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# Optimal allocation for electric vehicle charging stations using Trip Success Ratio

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ABSTRACT

This paper proposes a new model for optimally allocating Plug–in Electric Vehicle (PEV) Charging Stations (CSs) in the network. The model considers Trip Success Ratio (TSR) in order to enhance CS accessibility for PEV drivers. Diversity of usage and different driving habits are considered in the presented model, as well as different trip types (In-city, Highway). The allocation model has two stages: modeling TSR to estimate Charging Station Service Range (CSSR), and the CS allocation stage. In the first stage, the service range of charging stations has been estimated using TSR with consideration of the uncertainty of trip distances (In-city, Highway) and the uncertainty in the Remaining Electric Range (RER) of PEVs. The estimated CSSR is utilized in the CS allocation stage in order to optimize the CS location set that covers the network with a certain guaranteed TSR level. The allocation problem has been formulated as the Maximum Covering Location Problem (MCLP) in order to make the optimal decision for allocating CSs in the network.



## 1. Introduction

Increasing oil prices and energy demand are significant challenges facing transportation sectors, as reliance on oil as the main source of energy has some negative influences that can affect those sectors. Environmentally, the transportation sector overall produces a large percentage of emitted carbon dioxide, causing greenhouse gas (GHG) emissions to greatly increase. According to the U.S. Greenhouse Gas Inventory Report 2011 [1], 30% of carbon dioxide emissions in the US come from the transportation sector. In Canada, 35% of energy demand is represented by the transportation sector, and it is the second-highest source of GHG emissions [2]. Therefore, meeting future transportation energy demands by finding alternative energy sources has gained much attention.

The availability of charging infrastructure is a crucial factor in increasing the adoption of PEVs. It is normally expected that PEVs will be recharged nightly at home [3], but the limited Electric Range (ER) of PEVs makes public charging a requirement for long-distance trips. Therefore, providing a public charging service as a complement to home charging will be an essential need. Electrical CSs will eventually be dispersed in the network, but inefficient planning for implementing charging infrastructure will hold back PEV adoption. Hence, the siting of the charging stations should be properly planned.

The planning approach for implementing charging infrastructure should be done with a view to meet users' and suppliers' needs. PEV users require access to CSs whenever they need them, accompanied with a high quality of service. Therefore, a lack of charging facilities due to siting them inappropriately or not at all will have a negative impact on drivers' convenience. The planning model should also enhance PEV drivers' accessibility to charging points by optimally choosing those points from the candidate sites in the network.

This work proposes an optimization model for allocating plug-in electric vehicle charging stations from a new perspective, which is PEV drivers' convenience. The main purpose of the study is to optimally choose from the available candidate sites the charging station set that best enhances the ratio of trips completed successfully, based on the Trip Success Ratio (TSR) level of all PEV trips. A PEV trip can be completed successfully if the electrical energy remaining in the PEV's battery is sufficient to allow the PEV to reach the destination; otherwise, the PEV battery has to be recharged on route in order to complete the trip successfully. As a result, optimally selected CS locations can guarantee a certain TSR level for PEV drivers' convenience.

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The proposed work consists of two stages: the first stage is modeling PEV trip behaviors, followed by modeling the electrical energy available in PEVs' batteries at the beginning of trips. Hence, Charging Station Service Range (CSSR), which is the area that can be covered by the charging station, will be estimated for each TSR level. The estimation process can be achieved by considering the randomness of PEV trip behaviors and the randomness of the electrical energy available in PEVs' batteries. The second stage is to choose the best CS set using the estimated CSSRs of the TSR levels from the first stage. The allocation optimization problem will be formulated as the Maximum Coverage Location Problem (MCLP), and the cutoff impedance of the MCLP will be the estimated CSSRs [4]. The presented model for allocating CSs will be in generic form, so it should be applicable for different transportation networks (In-city and Highway), and different case studies will be presented for different network layouts (In-city and Highway).

The remainder of this paper is categorized into six sections. In Section 2, the related work that has been done on this topic will be investigated. Both the electrical and transportation literature on charging stations topic will be covered in this section. Modelling PEV trip behaviors and modeling the Remaining Electric Range (RER) of PEV battery will be presented in Section 3. In Section 4, the relationship between different CSSRs with different TSR levels is investigated with several battery capacities and types, as well as covering variety of battery combinations to describe these relationships. In Section 5, the CS allocation problem will be formulated as the MCLP, and the CSSRs will be utilized as cutoff impedances for the presented allocation model. The tradeoff between the available budget for implementing CSs in the network and different TSR levels will also be investigated in this section in order to obtain an optimal decision for CS locations. Different case studies on both In-city and Highway networks are covered in Section 6 to show that the presented model is in generic form and that it is applicable for different layouts. Finally, the major contributions of the present work will be discussed in Section 7.

## 2. Related work

In recent years, both in academia and industry, more attention has been paid to the optimal allocation of PEV charging stations. The placement of refueling and recharging stations has also been investigated recently in both electrical and transportation publications. Most of the existing research on the placement of electric charging stations has not considered the driver convenience issue as a perspective of locating the charging facilities. The diversity of the amount of energy available in PEV batteries during trips, also called the Remaining Electric Range (RER), is an essential parameter for users to switch to this new technology. The uncertainty of PEV RERs, which results from different PEV battery capacities as well as the diversity in State of Charge (SOC) levels at the beginning of each trip, has not been well addressed in previous research. Moreover, the diversity of travelers' habits, behaviors, and trip distances are not demonstrated well in the previous research, as well as the ability of charging station infrastructure to adequately meet PEV charging accessibility demand.

### 2.1. Previous work in the electrical field

Electrifying the transportation sector is projected to enhance energy efficiency. The key concern is with regard to the sufficiency and viability of the power infrastructure with large-scale PEV integration [5]. The diversity of travelers' habits, behaviors, trip distances, and the ability of charging station networks to cover the demand sufficiently are not well demonstrated in the previous electrical research on siting charging stations. A small number of studies have considered aspects related to the site selection of charging stations and the overall planning of a city's CS network [6–14].

The diversity of travel patterns and traffic flow aspects are not considered in [6–12], which may lead to locating charging stations at sites favorable for electrical utilities but not easy for drivers to access due to not including traffic flow aspects. In [13], the traffic flow and charging requirements are included as constraints in the model, but the diversity of trip mileages and the variety of PEV electric ranges are not considered. In [14], the planning strategy model maximizes the traffic flow to charging facilities and minimizes the investment and operation cost of the distribution system; however, the estimation of PEV demand is not considered in the model. Therefore, the proposed model will choose the minimum number of CSs in areas that have high levels of traffic flow; however, that number of CSs may not be adequate for the PEV demand, which leads to traffic network problems.

A study in [15] was done to look into the charging station placement from a new perspective of CS accessibility; however, the authors assumed that charging station service ranges are equal to the average of the electric ranges available in the market. This assumption is questionable due to the high diversity in the electric ranges of PEVs (80–300 km) which is not addressed in the model. In the model, if most PEV ranges are not concentrated in relation to the average battery capacity, the variations in ranges will have a real impact on the ratio of incomplete PEV trips.

### 2.2. Previous work in the transportation field

In recent transportation research on siting refueling stations [16–19], Flow–Refueling Location Models (FRLMs) have been developed to site Alternative Fuel Vehicle (AFV) stations for vehicles that need refueling during trips. FRLMs are an extended form of Flow–Capturing Location Models (FCLMs), which have been used for siting convenience stores [20]. FRLM formulation is obtained by adding vehicle travel range as a constraint. All trips from the same Origin–Destination (OD) pair have been assigned to one path in [16] or several detours in [17], but ignoring travelers' habits and behaviors will lead to inappropriate locations for CSs, especially In-city. Because the suitability of their model depends on the availability of trip destination data, the lack of PEV trip data will make their model inapplicable for locating PEV CSs In-city.

The diversity of vehicle ranges has not been considered in previous models [16–19]. In addition, in these models, they considered fixed battery capacities and did not consider different SOC levels during trips. The detours and alternative paths are assumed based only on a single scenario; however, considering different vehicle ranges – using different SOC levels and battery capacities – will accordingly change those detours and alternative paths. As a result, the number of PEV CSs planned in the system will be inadequate in an In-city network due to discounting the diversity of PEV RERs.

From the above discussion, it is observable that previous work on locating charging stations has some limitations, and that it has overlooked significant aspects that can affect the accuracy of the results. According to the authors' best knowledge, most of the previous electrical and transportation research has not considered various items, and these limitations can be summarized in the following:

1. The diversity in drivers' habits and behaviors has not been adequately addressed. Drivers can make a variety of daily trips according to drivers' habits and behaviors. Hence, the remaining energy of drivers' vehicles during the course of a day is influenced by the drivers' routines.
2. The randomness of PEV RERs has not been properly addressed. The variety of battery types and capacities can influence the electric range of PEVs. In addition, the energy efficiency of different PEV driving modes (In-city and Highway) can influence the electric range as well, so including these variations will lead to outcomes that are more realistic.
3. The diversity in trip purposes and mileages has not been effectively considered. Rather than taking the average distance of the daily mileage of drivers, trips in a day can have different mileages: short trips (within city), long trips (highway trips), or a combination of both. Hence, considering trip mileages should be done from an event base rather than a lumped sum of all daily trips.
4. Quantifying the quality of charging station infrastructure service has not been addressed. There is no measure in the previous work showing that the planned charging infrastructure can meet PEV drivers' needs. Contrariwise, most of the previous work has focused on the impact of these charging stations on the power grid. Hence, most of the proposed plans lack consideration of drivers' convenience.

The work presented here was thus undertaken with the goal of filling these gaps through the proposal of an allocation model for CSs based on TSR as a means of planning the site selection of PEV charging stations to provide the ability to serve PEV drivers conveniently. The results of this work are believed to provide an alternative plan to deploy and evaluate charging infrastructure with the consideration of drivers' desires. The main contributions of this paper can be summarized as follows:

- *The proposal of an allocation-planning model to select the best set of charging stations in order to meet the drivers' needs:* The presented model for allocating CSs will be in generic form, so it should be applicable for different transportation networks (In-city and Highway).
- *The development of the Trip Success Ratio Model based on MCS:* The presented model will be a useful tool not only for planning purposes, but also to evaluate existing charging station networks from a driver convenience perspective.
- *Modeling the diversity of trip mileages and the randomness of remaining electric ranges:* Travel survey data is used to mitigate the absence of actual PEV driving information that will not be available prior to significant PEV penetration levels. The addition of data that indicate trip purposes and user habits will enhance the model, allowing it to be more realistic.

## 3. Trip Success Ratio Model

This section presents the Trip Success Ratio (TSR) model. This proposed model evaluates the charging station network based on two components: the service range of charging stations and the trips completed successfully by PEVs. Instead of modeling the transportation network as OD pairs that have different detours and alternative paths, the transportation network is divided into smaller parts, and each of these parts should be covered by at least one CS. Hence, the CS locating problem will be modeled as a coverage problem rather than a flow-capturing problem. The division process is based on the Charging Station Service Range (CSSR), and the distance between CSs will be a major factor that influences the percentage of PEV trips completed successfully. When the CSSR is small, it means that more CSs will be installed in the transportation network; therefore, the ability of PEVs with a smaller battery capacity to complete their trips will be increased. However, the distance between CSs should be far enough to not waste resources. The TSR model investigates the relationship between different CSSRs and different TSR levels.

Not only does the distance between CSs influence the TSR of PEV trips, there are also two other factors: the PEV daily trip distances and the amount of energy remaining in the PEV's battery at the start of each trip. Hence, the TSR model has two submodels to demonstrate the uncertainty of PEV travel patterns and PEVs remaining electrical energy. As a result, the TSR model evaluates and estimates the adequate CSSRs, and is utilized in Section 6 to locate CSs in the network.

### 3.1. Travel pattern model

The travel pattern model will utilize the travel survey data for general transportation in order to generate Virtual Travel Distance (VTD) trips using a Monte Carlo Simulation (MCS). The travel survey data for general transportation include trips by different means (regular cars, trucks, etc.), while the model presented in this paper considers only trips conducted by privately owned vehicles. The National Household Survey Data (NHTS) is considered the most comprehensive transportation data for North America [21], which includes a large number of vehicle trips (about 140,000 trips) [21]. Although these data conducted in 2009, but still the most recent available comprehensive transportation data in North America; however, a new version of NHTS data was conducted in March 2016, and it will be available at the end of 2016 according to [22]. In order to obtain the virtual trip distance, the model classifies the actual trips data [23] into two classes: short trips (less than 20 mile) and long trips (more than 20 mile) to represent in-city and inter-city trips, and each class of trips is categorized to different time – intervals based on trips' starting times. Figs. 1a and 1b show the pdf of trip mileage and the percentage of in – city (short) and inter – city (long) trips, and Fig. 1c shows the pdf of trips based on the starting time of trips.

The actual data for each class [23] have been fitted to the closest Probability Distribution Function (pdf) by using the Maximum Likelihood method to estimate the pdf parameters. Then, the highest-likelihood pdf and its parameters are chosen to represent each class [24]. Finally, using Eqs. (1)–(3), the cumulative distribution function is calculated to obtain the VTD trips for each class.

$$f_1(td) = \frac{1}{td\sigma\sqrt{2\pi}} e^{-\frac{(\ln(td)-\mu)^2}{2\sigma^2}} \quad (1)$$

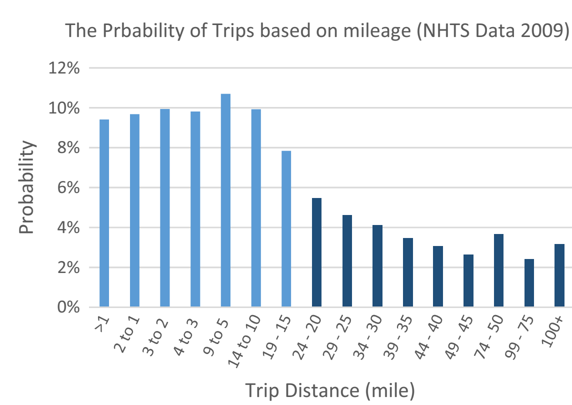


**Fig. 1a.** The probability distribution function of trip mileage (NHTS 2009) [23].

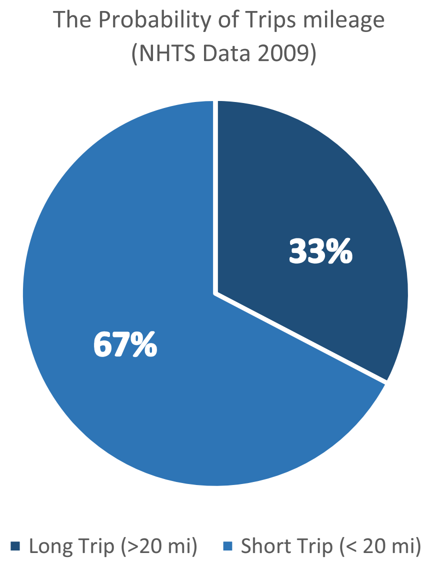


**Fig. 1b.** the probability of long trips and short trips (NHTS 2009) [23].

$$F_1(x|\mu_1,\sigma_1) = \frac{1}{\sigma_1\sqrt{2\pi}}\int_0^x \frac{e^{-\frac{(\ln(td)-\mu_1)^2}{2\sigma_1^2}}}{td}dtd \tag{2}$$

$$VTD_{(c)} = F_{1_{(c)}}^{-1}(z) \tag{3}$$

where

| | |
|---|---|
| $f_1$ | is the probability distribution function of the actual trip data |
| $F_1$ | is the cumulative distribution function of the actual trip data |
| $\mu_1,\sigma_1$ | are the estimated mean and standard deviation of the PDF of the actual trip data |
| $VTD_{(c)}$ | is the virtual travel distance in km of a trip in Class "c" |
| $F_{(c)}^{-1}$ | is the inverse of the cumulative density function, which describes the probability of a trip in Class "c" to be less than a certain distance |
| $z$ | is a normally distributed random variable between zero and one |
| $td$ | is trip distance in km |

National Household Travel Survey data contains different trips' purposes: Earn a living, School, church, Family, Personal Business, Social, Recreational and other. Hence, including these purposes when virtual trips are produced should represent the traveler's habits. Different trip purposes shares are presented in Fig. 2a. In addition, each trip purpose has modeled similarly by two pdfs (mileage and starting time). For example, the two pdfs of Earn a living purpose are shown in Figs. 2b and 2c. Similarly, the other trip purposes are modeled and all of them are utilized when virtual trips are generated to estimate the SOC means and standard deviations; as will be explained in Remaining Electric Range (RER) model.

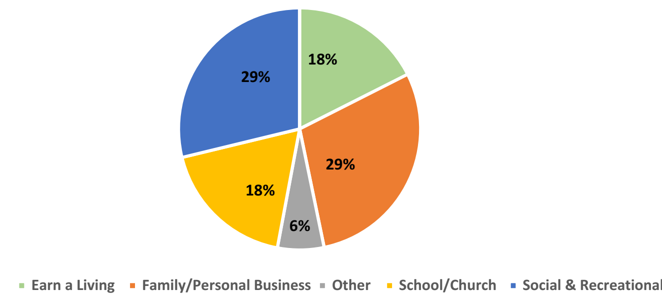


**Fig. 2a.** The probability of trips based on trip purpose (NHTS 2009) [23].

The outcomes of the travel pattern model are the virtual trip distances conducted by PEVs. Using the travel survey data for private gas-powered vehicles to mimic the mechanical energy required will lead to a more accurate estimation than monitoring PEVs due to the high maturity level of the gas station network compared to the CS network [12,18]. Fig. 2d shows how the PEV residential and FCS loads extract from the transportation data using Monte Carlo Simulation (MCS).

### 3.2. Remaining electric range model

Three components influence the Remaining Electric Range (RER) of PEVs: Battery Capacity (BC), State of Charge (SOC), and average Tractive Effort Factor (TEF). The RER is estimated with consideration of the diversity of BCs in the PEV market sales, different SOC levels at the beginning of each trip, and different TEFs (kW h/km). The latter factor is mainly based on the driving modes (In-city or Highway), so city driving requires higher energy consumption per kilometer (kW h/km). The RER model can be demonstrated using Eqs. (4)–(8).

$$RER_{(c)} = \frac{BC \times SOC_{(c)}}{TEF_{(c)}} \tag{4}$$

where

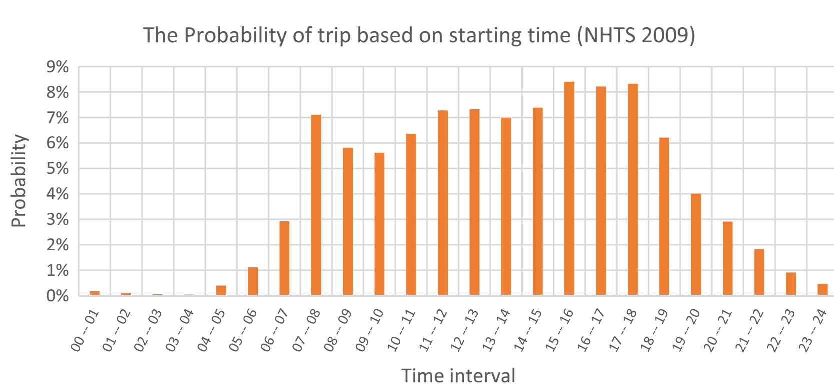


**Fig. 1c.** The probability of trips based on starting time (NHTS 2009) [23].

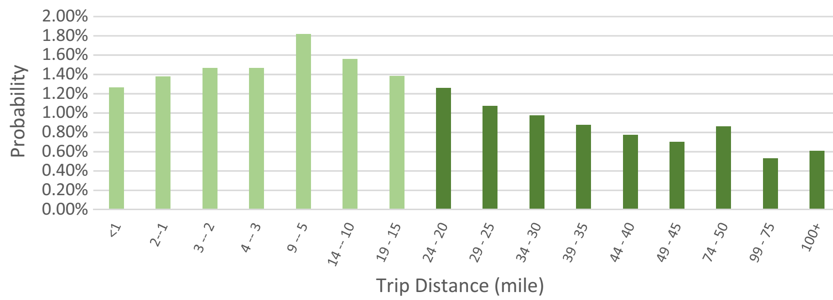


**Fig. 2b.** The probability of Earn a Living trips based on trip mileage (NHTS 2009) [23].

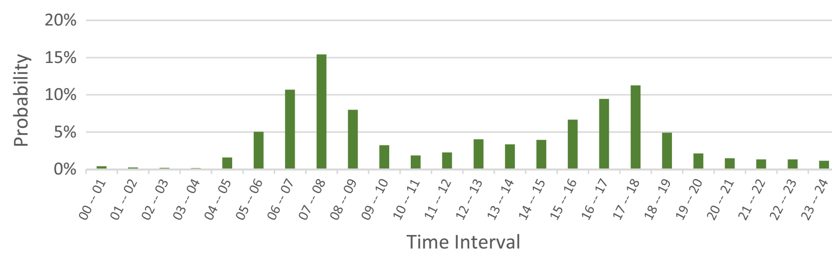


**Fig. 2c.** The probability of Earn a Living trips based on trip starting time (NHTS 2009) [23].

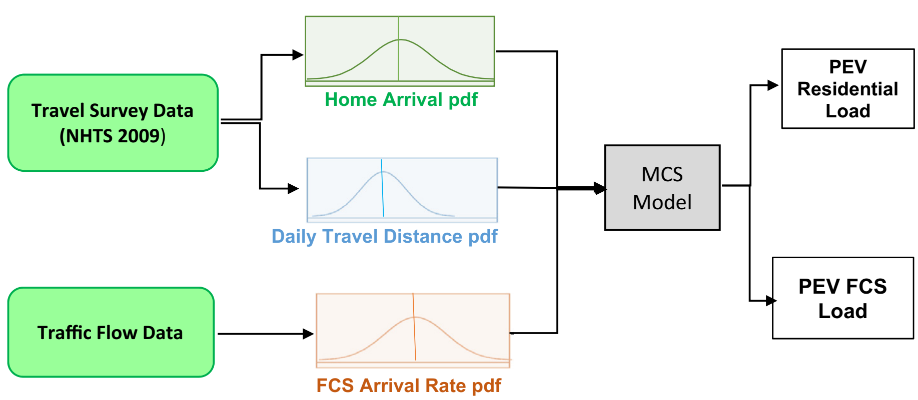


**Fig. 2d.** Stochastic model for estimating PEV residential and FCS loads.

| | |
|---|---|
| $RER_{(c)}$ | is the remaining electric range in km for a trip in Class "c" |
| $BC$ | is the battery capacity of a PEV in kWh |
| $SOC_{(c)}$ | is the state of charge of a PEV battery in (%) at the beginning of a trip in Class "c" |
| $TEF_{(c)}$ | is the average tractive effort factor of a PEV conducting a trip in Class "c" (kWh/km) |

The diversity of PEV battery capacities in the market can be considered by using previous market sales of PEVs and their battery capacities. As a result, the Battery Capacity (BC) in the model will represent the share of each battery capacity according to sales of PEVs. The Empirical Distribution Function (EDF) is utilized to consider the randomness of the battery capacities based on market sales, as shown in Eq. (5). In order to address the randomness of battery capacities in the market, the cumulative distribution function (CDF) of the Empirical Distribution Function (EDF) is utilized as a step function with a specific probability of each step (based on historical market sales of PEVs in North America [25]).

$$F_n(bt) = \begin{cases} 0, & for\ bt < BC_1 \\ n_k/n, & for\ BC_k \leqslant bt < BC_{k+1}, \quad k = 1, 2, \ldots, n-1 \\ 1, & for\ bt \geqslant BC_n \end{cases} \tag{5}$$

where

| | |
|---|---|
| $F_n$ | is the CDF (step function) of the Empirical Distribution Function |
| $n, k$ | are the number of samples and number of battery types, respectively, considered from the market sales data |
| $BC_k$ | is the battery capacities in kWh of PEVs available in the market [25] |
| $bt$ | is the observed random sample of battery capacities in the market |

The SOC of a PEV's battery can take any value in the range of 30–100% at the beginning of In-city trips [19], yet it is most likely that

PEVs will not have a low level (30–50%) of SOC at the beginning of highway trips due to the drivers' anxiety of energy shortage especially at the early adoption time. Furthermore, it is most likely that highway-driven PEVs will not have a very high level of SOC (90–100%) due to the consumption of energy to reach the highway. Therefore, the SOC for highway trips is concentrated mostly in the range of 50–90%.

Considering these assumptions, the SOC can be represented differently for the two trip classes. The diversity of SOC levels can be modeled efficiently if there are data available for the class of the trip and the SOC levels at the beginning of each trip. However, this information will not be available prior to a significant PEV penetration level, and hence the lack of available data about SOC levels at the beginning of each trip leads to utilizing MCS in order to generate random readings for SOC levels (up to 1 million readings to cover the randomness of SOC levels) for both trip classes.

The SOC level at the beginning of any trip has a significant influence on the range that the vehicle can travel to, so modeling the randomness of SOC efficiently will lead to outcomes that are more realistic. The work presented in this paper proposes a method to enhance the estimation of SOC levels at the beginning of trips by creating virtual daily trips (daily routines) that mimic the sequence of trips that conventional cars made daily, which are recorded in NHTS data [23]. We begin with a random number of daily trips by utilizing the probability distribution function of trip number is shown in Fig. 4. Then, a random purpose of the first trip is generated, and based on the randomly generated trip purpose, we generate the starting time of the first trip using conditional probability method. After that, we generate the travel distance for the first trip similarly using conditional probability method. Then, we move to the next trip that will start from the destination of the first step and so on till the end of last trip.

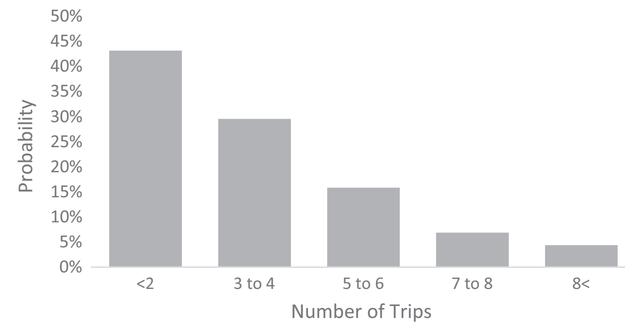


**Fig. 4.** Probability of daily trips per vehicle [23].

The estimation method of SOC levels is illustrated in Fig. 3, and it has the following assumptions and procedures.

**Assumptions**

- The first trip of the daily routine start from home.
- The SOC level (SOCprev) at the beginning of the day (before the first trip) is 100%.
- The battery will be recharged automatically up to 80% when it is empty during the daily routine using public charging facility.

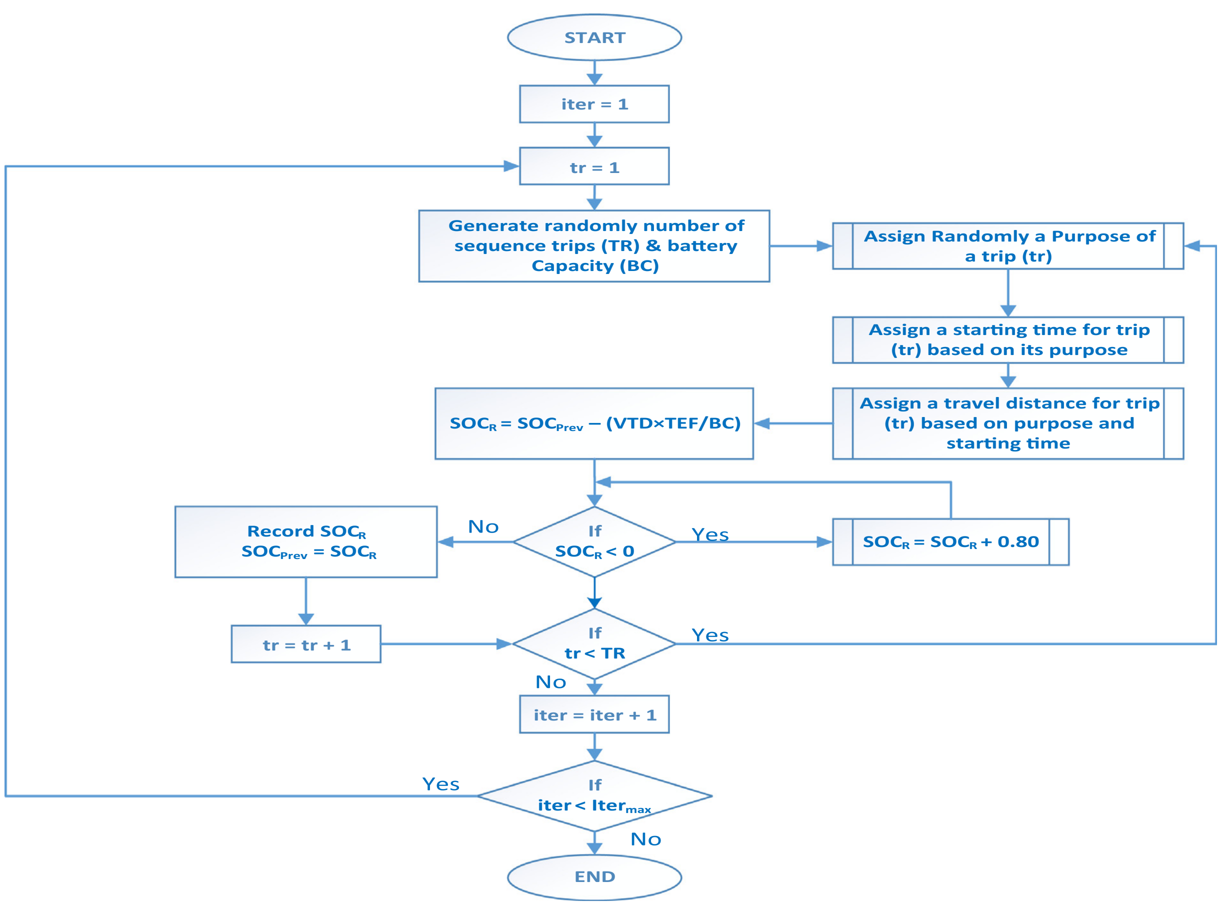


**Fig. 3.** SOC estimation method flow chart.

**Procedures**

| STEP | Procedure |
|---|---|
| 1 | Generate randomly number of sequence trips (TR) during a day (using the pdf in Fig. 4) |
| 2 | Assign randomly a purpose for trip (tr) based on the hourly probability of each purpose pdf |
| 3 | Assign a starting time for trip (tr) based on trip purpose in Step 2 using the pdf in Fig. 1C |
| 4 | Assign a travel distance for trip (tr) based on trip starting time using trip mileage pdf for the assign starting time |
| 5 | Calculate $SOC_R$ after trip (tr) using Eq. (6) |
| 6 | Record $SOC_R$ as a new data point (in %), then $SOCprev = SOC_R$ |
| 7 | tr = tr + 1 |
| 8 | if tr < TR, go to STEP 2 |
| 9 | i = i + 1 |
| 10 | if i < I_max, go to STEP 1 |
| 11 | End |

Finally, using MCS to run the previous routine for both classes (in – city, Highway) and recording SOCR readings for each case. MCS runs over 1 million iterations in order to cover long range of varieties at each class.

$$SOC_R = SOC_{prev} - \frac{VTD \times TEF}{BC} \tag{6}$$

$$f_2(soc_R, \mu_2, \sigma_2) = \frac{1}{\sqrt{2\pi\sigma_2^2}} e^{-\frac{(soc_R-\mu_2)^2}{2\sigma_2^2}} \tag{7}$$

$$SOC_{(c)} = F_2^{-1}(z) \tag{8}$$

where

| | |
|---|---|
| $SOC_R$ | is the PEV battery state of charge at the beginning of trip readings in (%) |
| $SOC_{prev}$ | is the initial state of charge used to generate the SOC level in (%) |
| $SOC_{(c)}$ | is the distributed random variable representing state of charge in (%) for Class “c” |
| $F_2^{-1}$ | is the inverse of the cumulative density function, which describes the probability of SOC at the beginning of a trip in Class “c” to be less than a given level |
| $\mu_2, \sigma_2$ | are the estimated mean and standard deviation of the PDF of the state of charge |

The outcome of the Trip Success Ratio (TSR) model is the estimated RER at the beginning of each trip, considering the diversity of BC, the randomness of SOC levels, and different driving behaviors (TEF).

## 4. Trip Success Ratio Model results

Sample results for the TSR model, which is described in the previous section, are presented in this section. As shown in Fig. 5, the virtual PEV travel distances from the travel pattern model is compared to the electric energy remaining estimated by the RER model. If a PEV's RER is large enough to cover the PEV's VTD, it is considered as being completed successfully. If not, the PEV's RER is compared to the distance to the nearest charging station, and the trip is considered as being completed successfully if the PEV's RER can cover the distance to the CS; otherwise, the trip is considered as a failed trip. MCS is utilized to obtain the TSR for different CSSRs. The CSSR increases in predefined steps (i.e., 10 km), and the outcomes of the MCS show the relationship between the TSR and different CSSRs.

The travel distances of PEVs that utilized in the Trip Success Ratio (TSR) model are obtained from the conditional probabilities in the procedure (Step 2–4) using MCS. Since there are two types of trip distance (City – Highway), there are two pdfs are used: Virtual Trip Distance in-city ($VTD_{city}$) and Virtual Trip Distance highway ($VTD_{HW}$). Table 1 shows the parameters of the best-fit PDFs obtained from the travel pattern model for both $VTD_{(city)}$ and $VTD_{(HW)}$. Table 1 also shows the State Of Charge (SOC) PDFs and their parameters in both in city and highway cases. Eqs. (6)–(8) as well as Step 5–6 are utilized to generate these data points, and the Maximum likelihood Method is used to obtained the best fitted pdfs as shown in Table 1.

The average tractive effort factors are assumed to be similar to [26]; $TEF_{(city)}$ = 0.2 kW h/km and $TEF_{(HW)}$ = 0.125 kW h/km. The battery capacities are assumed according to the market sales of US (2008–2015) [25], and four capacities are considered with their market shares as shown in Table 2.

As shown in Table 2, most of previous market sales of EVs were having a battery capacity of 24 kW h and the expected average of all sales is around 27 kW h. In the proposed model, we considered each Battery Capacity (BC) as a single entity as well as the combination (Mix) of these capacities based on the probability of their availability (Table 2) in order to address the randomness of different battery capacity in the market.

The relationships between the TSR and different CSSRs for the In-city and Highway cases are shown in Fig. 6 and respectively.

It was observed from the sample results that at least 92% of all In-city trips could be completed successfully in the absence of a CS network for all battery capacities. The reason behind this is that In-city trips distances are short and so PEV RERs can cover these trips easily. However, at least 78% of all highway trips can be completed successfully in the absence of a CS network for 24, 32, and 54 kW h battery capacities, while almost 45% of PEVs with a 16 kW h battery capacity cannot complete their highway trips in the absence of a CS network. According to the NHTS (2009) [23], 80% of daily trips are considered In-city trips, and only 20% of daily trips are considered highway trips. As a result, another important observation can be obtained from the sample results, and that is related to the number of failed trips. Therefore, even if the TSR level In-city is higher than the TSR level for Highway that does not mean the corresponding number of failed trips is lower. For instance, if there are 5000 PEVs in the system and each one conducts the average daily trips – three trips/day – according to [23], there will be about 3000 highway trips and 12,000 in-city trips daily. Hence, if the highway TSR increases from 95% to 98%, that will decrease the number of failed trips from 150 trips to only 60. However, increasing the TSR level in-city by 3% will decrease the failed trips by 360, which is about four times that of the highway ones. Therefore, the TSR level in the two cases has different representations in terms of trip numbers (see Fig. 7).

Since the State Of Charge (SOC) is a primary in put in TSR model, a sensitivity analysis on the SOC at the beginning of trips are shown in Fig. 8 (in city) and Fig. 9 (highway) for a battery capacity of 24 kW h.

It is observed from Fig. 9 that enhancing the SOC level at the beginning of highway trips improves the TSR; however, in reality, the planning model should consider all possibilities effectively (see Table 3).

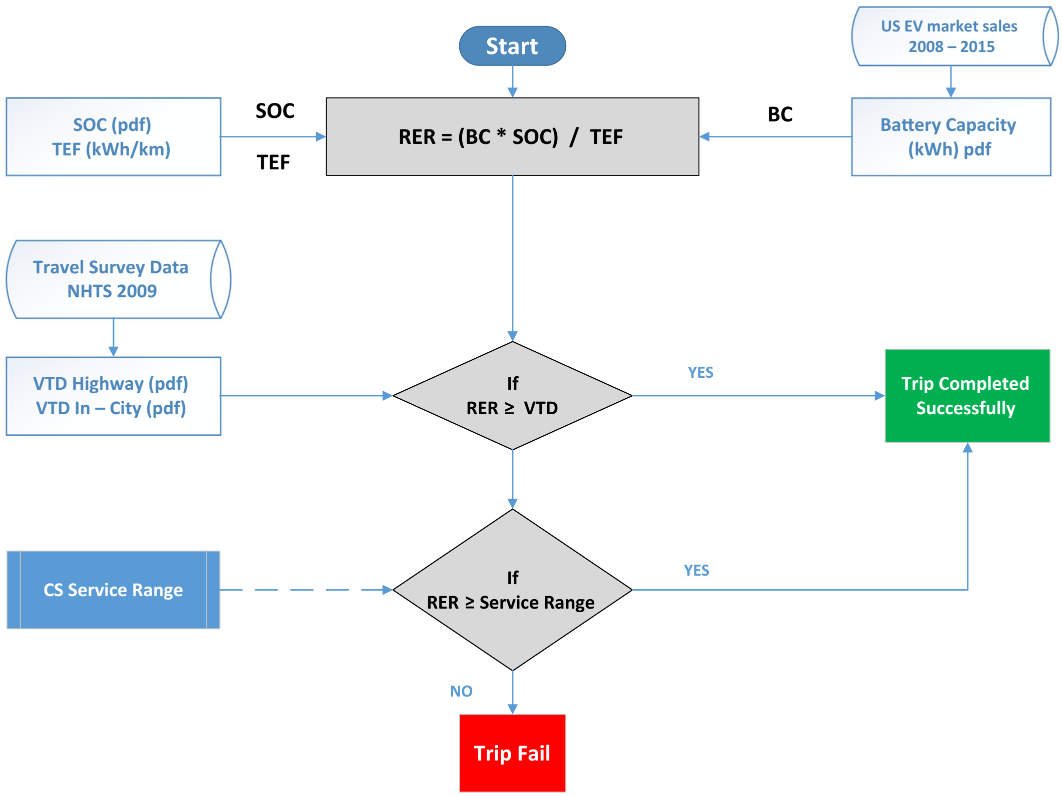


**Fig. 5.** The proposed Trip Success Ratio Model.

**Table 1**
Fitted pdf parameters of different TSR inputs.

| Input | Fitted pdf | Parameters | |
|---|---|---|---|
| $VTD_{(city)}$ | Lognormal distribution | $\mu_1 = 1.8285$ | $\sigma_1 = 1.0626$ |
| $VTD_{(HW)}$ | Weibull distribution | $\alpha = 1.8254$ | $\beta = 100.15$ |
| $SOC_{(city)}$ | Normal distribution | $\mu_2 = 0.56436$ | $\sigma_2 = 0.18512$ |
| $SOC_{(HW)}$ | Normal distribution | $\mu_3 = 0.6495$ | $\sigma_3 = 0.17585$ |

where:
$\mu_1$ and $\sigma_1$ are the mean and standard deviations respectively for the lognormal distributions that represents the Virtual Travel Distance in-city as input to TSR model.
$\alpha$ and $\beta$ are the shape and the scale for the Weibull distribution respectively that represents the Virtual Travel Distance inter-city (highway) as an input to TSR model.
$\mu_2$ and $\sigma_2$ are the mean and standard deviations respectively for the normal distribution that represents the SOC(city) at the beginning of in – city trips.
$\mu_3$ and $\sigma_3$ are the mean and standard deviation respectively for the normal distributions that represents the SOC(HW) at the beginning of inter – city (highway) trips.

**Table 2**
PEV battery capacities and their market share [24].

| PEV's Battery Capacity | US Market Share (2008–2015) |
|---|---|
| 16 kW h | 20% |
| 24 kW h | 50% |
| 32 kW h | 20% |
| 54 kW h | 10% |

## 5. Charging station allocation optimization model

In this section, the proposed CS allocation problem formulation is presented. The problem is modeled as the Maximum Covering Location Problem (MCLP) with a cutoff impedance (distance between demand node to the nearest supply facility) equaling the CSSR obtained from the TSR model. The optimization model is formulated as a mixed-integer non-linear problem (MINLP); with maximizing CS coverage as the objective function subject to service constraints.

**Objective function:**

$$\text{Max} \sum_{i=1}^{N_T} TD_i w_i \tag{9}$$

**Subject to:**

Location Constraints (10)–(16)

$$d_{i,j} = (|x_i^{cs} - x_j^{cs}| + |y_i^{cs} - y_j^{cs}|) \quad \forall i \neq j \tag{10}$$

$$M_{i,j} = \begin{cases} 1 & if \ (d_{i,j} \leqslant CSSR) \\ 0 & if \ (d_{i,j} > CSSR) \end{cases} \tag{11}$$

$$\sum_{j=1 \in M: d_{i,j} \leqslant CSSR}^{N_T} CS_j M_{i,j} \geqslant w_i \quad \forall i \in N_T, \ \forall j \in M \tag{12}$$

$$CS_i * CS_j \leqslant (1 - M_{i,j}) \quad \forall i \neq j \tag{13}$$

$$w_i, \quad CS_j \in \{0, 1\} \tag{14}$$

$$\sum_{i=1}^{N_T} CS_i < \frac{Area}{\frac{\pi}{2} \times CSSR^2} \tag{15}$$

$$\sum_{i=1}^{N_T} CS_i > \frac{Area}{2\pi \times CSSR^2} \tag{16}$$

where

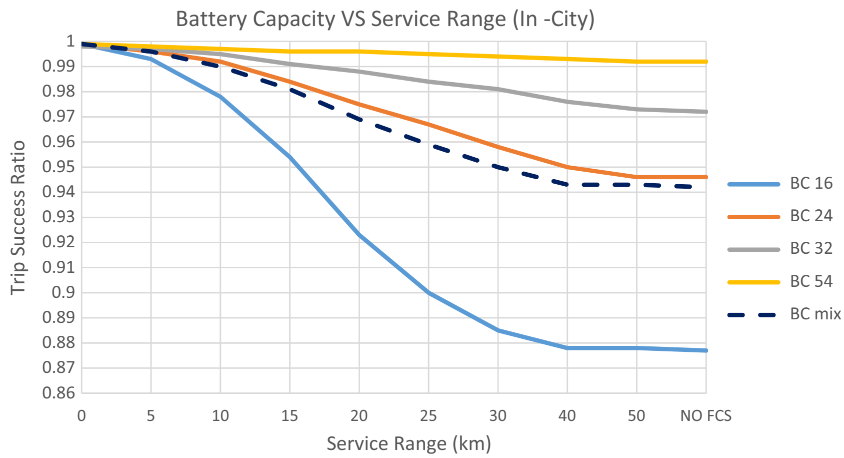


**Fig. 6.** The relationships between the Trip Success Ratio and Charging Station Service Range for different battery capacities (In - City).

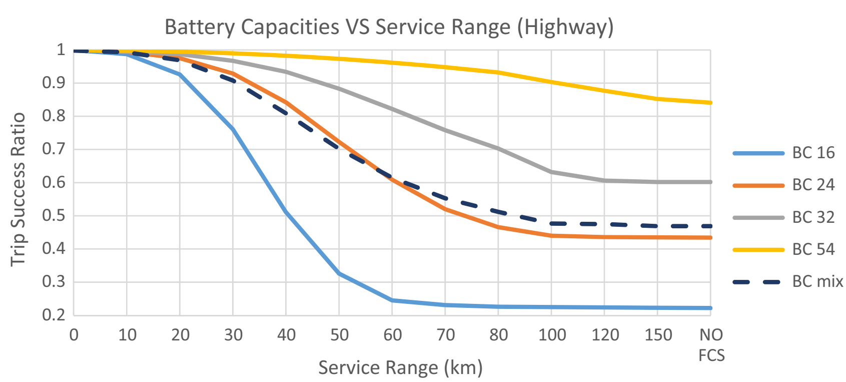


**Fig. 7.** The relationships between the Trip Success Ratio and Charging Station Service Range for different battery capacities (Highway).

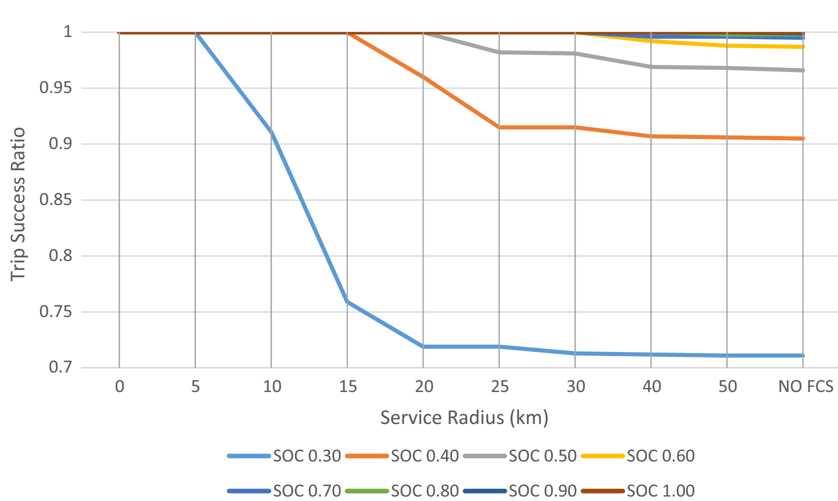


**Fig. 8.** The relationships between the Trip Success Ratio and Charging Station Service Range for different SOC (In - city).

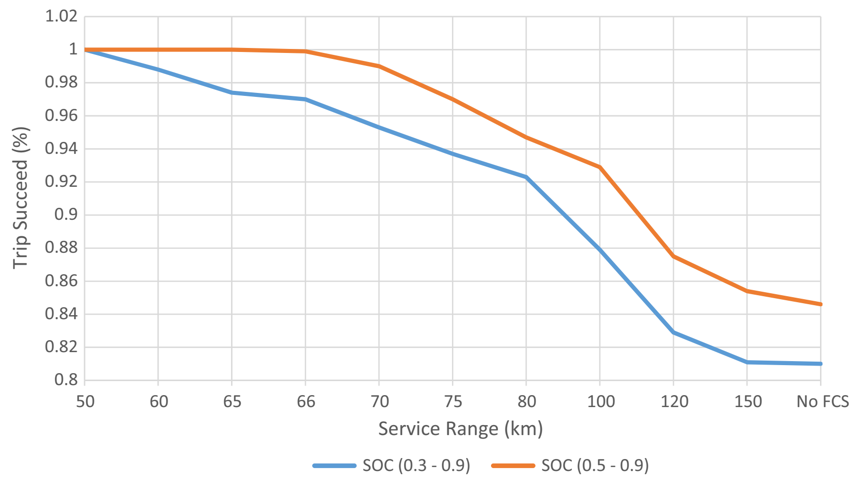


**Fig. 9.** The relationships between the Trip Success Ratio and Charging Station Service Range for different SOC (Highway).

**Table 3**
Comparison between MCLP model and MIP and Greedy methods proposed in [15] in locating CSs using different CSSRs.

| CSSR (km) | $Obj_{MIP}$ | $Obj_{Greedy}$ | $Obj_{MCLP}$ |
|---|---|---|---|
| 80 | 0.5473 | 0.5712 | 0.545 |
| 72 | 0.7824 | 0.8204 | 0.656 |
| 64 | 0.9375 | 0.9784 | 0.869 |
| 56 | 1.3774 | 1.4339 | 1.277 |
| 48 | 1.8374 | 1.8724 | 1.783 |
| 40 | 2.2146 | 2.2358 | 2.231 |
| 32 | 3.1412 | 3.1746 | 3.112 |
| 24 | 4.0834 | 4.0834 | 4.082 |

| | |
|---|---|
| $N_T$ | the number of transportation nodes in the network |
| $N_T$ | the number of transportation nodes in the network |
| $TD_i$ | the transportation demand according to location (i) |
| $w_i$ | a binary decision variable that equals ‘1’ if the transportation demand at location (i) is covered, and ‘0’ otherwise |
| $CS_j$ | the decision variable equaling ‘1’ if a station is located at node (j) and ‘0’ otherwise |
| $d_{i,j}$ | the Manhattan distance metric between transportation nodes in the network |
| *CSSR* | the station service diameter in km, which is obtained from the TSR model |
| $X_j^{cs}$ | the x-coordinate of Charging Station (j) |
| $Y_j^{cs}$ | the y-coordinate of Charging Station (j) |
| *Area* | the area in km$^2$ of the network under study |
| i, j | set to be transportation node indices where $j \in NT$ when (the distance between i and j) $\leq$ CSSR |
| **M** | **the set of nodes near to charging station node (i) when (the distance between i and j) $\leq$ CSSR** |

Power Balance Constraints (17)–(26)

*PEV load modeling*

$$p^H_{i,t} = \alpha NV \times (1-\gamma) \times \frac{U_{i,t}}{\sum_{t=1}^{T}\sum_{i=1}^{Nb} U_{i,t}} P^H \tag{17}$$

$$p^{FCS}_{i,t} = \alpha NV \times \gamma \times \frac{U_{g,t}}{\sum_{t=1}^{T}\sum_{g=1}^{N_{FCS}} U_{g,t}} P^{FCS} \tag{18}$$

$$p^H_{i,t} + p^{FCS}_{i,t} \leqslant TD_i \quad \forall t \tag{19}$$

*Power flow constraints*

$$P^{ss}_{(i,t)} - P^{Load}_{(i,t)} = \sum_{j=1}^{N_b} V_{(i,t)} V_{(j,t)} YBus_{(i,j)} \cos(\theta_{(i,j)} + \delta_{(j,t)} - \delta_{(i,t)}) \quad \forall i,t \tag{20}$$

$$Q^{ss}_{(i,t)} - Q^{Load}_{(i,t)} = -\sum_{j=1}^{N_b} V_{(i,t)} V_{(j,t)} YBus_{(i,j)} \sin(\theta_{(i,j)} + \delta_{(j,t)} - \delta_{(i,t)}) \quad \forall i,t \tag{21}$$

***Capacity constraints***

$$P^{ss^2}_{(i,t)} + Q^{ss^2}_{(i,t)} \leqslant SS^2_{(i)} \quad \forall i,t \tag{22}$$

$$0 \leqslant I_{(i,j,t)} \leqslant I^{max}_{(i,j)} \quad \forall i,j,t \tag{23}$$

$$0 \leqslant I_{(j,g,t)} CS_g \leqslant I^{max}_{(j,g)} \quad \forall j,g,t \tag{24}$$

***PEV demand constraint***

$$P^{Load}_{(i,t)} = [(1+DGR)^k \times P^D_{(i,t)}] + [p^H_{i,t}] + [p^{FCS}_{i,t}] \quad \forall i,t \tag{25}$$

*Voltage limit constraint*

$$V_{min} \leqslant V_{(i,t)} \leqslant V_{max} \quad \forall i,t \tag{26}$$

where $S_L$ is bus loading, i.e. $\mathbf{P_L}$ and $\mathbf{Q_L}$; $\mathbf{Q_G}$ stand for the generator reactive powers. **V** and $\boldsymbol{\delta}$ represent the bus phasor voltages and angles, respectively. The line current $\mathbf{I_{ij}}$ and $\mathbf{I_{ji}}$ thermal limits and bus voltage limits.

In this formulation, the objective is to maximize the number of PEV drivers served or “covered” within the desired service distance (CSSR). Eq. (10) allows $w_i$ to equal 1 only when at least one facility is established at a site in the set $N_{CS}$. The number of facilities allocated is restricted to upper and lower boundaries with the constraints in (15) and (16) from location point view and constraint (17)–(19) from the capability of power network perspective. The solution to this problem specifies not only the largest population that can be covered but also the number of CSs that can achieve this maximal coverage. The upper and lower boundary constraints are used to ensure that the whole area under study is covered by CSs; therefore, the service ranges of the CSs (CSSRs) divide the area under study in order to obtain the lowest number of CSs that can cover the area; see Eq. (15). However, the upper boundary constraint, Eq. (16), is used in order to not overdesign the charging station network, wasting resources.

If the network under study is a highway, the length of the highway in km is used instead of the area, as shown in (27) and (28), to obtain the upper and lower boundaries for CSs respectively.

$$\sum_{j=1}^{N_{CS}} CS_j < \frac{HWL}{CSSR} \tag{27}$$

$$\sum_{j=1}^{N_{CS}} CS_j > \frac{HWL}{2CSSR} \tag{28}$$

where

| | |
|---|---|
| *HWL* | is the length of the highway under study in km |

The non-linearity of the problem results from Eq. (13), and therefore, the Branch-And-Reduce Optimization Navigator (BARON) is utilized to solve mixed-integer nonlinear programs (MINLP) using the GAMS platform. While traditional NLP and MINLP algorithms are guaranteed to converge only under certain convexity assumptions, BARON implements deterministic global optimization algorithms of the branch-and-bound type that are guaranteed to provide global optima, and no starting point is required [27]. Since the lower and upper boundaries are provided in the problem formulation, BARON guarantees that the global optimal solution is achievable [27].

To investigate the feasibility and robustness of the proposed optimization model, the problem is reformulated as a Mixed Integer Problem (MIP) by considering only the shortest paths between the transportation nodes. Hence, constraint (13) is replaced by the following:

$$d_{j,k} = D_{j,k} \quad \forall j \neq k \tag{29}$$

where

$D_{j,k}$ is the matrix of the shortest paths between any transportation node (j) and node (k) in the transportation network

Although this formulation, MIP, guarantees the global optimal solution, it requires the provision of a starting point in order to obtain a solution [19]. According to [19], the problem should be solved iteratively using each of the charging station candidate nodes as a start point, and then choosing the best among them to be the global optimal solution for our problem. Conversely, BARON does not require any starting point to reach an optimal solution, and the optimality of the solutions obtained by BARON is assured by comparing them with the best solutions obtained by the iterative MIP proposed in [19].

## 6. Sample results

In this section, three case studies are considered to validate the proposed model. The first case study is adopted from [15] in order to validate the feasibility and robustness of our model. The second case study is adopted from [14] to investigate the different between our proposed model and the flow-capturing one. Different CSSRs have been considered in the second study to illustrate several TSR levels. Finally, to demonstrate the ability of our proposed model in dealing with different network topologies and driving modes (in-city and highway), we present a case study considering a real highway network (Highway 401 in Ontario, Canada) with candidate CSs located on the OnRoute™ network.

### 6.1. Virtual network case study

This case study is presented to demonstrate the robustness of our proposed optimization model based on Maximum Covering Location Problem (MCLP) to locate charging stations using different Charging Station Service Ranges (CSSRs). Our model is compared to models presented in [15] where the In-city area being 100 km$^2$ and 10 candidate CSs located randomly in the network. The installation cost is assigned randomly (0–1) to the candidate CSs, and the transportation demand ($t_i$) is set to be 1. The transportation demand cover by each station ($w_i$) is set to be 0.5, and the CSSRs are (80–24 km), similar to [15]. The CSSRs in this case study are similar to [15] rather than utilizing the TSR model to focus on the performance of our optimization model. Fig. 10 shows the selected CSs based on a CSSR = 40 km.

Five CSs can cover the area, and the CS set is {2, 6, 7, 9, and 10}, with a total output equaling 2.231. The total outputs in [15] equals (2.215 and 2.235) in MIP and Greedy methods prospectively, and therefore the outcome of our proposed model is consistent with [15].

### 6.2. In – City network (20 transportation nodes and 23 distribution nodes)

The 20-node transportation network and the 23-node distribution system are available in [14]. The voltage level of this radial distribution system is 15.0 kV. There are two candidate substations and 35 candidate feeders to be considered. Each node in the 20-node transportation network represents an intersection between links and roads. The coupled transportation – distribution network is illustrated in Fig. 11. In this case study, three scenarios are presented to demonstrate first the significance of MCLP model to locate CSs to satisfy PEV drivers' convenience, second the tradeoff between using different CSSRs and the total construction cost of CS network, and third the effect of different TEFs, as different traffic and weather conditions, on TSR levels.

**Scenario 1**

The same transportation network topology and traffic volume data presented in [14] is used. A 25 km CSSR is utilized to allocate FCSs in the network with corresponding TSR level of 0.99. In order to satisfy at least 99% of trips in the coupled network, five FCSs have to be installed. Fig. 11 shows the selected FCSs (in blue) using our proposed model. The best set is {6, 7, 11, 17, and 20}, while the selected FCSs (in silver) using the maximum flow-capturing method proposed in [14] are {6, 12, and 13}. It is notable that the number of FCSs in our optimal set is greater by two stations compared to [14]; however, the charging station installation cost is increased by only 35% compared to [14]. Conversely, the success level of the charging station set obtained in [14] is analyzed using our TSR model. {6, 12, and 13} do not cover parts of the coupled network. For instance, the paths between node 1 and node 17 and between node 4 and node 20 are not covered, and the extra distance for detouring via nodes 12 and 13 makes the TSR level about 0.965. More than 700,000 failed trips will be saved annually by using our proposed model with a 0.99 TSR level, so it is clear that PEV drivers' convenience is a significant matter in the proposed model.

In Case B, we have the typical system load profile with no EVs (Blue area) that has a peak demand occurs around 6–9 pm and the PEV peak demand that has occurred around 5–8 pm, and they overlapped 6–8 pm as the worst case. The distribution network capacity is shown in red; Fig. 12.

The voltage profile for different PEV penetration levels shows that Bus 18, which is located at the end of a line that fed two FCS, has the minimum acceptable voltage limit (0.92pu) with 30% penetration level; Fig. 13.

**Scenario 2**

In this scenario, the tradeoff between trip success levels and CS construction costs is demonstrated, and the same problem is solved over using different CSSRs (5–70 km). When the distance

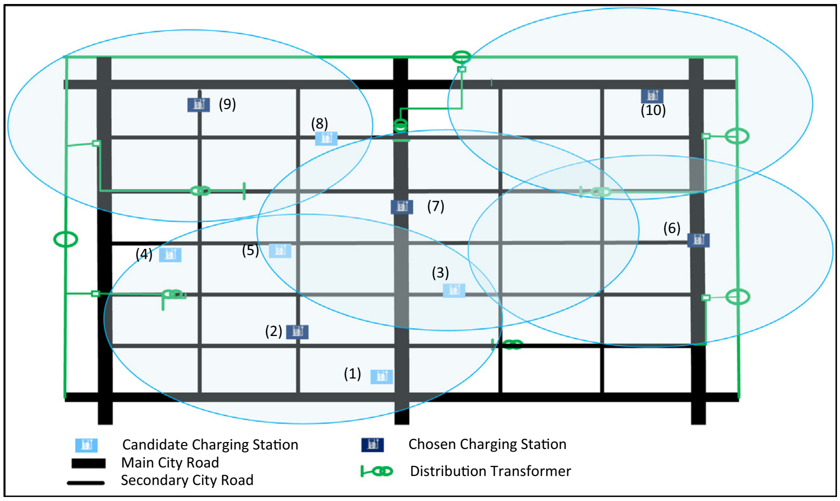


**Fig. 10.** Selected Charging Stations (In-city Network, CSSR = 40 km).

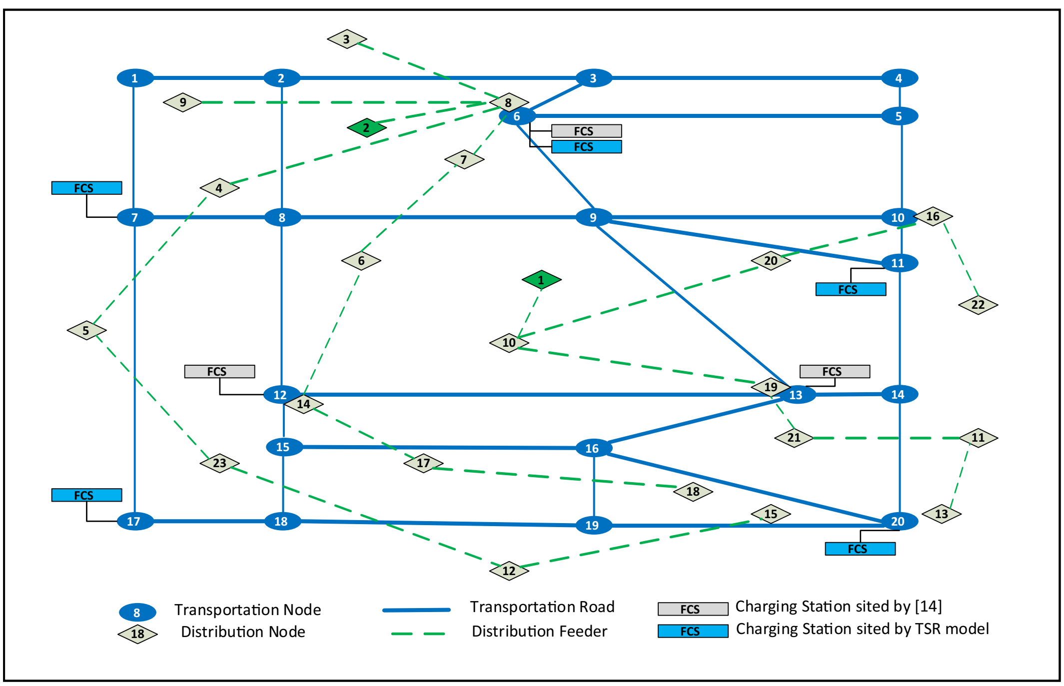


**Fig. 11.** The 20 transportation nodes, 23 DS nodes, and the selected charging stations, based on a CSSR = 25 km.

between charging stations (CSSR) is short, more charging stations are required to be installed in order to cover the network; hence, the possibility of trips to reach their destinations successfully (TSR) is high and vise versa. Fig. 14a shows the relationship between the CS construction cost and different CSSRs as well as the required number of CSs.

In order to consider the tradeoff between the PEV drivers' convenience and the CS construction cost, the annual number of saved trips from being failed is estimated for each CSSRs. The annual number of saved trips curve has been added to Fig. 14b, and it shows that (CSSR = 20 km) is the most cost-effective service range in this transportation network. However, limited cost-effectiveness is obtained when using (CSSR $\geq$ 55 km) since the number of saved trips regarding charging stations is very low compared to the number of saved trips regarding PEVs' Electric Range (no FCS).

**Scenario 3**

In this scenario, the effect of considering different traffic conditions (heavy and light) and weather conditions (summer/winter and fall/spring) on the Trip Success Ratios. Changing the weather conditions will influence PEV drivers to use AC in the summer season and Heater in the winter season, and that will affect the efficiency of PEV in terms kW h/km. In addition, more energy is consumed when driving in heavy traffic condition compare to light traffic condition due to different speeds and accelerations. As a result, modeling the weather and traffic changes effect can be achieved by changing the Tractive Effort Factor (TEF) to represent the extra loading of (AC/heater) as well as driving condition. According to the experimental investigation of the energy efficiency of an EV in different driving conditions [26], the lower TEF limit (no AC/no heater, light traffic) is ($TEF_{low}$ = 0.14 kW h/km). Where the upper TEF limit of TEF (AC/Heater, heavy traffic) is

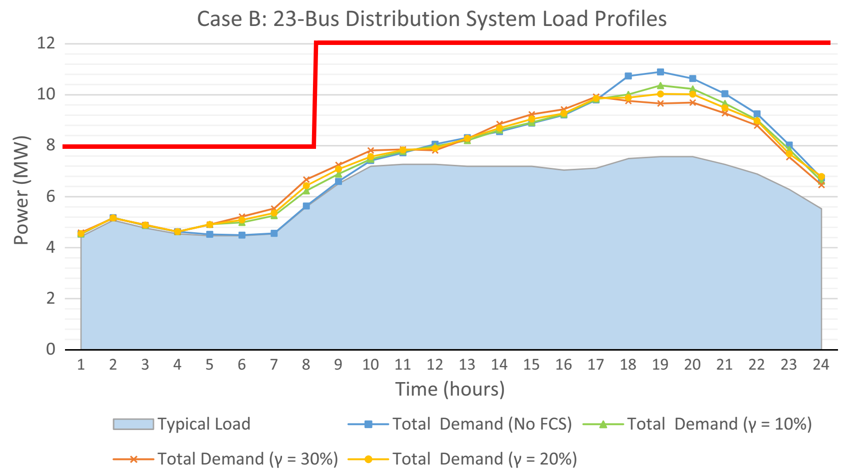


**Fig. 12.** The 20 transportation - 23 Bus DS system load profile.

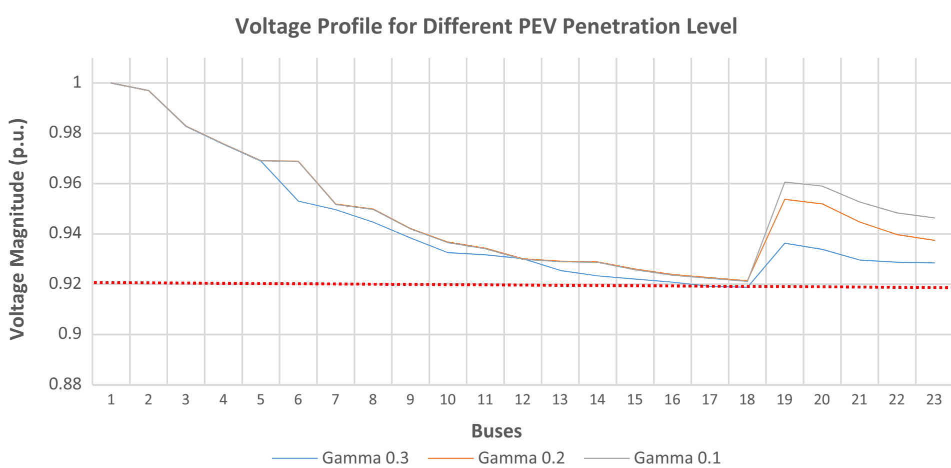


**Fig. 13.** The Voltage profile of the coupled 23 – node distribution and 20 – node transportation system.

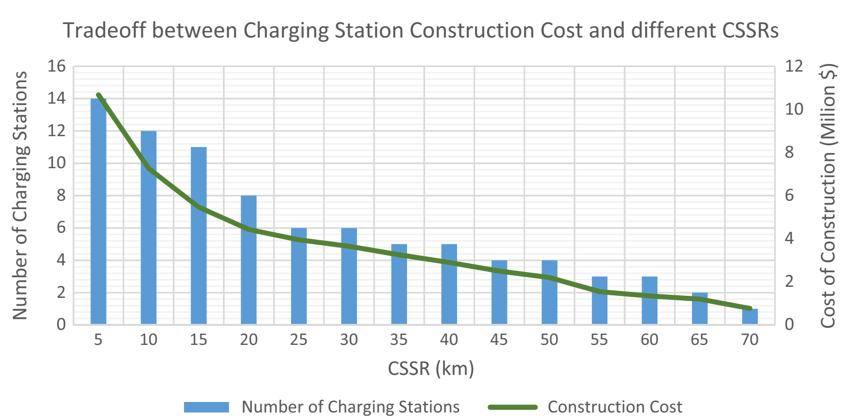


**Fig. 14a.** The relationship between charging station construction costs and different CSSRs.

($TEF_{high}$ = 0.27 kW h/km). The upper and lower boundaries are utilized by TSR model in order to obtain a sensitivity analysis for the mixed-battery curve ($TEF_{mid}$ = 0.20 kW h/km) presented in Fig. 6. The effect of considering different traffic and weather conditions is shown in Fig. 11.

Fig. 13 shows that in order to have at least 99% TSR level, CSSR should be (A = 15 km, B = 20 km, and C = 30 km) for ($TEF_{high}$, $TEF_{mid}$, and $TEF_{low}$) respectively. The corresponding construction cost according to Fig. 12a is (A = $5.46 \times 10^6$ $, B = $4.43 \times 10^6$ $, and C = $3.65 \times 10^6$ $). However, the lower and upper boundaries for TSR levels when (CSSR = 20 km) is used are (D = 98.6% and E = 99.3%), so the range of variation in TSR level due to the weather and traffic conditions is limited to ±0.4%. The corresponding number of (success/ failed) trips annually according Fig. 10b is limited to ±135,000 trips/year.

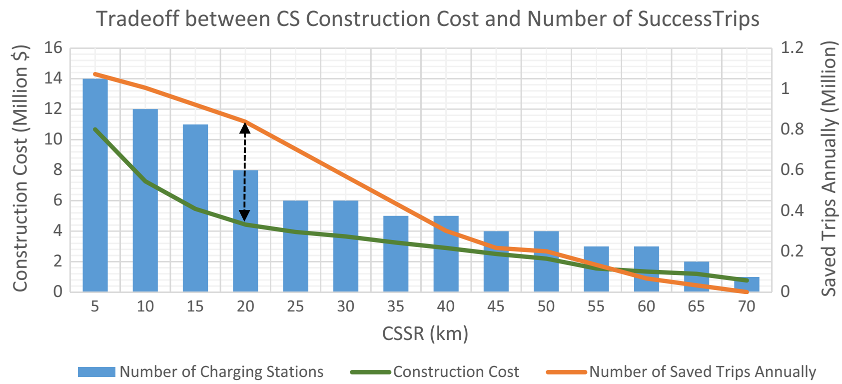


**Fig. 14b.** The relationship between charging station construction costs and number of success trips.

### 6.3. Ontario 401 highway

King's Highway 401, also known as Ontario's 401 Highway, is a 400-series highway in the Canadian province of Ontario. It stretches 817.9 km (508.2 mi) from Windsor to the Quebec border. The part of Highway 401 that passes through Toronto is the busiest highway segment in the world [28]. In order to maximize coverage of the 401 highway, the proposed model has been applied only for a 0.90 TSR level due to the long distance between the candidate locations. The OnRoute™ gas station network [28] is assumed as candidate locations for installing CSs along the highway. Fig. 14 shows the highway and the candidate locations [28]. The installation cost is assumed based on the land price of the candidate locations adopted from [29], and the footprint of each station is assumed to be 0.8 ha. Table 4 shows the candidate CS locations and cost according to [27,28].

The results show that a minimum of 11 CSs are required to cover Ontario's Highway 401, and the total land cost is about 256,000 dollars. The CSs are proposed for: Tilbury, West Lorne, Ingersoll, Cambridge, Maple, Newcastle, Trenton, Odessa, Mallorytown (N), Morrisburg, and Bainsville. The average distance between the CSs is 69.09 km, and the proposed CS network assures a 0.90 TSR level. However, the current network cannot achieve the 0.95 TSR level since there are four segments longer than CSSR = 70 km, which is the cutoff impedance to guarantee TSR equals 0.95 : (1) Tilbury – West Lorne, (2) Dutton – Ingersoll, (3) Cambridge – Maple, and (4) Maple – Newcastle. Therefore, to achieve the 0.95 TSR level, additional candidate CSs have to be considered along these segments (see Figs. 15 and 16).

**Table 4**
Ontario 401 Highway candidate CS locations and cost [27,28].

| CS | L (km) | Cost ($) | CS | L (km) | Cost ($) |
|---|---|---|---|---|---|
| Tilbury | 53 | 30,000 | Trenton | 530 | 50,000 |
| West Lorne | 136 | 21,000 | Napanee | 590 | 8000 |
| Dutton | 147 | 18,000 | Odessa | 610 | 9000 |
| Ingersoll | 226 | 32,000 | Mallorytown (N) | 670 | 16,000 |
| Woodstock | 236 | 34,000 | Mallorytown (S) | 690 | 18,000 |
| Cambridge | 275 | 16,000 | Morrisburg | 750 | 23,000 |
| Maple | 365 | 17,000 | Ingleside | 780 | 24,000 |
| Newcastle | 455 | 22,000 | Bainsville | 813 | 20,000 |
| Port Hope | 470 | 25,000 | | | |

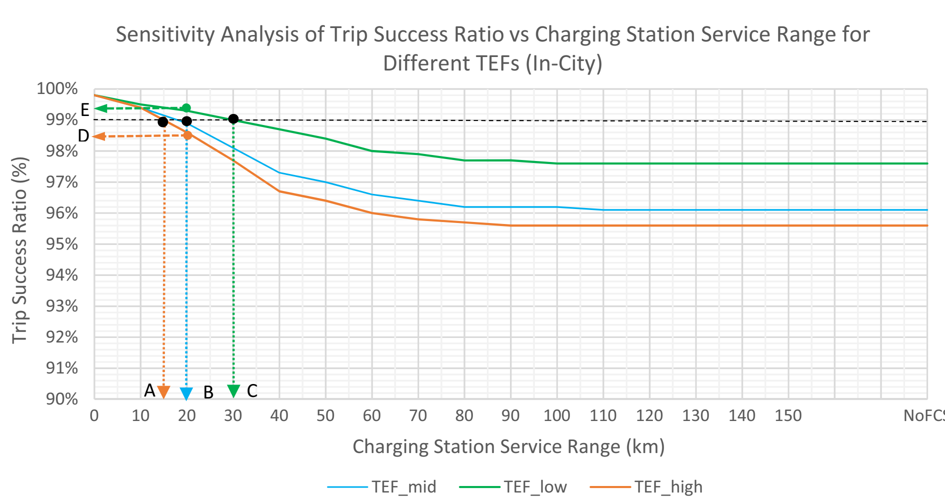


**Fig. 15.** The sensitivity analysis of Trip Success Ratio and CSSR for different TEFs (in - City).


**Fig. 16.** Candidate Charging Stations (Ontario Highway 401, OnRoute™) [28].

## 7. Conclusion

In this paper, a new PEV charging station allocation model has been presented. The model consists of two parts. In the first part, investigating the relationship between charging station service range and the probability of PEVs completing trips successfully is discussed. The model utilizes MCS to generate virtual trip distances and PEV remaining electric ranges. It takes into consideration variations in driving habits, battery capacities, states of charge, and trip classes. Consideration of the variations in these factors is assumed to present a more realistic and accurate model for estimating the Trip Success Ratio for each charging station service range as compared to the literature.

The results obtained from the first part, the TSR model, have shown the performance of each battery capacity to fulfil its daily trips when a CS is absent or located at a predefined distance. It is observed that PEVs with a battery capacity of 16 kW h showed huge dependability on the charging station network for highway trips. However, about 97% of all highway trips are completed successfully in the absence of CSs if all PEVs' batteries are 54 kW h and above. Another important observation from the TSR model results is that PEV battery capacities influence CS service range, and therefore, considering the data from PEV market sales in selecting optimum CS sites leads to more realistic and accurate outcomes.

In the second part, different CSSRs are utilized in the allocation optimization problem in order to locate the charging stations in the optimal locations in order to assure that the TSR of PEVs is above a certain threshold. Instead of using a single service range or Origin-Destination (OD) pair path, the model locates the CSs using different CSSRs by applying MCLP. The results obtained show the differences in quality of service based on their TSR levels. Therefore, the proposed model is able to measure how successful the CS network is in meeting PEV demand in order to make the optimum decision based on the available resources. Moreover, the proposed model considers PEV accessibility in the locating problem by using TSR levels, so the model outcomes are influenced by drivers' needs rather than electrical utilities' requirements.

The proposed model has been applied to different scenarios for two types of network: In-city and Highway. The results validate the robustness of the proposed model, and the outcomes demonstrate the significance of the proposed model compared to the literature. It is also observed that the number of CSs in-city is very sensitive to the CSSR due to the quadratic relationship between the service range and the covered area. In the highway scenario, the CSSR should be smaller than the segments between any two neighboring CSs; otherwise, the TSR level would be reduced in order to get a proper CSSR.

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