



Environmental sustainability with free-floating carsharing services: An on-demand refueling recommendation system for Car2go in Seattle



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ABSTRACT

Free-floating carsharing has become an increasing concern in recent years. It is a key contributor to the sharing economy, which is beneficial to environmental sustainability through energy conservation, pollution reduction, and low carbon emissions, ultimately improving people's quality of life. This study proposed an on-demand refueling recommendation system to enhance the service performance of free-floating carsharing businesses for better mobility and environmental sustainability. In this system, a method based on data analytics for identifying the appropriate refueling level is designed. One of the most popular free-floating carsharing services, Car2go, is taken as a case study. Based on relevant data from Car2go in Seattle, the on-demand refueling recommendation system is developed and evaluated. This system could be adapted by other free-floating carsharing companies into similar recommendation systems to improve the companies' operations. It would provide further support for sustainable mobility and have an even greater impact on people's quality of life.

1. Introduction

With increasing attention on the need for a balanced approach to environmental, societal, and economic considerations, sustainability has emerged as the paradigm for responsible decision-making (Hicks et al., 2016; Etzion, 2018; Calabrese et al., 2019; Liang et al., 2019). Through measures aimed at sustainability, governments rethink their developmental paths adapted to ensure a better quality of life for all citizens (Lv et al., 2018). Meanwhile, industries, academic institutions, and public sectors take serious steps to advance this agenda (Canitez, 2019). Individuals with a greater awareness of and appreciation for the sustainability paradigm are more likely to engage in environmentally friendly behaviors, such as resource sharing (Côte-Real and Ruivo, 2019), which reduces the need for individual ownership of limited resources. Sharing solutions are usually viewed as being more in line than non-sharing ones with environmental sustainability (Stoelab, 2012). Four mainstream modes of sharing solutions are commonly available today: peer-to-business (P2B); business-to-peer (B2P) (Schor and Fitzmaurice, 2015); peer-to-peer (P2P) (Schor and Fitzmaurice, 2015); and business-to-business (B2B). The B2P carsharing services (e.g., Car2go, Avis and Hertz) and P2P services (e.g., DiDi, Uber, and Lyft) are the two modes that most emphasize sustainability (Yedla, 2015). Rental car companies are part of the B2P mode, in which

a company rather than a customer user owns the vehicle. Service providers in the P2B mode, on the other hand, are individual car owners, whereas customers are mere passengers.

The B2P carsharing today falls into two categories: station-based and free-floating. Traditional carsharing systems are station-based (e.g., Europcar, Avis, Hertz, and Sixt). In these systems, users are required to initiate and terminate the rental at the same locations (Schaeffers, 2013). These set-ups, which provide users with many of the benefits of using private cars without the usual costs and responsibilities of ownership, are best suited for persons with occasional or low vehicle usage demands (Vine et al., 2014). With the prevalence of mobile applications, new B2P mode carsharing systems (i.e., free-floating carsharing systems) are emerging to satisfy consumer demands (Truffer et al., 2017; Marletto, 2019). The free-floating carsharing (FFCS) systems allow users to pick up and drop off vehicles at any points within city limits. Compared to traditional car rental companies, companies with FFCS offer more flexible services and may attract additional customers since they allow for one-way trips (Ciari et al., 2014). These carsharing systems may reduce the demand for personally owned vehicles and are becoming an integral part of sustainable mobility, an idea whose popularity has grown in the last decades (Agatza et al., 2012; Furuhashi et al., 2013; Li et al., 2014). Based on a survey conducted in 2010, more than a quarter of respondents stated

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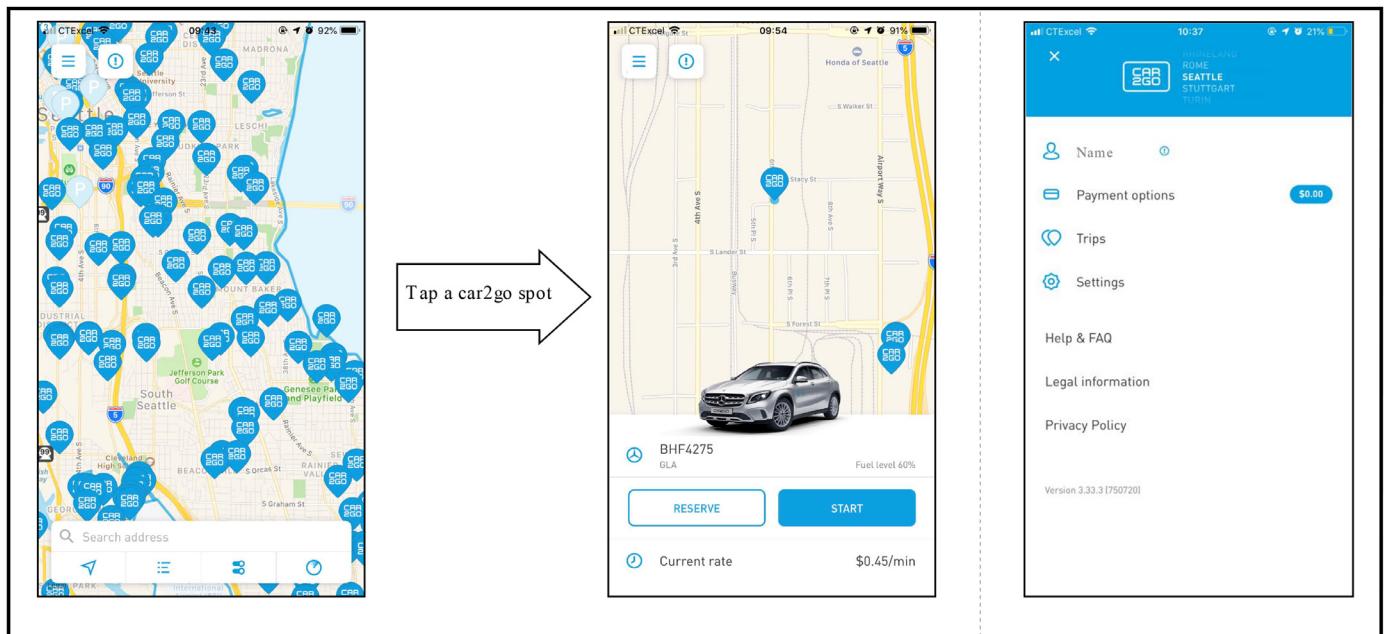


Fig. 1. Example of FFCS smartphone application provided by Car2go.

that they might forgo a car purchase if FFCS systems were permanently available (Firnkorner and Müller, 2015). In sum, these FFCS systems are beneficial for better mobility and environmental sustainability.

Today's FFCS system provides real-time vehicle locations to users through its smartphone application (APP), allowing them to reserve cars for a user prior to the rental (see the Car2go example in Fig. 1). In the APP, customers can view the vehicle information on any parking spot, including the rental fee and fuel level of the car. Based on this information, they can make decisions on reserving a car or not. When users with reservations arrive at the vehicle location, they can enter the PIN into the FFCS APP to initiate the rental. In some cities, when users are finished with the rental, they can simply park the car in any approved public, on-street parking space within the operation area. They can terminate the rental transaction with a single tap on the APP screen. Users can also view their accounts, balances, recent trips and other information through the APP. Some FFCS services are flexible, allowing for one-way trips, commutes, and other kinds of trips since consumers only pay for the time they spent driving the cars. Fuel costs are covered by the companies, which place fuel cards in each car. Customers or employees of companies can use these cards to purchase fuel at a partnering gas station. However, FFCS companies incur higher personnel and transportation costs when relying on employees to refuel the tanks of widely dispersed rental cars. For this reason, most companies offer rewards programs to entice customers to do the refueling. For example, DriveNow in London uses dashboard reminders to alert the user when the fuel level falls on or below 25%. It offers the driver 20 bonus minutes (good for 3 months) to refuel the car using the company fuel card (DriveNow, 2019). Similarly, Car2go in the US offers each driver \$5 (equivalent to 11 bonus minutes at the rate of \$0.45/minute) for refueling (Car2go, 2019). Nonetheless, the rewards are often not enough to incentivize customers to refuel the car, considering the time and effort involved in refueling. Generally speaking, individuals prefer to rent cars with high fuel levels, low rental rates, and convenient spots. For the same class of cars in a given area, rental rates are equivalent, and users can select the most convenient location for the car in their desired class in the APP. Regarding the fuel level, most customers (especially those who are time- or distance-sensitive) avoid renting cars with low fuel levels because of the penny-pinching refueling policies.

To minimize costs and maximize service levels, the timing of refueling is very important in this business. Leaving cars with lower fuel

levels in parking spots discourages customers from renting the cars or may result in the cars being driven shorter distances. This causes the cars to be underutilized, rendering a waste of resource and dampening the profitability of the business. Thus, it is necessary to know at which fuel level the cars should be refueled to maintain the economic sustainability of the company. Once this fuel level is identified, an FFCS company can formulate an appropriate refueling policy offering customers the highest rewards for refueling that are equivalent to the costs of paying employees to do so. A scrutiny of the extant literature reveals that several studies (Barth et al., 2003; Herrmann et al., 2014; Niels and Bogenberger, 2017) have underscored the importance of the appropriate refueling level in the FFCS systems. However, none of them has offered any solution to identify this level. This paper attempts to fill this void by studying relevant data in an FFCS system to design an on-demand refueling recommendation system for sustainable development of the business. Once the company has determined the appropriate level for refueling, it can improve its service performance and profitability. The remainder of this paper is organized as follows. Related literature is reviewed in Section 2. A data-driven method for identifying the appropriate refueling level is illustrated in Section 3. A case of Car2go in Seattle is discussed in Section 4. The conclusion is presented in Section 5. Social implications are provided in Section 6. Limitations and opportunities for future studies are described in Section 7.

2. Literature review

2.1. The threats to environmental sustainability

Human activities have for centuries been harmful to the world, resulting in significant deleterious outcomes such as pollution, climate change, transportation disorder, and resource deficiency. This destructive process has accelerated over the past decades (Etzion, 2018). Most economies now are developing at tremendous speeds and are becoming epicenters of unsustainable global growth (Lv et al., 2018). Ecological irresponsibility, the depletion of natural resources, and the accumulation of waste have resulted in increasing threats to environmental sustainability, attracting increasing concern from all walks of life (Belaud et al., 2014; Etzion, 2018; Lv et al., 2018). In response, researchers have begun to explore how societies can mitigate these threats (Liu et al., 2015; Stern et al., 2016; Hartl et al., 2018;

Danso et al., 2019). Liu et al. (2015) investigated systems integration toward global sustainability and illustrated the development and quantification of some important integration frameworks for human and natural systems that lead to substantial advances of systems integration for sustainability. Stern et al. (2016) analyzed problems of energy sustainability and climate change to identify some key non-technological factors (e.g. risk and policy) linking greenhouse gas emissions and economic activity. They described a multi-dimensional space in which humans interact with climate and energy issues. Hartl et al. (2018) applied quantitative and qualitative methods to explore the role of sustainability in P2P and B2P carsharing from the consumers' perspective. They showed that consumers perceive carsharing as greener than owning a car, while environmental concerns played a role in consumer carsharing decisions. Danso et al. (2019) found that the relationship between stakeholder integration and financial performance was mediated by a firm's environmental sustainability orientation. They demonstrated that the indirect effect of the environmental sustainability orientation was stronger with more intense industry competition. Meanwhile, the business world has also responded to the growing threat of environmental degradation, with innovative business models being developed to address environmental sustainability and ensure the quality of life of future generations. One such business model is carsharing. This study explores ways that carsharing companies can improve their approaches to fuel-level management and thereby, continue to address threats to environmental sustainability.

2.2. FFCS services for environmental sustainability

In an FFCS system, potential customers can use mobile phones to search for available vehicles, which can then be picked up and dropped off at various locations in cities. This system can alleviate some of the pressures of urban living, particularly energy savings and emission reductions (Zhang et al., 2018). Free-floating vehicle fleets reduce the need for individual car ownership as well as lower the total number of vehicles in cities, resulting in a reduction in static land consumption (Firnkor and Müller, 2011). Since the FFCS is advantageous for environmental sustainability, many studies have focused on this topic, especially on the Car2go. Firnkorn and Müller (2011) analyzed the environmental effects of new FFCS systems by using the Car2go in Ulm as a case and determined the carbon emission reduction per average user. Further, in 2015, they reported on the private car reduction potential of Car2go and showed that an electrification scenario in FFCS would increase people's willingness to forgo a private car purchase (Firnkor and Müller, 2015). Kopp et al. (2015) studied the travel behavior of FFCS members and found that they have a higher trip frequency and more intermodal behavior compared to non-car-sharers. Wang et al. (2017) used data from Car2go in Seattle to develop methods for trip identification and to estimate driving, public transit and walking time for trips. Recently, Li et al. (2018) proposed a tolerance-based dynamic user equilibrium model for activity-travel scheduling that incorporated FFCS. The model they developed could capture the dynamic supply-demand interactions of shared cars. Molnar et al. (2019) designed a novel method to allow for long-term FFCS reservations and showed that this method could keep the system profitable with up to 60% reservations. Despite these prior studies are helpful for the development of the FFCS, there is a lack of research on FFCS refueling strategies, which can benefit the sustainability of the environment and the business. As mentioned previously, FFCS companies provide services that promote environmental sustainability through urban energy savings, more effective resource utilization, and reductions in pollution, carbon emissions, and static land consumption. These companies also offer a wide range of benefits for customers. For example, customers have access to reliable vehicles without having to worry about vehicle maintenance, which is overseen by the FFCS companies, most of which implement rigorous and systematic vehicle

maintenance programs using standardized automobile parts to reduce the risk of breakdowns and accidents. Further, customers can pick up vehicles at any points within the geographical limits of service regions, and they do not need to waste time refueling if fuel levels are adequate for their trips. They can choose vehicles that are appropriate for the time and distance of their trips, which may result in time cost savings. In sum, FFCS systems deliver a multitude of benefits and are a worthy subject for further research. Hence, this study intends to develop an on-demand refueling recommendation system to improve FFCS performance for better mobility and environmental sustainability.

2.3. Back propagation neural networks (BPNNs) for FFCS fuel-level management

The timing of refueling is critical to cost and service level optimization in FFCS systems. Once an FFCS company has determined the appropriate refueling level, it can design a refueling recommendation strategy to provide customers with rewards for refueling. Several studies have highlighted the importance of the appropriate fuel level in the FFCS systems. Barth et al. (2003) indicated that the fuel level was an important factor for the system efficiency, and noted that predicting an optimal fuel level for vehicles might prove challenging. Herrmann et al. (2014) confirmed that the fuel level was a key factor in the decision to use a specific FFCS system and that the availability of cars was crucial for customer acceptance. Niels and Bogenberger (2017) assessed the preferences of customers booking cars by analyzing relevant data (including the fuel level) from an FFCS operator in Munich, Germany. They showed that the fuel level would influence the booking preferences. However, these papers have not offered any solution to identify the appropriate fuel level. This study aims to fill this void, using relevant data from an FFCS system to design an on-demand refueling recommendation system for sustainable development of carsharing businesses. If an FFCS company could identify an appropriate fuel level, it could use this information to improve its service performance and profitability.

To identify the appropriate fuel level, data analytics tools could be utilized. One effective tool, artificial neural network, has outperformed other data mining methods, having been widely used since 1943 (McCulloch and Pitts, 1943). Li (1994) elaborated artificial neural networks and their applications in the business field, such as airline security control, investment management, and predictions of thrift failures and stock price index. Namazi et al. (2016) adopted artificial neural networks to identify and rank the relative significance of factors that influenced free cash flows. Sharifi et al. (2019) employed an artificial neural network analysis to identify the advertising effectiveness for renewable energy technologies based on the AIDA (Attention, Interest, Desire, and Action) framework. As one of the most popular types of artificial neural networks, BPNNs have been used to resolve a wide range of practical problems in environmentally sustainable transportation systems. Wu and Liu (2011) proposed a predictive system for the fuel consumption of a new car and applied a BPNN to verify the performance of this system. Du et al. (2017) used a BPNN to establish a fuel consumption forecasting model. They employed this model to explore fuel consumption and congestion patterns based on large samples of historical data from floating vehicles. Further, Wang et al. (2018) employed a BPNN to estimate emissions for buses using different types of fuel under real conditions. These previous works have inspired us to use a BPNN-based method in our approach. In sum, this study contributes to the literature by applying a BPNN-based method to determine optimal fuel levels for carsharing vehicles. The results of the study are intended to help FFCS companies improve their approaches to fuel-level management for environmental sustainability and a better quality of life.

Table 1
Parameters used in this study.

Parameter	Definition
FL_i	Initial fuel level of trip i
ST_i	Start time of trip i
ET_i	End time of trip i
DT_i	Time of duration for trip i
IT_i	Interval time between trip $i-1$ (ET_{i-1}) and trip i (ST_i) using same car
UR_i	Usage rate for trip i
BUR_i	Binary variables of the usage rate for trip i
BFL_i	Binary variables of the fuel level for trip i
TUR	Threshold value of binary variables for the usage rate of trip i
TFL	Threshold value of binary variables for the fuel level of trip i

3. Developing a data-driven BPNN-based method

In this section, a data-driven method to determine the appropriate refueling level in FFCS services is developed, which serves as the basis for an on-demand refueling recommendation system—a kind of smart mobility to promote environmental sustainability. This is the first study to apply the BPNN model to the FFCS setting. More specifically, it proposes an on-demand refueling recommendation system for a car-sharing company with relevant parameters extracted from a real operational database. The BPNN-based method is explained below.

3.1. Parameters

The following mathematical parameters are used in this study (see Table 1).

3.2. Method

3.2.1. Interval time

In FFCS systems, the start time (ST), end time (ET), initial fuel level, and final fuel level are common data that can be collected on every trip. To explore the relationship between the usage rate (UR) and fuel level for determining the appropriate refueling level, the usage rate should be described based on these common data first (Wielinski et al., 2017). The interval time between two trips using the same car in FFCS systems reflects the attractiveness of the car with the fuel level of the first trip (Hui et al., 2017). To analyze the usage rate, the interval time between trip $i-1$ and trip i is calculated as follows:

$$IT_i = ST_i - ET_{i-1} \tag{1}$$

where ST_i is the start time of trip i and ET_{i-1} is the end time of trip $i-1$.

3.2.2. Usage rate

Interval time may be influenced by factors other than the fuel level. Therefore, a function for describing the usage rate should be developed. When considering the usage rate in FFCS systems, the duration time of the trip also plays an important role. The duration time (DT) of trip i can be calculated as follows:

$$DT_i = ET_i - ST_i \tag{2}$$

where ET_i and ST_i are the end and start times of trip i , respectively.

Based on the duration time and the interval time, the usage rate can be expressed as:

$$UR_i = \frac{DT_i}{IT_i + DT_i} \tag{3}$$

where DT_i is the duration time of trip i , and IT_i is the interval time between trip $i-1$ and trip i .

From Eqs. (1) and (2), the usage rate can be calculated by the start time and end time of every trip:

$$UR_i = \frac{DT_i}{IT_i + DT_i} = \frac{ET_i - ST_i}{ET_i - ET_{i-1}} \tag{4}$$

where ST_i is the start time of trip i , respectively, and ET_{i-1} and ET_i are the end time of trip $i-1$ and trip i , respectively.

3.2.3. BPNN

The BPNN, which is a multilayer feed-forward neural network based on error back-propagation learning, is one of the most common neural network models (Fletcher and Goss, 1993; Li, 1994; Law, 2000; Jin et al., 2012). This neural network model includes an input layer, one or more hidden layers, and an output layer. The data is divided into three parts: training set, validation set, and testing set. The adjacent layers demonstrate full connectivity between neurons, and there is no connection between neurons on the same layer. One hidden layer with two hidden neurons is adopted for the BPNN in this study following Jin et al. (2012). There are some classical transformation functions for hidden neurons, such as the sigmoid function. This study employs a sigmoid function expressed as follows (Fletcher and Goss, 1993).

$$\text{sigmoid}(z) = \frac{1}{1 + e^{-z}}$$

In this sigmoid function, z is the sum of all connections between the hidden layer nodes and the respective output node. In addition, some measures are applied to analyze the difference between outputs and targets, such as mean squared errors (MSEs). The MSE function is as follows.

$$MSE = \frac{1}{n} \sum_{i=1}^n (\hat{y}_i - y_i)^2$$

In this MSE function, \hat{y}_i is the computed output and y_i is the target output, $i = 1, \dots, n$; n is the number of the input node. Since a lower MSE means a lower average squared difference between outputs and targets, the fuel level with a lower MSE is a more appropriate level for refueling. An example of the structure of the BPNN is shown in Fig. 2.

To identify the appropriate refueling level, data on vehicle usage and fuel level are converted into binary variables as target and input data. Data on vehicle usage (i.e., the usage rate) are converted into binary variables using Eq. (5):

$$BUR_i = \begin{cases} 1 & \text{if } UR_i \leq TUR, \\ 0 & \text{otherwise,} \end{cases} \tag{5}$$

where TUR is a threshold value determined by decision-makers based on collected data for the output layer.

Data on the fuel level are translated into binary variables based on Eq. (6):

$$BFL_i = \begin{cases} 1 & \text{if } FL_i \leq TFL, \\ 0 & \text{otherwise,} \end{cases} \tag{6}$$

where TFL is a threshold value that can be adjusted to generate different datasets for the input layer.

3.2.4. Framework

The framework of the method for identifying the appropriate refueling level, as shown in Fig. 3, is divided into two parts: data processing, and BPNN. The method starts with extracting the data to be used in the study (i.e., FL_i , ST_i , and ET_i). After that, the data are analyzed to derive several parameters (i.e., DT_i , IT_i , UR_i , and TUR) that are inputted into the BPNN. To study the relationship of the fuel level with usage rate, the binary variables of the fuel level (i.e., BFL_i) are taken as the input data for the BPNN, and the binary variables of the usage rate (i.e., BUR_i) are taken as the target data. Then the usage rate (i.e., UR_i) and the corresponding threshold value (i.e., TUR) should be used to generate these binary variables based on Eq. (5). The binary variables of the fuel level (i.e., BFL_i) are calculated by Eq. (6). To explore the

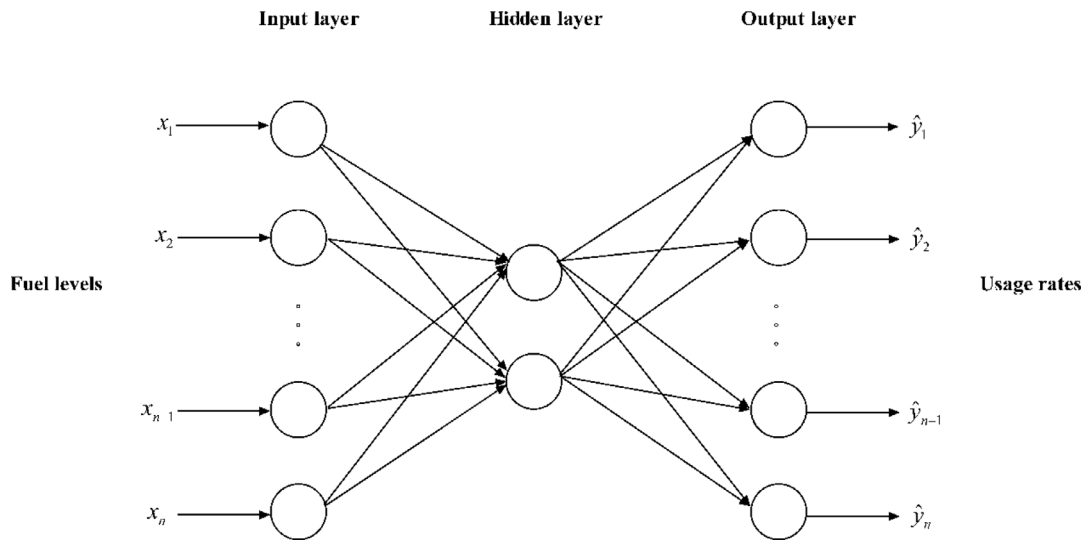


Fig. 2. The BPNN structure.

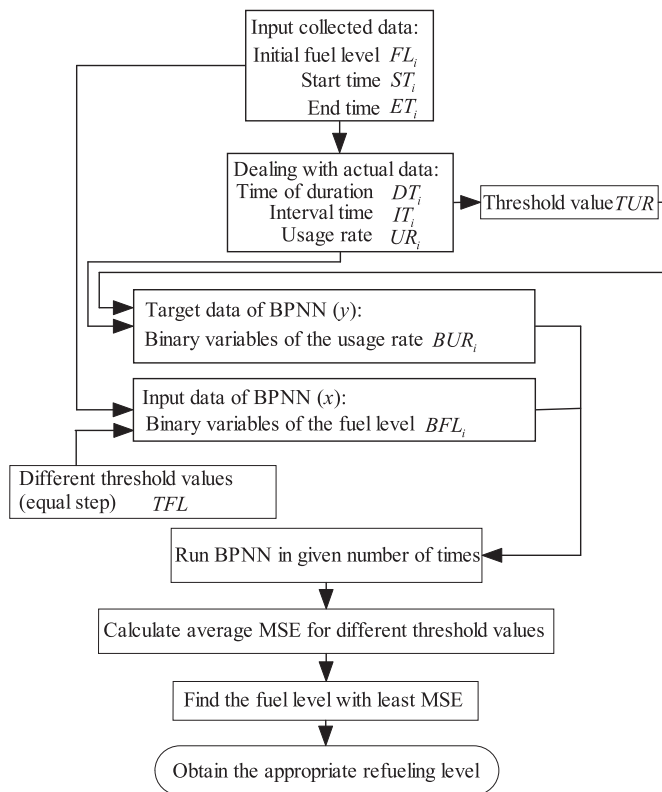


Fig. 3. Framework of the method for determining the appropriate refueling level.

influence of different fuel levels on the usage rate, different threshold values of binary variables for the fuel level (i.e., TFL) are inputted to generate different datasets of the binary variables. Then, the BPNN is conducted to calculate MSEs for different threshold values within several epochs. For each threshold value of binary variables for the fuel level, the BPNN is run a given number of times to reduce errors. After running it a number of times (e.g., 30 times), the average MSE for each threshold value is calculated and the fuel level with the lowest MSE can be found. Finally, the fuel level with the lowest MSE is outputted as the appropriate refueling level.

4. The case of Car2go in Seattle

In this section, the case of Car2go in Seattle is used to demonstrate the method for identifying the appropriate refueling level, which is the key to the design of an on-demand refueling recommendation system for environmental sustainability toward a better quality of life.

4.1. On-demand refueling recommendation system

Based on the aforementioned data-driven BPNN model, an on-demand refueling recommendation system can be developed for the car-sharing smartphone APP to advance better mobility for environmental sustainability. The design of the system is as described below.

Fig. 4 illustrates the flowchart for the on-demand refueling recommendation system for the Car2go smartphone APP. First, data input and transformation are conducted based on related data (i.e., initial fuel level, start time, and end time of each trip) in a preset period (e.g., one month, one week, or even one day). Then the BPNN is applied to determine a suitable refueling level. If the fuel level of a car is not currently more than this level, the system pushes a recommendation notification to customers who are viewing the car's information screen, encouraging them to refuel the car by offering rewards (e.g., free driving time, fuel cards, or other gifts), which are highlighted in the notification. Meanwhile, information about Car2go parking lots is also provided to the customers. If a car remains static during a given period (e.g., three days, one week, etc.) as predetermined by Car2go, the company allows an employee to fill up the fuel tank. As such, the on-demand refueling recommendation system can be applied to automatically push refueling notifications to users in the Car2go smartphone APP.

4.2. Data collection

The FFCS system of Car2go was first deployed in Ulm, Germany in October of 2008 and then in Seattle, USA in December of 2012 (Kortum and Randy, 2012; Shaheen et al., 2018). As of July, 2018, it was the largest FFCS system in the world, with over 3 million registered members and a fleet of nearly 14,400 vehicles in 25 locations in North America, Europe and Asia (LLC, 2018). Car2go is flexible for one-way trips, commutes, and other kinds of trips, since consumers pay out-of-pocket only for the time spent driving the cars; the fueling cost is paid by the company. Similar to other FFCS systems, Car2go places a fuel card in each car and offers free driving time to users as an incentive to fill up the car. Since Car2go is the largest FFCS company, this study

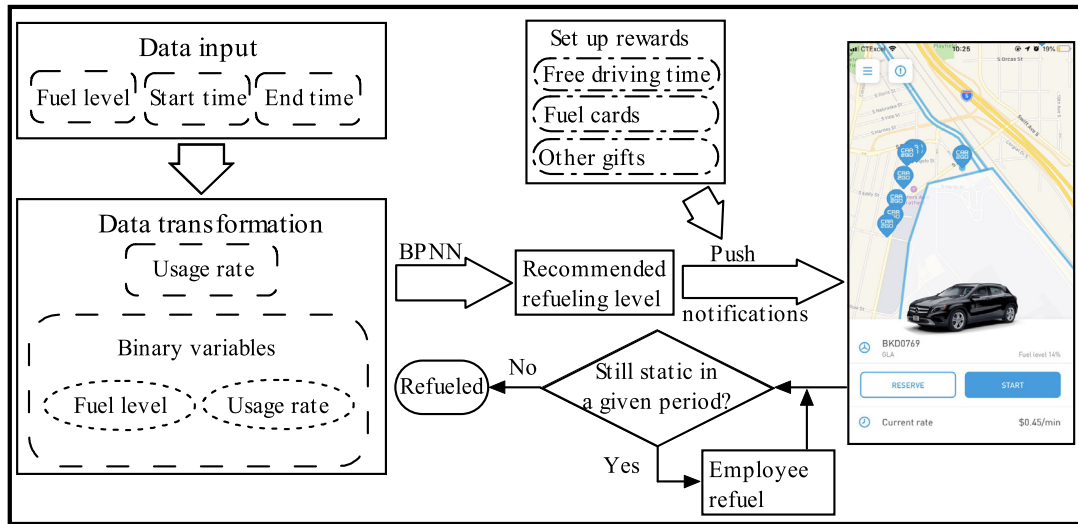


Fig. 4. The on-demand refueling recommendation system for Car2go.

Table 2
Statistics summary for the interval time, duration time and the usage rate.

Factor	Min	Max	Mean	Median	Mode	Lower quartile	Upper quartile
Interval time (min)	1	12013	290.64	90	1	24	331
Duration time (min)	1	29259	63.53	27	20	17	38
Usage rate (%)	0	99.99	33.25	22	3	7	55

retrieves data about Car2go in Seattle from the Digital Roadway Interactive Visualization and Evaluation Network (DRIVE Net), a platform that serves as an ideal tool for visualizing historical observations both spatially and temporally (Xiao et al., 2015). The dataset included the vehicle identification number, start time, end time, start location, end location, travel distance, initial fuel level, and final fuel level of every trip. There were 734 vehicles with 83882 available cases recorded from March 7, to April 6, 2017. From the raw data in the dataset, the initial fuel level, start time and end time of every trip were used. By Eqs. (1)–(4), the usage rate was calculated. As the first trip of one car did not have the last trip in the period, the data volume for the usage rate of one car was one less than that of the raw data. Therefore, the data volume of the usage rate was 83,148 (= 83,882-734). Table 2 illustrates the relevant statistics of the interval time, duration time, and usage rate.

As shown in Table 2, the mean interval time was 290.64 minutes (nearly 5 hours), which is undesirably long from the perspective of an FFCS company. From Fig. 5, the frequency distribution for the interval time was left-skewed and the data were concentrated in the range from 0 to 1000 minutes. The median interval time was 90 minutes (1.5

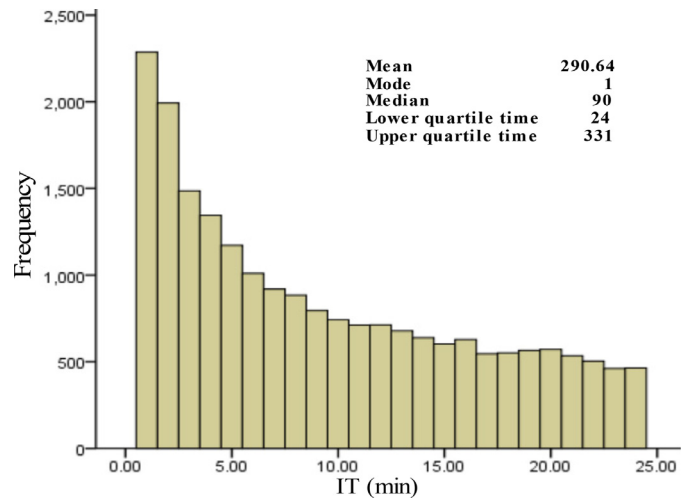


Fig. 6. Chart of the frequency distribution for the interval time of first quartile time.

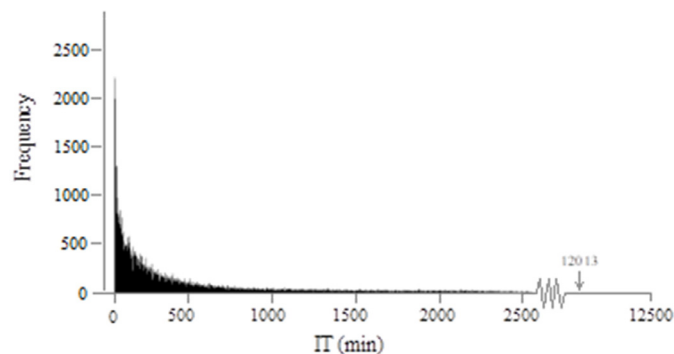


Fig. 5. Chart of the frequency distribution for the interval time.

hours), which was 66 minutes longer than the lower-quartile time (24 minutes). Fig. 6 demonstrates the frequency distribution for the interval time of the first-quartile time. It can be seen that the most frequent interval time (the mode) is 1 minute, and the frequency decreases with increasing interval time.

In contrast, Fig. 7 illustrates that the frequency distribution for the duration time is left-skewed, and these data are concentrated in the range from 0 to 200 minutes. Fig. 8 reveals that the most frequent duration time (the mode) is 20 minutes. The upper quartile was 38 minutes, indicating that over 75% of duration times were less than 40 minutes. The frequency distribution for the usage rate was concentrated in the range between 0 and 25%, as shown in Fig. 9. The median usage rate (22%) was selected herein as the threshold value of binary variables for the usage rate. Therefore, $TUR = 22\%$. The threshold value of

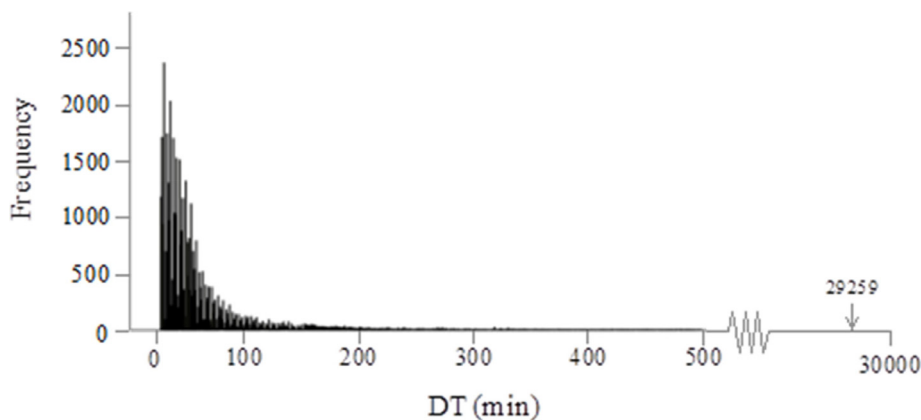


Fig. 7. Chart of the frequency distribution for the duration time.

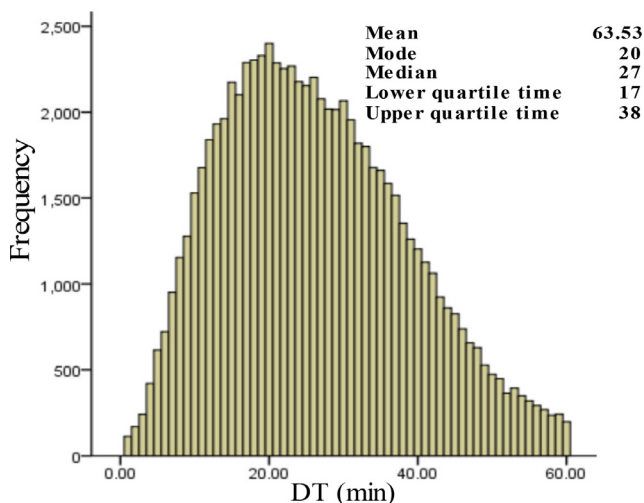


Fig. 8. Chart of the frequency distribution for the duration time within 1 h.

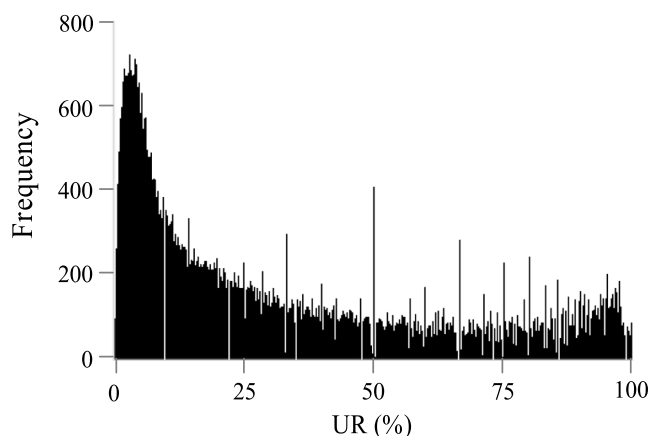


Fig. 9. Chart of the frequency distribution for the usage rate.

binary variables for the fuel level was set at 10~50% (step-size was 5%). After identifying the lowest point of the average MSE, the step-size was set to 1% for a smaller range of fuel levels below and above the lowest point. In actual situations, decision-makers could choose suitable threshold values of binary variables for the usage rate based on collected data and other rules.

4.3. Analysis and results

4.3.1. Multi-method comparative analysis

The first step of our analysis is to ascertain that BPNN is the most suitable method for our recommendation system. We compared it with two other popular data mining techniques (Sampaio et al., 2011; Xue et al., 2016), namely, Convolutional Neural Network (CNN) and Support Vector Machine (SVM), in terms of the level of MSE. Running on Matrix Laboratory (MATLAB), the focus of analysis was to obtain the fuel level with the lowest MSE using the data from Car2go in Seattle. Before executing the BPNN, some preparatory works were performed. The BPNN included an input layer, an output layer, and one hidden layer with two neurons in this case. A sigmoid function was used as the transformation function of each neuron, and the data were divided into three parts: a training set (60%), a validation set (20%), and a testing set (20%). Then the data volumes of the training set, validation set, and testing set were 49,888, 16,630, and 16,630, respectively. Following Setiono and Liu (1997), the BPNN was run 30 times with changing threshold value of binary variables of the fuel level from 10~50% (step-size was 5%) within 3 epochs. The binary variables of the usage rate (i.e., BUR_i) were the target data with the binary variables of the fuel level (i.e., BFL_i) as input data. Subsequently, CNN and SVM were executed on MATLAB and the results are contrasted in Fig. 10 and Table 3. Fig. 10 illustrates the MSE generated by the three methods with a 5% increment. Among these methods, BPNN suggests MSE values that are lower than those from the other two methods. The figure indicates that the lowest MSE falls in the range of 25%~35% of the fuel level. To explore this in detail, a 1% increment of the fuel level is used to generate MSE values between 20%~40% (i.e., 5% above and below the lowest range of 25%~35%) to analyze the boundary conditions. Table 3 shows the results of computations with a 1% increment. It indicates that a fuel level of 28% yields the lowest MAE value, followed by 27%. As customers may not always be able to fill up the gas tank in a timely manner, the range of 27%~28% is buffered by 1% and extended to 26%~29%. The design is appropriate as the MSE values on the two ends of this range are lower than the neighboring fuel levels (i.e., 25% and 30%). Based on the results in Fig. 13, the carsharing company should start posting a fuel-level warning message on the driver's cellphone and vehicle's dashboard to offer an incentive to fill up the gas tank as soon as the fuel level decreases to 29%. This practice should continue until the fuel tank is refilled. However, when the fuel level decreases to 25%, the incentive value should be reduced. Such a two-level incentive mechanism could entice the driver to refill the fuel tank earlier, during the recommended range of fuel levels.

4.3.2. Decision making analysis

To facilitate decision making, a computational experiment was conducted using BPNN with a 5% increment of usage rate ranging from

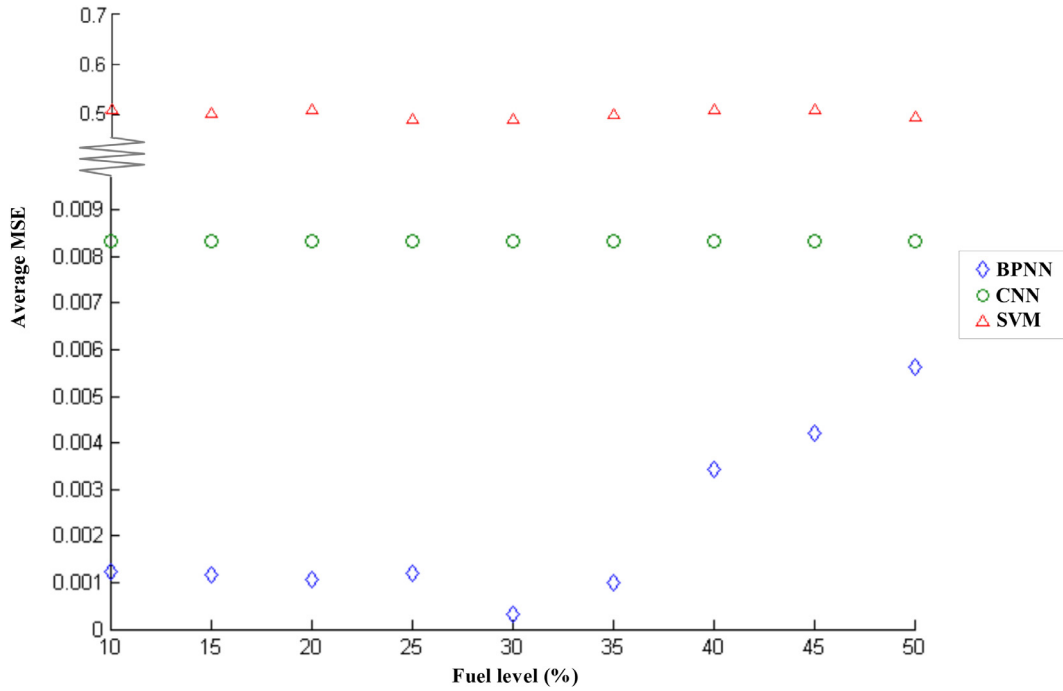


Fig. 10. Method comparison when usage rate is 22% with changing FL (step-size = 5%).

Table 3
Method comparison when usage rate is 22% with changing FL (step-size = 1%).

Fuel level	Mean Squared Error (MSE)		
	Back-Propagation Neural Network (BPNN)	Convolutional Neural Network (CNN)	Support Vector Machine (SVM)
20%	0.0010618704	0.0083309024	0.5085510175
21%	0.0010592800	0.0083311084	0.5019242796
22%	0.0011360122	0.0083292830	0.5004810699
23%	0.0011306284	0.0083285715	0.5001082407
24%	0.0011648523	0.0083296977	0.5001082407
25%	0.0011988324	0.0083272187	0.4914489825
26%	0.0011091445	0.0083267329	0.4914489825
27%	0.0000855102	0.0083272630	0.4914489825
28%	0.0000501360	0.0083217306	0.5085510175
29%	0.0001293268	0.0083269662	0.5000601337
30%	0.0003316062	0.0083302287	0.5000601337
31%	0.0004155312	0.0083310804	0.4992182614
32%	0.0004683465	0.0083324944	0.4992182614
33%	0.0006498601	0.0083308261	0.4914489825
34%	0.0009924001	0.0083309497	0.5011305143
35%	0.0009834595	0.0083312715	0.4990138067
36%	0.0010279884	0.0083352283	0.4990138067
37%	0.0015997630	0.0083330756	0.4914489825
38%	0.0027908403	0.0083339386	0.4914489825
39%	0.0033326590	0.0083339436	0.4970534469
40%	0.0034150768	0.0083339000	0.5085510175

7% to 57% based on the dataset available in this study, as shown in Fig. 11. This range covers the lower quartile (7%) and the upper quartile (55%) of usage rates of the dataset, in addition to the medium one (22%). An FFCS company could use this figure to determine the desired usage rate and fuel level based on the goals and objectives of the company and the total cost of giving rewards (see Eq. (7)). For example, in Fig. 11, when a company adopts a 29% fuel level to start warning the driver, the average usage rate would reach 22%. If the company prefers a 32% usage rate, the fuel level at which to initiate the warning would be 34%. The initial 4 fuel levels of 31% to 34% will receive a higher reward for refueling, while the remaining fuel levels of 1% to 30% will receive a lower reward. The total cost of giving rewards for refueling can be estimated by Eq. (7). Please note that the entries of

the figure must be updated whenever a new rental transaction occurs and the medium usage rate is updated. Please see the Fig. 11 below.

$$RC = \sum_{i=1}^{u-4} R_i Q_i P_i + \sum_{i=u-3}^u R_i Q_i P_i \tag{7}$$

where RC is the reward cost, u is the starting fuel percentage level, R_h is the higher reward amount during the initial 4 fuel levels, R_l is the lower reward amount of the remaining fuel levels, Q_i is the number of times refueling occurs at the $i\%$ fuel level, and P_i is the probability of Q_i .

4.4. Discussion

Currently, Car2go in Seattle allows employees to refuel cars when fuel levels are lower than a threshold value (e.g. 20%) daily. If the on-demand refueling recommendation system is adopted in the Car2go smartphone APP, fuel tanks could be fulfilled in a more timely manner and service efficiency and effectiveness could be enhanced. In this study, we found that for Car2go services, more than 75% of duration times were shorter than 40 min. Considering that the average time needed to travel to a nearby gas station and fill up the gas tank is at least 10 min, most customers with a short duration time demand (less than 40 min) would probably avoid a vehicle with a low fuel level. As such, the on-demand refueling recommendation system is critical for helping companies to maintain acceptable fuel levels in their vehicles and thus, to attract more customers.

Using FFCS services more frequently is in line with environmental sustainability and promotes a higher quality of life for all. Since shared cars would be used more often in FFCS systems, static land consumption would be reduced, as would the need for private car ownership. Fewer privately owned cars would also mean fewer traffic jams. According to Firnkorn and Müller (2011), a carbon emissions reduction could even be calculated for the average Car2go-user, suggesting that FFCS systems can also support pollution-reduction efforts. FFCS services conserve resources and time, as they allow for one-way trips and flexibility of usage (e.g., starting easily and parking at any approved places), unlike traditional car rental companies.

Another interesting feature of the notification systems is the ability for forecasting based on the most recent data. In other words, refueling

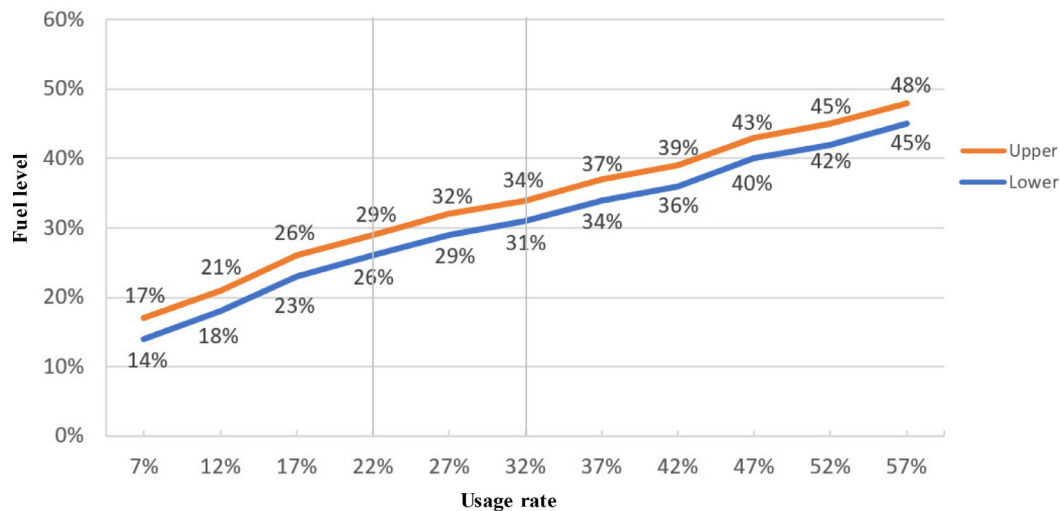


Fig. 11. Appropriate range for fuel levels with changing UR (step-size = 5%) by BPNN.

notifications could be issued based on regularly updated data in the recommendation systems. To update each period's on-demand refueling recommendations, the recommended refueling fuel levels of the previous several periods would first be assessed. Forecasting based on a machine-learning method, such as a recurrent neural network (Pearlmutter, 1989; Campolucci et al., 1999) with long short term memory (Hochreiter and Schmidhuber, 1997), could be applied to predict the next period's recommended refueling fuel level.

5. Conclusion

This study proposed an on-demand refueling recommendation system for FFCS services; these services play a key role in environmentally sustainable transportation systems. The proposed system employs a data-driven method for identifying the refueling level at which an FFCS company should push notifications to users to encourage them to refuel shared cars. The method was based on an analysis of usage rates and fuel levels in a preset period. A BPNN was used to classify usage rate values based on fuel levels, and MSE was used to determine the appropriate refueling level. The refueling level was that with the lowest MSE. Next, Car2go in Seattle was explored as a case. The appropriate refueling level was identified based on results calculated via the data-driven method, and the identified fuel level was used as the threshold at which notifications with reward offers should be sent to users to incentivize them to refuel. The on-demand refueling recommendation system could help Car2go improve its business performance, which would support environmental sustainability in a variety of ways, inspiring other companies with FFCS systems to deploy similar recommendation systems for sustainable mobility and a better quality of life.

6. Social implications

The on-demand refueling recommendation system supports environmental sustainability on numerous levels. First, FFCS efficiency improvements could further mitigate urban pressures through energy savings, pollution reduction, and carbon emissions mitigation. The efficiency improvements could also help companies minimize profit losses and resource wastage. Moreover, improvements in the usage rates of vehicles would reduce static land consumption. The recommendation system might also reduce the risk of accidents, as vehicle maintenance would occur more frequently with higher usage rates. FFCS services could undergo rapid expansion, resulting in additional carsharing vehicles being made available and thus, fewer privately owned vehicles on the road, reducing customers' time costs and

further enhancing their mobility. In other words, people's quality of life could improve considerably.

7. Limitations and future research

Although the proposed on-demand refueling recommendation system has the potential to provide numerous benefits to companies and individual users and to society as a whole, the study still has some limitations. For example, it is not fully understood how companies structure their rewards programs to maximize the effectiveness of on-demand refueling recommendation systems. Furthermore, information on the current demand for Car2go services could also improve the recommendation system. Unfortunately, however, due to inadequate communication with the Car2go company, some details relevant to the on-demand recommendation system were unavailable. Moreover, many other factors have not been considered due to data limitations: the rate of rentals, car models, ages of the car, locations of vehicles, type of the day, the day of the week of the rental, the location of gas stations, the speed of the vehicle, and others. Another related piece of information concerns current operation strategies, including those pertaining to vehicle relocation and rental pricing. If information on rewards standards, relocation, and pricing strategies could be integrated into the current on-demand refueling recommendation system, the performance of the system could be improved.

Future research could expand upon the on-demand refueling recommendation system by employing effective machine learning methods. A data-driven method based on additional related factors could also be explored. By combining improved refueling strategies (e.g., rewards standards) and other management methods (e.g., relocation and pricing strategies), a more comprehensive on-demand refueling recommendation system could be developed for FFCS.

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Supplementary materials

Supplementary material associated with this article can be found, in

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