide to transfer vehicles between two cities or activity areas overnight.

The study offered by Angelopoulos et al. (2016) address the problem of the optimal fleet sizing of docked bicycle sharing services collaterally with the optimal positioning of dock stations. The authors examine the strategic design of a docked bicycle sharing system by recognizing that it is important to jointly minimize investment costs and maximize travelers' utility. Important aspects toward this direction are deemed to be the number, location, and capacity of stations, as well as the setup of bicycle lanes. Given that each station should be equipped with an adequate number of bicycles and these stations should be properly distributed in space to ensure an adequate level of service, present a mixed integer linear program is used oriented to provide a solution to the capacitated facility location problem. Inputs to this program constitute a set of demand points and a set of potential facility locations. The objective is to identify the optimal number, positions, and capacity of these facilities to ensure demand coverage considering operational and expansion costs subject to budget constraints. Numerical testing reveals that the higher the budget, the larger the number of dock stations suggested by the program.

Finally, as suggested by Sayarshad et al. (2012) the fleet sizing problem of shared-mobility services should be formulated considering both the multi-periodic and stochastic dimension of the demand for such services. The multi-periodic dimension implies that the rate of end users arriving at a rental station or requesting to book a vehicle, e.g., via an app is not constant during a day. In contrast, there are time intervals within a day during which the level of demand is higher (peak period) and time intervals during which the level of demand is lower (off-peak period). The stochastic dimension implies, among others, that the exact time at which users arrive in a rental station or request to book a vehicle (within each time period) is subject to uncertainty.

3. Use case analysis

The current subsection aims to elaborate and highlight the technical aspects behind the problem of determining the optimal fleet size of a shared-mobility service by adopting a use case analysis approach. This use case has been conceptualized based on the willingness of decision-makers in Milan to improve the processes of issuing tenders for shared-mobility services, given that they provide a fixed number for the required fleet, which creates complexity in the sense that the market can fluctuate, and demand can change over the time of operation. In addition, it is a concern of the city to ensure a sufficient level of service at an accessible price not only within the inner city of Milan but across the whole metropolitan area. Moreover, as suggested by Shaheen and Cohen (2019) and Nikitas (2019) there is a need to define proper fleet management policies, in the sense of rebalancing fleet to achieve a proper density and service equity. In this respect, both the optimization of the operable fleet and the enforcement of fleet management will prove ineffective if the size of the fleet is a priori not adequate. The presented use case is comprised of a technical description targeting the development of a relevant strategic planning tool as well as the clarification of the targeted users and data inputs and outputs.

3.1. Technical description

The scope of the tool addressed by the current use case is to support policy makers to determine properly the fleet size of shared mobility services to be operated within a given area. The fleet size will be determined considering both the perspective of service operators and the perspective of end users. According to the former, there is a need to identify a value for the fleet size that will lead to the maximization of revenues and the minimization of financial losses. According to the later, there is a need to identify a value that will lead to the minimization of the generalized cost of trips. By that means, the suggested value will enable the provision of beneficial services for service operators that will jointly comply with minimum level of service requirements, i.e., fleet size will not be extremely large to exceed the desired operational costs and concurrently the end users will be adequately served without having to wait for a long time or walk long distances. To this end, the tool will provide solution to an optimization problem, which will involve the minimization of an objective function that will be multi-parametric to cover both perspectives mentioned above. This optimization problem will also include constraints reflecting the maximum waiting and walking of end users. The parameters mentioned above will be either user-defined or approximated by the tool itself using geometric probability distributions. Having defined these parameters and constraints, the tool will execute iterative calculations to identify the optimal value for the fleet size. Finally, the tool will provide information concerning operating costs and generalized trip costs (e.g., average walking time/distance) corresponding to both the optimal solution and a range of fleet size values.

3.2. Targeted users, data inputs and outputs

There are several actors involved in the ecosystem of this tool, including, for instance, service operators, information service providers, policymakers, transport planners, and travelers (end-users). However, the targeted users are policy makers and transport planners supporting policy makers, who are tasked with finding an optimal balance between the perspectives analyzed above. In this respect, the tool is expected to be used not in a real-time context but in a periodic basis, specifically when there is a need to identify the fleet size of a shared-mobility service to be operated within an area of interest (or assess whether an operated service consists of an adequate fleet). The data input and output requirements are presented in Table 1.

Table 1. Data input and output requirements

Data inputs	Data outputs
Historical demand data (trips/day hour)	Optimal fleet size
Expected daily demand (trips/day)	Demand coverage corresponding to the optimal solution
Type of service (station-based or free-floating)	Profits corresponding to the optimal solution
Size of the area of interest (km^2)	Walking time corresponding to the optimal solution

Operating cost per vehicle per minute	Waiting time corresponding to the optimal solution
Expected revenues per minute of rent	Demand coverage for several fleet size values
Average users walking speed	Profits for several fleet size values
Mean trip duration	Walking time for several fleet size values
Weighting factors (service operator's and social perspective)	Waiting time for several fleet size values
Minimum and maximum value of the fleet size	

4. Operational prototype

4.1. Conceptual framework and computational flow

In line with the suggestions of Sayarshad et al. (2012) presented in Section 1, the adopted solution to the problem of the optimal fleet sizing of shared mobility services preserves the multi-periodic dimension and stochastic dimension of the demand for these services. Its overall computational flow is presented in Fig. 1.

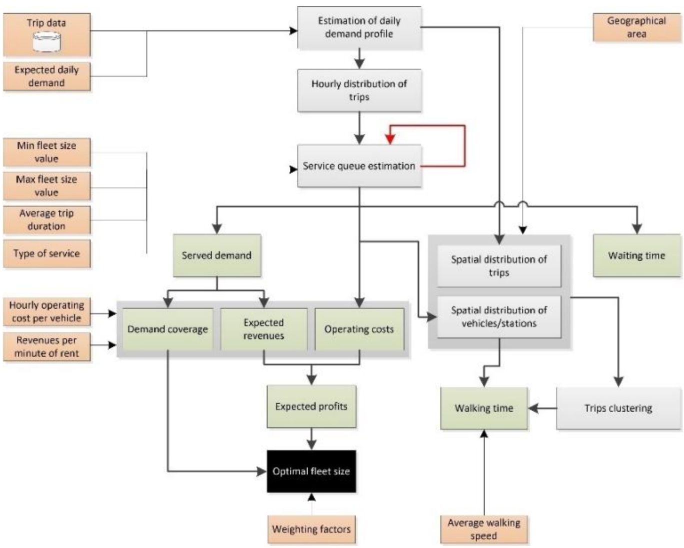

Fig. 1. Adopted computational flow.

The first step involves the estimation of a daily demand profile. This is achieved through demand factors calculated based on acquired input by the user or implied by the tool itself making use historical data from the operation of the same or comparable service within an equivalent area in socioeconomic terms. The next step includes the distribution of the demand corresponding to each day hour within each day hour, with the aim of taking into consideration the uncertainty characterizing the arrival rate of end users in stations or the rate with which end users demand to book a vehicle, e.g., via an app. For this purpose, a uniform probability distribution is utilized building upon available empirical data from taxi services that suggest the demand for taxi trips is uniformly distributed in each day hour with minor exceptions.

Having distributed the hourly demand, the next step involves the quantification of the number of served demand for each value of the fleet size falling into the range stated by the user (i.e., minimum and maximum fleet size). This quantification is achieved by adopting a queue theory-based approach. According to this approach, a demand unit (end user) can be served only in the premise that a vehicle is available. Occupied vehicles become re-available after a period of time equal to the average trip duration. Furthermore, it is assumed that end users who are not served until the upper bound of each daily interval disappear from the queue. By that means, the effect of the provided level of service to the level of demand is taken into consideration (i.e., end-users may choose an alternative transport mode if they keep waiting for long). End users are served through the First-In-First-Out (FIFO) principle if the analyzed mobility service is station-based. In contrast, end users are randomly served (irrespective of their arrival time) if the analyzed mobility service is free-floating. The adopted approach is schematically represented in Fig. 2a.

From a technical perspective, the amount of served demand is calculated by assessing the value of the trip end time. In particular, when a demand unit appears in time t_i falling into period $[t_1, t_4]$ it is assigned with a trip start time equal to t_1. This demand unit is also assigned with a trip end time equal to infinity. Depending on the availability of vehicles, each demand unit is also assigned with an actual trip start time equal to t_i plus the time needed for a vehicle to become available. If a vehicle is already available when a demand unit appears in time, then the trip start time and the actual trip start time is one and the same. The value of the trip end time of served demand units is replaced with a value being equal to the actual start time plus the average trip duration. By that means, the amount of served demand is equal to the number of demand units the trip end time of which is finite. Moreover, the actual trip start time of non-served demand units is replaced with a value being equal to t_4. By adopting this approach, the waiting time on behalf of users, is also available by subtracting the trip start time from the actual trip start time.

Walking time is approximated through the spatial distribution of the maximum value of the hourly demand (hereafter referred to as maximum hourly demand) as well as the spatial distribution of either vehicles or stations within a geographical area of square shape and size equal with that declared by the user. The number of stations, in station-based services, is estimated by following a rule-based approach, i.e., a) if the analyzed area is less than 5 km^2, it is assumed that one station hosts up to 10 vehicles, b) if the analyzed area is greater than 5 km^2 and less than 15 km^2, it is assumed that one station hosts up to 15 vehicles, and c) if the analyzed area is greater than 15 km^2, it is assumed that one station hosts up to 20 vehicles. Such a spatial distribution is achieved with the use of a uniform probability distribution for both demand and vehicles or stations. For the case of stations, a constraint is utilized aiming to ensure that they are placed to a satisfactory extent apart from each other.

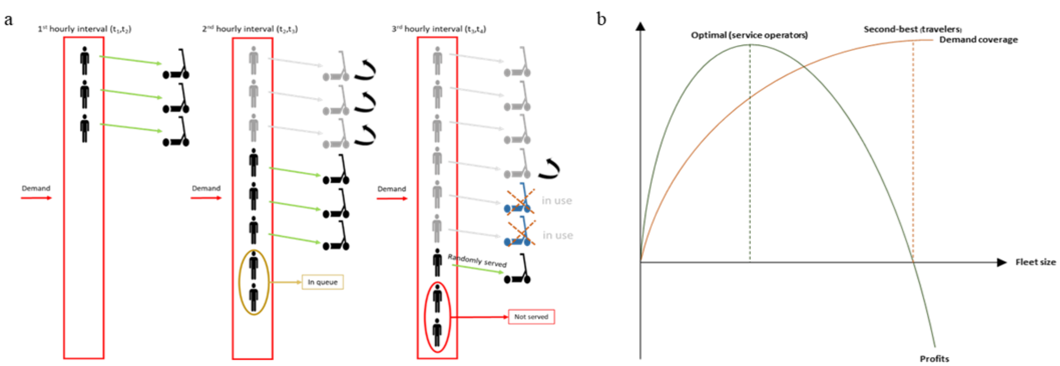

Fig. 2. (a) Adopted queue theory-based approach for estimating served demand; (b) Adopted decision-making approach relying on the second-best theory.

Having distributed the maximum hourly demand and vehicles or stations in space, an average walking distance is calculated by clustering the demand into an equal number of clusters with the number of stations (if the analyzed service is station-based) or with the looped number of fleet size (if the analyzed service is free-floating). The calculated average walking distance is then utilized for the estimation of the average walking time considering the value provided by the user for the average walking speed parameter.

The last step of the computational flow involves the calculation of the optimal fleet size. The decision variables utilized by the tool include the demand coverage and the profitability corresponding to various values of the fleet size. The former is assumed to reflect the perspective of travelers (or end users), while the latter is assumed to reflect the perspective of service operators. From a mathematical point of view, it should be borne in mind that shape of the demand coverage curve closely resembles the shape of a square root function’s curve, while the profitability curve is concave. Given that end users always wish to enjoy a greater level of service, the demand coverage curve is monotonically increasing. This does not hold true for the shape of the profitability curve, which is increasing for a lower range of fleet size and decreasing for a higher range of fleet size. This is attributed to the fact that while service operators require a considerable fleet size to serve demand and thus increase their profits, there is a certain value of fleet size beyond which the profits are decreasing given that the utilization rate of vehicles gets steadily lower. Furthermore, for considerable high values of fleet size, the profits may become even negative given that the cost of operating a large size of fleet exceeds the revenue margin of service operators.

Moreover, the maximum value of demand coverage may occur for a value of fleet size leading to negative profits. In this respect, the maximization of demand coverage concludes to a negative externality for service operators. This situation purely implies the need to incorporate in the tool's algorithm the principles of the general theory of the second best. According to this theory, which was originally postulated by Lipsey and Lancaster (1956) with the aim of analyzing how the removal of a market distortion may lead to the introduction of a new market distortion, there is a second-best policy that maximizes social welfare from a utilitarian point of view. This can be achieved as suggested by Bennear and Stavins (2007) through the introduction of an appropriate constraint. In the context of the problem to be solved, this constraint involves the exclusion from the analysis of the values of the fleet size that leads to negative profits (Fig. 2b). In this respect, it is accepted that there is a solution that maximizes the welfare of service operators and a second-best solution maximizing to the extent possible the welfare of travelers (end users).

The optimal solution derives from the weighted combination of the fleet size values corresponding to the optimal solution from the operator's perspective and the second-best solution from the perspective of travelers.

4.2. Demonstration and testing

This section aims to demonstrate and assess the validity of the results produced by the tool presented in Section 4.1, which is prototyped in Python with the use of the appropriate libraries. Such a purpose is served via a base scenario and two test scenarios. The input parameters of these scenarios are provided in Table 2.

Table 2. Parameters of the base-case and alternative scenarios

Data inputs	Base scenario	1st scenario	2nd scenario
Expected daily demand (trips/day)	5000	7500	5000
Type of service (station-based or free-floating)	Station-based	Station-based	Station-based
Size of the area of interest (km^2)	5	5	5
Operating cost per vehicle per minute	0.20	0.20	0.20
Expected revenues per minute of rent	0.45	0.45	0.45
Average users walking speed	3.6	3.6	3.6
Mean trip duration	18	18	9
Weighting factors (service operator's and social perspective)	0.5 and 0.5	0.5 and 0.5	0.5 and 0.5
Minimum and maximum value of the fleet size	1 - 500	1 - 500	1 - 500

In the first test scenario, it is assumed that the user provides a greater input value to the expected daily demand. In the second scenario, it is assumed that the user provides a lower input value to the mean trip duration. The outputs of the algorithm for the base scenario as well as for the two alternative scenarios are presented in Table 3.

Table 3. Outputs of the base-case and alternative scenarios

Data outputs	Base scenario	1st scenario	2nd scenario
Optimal fleet size	108	174	55
Demand coverage corresponding to the optimal solution	83.70%	87.40%	73.60%
Expected profits corresponding to the optimal solution	€6.980 (daily)	€9.511 (daily)	€2.764 (daily)
Average walking time corresponding to the optimal solution	0:06:39	0:04:59	0:09:10
Average waiting time corresponding to the optimal solution	0:02:30	0:01:47	0:04:29

The expected response of the algorithm in the first test scenario constitutes an increased optimal fleet size value compared to the base-case scenario considering that a higher number of users should be served. Similarly, in the second test scenario a decreased optimal fleet size value is expected, considering the increased service rate of vehicles composing the fleet of the analyzed shared mobility service. As it becomes evident by Table 2, the outputs of the tool are in line with the initial expectations.

Conclusions and future steps

This paper provides a brief overview of the literature related to the strategic planning of shared mobility services, placing special emphasis on the identification of the optimal fleet size of such services. On that basis, it presents the conceptual and computational framework of a new tool supporting this purpose. The application of the developed tool in specific test scenarios showcase that the derived results are rational and in line with the initial expectations. Future steps include the excessive stress test of the tool as well as its further evaluation building upon real data input from the pilot city of Milan. Based on the derived results the parameters of the tool will be further refined/calibrated. Finally, new functionalities will be incorporated involving, among others, demand elasticity.

Acknowledgements

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 101007153. This paper was the result of the excellent joint efforts and contributions of all the project partners involved. We wish to especially mention the following co-authors: Sven Maerivoet, Bart Ons and, Kristof Carlier (Transport & Mobility Leuven, TML), Steven Boerma, Rick Overvoorde, Anton Wijbenga, Tessel van Ballegooijen, Dennis Hofman, Levi Broeksma, Martijn Harmenzon, Luc van der Lecq, and Jaap Vreeswijk (MAPtm), Carola Vega, Josep Laborda, and Eglantina Dani (Factual Consulting), Ondřej Přibyl, Magdalena Hyksova, André Maia Pereira, Tomas Horak, and Jan Přikryl (Czech Technical University in Prague, CTU), Valerio Paruscio, Valerio Mazzeschi, Alessandro Luè, Gabriella Atzeni, Fabio Vellata (Poliedra-Polytechnic Milano), Pablo Recolons, Ramon Pruneda, and Xavier Conill Espinàs (Àrea Metropolitana de Barcelona, AMB Informació), Cristina Covell, Valentino Sevino, Alessandro Giovannini, Paolo Campus, and Adriano Loporcaro (Agenzia Mobilità Ambiente Territorio, AMAT), and Eli Nomes, Tim Asperges, and Fatma Gözet (City of Leuven).

References

Angelopoulos, A., 2016. An Optimization Model for the Strategic Design of a Bicycle Sharing System: A Case Study in the City of Athens. In: Proceedings of the 20th Pan-Hellenic Conference on Informatics. Association for Computing Machinery, New York, USA, Article 5, pp. 1–6.

Bennear, L. S., Stavins, R. N., 2007. Second-best theory and the use of multiple policy instruments. Environmental and Resource economics 37.1, 111–129.

Li, Z., Tao, F., 2010. On determining optimal fleet size and vehicle transfer policy for a car rental company. Computers and Operation Research 37.2, 341–350.

Lipsey, R. G., Lancaster, K., 1956. The general theory of second best. The review of economic studies 24.1, 11–32.

Narayan, J., Cats, O., Oort, N. Van, Hoogendoorn, S. P., 2021. Fleet size determination for a mixed private and pooled on-demand system with elastic demand. Transportmetrica A: Transport Science 17.4, 897–920.

Nikitas, A., 2019. How to save bike-sharing: An evidence-based survival toolkit for policy-makers and mobility providers. Sustainability 11.11, 3206.

Sayarshad, H., Tavassoli, S., Zhao, F., 2012. A multi-periodic optimization formulation for bike planning and bike utilization. Applied Mathematical Modelling 36.10, 4944–4951.

Shaheen, S., Cohen, A., Zohdy, I., 2016. Shared Mobility Current Practices and Guiding Principles. U.S. Department of Transportation, Federal Highway Administration. Retrieved from: https://ops.fhwa.dot.gov/publications/fhwahop16022/fhwahop16022.pdf

Shui, C. S., Szeto, W. Y., Engineering, C., Kong, H., 2020. A review of bicycle-sharing service planning problems. Transportation Research Part C 117.June, 102648.

Wallar, A., Schwarting, W., Alonso-mora, J., Rus, D., 2019. Optimizing Multi-class Fleet Compositions for Shared Mobility-as-a-Service, In: Proceedings of the 2019 IEEE Intelligent Transportation Systems Conference (ITSC). IEEE, pp. 2998–3005.

Zhai, Y., Liu, J., Du, J., Wu, H., 2019. Fleet Size and Rebalancing Analysis of Dockless Bike-Sharing Stations Based on Markov Chain. ISPRS International Journal of Geo-Information 8.8, 334.