

Review Article

Optimization and Simulation of Carsharing under the Internet of Things

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Internet of Things devices are popular in civilian and military applications, including smart device cities, smart grids, smart pipelines, and medical Internet of Things. Among them, carsharing supported by the Internet of Things is developing rapidly due to their advantages in environmental protection and reducing traffic congestion. The optimization of the carsharing system needs to consider the uncertainty of demand and the coupling relationship of multiple decision variables, which brings difficulties to the establishment of mathematical models and the design of efficient algorithms. Existing studies about carsharing optimization are mainly divided into four subproblems: the operation mode selection, vehicle type selection, demand analysis, or decision-making, rather than comprehensive consideration. This paper summarizes the four subproblems from the perspective of mathematical models, solving algorithms, and statistical methods and provides references for more comprehensive research in the future.

1. Introduction

In 1999, the Massachusetts Institute of Technology defined the Internet of Things: connecting all items to the Internet through information sensing devices such as radio frequency identification. The Internet of Things was widely used in smart device cities, smart grids, smart pipelines, and medical Internet of Things. The Internet of Things used the Internet as a cornerstone of further expansion and development. With the help of GPS, infrared sensor, and other sensing devices, it transmitted and exchanged information between different mobile digital devices, namely, different entities. It had three characteristics: (1) intelligent sensing, (2) two-way transmission, and (3) intelligent control. There had been several proposals for unique object identifiers that uniquely identified objects and locations in the real world. Information could be associated with objects and places, and decoding could be used to retrieve relevant information. Karakostas [1] proposed a Domain Name Service (DNS)

infrastructure of the Internet of Things that could translate the unique identifier of a physical object into a specific network address and then extract information such as status and location. Due to the advantages of large capacity and high reliability of the Internet of Things, it provided an opportunity for the development of a new transportation mode named carsharing. Users could download the APP and register online to become a customer. Although the Internet of Things provided technical support for carsharing, there were still various problems in terms of its application and promotion. Figure 1 shows the operation process of the carsharing system. The user placed an order to reserve a car that has been charged or refueled. After the order was completed, the operator needed to relocate the car to meet the balance of supply and demand. The Internet of Things realized data feedback and instruction issuance.

Carsharing emerged informally as a consequence of gasoline prices rising in the 1940s [2] and had become popular in Europe and the United States since the 1980s and

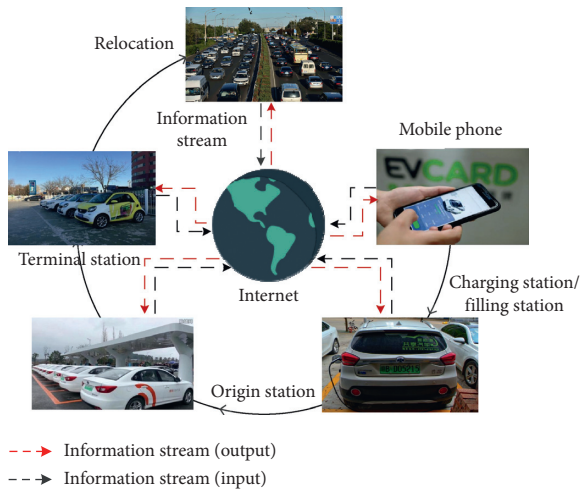


FIGURE 1: Structure of carsharing system.

then was introduced to many other countries. The growing number of private cars in developed cities brought about problems such as traffic congestion, environmental pollution, and insufficient social resources. For example, the average daily number of trips increased to more than 28 million, and the number of private vehicles covered more than 31% in Beijing which was affected by these problems deeply [3]. Studies showed that the introduction of carsharing had alleviated the seriousness of the congestion and air pollution problems to a certain extent and made the social resources more fully utilized [4–6]. It also increased the mobility of the city and provided a new transportation option.

The research on optimal design and operation of carsharing was divided into four subproblems, as shown in Figure 2. The characteristics of each part of the main decision-making contents are listed in the rectangle in Figure 2. Operation modes' selection should consider operating costs and demand. Vehicle type selection should consider the feasibility and environmental pollution. The total customer demand needed to be predicted by function fitting or neural network, and changes in uncertain demand over time and space should be considered. Decision-making was the most difficult research content because there were many decision variables and the variable coupling relationship was complicated.

2. Operation Modes

The operation modes of the carsharing were mainly divided into three types according to the terminal location: round trip, one-way trip, and free floating. Round trip and one-way trip were based on stations that differed from free floating [3]. The round trip required customers to return a car to the station where they picked up. Free floating was the most convenient for customers that they could return cars anywhere just within the operation areas [7]. While the one-way trip was a compromise between the two modes, in which customers should return cars at any station. The driving routes of the three operation modes are shown in Figure 3.

Apparently, the round trip cannot satisfy a lot of demands due to the rigorous stop condition [8], but the cost of relocation was decreased simultaneously. For the one-way trip and free-floating trip, the relocation aiming to rebalance the demand and supply was a critical factor that contributed to the cost [9, 10].

Brendel et al. [11] summarized 22 influential pieces of literature on carsharing. The results showed that most of the pieces of literature (about 82% of the total literature) studied station-based trip, while free floating is less studied due to the difficulty of rescheduling. Although a station-based one-way trip was suitable for more travel demands compared to a round trip, the round-trip demand would not be significantly reduced under the introduction of a one-way trip because that round trip was appropriate for purposes such as shopping, entertainment, and sightseeing [12, 13]. In addition, there were other factors affecting the choice of operation modes, such as age, gender, income, car ownership, and weather [14]. Some companies such as Zipcar have two modes named round trip for short trips and a one-way trip for long-distance travel. Customers who chose round trip had priority to reserve. This kind of service had already been studied. On one hand, some scholars started to add new services to the present modes to maximize the profit. Jorge et al. [15] developed an integer programming model to determine the station location that should be open to a one-way trip when integrating both one-way trip mode and the original round-trip mode. It was proved that there was a potential market for this model and it would greatly satisfy demands with the case study of Boston. But the disadvantage of this model was that it could only show its efficiency in some specified cases. On the other hand, some other scholars also started to add new services to the present modes to improve the service. Molnar and Correia [16] proposed a kind of long-term reservation service for a one-way and free-floating trip to improve user's satisfaction. And he developed the relocation-based reservation enforcement method (RB-R) to provide customers the ideal car. What is more, a quality of service model was developed and used to estimate and guarantee the satisfaction of customers. Finally, this model was tested in both small town and large major city and a case of Lisbon Municipality was studied to prove the utility of this model.

3. Vehicle Types

There were two main types of vehicles according to the power system: green energy vehicles (GEVs) and gasoline vehicles (GVs). GEVs could better reflect the main characteristic of carsharing, which was environmental protection. The most studied and introduced type of GEVs among the studies was the group of electric vehicles (EVs). Further discussion about the GEVs would mainly focus on EVs. The charging time of EVs was long, the travel distance was limited, and the investment could be enormous (the cost of charging station and charging facility). Normally, GEVs were more suitable for a round trip and a one-way trip. GVs were just the opposite, so they were more suitable for free-floating mode. It was the main research direction for

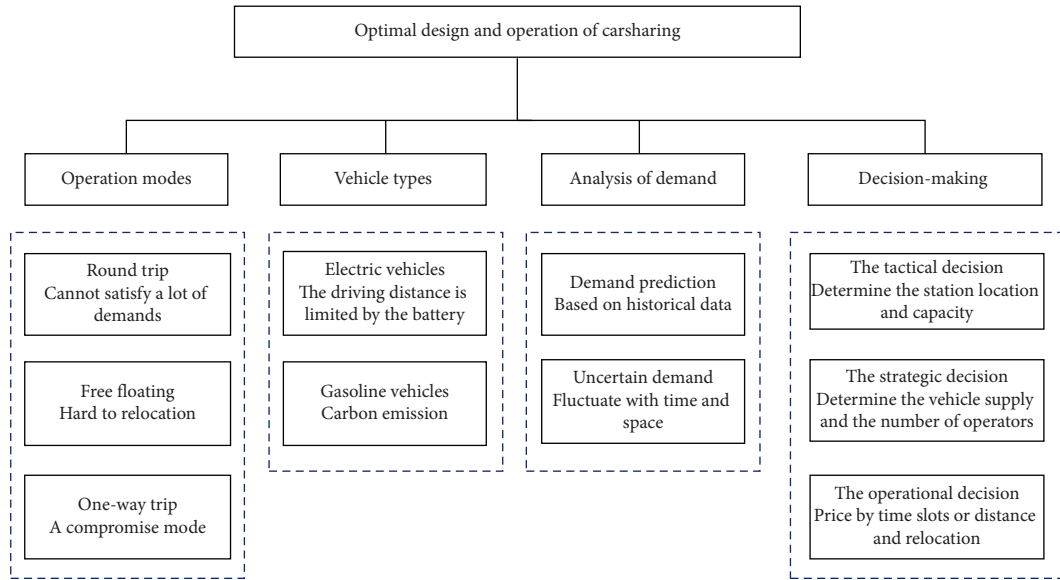


FIGURE 2: Classification of the research on optimal design and operation of carsharing.

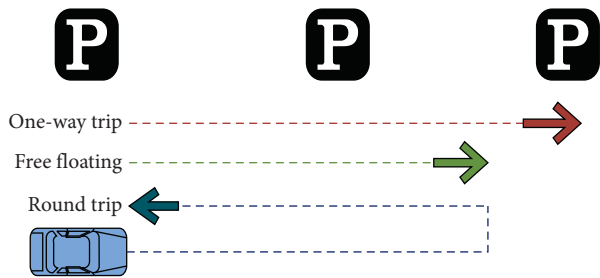


FIGURE 3: The driving routes of operation modes.

operators to choose which type of vehicles was more economical or whether operators that had adopted GVs in the early stage should introduce GEVs.

The social costs of electric vehicles and conventional vehicles could be a standard to determine which way was more profitable, and we should also consider the air pollution costs and the noise costs of conventional vehicles [17]. Based on a large number of GPS data, Kihm and Troomer [18] analyzed the prospects for the use of EVs considering different consumption attitudes. The results showed that it was more effective to reduce the cost of electric cars, improving public charging facilities and increasing government subsidies rather than increasing battery capacity in increasing the potential of electric cars. In addition, a powertrain selection model could be developed considering economic, technical, and social condition constraints on vehicle registration and inventory to analyze the market development and estimate the demand for vehicles [19]. For the problem of introducing electric vehicles to the original gasoline vehicles market, Yoon et al. [20] built a simulation model considering that the car might not be fully recharged before reentering the market which was always simplified in other papers and studied whether the electric car could compete with the gasoline fuel car under different market

conditions. Actually, the battery capacity of electric vehicles also needed to be selected economically. According to the battery capacity, it can be divided into level 2 charging and level 3 charging. The level 3 charging was more expensive but drives a longer distance than level 2 charging. Comparing the type of vehicles and the charging level of electric vehicles, the most economical scheme could be more forceful [21].

4. Analysis of Demand

The demand in a certain area was partly affected by many territorial factors, such as population density, education levels, age, and private car park rate [22]. Also, the operation mode (round trip, one-way trip, and free floating) was another aspect that greatly accounted for a large proportion since there were different demands for different travel modes. Particularly, the free-floating mode could lead to many uncertainties. The determination of demand could be predicted by mathematical models based on the historical travel data of the region. To ensure the quality of the model, the data collection and analysis tools must be comprehensive and precisely suitable. In addition, there had been many pieces of literature accounting for the asymmetry and elasticity of the demand.

4.1. Demand Prediction. This subsection was to state how to predict the demand for a new region to provide advice for operators. When we make the demand prediction, various scenarios needed to be considered, including the travel distance, the number of travelers, the ratio of public transportation users, and the ratio of households without cars [21]. Because there were many factors affecting the demand, the differences in different regions lead to large errors in the prediction model [23], so the prediction model might only be used in specific regions. In order to predict the demand of a new region based on historical data of another region, it was necessary to clarify the differences between the

two regions and which differences were the main factors affecting the demand; then we used regression models to solve the functional relationship between the demand and these factors.

In the early years, scholars studied key indicators of whether or not the carsharing system could be successfully introduced [24]. Later, scholars explored agent-based simulation software to estimate the demand in different scenarios [25]. The GPS data of mobile phones can also be used to count the travel state of users during each period, and then the potential demand for EVs was analyzed [26–29]. After the carsharing was put into operation, the relationship between urban structure and high demand areas as well as the spatial and temporal distribution of supply and demand imbalance could be analyzed based on the historical data [7]. To predict the demand of vehicles, papers should consider multiple objective functions (such as minimum customer wait time and the minimum number of scheduling) and characterize the system performances according to the proposed evaluation indicators, such as the average wait time of the users, the total wait time, the number of waiting users, and the ratio of the number of available vehicles to the total demand of the trip [30]. The spatial decision support system was widely used to identify areas with high demand and exclude areas with low demand and Point of Interests (POIs) (such as shopping malls and schools) which could interpret the spatiotemporal dynamics and helped managers understand customer's behavior better [31]. In addition, some scholars summarized the factors affecting the use of carsharing in small- and medium-sized cities and determined the possibility of introduction [32, 33].

4.2. Uncertain Demand. This subsection was to state how to consider the uncertain demand in space and time.

The uncertain demand was a hot spot. Scholars before generally studied the linear elastic demand function [34]. In addition, the elastic demand could be considered as a random variable, and the Scenario Tree Approach could be used to solve the stochastic programming model, the first step of which was obtained by SAS macrocode. Others were assumed to follow a discrete distribution (such as low, medium, and high) and were predicted in turn according to the stochastic programming approach [35]. Xu et al. [36] firstly described the elastic demand more accurately as a nonlinear model. When the price was less than a threshold value, the demand satisfied the logistic regression function related to the price; otherwise, the demand became zero because the price was too high. Particularly, the mixed-integer nonlinear and nonconvex programming models were forged to be mixed-integer convex programming models. It could be solved by an efficient outer-approximation method. In addition, some scholars obtained specific functional relationships to describe the elastic demand through the logistic regression model considering the utility of carsharing and its competitors [37]. Developing an efficient algorithm could greatly reduce the time of solving and find the optimal or near-optimal solution. An et al. [38] adopt adaptive a heuristic algorithm of large-scale

neighborhood search to solve the complicated model. Considering the stochasticity of demand to establish a mixed-integer programming model with a nonconvex feasible region, a partial redistribution plan would be generated if the demand exceeded the supply [39]. Li et al. [40] proposed a continuum approximation model to determine the optimal station location and the corresponding fleet size of EVs considering stochastic and dynamic travel demand. By dividing the study area into multiple small neighborhoods, each small neighborhood approximates as an Infinite Homogeneous Plane and is finally solved by the bisection algorithm. Zhang et al. [41] considered the uncertain demand and established a multiscenario integer linear programming model to optimize the rebalancing procedures.

Due to so many factors affecting the demand, the model might not be realistic considering the limited factors. Therefore, some scholars used the neural network and support vector machine based on historical data to predict demand. The support vector machine could accurately predict the demand by selecting the appropriate kernel function. Cheu et al. [42] chose the radial basis kernel function and the average error was 0.42–0.83 vehicles per three hours. The calculation result was accurate but slightly worse than the multilayer perceptron. A mixed approach of genetic algorithm and backpropagation was proved to be efficient to train the neural network. The genetic algorithm was used to avoid that the neural network falls into local optimum and the backpropagation was used to accelerate convergence. Each chromosome represented a neural network model and had different weights from each other (the number of nodes in the neural network model) but the same structure (the number of layers in the neural network model) and thus limited the diversity of the offspring [43]. Xu and Lim [44] improved the model by keeping the structure and weights different between chromosomes, and for each generation, backpropagation only works on one chromosome, which accelerates the calculation. It should be noted that the neural network required a large amount of data for training.

5. Decision-Making

The business strategy could be classified into the following three decision level: strategic decision, tactical decision, and operational decision. The strategic decision determined the station location and capacity (the number of parking spaces). The tactical decision determined the vehicle supply and the number of operators, while operational decision determined the relocation scheme and how to price by time slots or distance. Actually, the established model should consider the three levels simultaneously for the strong interaction among them, but the model would be too large and cannot be used in cities with large demand. To address this problem, Boyacı et al. [45] introduced the aggregation model using the concept of a virtual hub which made a branch-and-bound approach available. For the optimization of one-way electric carsharing systems, Huang et al. [46] tracked the stage of charge over time and optimized the fleet size, station capacity, demand satisfaction, and vehicle relocation. A hierarchical strategy was adopted to solve the two

subproblems of strategy and operation. However, other existing pieces of literature often studied the three aspects separately or considered two aspects to avoid the surplus size of the model.

5.1. The Strategic Decision. The places with more parking spaces, longer business hours, and higher population density had more booking demands and higher turnover rates, and they provided a basis for station selection [47]. The choice of station location should consider not only the demand but also the least relocation operations which minimize the imbalance between supply and demand. Actually, relocation during the day could lead to a tremendous cost, so that the model could consider the maintenance costs and the relocation costs only at the end of the day which provided a new strategy for companies [2]. Heuristic algorithms were popular these years, but they could only handle medium-sized instances [45]. Huang et al. [37] established a MINLP model to solve the station positioning and capacity considering the relocation operations and relocation costs except the allocation of staff and solved it with a customized gradient algorithm.

5.2. The Tactical Decision. The carsharing system could be expressed as a hybrid queuing network model which took the road congestion into account in the optimization model to solve parking capacities and fleet size [48]. There was a function between the size of the city and demand density which was always used to explore the balance between fleet size and vehicle relocation [49]. Scholars mostly optimized the fleet size as well as the operational decision or the strategic decision rather than the fleet size individually. Cepolina and Farina [50] used the position, quantity, and capacity of the station as the input of the model and used the simulated annealing algorithm to solve the fleet size and vehicle distribution. For the optimization problem of the University of Tennessee (UT) motor pool, Yoon and Cherry [51] proposed a queuing model with the constraints of the limited distance and the limited charging time of electric vehicles to solve the fleet size of different types of the vehicle when the customer waiting time was close to zero.

5.3. The Operational Decision. Relocation of vehicles which belonged to the operational stage could be operated in two ways, including operator-based location and user-based location [52]. The operator-based relocation was that the company hires employees for vehicle scheduling [53]. The user-based relocation was to provide customers with a reward and punishment mechanism to encourage customers to return the cars to places with larger demand or pick up a car from the lesser one [34].

For the operator-based location problems, scholars might adopt two-stage optimization or three-stage optimization to reduce the size of the model which could reduce the scheduling cost and shorten the time of solving simultaneously [54].

Establishing both the optimization model and the simulation model was adopted in some papers which could find an optimal scheme and study different real-time relocation strategies [55, 56]. The model of relocation was generally large and difficult to solve due to the large driving demand, so developing an efficient algorithm was a hotspot. Bruglieri et al. [3] developed an Adaptive Large Neighborhood Search metaheuristic solution for a relocation model and compared it with the Tabu Search. A previous Ruin and Recreate metaheuristic and the optimal results are obtained via Mixed-Integer Linear Programming to verify the superiority of the proposed algorithm on time of solving and optimization results. In addition to algorithm research, there are scholars who simplified models through mathematical reasoning to accelerate the solution and improve the quality of the solution. Zhao et al. [57] proposed a Lagrangian relaxation-based solution approach to divide a MINLP model into two MILP models and finally solved it with a three-phase implementing algorithm.

In addition, the regions were divided into blocks according to the demand or peak and nonpeak periods according to time, and different pricing strategies were adopted for different blocks to minimize the relocation operation [34, 58]. The most profitable pricing mechanism could be formulated by increasing the travel costs that would cause an unfavorable imbalance and reduce the travel costs that would help to slow down the imbalance [34]. Combining the two rescheduling mechanisms (operator-based relocation and user-based relocation) was sometimes more profitable. It rewarded the customer dynamically and periodically planned the routing for the dispatcher [59].

6. Conclusions

In the past fifteen years, research on carsharing has become more and more plentiful. Scholars have optimized and simulated the carsharing system through mathematical models and advanced algorithms, which provide a theoretical basis for future research. Future research can be based on the following aspects:

- (1) In the modeling solution, literature introduces the assumptions for the simplified model, and the solution results deviate from the actual situation. For example, (1) there are few documents that consider the situation of delaying or canceling travel after the customer has made a reservation and the flexible choice of destination choice for customers; (2) charging time and level are ignored mostly.
- (2) The model size of relocation in the carsharing system increases greatly with the increase of the number of stations and the demand for carsharing services. Therefore, it is urgent to develop an efficient algorithm or learn from mature fields such as refined oil scheduling and shared bikes scheduling.
- (3) The model should be closer to the real-world instance and integrate the three decisions under uncertain demands, which is rarely considered in the existing research.

- (4) Most researches lead providers to choose large cities with high demand. However, from a social perspective, the underdeveloped areas with lower demand should also enjoy the same convenience of sharing cars. Future research can focus on the operation of low-demand areas under the support of the government.

Disclosure

Yuxuan Wang and Huixia Feng are co-first authors of the paper.

Conflicts of Interest

The authors declare that they do not have any commercial or associative interest that represents a conflict of interest in connection with the work submitted.

Authors' Contributions

Yuxuan Wang wrote the initial paper. Huixia Feng provided the overall idea of the paper and revised it. All authors contributed to the final paper.

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