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BEV Fast Charging Strategy Optimization

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Abstract: This paper presents different approaches to optimize battery electric vehicles (BEVs) fast charging strategy. A rule-based model was built to simulate BEV charging behavior. Monte Carlo analysis was performed to explore the potential variance of congestion at fast charging stations, which could cause longer than four-hour waiting at the most congested station. Genetic algorithm was performed to explore the potential minimum waiting time at fast charging stations, and it can decrease the waiting time at the most congested station to be shorter than one hour. A deterministic approach results in feasible suggestions that people could consider to take fast charging as soon as the state of charge is approaching 40-miles range while remaining relative short waiting time at charging stations.

Keywords: Optimal operation and control of power systems, Modeling and simulation of power systems, Control of renewable energy resources

1. INTRODUCTION

California State Government proposed to have 1.5 million zero-emission vehicles (ZEVs) on the state's roads by 2025 (Brown, 2013). In order to achieve this goal, a large number of battery electric vehicles (BEVs) must be sold. However, one major consideration for consumers to adopt BEVs is range anxiety (Lin and Greene, 2011).

In recognition of this, the U.S. Department of Energy (DOE) announced 16 electric vehicle planning grants totaling \$8.5 million in 2011 to help preparing for plug-in electric vehicles (PEVs) and charging infrastructure in 24 states (U.S. DOE, 2011) in order to extend the limited range of BEVs. There are three common charging levels: AC level I uses a standard 120 volt alternating current to provide slow charging (typically of 1.4 kW – 1.9kW); AC level II uses a 208/240 volt alternating current to provide charge power of 1.5 kW – 19.2kW; "fast charging" typically refers to DC level II and uses a high voltage direct current to provide power from 36 to 90 kW, although DC level I—which is less than 36kW—could be considered as fast charging as well (SAE Hybrid Committee, 2011). Taking the 2015 Nissan Leaf with its 84-mile range and 24-kWh battery capacity (U.S. DOE, 2015) as an example, it could take around half an hour to fully charge it by fast charging and two to twelve hours by AC level I/II. There are 148 CHAdeMO fast charging stations in California by 2013 (United States Department of Energy, 2014). Considering the limited number of fast charging stations and relative longer time to fully charge an electric vehicle using fast charger than to refuel a gasoline vehicle, the waiting time at fast charging stations could easily become too long, leaving users with bad experience and discouraging them from using fast charging.

There are many factors that could influence a person's decision on whether to use fast charging or not. Tour distance, which is the total travel distance after the driver leaving home till he/she gets back to home, is one of the primary factors. Since fast charging usually has higher cost than level II charging and fast charging stations are usually along freeways instead of at destinations, it makes the waiting time at fast charging stations more boring. Thus, it is reasonable to assume that people will not use fast charging unless the tour distance exceeds the battery range.

According to previous studies about PEV drivers (Nicholas et al., 2013a), the number of fast charging required to complete a tour will influence people's decision on using BEVs. Non-routine tours within one-charging-event distance is acceptable for most BEV drivers; half of the respondents will drive BEVs for occasional tours which require twice fast charging events, and the willingness decreases along with the increase of fast charging events required to complete a tour.

The battery state of charge (SOC) when a vehicle approaches a fast charging station could also influence people's decision on whether to do fast charging or not. The design of traditional internal combustion engine (ICE) vehicles makes drivers accustomed to not consider refueling unless the level of gasoline is less than a certain threshold. This habit will influence drivers' decision on when to use fast charging as well, and it is reasonable to assume that the probability to use fast charging increases as the SOC drops.

What's more, the availability of fast charging stations is also an important factor. Unlike quick gasoline refueling, fast charging could take half an hour even longer to complete depending on charging power and battery SOC. Therefore, congestion at fast charging stations could easily get much worse than at gasoline stations, and bad experience at charging stations could impact drivers' impression on fast charging and might discourage them from taking BEVs.

There are studies regarding the possibility of building conceptual models to simulate charging demand of large PEV population based on game theory (Ma et al., 2013), to optimize charging activity based on time-of-use price and state of charge (Cao et al., 2012), and to build decentralized protocols to shift peak electric vehicle charging demand (Gan et al., 2013). But most of these studies are theoretical analyses without validation on real data. This paper presents rule-based models based on real travel data to simulate and optimize fast charging activity for non-commute purpose trips. Optimization of fast charging decision is expected to help reduce congestion at charging stations and to improve user experience, so as to encourage electric vehicle driving.

2. DATA EXPLORATION

Based on existing survey (Nicholas et al., 2013a) about households who own BEVs, it was found that most of households have at least one conventional gasoline vehicle besides the BEVs. Based on this finding, it is expected that, in the near future, most households who possess BEVs will also have at least one conventional gasoline vehicle. Thus, people's travel patterns won't be significantly different from current situation, and they will choose a BEV or conventional vehicle based on their travel needs.

The California Household Travel Survey (CHTS) dataset (CalTrans, 2013) was used in this study to analyze California residents' travel patterns and to examine what travel demand can be satisfied by BEVs. The CHTS dataset has one-day travel diary from 42,431 households. The travel diary has detailed information about all trips that sample households made on the assigned day including trip origin and destination, start and end time, trip purpose, travel mode, etc. Each sample household is assigned with a sample weight to make sure the weighted sample is representative in terms of the socio-demographic characters of the population.

Since the primary charging location of most BEV drivers is their home (Lin and Greene, 2011), trips are re-organized into tours. All trips that happened between driver leaving home and getting back home belong to the smae tour. As a result, there are totally 71,000 tours being generated based on the CHTS travel diary data.

In terms of travel purposes, tours can be classified as commute tours and non-commute tours. If one tour contains at least one commute trip, that tour is considered as a commute tour. Considering the weight of each sample household, one-third of tours are for commute purpose while the other two-thirds are for non-commute purpose. In terms of travel distance, 79.47% of tours are within 30 miles, 13.1% of tours are between 30 miles and 60 miles, 3.88% of tours are between 60 miles and 90 miles, and 3.55% of tours are over 90 miles (Fig. 1).

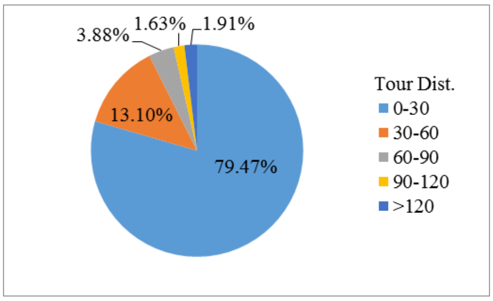

Fig. 1. Composition of Tour Distance

It is assumed that people's travel pattern remains the same when they shift from conventional gasoline vehicles to BEVs. Thus, travel diary data from the CHTS dataset including gasoline vehicle drivers' travel dairy is used for the fast charging strategy analysis. Since home is the primary charging location for most BEV drivers (Lin and Greene, 2011), only tours that start and end at home will be analyzed, and 93.2% of tours in CHTS dataset are home based (Table 1).

To simplify the analysis, it is assumed that all travelers are driving BEVs with a 100-mile range (BEV100). Since commute tours are usually routine travel and are less likely to use fast charging, so only non-commute tours are used for fast charging analysis. Considering the inconvenience of extra charging and the effective driving range of BEVs, it is assumed that people with BEV100 will not use fast charging for tours shorter than 80 miles. Besides, people's willingness to use BEVs decreases along with the increase in the number of charging events required to complete the tour (Nicholas et al., 2013b). It means that, taking BEV100 as an example, people are significantly less likely to drive BEVs for a tour longer than 300 miles. Therefore, there are only 1,567 tours that are for non-commute purpose and with a distance between 80 and 300 miles, and those tours will be considered for further analysis (Table 1).

Table 1. Criteria of Choosing Sample Tours for Analysis

Criteria to Choose Tours	Number of Qualified Tours	Percent of Total Sample
Tours from CHTS Travel Diary	71,000	100%
Home-based Tour	66,162	93.2%
Non-commute purpose, 80-300 miles distance	1,568	2.2%
Chargers available along route (5 miles radius)	1,252	1.8%
Interval between chargers and from/to home within range	1,173	1.7%

According to the U.S. DOE, there are 148 existing CHAdeMO fast charging stations in California along with 53 proposed fast charging stations by 2013 (United States Department of Energy, 2014). Locations of these stations are used for station availability and congestion calculations. The service radius of each charging station is assumed to be 5 miles. For each charging station, a 5-mile buffer was created. If the buffer intersects with a tour line, it means the corresponding charging station is accessible for this tour. Based on the location of existing and proposed fast charging stations, there are 1,252 sample tours out of the 1,568 candidate tours that have accessible charging stations along the road. Considering the distance between home and fast charging stations and the distance between adjacent charging stations, 1,173 of the 1,252 tours can be completed with a BEV100. Therefore, there are eventually 1,173 sample tours being used for later analysis.

For simplification purposes, all sample tours have a weight of one, so they represent only themselves. This ensures consistency and makes the results comparable among different optimization approaches.

3. MODELS

Similar to the process of conventional gasoline vehicle drivers to determine when to refuel based on gasoline level, it is assumed that the primary factor influencing a person's decision on whether to use a fast charging station or not is the SOC when approaching charging stations. Assuming the service radius of a fast charging station is 5 miles, all fast charging stations within service radius along the tour are within acceptable detour distance, so they are considered as potential locations to charge. SOC when reaching each potential location is calculated based on vehicle efficiency and previous charging events.

Taking the route in Fig. 2 as an example, the tour distance from Roseville to Fairfield and back to Roseville is 122.6 miles. It requires at least one fast charging event to complete the tour using a BEV with a 100-mile range. There are three potential fast charging stations along the tour: one located in Davis and two in Vacaville. The probability of using each station is inversely proportional to the SOC when reaching that station. A detailed description about how to calculate the SOC is given in Equation (1). On the way back from Fairfield to home, the SOC when reaching Davis is about 10%, which is the lowest among all potential stations, so the driver is most likely to use the Davis fast charging station on his/her way back from Fairfield to Roseville.

Fig. 2. Model Demonstration

A rule-based model was built to simulate battery SOC (Equation 2), to predict charging decisions at each charging station (Equation 1), and to calculate the waiting time at chosen charging stations (Equation 3-5). For simplification purpose, all sample households are assumed to drive BEVs with a 100-mile range. Notations used for later equations are given as following:

- v Vehicle ID
- t Trip ID
- s Charging station ID
- s_{prev} Previous used charging station
- $SOC_{v,t}$ State of charge of vehicle v after trip t
- $C_{v,s}$ A binary variable which is the charging decision of vehicle v at charging station s; 1 means charge and 0 means not charge.
- R_v Range of vehicle v
- $D_{v \cdot t}$ Distance of trip t of vehicle v
- $D_{v,s,s+1}$ Distance between charging station s and $s+1$ for vehicle v
- $ET_{v,s}$ Charging event end time for vehicle v at charging station s
- $AT_{v,s}$ Arrival charging station time for vehicle v at charging station s
- $CT_{v,s}$ Charging time for vehicle v at charging station s
- $WT_{v,s}$ Waiting time for vehicle v at charging station in order

3.1 Monte Carlo approach

The Monte Carlo approach is implemented to examine the performance of each charging station. The charging decision is described as Equation (1). If the distance between this station and the next available station is longer than current vehicle remaining range, the vehicle will be charged at this station. If there is more than one station available within the current vehicle remaining range, the probability that the vehicle will use each potential charging station decreases proportionally along with the distance from current location to corresponding charger location. One of the potential charging stations will be chosen after the previous charging decision is made based on the probability to charge at each potential station.

$$C_{v,s} \sim P\left(D_{v,s,s+1}, D_{v,s,s_{prev}}, R_v, SOC_{v,s}\right) =$$

$$\begin{cases} 1, & D_{v,s,s+1} > SOC_{v,s} \\ \frac{D_{v,s,s_{prev}}}{\sum_s D_{v,s,s_{prev}}}, & \forall D_{v,s,s_{prev}} < R_v,\ D_{v,s,s+1} \leq SOC_{v,s} \end{cases} \tag{1}$$

SOC at a specific location is calculated based on the number of charging events that happened before arriving at that location and the total travel distance from home, as Equation (2) shows.

$$SOC_{v,t} = \left(1 + \sum_s C_{v,s}\right) \cdot R_v - \sum_t D_{v \cdot t} \tag{2}$$

After all tours make their charging decision, the waiting time of each charging event at the corresponding charging station can be calculated based on the driver's arrival time and the occupation situation when he/she arrives, as shown in Equation (3)-(4). The congestion status at each charging location is represented as the total waiting time of all charging events at each location over one day, as Equation (5) illustrates.

$$ET_{v,s} = f(ET_{v-1,s}, AT_{v,s}) =$$

$$\begin{cases} ET_{v-1,s} + CT_{v,s}, \ ET_{v-1,s} > AT_{v,s} \\ AT_{v,s} + CT_{v,s}, \ ET_{v-1,s} \le AT_{v,s} \end{cases} \tag{3}$$

$$WT_{v,s} = ET_{v,s} - AT_{v,s} - CT_{v,s} \tag{4}$$

$$WT_s = \sum_v WT_{v,s} \tag{5}$$

Fifty datasets were generated based on the Monte Carlo approach as described above. The only uncertain parameter is the charge decision among all accessible potential charge stations. Random numbers were generated obey the probability from Equation (1) to determine charge decisions in each dataset. The results of these fifty datasets were used to explore the possible extremum of the system performance. Based on the Monte Carlo results, 80% of charging stations have an average waiting time shorter than one hour. But there are some stations with an average waiting time over two hours, which would results in worse user experience.

3.2 Genetic algorithm

Genetic algorithm has been widely used for optimization especially for non-linear models (Deb, 2001). A genetic algorithm is performed to minimize the longest waiting time among all charging stations while ensuring the tour can be made, as Equation (6)-(8) show.

$$WT_{max} = \max(WT_s), \ \forall s \tag{6}$$

$$\min(WT_{max}) \tag{7}$$

$$\text{S. T.} \qquad SOC_{v,t} > 0, \qquad \forall v, t \tag{8}$$

Fifty independent datasets generated through the Monte Carlo approach are used as the initial population, as Stage 0 in Fig. 3.

The strategy of the genetic algorithm to minimize the longest waiting time is to find out the most congested charging station and reassign some tours, which charge at the most congested station, to less congested stations. Detailed process for each evolution iteration is as following:

1. The first step is to select the most congested station in each dataset as the potential target station.

2. The average waiting time among all potential target stations is calculated, and those potential target stations with waiting time longer than the average waiting time are called target stations. The dataset whose potential target station has the shortest waiting time among all datasets is called the example dataset, and there is only one example dataset among all. For example, the average waiting time of all potential target stations in Fig. 3 is 2.5 hours, so station 35 in dataset 2 and station 26 in dataset 50 are target stations, and dataset 3 is the example dataset, as step 2 shows.

3. All tours that charge at the target station are target tours. All target tours will "clone" the charging decision of the corresponding tour in the example dataset. For example, Tour 00203 in dataset 2 charged at station 35 in stage X. But this tour in dataset 2 will be assigned to charge at station 64 in stage X+1 because the tour 00203 in dataset 3 charged at station 64 in stage X and dataset 3 is the example dataset in stage X, as step 3 shows. For non-target dataset, there will be no modification.

These three steps described above are considered as one evolution. After twenty evolutions, the system performance got steady with no further significant improvement as Fig. 6 shows and the evolution was then stopped.

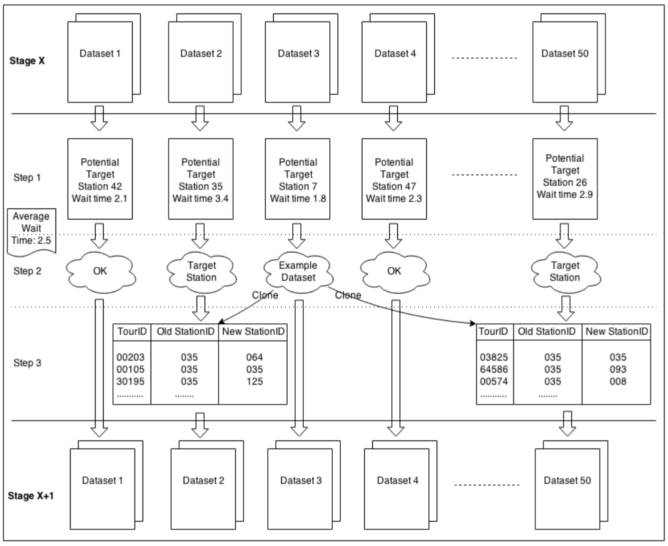

Fig. 3. Illustration of Genetic Algorithm

3.3 Deterministic approach

A deterministic approach is proposed to find out a universal SOC threshold, so that it can be easily implemented from the policy perspective. The idea is to recommend BEV drivers to use first accessible fast charging after its SOC is below the proposed threshold, and this recommendation aims to minimize potential congestion at fast charging stations. To determine the SOC threshold, a rule-base model is built as shown in Equation (9), tour completion and congestion at fast charging stations under different SOC thresholds are calculated, and these results are compared with the optimized situation achieved through the Monte Carlo and genetic algorithms.

$$C_{v,s} \sim P(SOC_{v,s}, SOC_{threshold}) =$$

$$\begin{cases} 1, & SOC_{v,s} \le SOC_{threshold} \\ 0, & SOC_{v,s} > SOC_{threshold} \end{cases} \tag{9}$$

4. RESULTS AND DISCUSSION

The Monte Carlo approach generated 50 datasets based on the charging decision model described in Equation (1)-(5). Fig. 4 shows the distribution of waiting time at each charging station in one dataset. As the figure shows, most charging stations have an average waiting time (before start to charge) shorter than half an hour, while the longest waiting time is around two hours. Taking the longest waiting time as the measure of dataset's performance, two-hour longest waiting time is the average performance among all 50 datasets (Fig. 5). Among the 50 datasets using Monte Carlo, the best performance is a dataset in which the longest waiting time is between 0.04-0.05 days (one hour). The average longest waiting time among all datasets is about 0.08-0.1 days (two hours). The worst cases have a waiting time between 0.16-0.17 days (four hours).

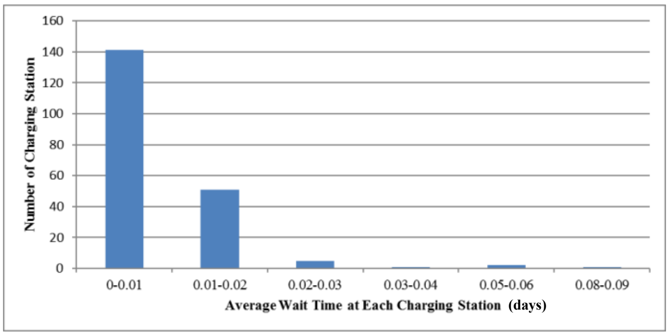

Fig. 4. Frequency of Waiting Time in One Dataset by Monte Carlo

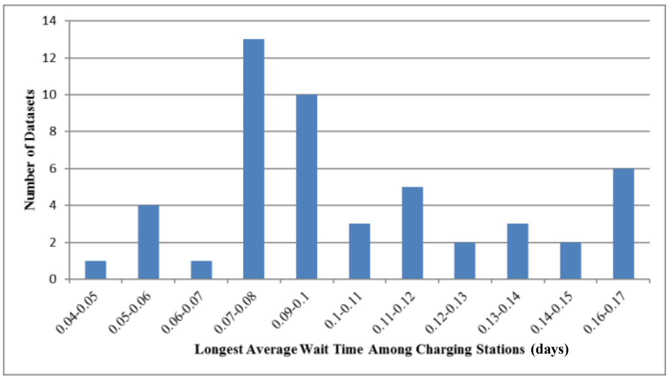

Fig. 5. Frequency of the Longest Waiting Time of All Datasets by Monte Carlo

The genetic algorithm was then implemented to optimize the results from the Monte Carlo approach. The 50 datasets generated by Monte Carlo were used as the initial population (stage 0 in Fig. 6). By taking the evaluation algorithm, performance of all datasets gets steady after 15 times of evolution (stage 15 in Fig. 6). At stage 20, the average longest waiting time is shorter than 0.04 days, and all datasets have consistent performance.

Although the genetic algorithm improves the performance of the most congested stations, the results also show that the most congested stations are similar among different evolution stages (Fig. 7). In stage 0, charging station 11 is the most congested station in 37 datasets, and in stage 20, charging station 11 is still the most congested station in most datasets. This indicates that congestion is driven by demand. Even with optimization, stations with higher demand are still more likely to be congested than other ones with lower demand.

By comparing the results of the Monte Carlo and genetic algorithm, it can be found that the best result of Monte Carlo is close to the final results of genetic algorithm. In other words, Monte Carlo can give a pretty good indication of what the extreme performance could be. Another advantage of Monte Carlo is this algorithm is relatively easy to implement and understand. However, genetic algorithm can give even better performance and much steadier performance among all datasets by reassigning charging demand at congested stations to other accessible stations with less congestion.

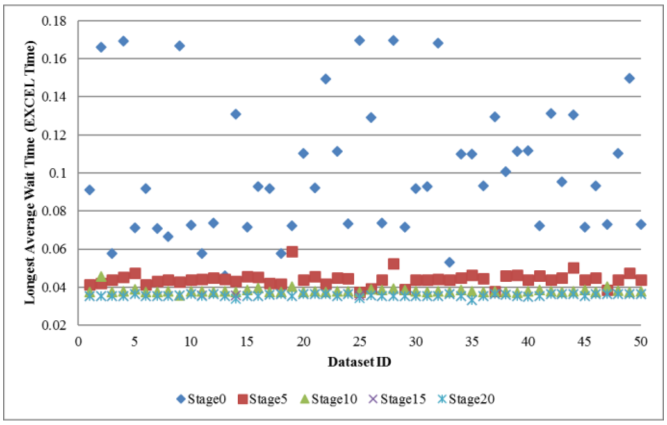

Fig. 6. Genetic Algorithm Results

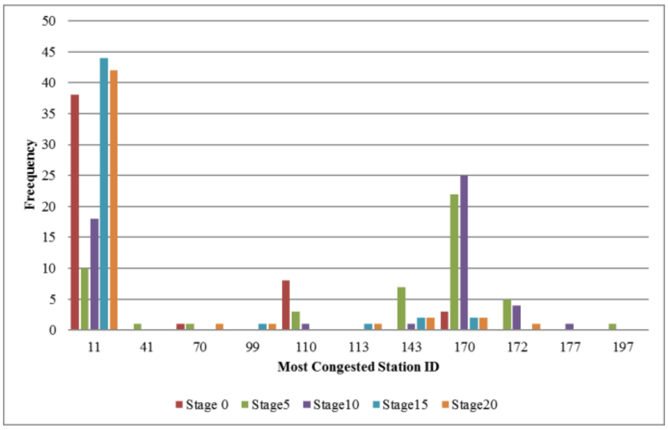

Fig. 7. Most Congested Station by Genetic Algorithm

From the policy perspective, both Monte Carlo and genetic algorithm approaches help to show the usage at each charging location in an optimized situation. However, there is a drawback of both approaches that the optimized charging strategy is like a black box that cannot be described clearly and easily. The steady result of the genetic algorithm requires all tours to be known in advance in order to calculate the best charging strategy, while the fifty datasets from Monte Carlo shows the wide range of possible system performance variance if everyone randomly choose their charging stations. In other words, the optimized results can be difficult if not impossible to achieve in the real world since we are unable to foresee all future tours.

A deterministic approach examined the performance of different SOC thresholds following the charging strategy as Equation (9). As a result, higher SOC threshold could achieve a higher percentage of tour completeness but also longer waiting time (Fig. 8). By comparing different SOC thresholds, it was found that the system achieved a relatively high percentage of tour completeness (90%) with a relatively low waiting time (nearly 0.045 days) when the SOC threshold is 40 miles. What's more, the average charge interval with SOC threshold of 40 miles is 70 miles, which is similar to the 71.7 miles charge interval achieved based on the genetic algorithm.

A similar deterministic approach was also performed assuming BEV range is 150 miles, and the best performance is also achieved when the SOC threshold is 40 miles. Thus, a 40-mile SOC could be the universal threshold, and BEVs with different ranges are recommended to use fast charging when their SOC drops below 40 miles unless the remaining range can afford to get to destinations where drivers can take level II charging.

However, BEV ranges are determined by not only the SOC but also many other factors such as driving behavior, A/C usage, and aerodynamic factors. Therefore, it would be helpful if there are instructions about how to achieve maximum vehicle efficiency when the SOC is low.

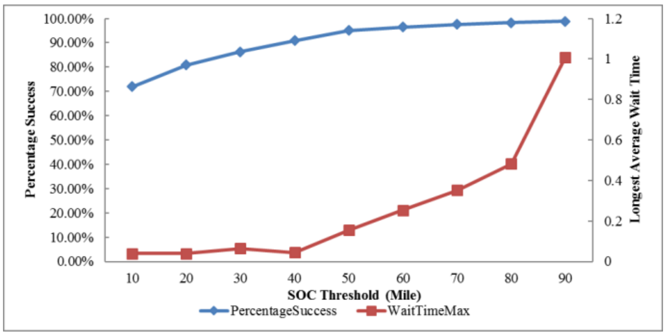

Fig. 8. SOC Threshold Influence on System Performance

5. CONCLUSION

This paper presents three approaches to optimize the fast-charging strategy for non-commute tours. Monte Carlo is relatively easier to implement and understand than the genetic algorithm, and it gives a fairly good indication of what the extreme performance could be. The best performance by Monte Carlo is close to the optimized results achieved by the genetic algorithm, while the genetic algorithm gives better and steadier results. The genetic algorithm optimized the overall charging strategy by reducing waiting time at the most congested stations to be shorter than one hour. However, one drawback of both genetic algorithm and Monte Carlo approaches is that the optimized charging strategy is hard to implement in the real world. Therefore, a deterministic approach was performed to generate a feasible while less optimized fast charging strategy. It was found that a 40-mile threshold will help achieve generally shorter waiting time and relatively higher tour completeness at the same time.

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