# Agent-based Modeling and Simulation on the Electric Vehicle Travelling Ability in the Smart Grid

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**Abstract.** The massive adoption of the electric vehicles in the near future with the rapid development of the smart grid shall significantly affair the resident transportation worldwide, while the modeling and simulation are the key approaches in analyzing the effect of the electrification of the vehicles. This paper firstly analyzed the procedures of the electric vehicles' refueling activities in the smart grid. Moreover, based on the complex adaptive system theory and agent-based modeling methodology, the paper further proposes the electric vehicle model through constructing the state-chart and rule base, and the agent-based electric vehicle model is derived. Furthermore, in order to compare the travelling ability between the electric vehicle and the original vehicle, the simulation platform is constructed and the corresponding interfaces, 3D module as well as the necessary functions are constituted. Based on the platform, this paper proposed two case scenes focus on the original internal combustion engine vehicle and electric vehicle respectively, and the simulation results denotes that the electrification of the vehicle shall reduce the travelling ability and confirms the effectiveness of the proposed model and simulation platform in studying the key phenomenon of the electric vehicles in the smart grid.

## Introduction

With the rapid development of the information and computer technology (ICT) as well as the massive energy demand to the electrical industry, the electricity grid worldwide is in the evolution toward the smart grid, which aims at providing the electricity service in an environmental, economic and interactive way with innovative technologies, preferred management and fine-rate openness [1]. The construction of the smart grid shall greatly enhance the adoption of the smart electrical appliances, and the electric vehicles (EVs), with the ability of driving partly or totally by the equipped electricity battery with less or even no harm to the environment, are supposed to be a competitive alternative transportation with the development of the smart grid [2].

However, the operation of the EV, hereinafter referred to the BEV, is heavily relied on the construction of its refuel infrastructure, i.e. the electric vehicle supplement equipment (EVSE), and the massive adoption of the EVs in the smart grid shall require abundant EVSEs which are under proper unified management of the formal facility, i.e. the EV central charging station (CCS) [3]. The EV travelling ability affected by the charging time shall be a critical factor that matters the popularization and the success of the EVs in the end. And on account of the fact that the massive adoption of the EV has not yet been achieved, modeling and simulation techniques are the ideal approach for discovering and assessing the driving ability with the electrification of the vehicles compared with the traditional vehicles with ICEs (ICEVs). Many modeling methodologies toward the EV operation in the smart grid have been studied within the global enterprises, colleges and research institutes. Musio and Damiano [4] models the EV routine drive and charging regularity based on the statistics of the driving objective, and Qian et al [5] proposes the EV charging load model based on the EV battery type, charging start time and state of charge. With the enhancement of the computing power, the heuristic modeling approaches have been adopted in the modeling of the EV. Zheng et al [6] constructs the charging model of the massive adopted EV and proposes the optimization algorithm based on the genetic algorithm, and Sousa et al [7] studies the EV

 

management optimization with the simulated annealing approach in the modeling and simulation. Following the development of the object-oriented programming method and unified modeling language. Dallinger et al [8] proposes the EV agent that can be adopted in studying the EV battery aging phenomenon and the EV-grid operation optimization, and Han et al [9] propsoes the EV agent to analyze its operation in the micro grid.

Considering the present modeling approaches' deficiency in revealing the refueling procedure and travelling ability of the EVs, this paper, with the consideration of the massive EV operation in the smart grid as a complex system, models the EVs with the agent-based modeling (ABM) methodology, studies the refueling procedure's impact to the EV travelling ability, and carries out the corresponding case scene simulation in order to verify the effect of the proposed model.

## Agent-based Modeling of the EVs

With the various energy, matter and information exchanges between the a huge amount of electricity consumers and the various electricity generators, the electricity grid itself is a prototype of the complex system, and the smart grid, with the operation of the massive adopted EVs, further enhances the complexity of the grid [10]. By regarding the EV's operation as a complex process, complex adaptive system (CAS) theory can be adopted to its modeling [11].

In order to better reveals the key phenomenon of the massive EV adoption with the agent-based modeling methodology, this paper reasonably simplifies the EV operation and refueling procedures by providing the following basic assumptions:

*Assumption 1*: The driving regularity and travelling requirements of the EV owners keeps unchanged with the electrification of their vehicles.

*Assumption 2*: The amount of the EVs is the same as the present ICEVs.

*Assumption 3*: The CCS is available for providing charging service to all the in-coming EVs.

The construction of the EV agent is based on the establishment of the state-chart as well as the rule base. The state-chart indicates the key states of the agent that needs to be analysis in the operation process, while the rule base forms the regulation for the agent during its operation. According to the analysis of the key EV states corresponding to its operation, the state-chart of the EV agent is proposed in the Figure 1. Its main operation space can be divided into the electricity network and transportation network, and the containing main states are as below:

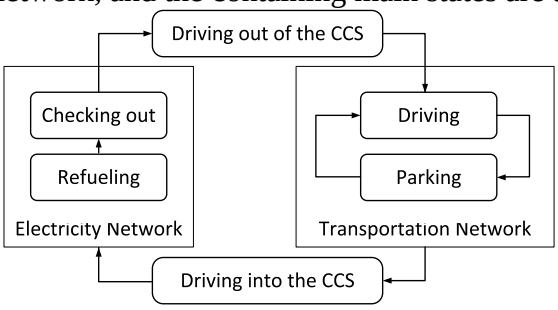


Fig.1. State-chart of the EV agent

*Driving*: The EV agent drives in the transportation network. Its driving start-up time, driving speed and destination distance depends on the related regulations in the rule base of the agent, and the energy stored in the battery shall be consumed to provide the power needed in the driving state.

*Parking*: The EV agent reaches the destination, its speed turns to zero and the no more energy shall be consumed in this state.

*Driving into the CCS*: After the EV agent’s battery depletes due to the driving energy consumption, the EV drives into the CCS and a request for the refueling service.

*Refueling*: By connecting with the EVSE, the EV agent’s battery in the CCS shall be charged.

*Checking out*: The EV agent shall go through the check out state to finish the refueling process.

*Driving out of the CCS*: The EV agent leaves the CCS with fully charged battery and continue its operation in the transportation network.

The rule base of the EV agent contains mainly the rules of the EV driving regularity, driving speed, state-of-charge (SOC) as well as the charging and discharging activities, which form the key

operation and property of the agent.

*EV Driving Regularity Rule*: The driving regularity rule mainly controls the agent-based on the proposed assumptions, the statistics of the present ICEV owners' driving record is adopted to form the driving regularity of the EV owners. Therefore the national household travelling statistics (NHTS) published by the U.S. Department of Transportation is applied in this paper [12]. There are four main vehicle types in the NHTS, i.e. auto, van, Sports Utility Vehicle (SUV) and pick-up. By adopting the IBM SPSS Clementine, this paper carries out the data mining task toward the driver weekday trip records of the four types of vehicles in the NHTS database, then the statistics of the ICEV owner driving start-up time per trip is illustrated in the Figure. 2, and the driving distance per trip statistics is illustrated in the Figure. 3. And the EV agent, with the same driving habit as the ICEV owners, shall have its trip start-time and trip distance $l(t)$ following the same distribution in their trip start-time selection and trip distance.

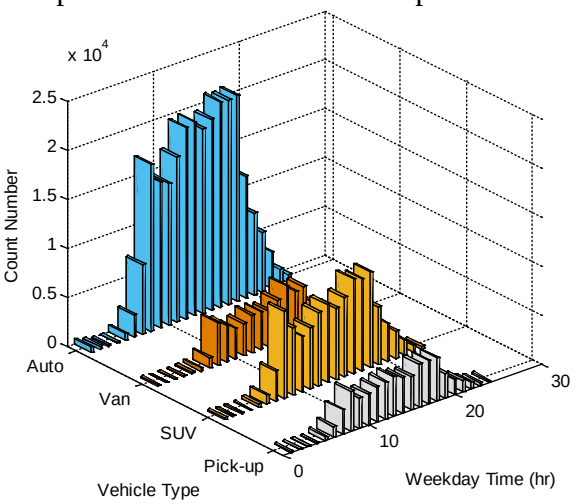


Fig. 2. The driving start-up time per trip

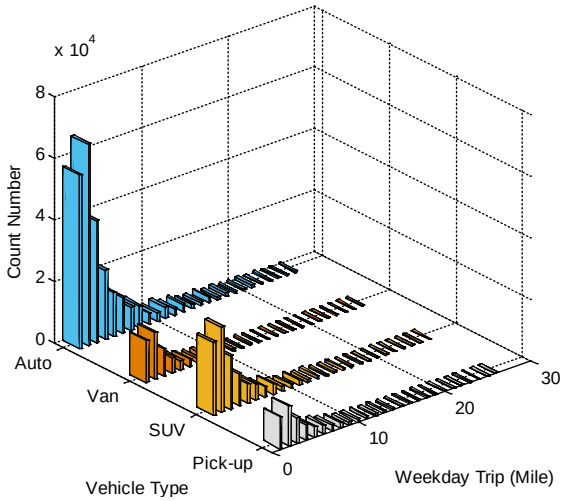


Fig. 3. The driving distance per trip

*EV Driving Speed Rule*: The driving speed of the EV agent $v(t)$ correlates to the road crowdness condition $\gamma_c(t)$ in the transportation network, and can be calculated in the Eq. 1:

$$v(t)=\begin{cases}(1-\gamma_c(t))v_{\max}, & \text{driving state}\\ 0 & \text{, else}\end{cases} \tag{1}$$

where $v_{\max}$ is the maximum speed of the EV agent, and the road crowdness condition $\gamma_c(t)$ can be derived from the Eq. 2 by given the present EV agent amount on the road $N_{\text{road}}(t)$ and its maximum avaible EVs $N_{\max}$.

$$\gamma_c(t)=\frac{N_{\text{road}}(t)}{N_{\max}} \tag{2}$$

*EV SOC Rule:* The state-of-charge of the EV battery $\beta(t)$ denotes the ratio of the remained enengy $C(t)$ to the battery's rated capacity $C_r$, and can be calculated through Eq. 3.

$$\beta(t)=\frac{C(t)}{C_r}\times 100\% \tag{3}$$

Considering the practical operation of the EV, $\beta(t)$ shall range between the maximum and minimum available SOC as is shown in Eq. 4:

$$\beta_{\min}\le\beta(t)\le\beta_{\max} \tag{4}$$

*EV Charging and Discharging Rule:* The charging and discharging process changes the SOC directly. By given the charging power $P_{\text{Ch}}(t)$ and discharging power $P_{\text{Disc}}(t)$ of the EV agent, the charged energy $E_{\text{Ch}}(\Delta t)$ and discharged energy $E_{\text{Disc}}(\Delta t)$ of the battery during time $\Delta t$ can be derived through Eq. 5 and Eq. 6:

$$E_{\text{Ch}}(\Delta t)=\int_0^{\Delta t}P_{\text{Ch}}(t)\eta_{\text{Ch}}dt \tag{5}$$

$$E_{\text{Disc}}(\Delta t)=\int_0^{\Delta t}\kappa(t)P_{\text{Disc}}(t)\eta_{\text{Disc}}dt \tag{6}$$

where $\eta_{\mathrm{Ch}}$ and $\eta_{\mathrm{Disc}}$ are the charging and discharging efficiency of the EV agent, and $\kappa(t)$ is its driving factor that denotes its driving states, and can be derived through Eq. 7:

$$\kappa(t)=\begin{cases}1, v(t)>0\\ 0, v(t)=0\end{cases} \tag{7}$$

The key parameters matters the vehicle travelling ability is the vehicle amount $N_{\mathrm{EV}}$ in the case scene, which can be calculated through Eq. 8:

$$N_{\mathrm{EV}}=e\eta_P\eta_R \tag{8}$$

where $e$ is the population of the case area, while $\eta_P$ and $\eta_R$ are respectively the vehicle occupancy and the EV ratio in the vehicle market.

The travelling ability of the EV can be assessed by the trip times. The trip starts with the probability of the EV owner's driving habit, during the trip the EV shall go to the CCS for refueling when its SOC drops to the minimum required SOC, and after being refueled the EV agent shall return to finish the trip or refuel again when needed. And based on the proposed state-chart and rule base, the EV agent shall be constructed through the UML and by the object-oriented programming methodology. And during the modeling of the EV agent, its travelling ability can be formed by establishing a corresponding parameter that records the finished trip times at set intervals.

## Case Scene Similation

Based on the former analysis to the EV's operation, the paper further carries out the following two case scenes denoting the travelling ability of the ICEV and EV, and the simulations are carried out to assess the travelling ability of the EV with the proposed EV agent. By executing the simulation platform, the operation scene of the proposed agent-based simulation platform is shown in Figure 4, through which the researchers can efficiently study the phenomenon when massive EV agents gathering together in the CCS during the simulation, and the relative database, 3D module and chart module are constructed and connected to the platform enhance the simulation by recording and visualizing the simulation result of the key parameters, as is shown in Figure 5.

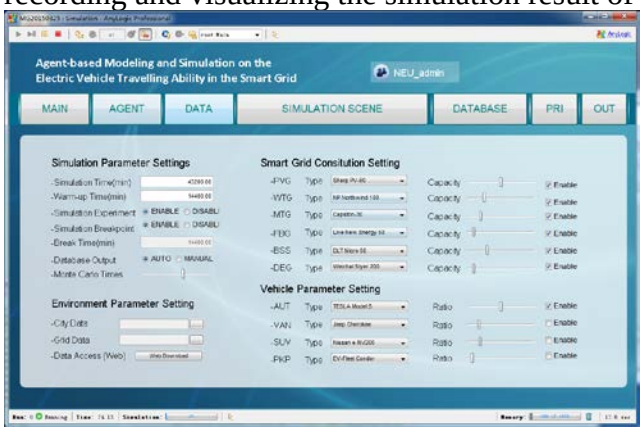


Fig. 4. Parameter setting interface


Fig. 5. Operation scene of the platform

Based on the proposed simulation platform, the case scenes of both the ICEV and EV shall be constructed, where the case scene I denotes the operation of the ICEV, while the scene II denotes that of the EV. This paper adopts all the parameters related to the case scenes with the NHTS statistics and the data from the U.S. Department of Energy [13]. The case population of the two scenes is set to be one over ten thousand of the population in Texas, i.e. 2300, and given the DOE provided $\eta_P$ to be 0812, the total vehicles in the proposed case area is 1868. And in order to reveal the phenomenon of massive adopted EVs, $\eta_R$ is set to be 0.8 and the EV amount in this case area is 1308. The brand and type of the EV as well as its parameters related to the refueling are also critical for assessing the travelling ability, and this paper assigns the latest Tesla Model S electric vehicle to be the specific EV in the case, and its key parameters are listed in the Table 1.

Based on the proposed simulation platform and the parameter settings, the simulation on the EV

travelling ability, i.e. the trip times is firstly carried out. By the long-time Monte Carlo operation, the results of the EV and ICEV daily trip times is given in the Figure 6. Meanwhile, in order to reveal the differences in the travelling ability, the monthly accumulation of the daily trip times' difference has been taken into statistics, and the average trip times of the two types of vehicles are listed in Table 2, while the corresponding monthly accumulation figure is illustrated in Figure 7.

Table 1 Key parameter settings

| Parameter | Value |
|---|---|
| Battery Capacity | 60.0 kWh |
| Charging Power | 10.0 kWh |
| Distance per Charge | 208 mile |
| Charing Efficiency | 0.90 |

Table 2 Average daily trip times of two case scenes

| Case Scene | Vehicle Type | Average Daily Trip Times |
|---|---|---|
| I | ICEV | 2.88 |
| II | EV | 2.66 |

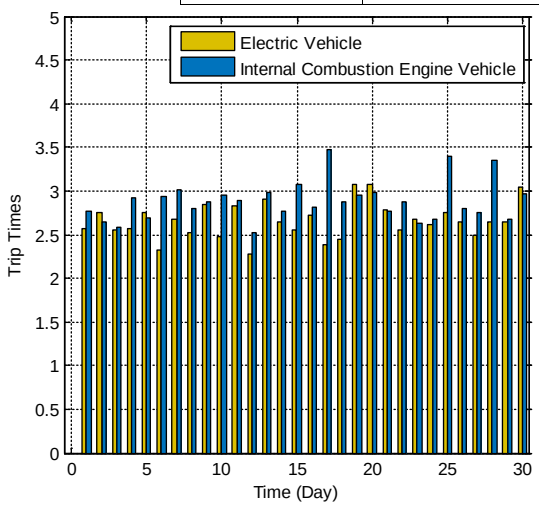


Fig. 6. Daily trip times of EV and ICEV

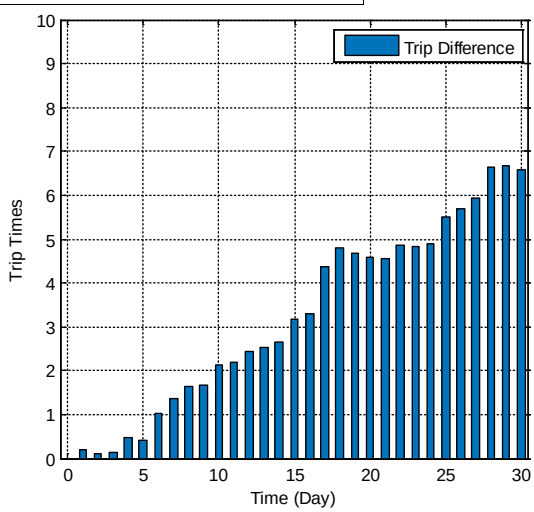


Fig. 7. Monthly accumulation of the daily trip times' difference

As can be concluded from the simulation results, the average daily trip times of the traditional ICEV is 2.88, which is quite similar to the NHTS statistics, denoting the efficiency of the proposed agent-based EV model in revealing the operation of the practical vehicle operation. And due to the Figure 7 and Table 2, the daily trip times of EV is less than the ICEV in general by 7.64% due to the refueling time, and the differences between the trip times of the EV and ICEV is up to over one time at certain days, denoting that the travelling ability of the EV is reduced by over 30% at maximum.

Moreover, according to the accumulated statistics in Fig 7, the trip differences shall add up with the daily operation of the EVs, therefore the EV owners shall lose over six times of the trip by average, confirming the travelling ability differences of the EV and ICEV from the view of the statistics. Furthermore, it should be noted that the simulation cases is based on the assumption that the service ability of the EV refueling infrastructure, i.e. the CCS is abundant for the EV refueling request, and considering the shortage of the EVSEs in the CCS due to the massive adoption of the EVs, which shall be a critical factor for the popularity of the EVs.

## Conclusion

This paper studies the agent-based modeling and simulation toward the EV travelling ability. Considering the present modeling approaches' deficiency in revealing EV operation in detail, by regarding the grid with the EV as a prototype of the complex system, the CAS theory and agent-based modeling methodology is adopted to the analysis of the massive EV operation, and by the construction of the state-chart as well as the rule base, the EV agent is proposed. To better reveal the EV operation and to enhance the model's practicability, the simulation platform is established,

meanwhile the case scenes of ICEV and EV are proposed based on the actual data from the statistics. With the complete analysis of the key procedures of the EV in the CCS and the EV agent model, the case scenes simulations are carried out. The simulation result verifies the efficiency of the proposed agent-based EV model in revealing the EV operation, and quantitatively confirms the obvious decrease of the vehicle after electrification due to the relatively long-time refueling time, indicating the significant meanings of the proposed agent-based model as well as the simulation platform in the modeling and simulation tasks toward the indepth analysis of the EVs in the smart grid.

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