A distributed EV charging strategy in an integrated energy system

Tao Zhu¹, Xiaoying Shi², Ronghua Duan³, Yizhen Wang³ and Yinliang Xu²

¹ Kunming Power Supply Bureau, Yunnan, China.
Email: 77066375@qq.com
² Electrical Engineering Department, Tsinghua University, Beijing, China
E-mail: shixy17@mails.tsinghua.edu.cn; xu.yinliang@sz.tsinghua.edu.cn.
³ Yunnan Power Grid Company, Yunnan, China.
Email: duanronghua@im.yn.csg; 51676390@qq.com.

Abstract. Electric vehicles (EV) are viewed as an environmental-friendly travel device but bring the driver with range anxiety. One of the solutions to tackle this issue is to recharge at the fast charging station (FCS). Since the traffic flow of the transportation network and the operation condition of the fast charging station varies from time to time, it is important to implement real-time charging guiding for the EV drivers. In this paper, we propose a distributed guiding method to search for the best FCS with minimum sum of time cost and electricity purchasing cost. The EVs are viewed as a distribution of spatial and temporal electrical loads, which would affect the locational marginal price (LMP) of the FCS. The varied LMPs would also react upon the EV driver’s choice. The proposed guiding method utilizes the wireless communication technologies. Simulation test demonstrates the effectiveness of the proposed EV guiding method in an integrated energy system.

1. Introduction
The EV has gained its popularity for its characteristic of less greenhouse emission and power consumption [1]. The EV technology has brings changes and challenges to the transportation system as well as the power system. For the transportation system, in order to relieve the EV driver’s range anxiety incurred by the limited driving range of EVs, the fast charging stations are gradually installed in the transportation system. On the other hand, the power system regards EVs as newly emerged dynamic loads, which requires additional power supply. Because of the indispensable charging process, the transportation system has faced the problem of the siting and sizing of the charging stations while the power system needs to tackle the increasing electrical load when a massive fleet EVs arrive at the charging stations.

The EV charging equipment can be divided into three types according to the charging power level they offered. The type I has a charging power less than 1.9kW and usually takes more than 4 hours to complete the charging process, thus the typical installation scenario of type I is home or office. The charging power of type II is less than 20kW and the charging time requires less than 4 hours and more than 1 hour, which result in its typical use as private or public charging. Type III is known as the fast charging type provides a charging power more than 50kW and can complete the charging process within 1 hour [2]. FCS for EVs is just as the filling stations for the combustion engine vehicles. The FCS is chosen to be installed in the transportation networks for convenience.

The FCS can be viewed as the coupling point of the transportation system and the power system. The FCSs tend to be connected to the feeders of distribution network, receiving the electrical power from
the feeders. The EVs arrive at the FCSs and get recharged. Generally, there are several FCSs scattered in the city transportation network. Since the EV drivers prefer a quick recharging process and resume their journey soon, traditional guiding applications tend to lead the EV driver to the nearest FCS. However, this may incur the congestions on certain road segments because EV drivers close to each other may be led to the same FCS thus the recharging requires longer time. One the other hand, the feeder where the FCS locates would suffer from heavy load burden, which may cause problem for the power system, i.e. voltage drop or the thermal overloads [3]-[5].

The multi-agent system (MAS) framework is originated from the field of artificial intelligence and has been wide adopted in the power system as well as the transportation system. Lagorse et.al performs the distributed energy management based on the MAS and the power trading between households can also be achieved by the MAS [7], [8]. The MAS has also been used in constructing the vehicular relay network. Unlike the central control strategies proposed in the [6], this paper implements the MAS for distributed communication and guiding. Agents, who are located at road intersections and FCSs respectively, work together for guiding.

This paper proposed an innovative EV charging guiding method, which considered both the electricity purchasing cost and the time cost. The electricity purchasing cost is calculated by the LMP and the driver’s charging demand. The time cost is composed of the driving time, the waiting time and the charging time. In our work, the connection between the two systems is reflected by the LMPs, the EVs can be viewed as the spatial and temporal distributed electrical loads, the charging behaviours of EVs would influence the loading condition of the feeder and then influence the LMP at the feeder. If there are massive fleets of EVs arrive at a certain FCS, it may cause the overload situation and pose threat on the power system security. At this heavy load situation, the increased LMPs can act as a signal and cause a negative effect on the decision of charging choices of drivers. The drivers tend to choose other FCSs with cheaper electricity price and then the heavy load situation at the FCS can be relieved. To find the minimum total cost, the discrete biased min consensus (DBMC) algorithm is implemented. DBMC algorithm has been proved to be useful in addressing the shortest path problem [9]. The DBMC has also shown its effectiveness in finding the shortest path in the graph theory based problem, i.e, the peer to peer power trading in the DC microgrid [10].

The proposed guiding method can be divided into the following steps: Firstly, the driver updates the charging demand with smart devices; the agents at intersections would collect the charging demand and broadcast it to their neighbouring agents with wireless communication technology. The charging demand is broadcasted to the agents at FCSs, and then the LMPs would be recalculated with all the additional charging demands at the time slot. Agents at FCSs provide waiting time, charging time and electricity purchasing cost, agents at intersections provide driving time, and then the best charging route is selected while considering the driver’s preference. The proposed EV charging guiding method is proved with effectiveness and adaptiveness in the coupling systems through simulations with a 24-intersections transportation network coupled with a 108-bus distribution network.

The main contributions of this paper are listed as follows:

- The proposed guiding method adopts the MAS technology and the consensus algorithm. Few literatures implement the combination of those two artificial intelligence technologies to address the EV guiding problem.
- This paper proposes a distributed EV guiding method which considering the interaction between the transportation system and the power system by using LMPs as a signal.

Section II introduces the basic graph theory, the utilization of the MAS framework and the distributed biased min-consensus algorithms. Section III presents the model of time cost and purchasing cost as well as the whole procedure of the proposed guiding method. In Section IV, the proposed guiding method is verified to be effective by different simulation studies and Section V concludes this paper.

2. PRELIMINARIES

2.1. Graph theory

In the transportation system, the transportation network can be represented by the undirected connected graph, which is denoted as $G=(N, E)$. The nodes are denoted by $N = \{N_1 \ldots N_n\}$, with $n$ representing
the number of road intersections. The set of links is $E_T = \{E_{T1}, \ldots, E_{Tm}\}$ with $m$ denotes the number of links in the graph as well as in the transportation system. Two nodes are neighbors if they are distinct and directly connected by a link, and $N_i$ represents the set of node $i$’s neighbors. $E_{i,j}$ represents the link between $i$ and $j$ and the weight of it is denoted by a non-negative $d_{ij}$.

2.2. Implementation of multi-agent system

The MAS is used in the proposed guiding method for the following three objectives, which are data collection, communication and algorithm implementation. The agents at road intersections are responsible for collecting traffic data, such as the arriving rate of vehicles. Agents collect the charging demand of the EV driver and then broadcast it to the neighbouring agents and then gradually broadcast it to all agents. Agents at intersections calculate the driving time on the road and transmit the time cost; the agents at FCSs update the collected charging demand and update it to the distribution system operator (DSO) and receive the updated LMPs, then the agents return the purchasing cost, time and charging time to the driver by the communication between agents. The driver can receive the result and then can make their own charging choice with their inclinations.

2.3. Distributed biased min-consensus algorithm

The biased min consensus algorithm has been proved to be equivalent to be the shortest path problem [11]. Shi et al has implemented the algorithm in the optimal power trading by finding the transmission path with minimum power loss [10]. Inspired by this algorithm, the authors use the algorithm and apply it in the road guiding problem. The DBMC algorithm is shown as follows [9]:

$$x_i(k+1) = 0, i \in S_1$$

$$x_i(k+1) = \min_{j \in N_i} \{d_{ij} + x_j(k)\}, i \in S_2$$

where $x_i$ is the state value of node $i$, $d_{ij}$ is the biased value, the $S_1$ is the set of leader nodes and the $S_2$ is the set of the follower nodes.

3. COST MINIMIZATION PROBLEM FOR ELECTRIC VEHICLES

The main charging methods of the EV are the plug-in charging [12]. The FCS can achieve fast charging for the EVs, the FCSs are scattered at the important intersections of the cities, this is aimed to relieve the range anxiety of the EV drivers [13], since the limited driving range of the EV when compared with the combustion engines vehicles. Therefore, it is virtually important to do the real-time charging guiding for the EV drivers in case they cannot reach the destination because of the roadside breakdown.

![Figure 1. The integrated electrical vehicles charging guiding framework.](image)
The drivers tend to be selfish and desire to minimize both the time cost and the electricity purchasing cost. But the two terms may have different importance to the EV driver, sometimes the driver has plenty of time and prefer cheaper electricity and do not mind wait for longer time, vice versa. The time cost mainly involves three types: the time drive to the charging station, the time waiting for recharging and the recharging time. The financial cost is the payment for purchasing the needed electricity. The guiding method of coupled systems is illustrated in Fig.1. For the possibility of roadside breakdown before reaching the FCS, it is assumed that:

- The remaining energy of the EV battery is enough to support the driver to reach the FCS.
- The charging price offered to each driver, once settled, would remain the same despite the load conditions changes during the time the driver driving to the FCS.

### 3.1. Time cost model

#### 3.1.1. The vehicle arriving model

The arriving process of each vehicle is independent, which can be modeled as the Poisson distribution, the parameter $\lambda$ of the Poisson distribution describe the average arriving rate of the vehicles at a road segment or an FCS. The probability that there are $k$ vehicles on the road segment or an FCS is listed as follows [14]:

$$
f(k, \lambda) = \frac{(\lambda)^k e^{-\lambda}}{k!}, \quad k \geq 0.
$$

#### 3.1.2. Driving time $t_{i,td}$

In the urban transportation network, the congestion situation varies according to the time periods of a day. For instance, there is tend to be heavy traffic flows during the morning time because people are heading to work and during the dusk time when people coming back home. Dynamic congestion situation can change the fast path to reach destination for each driver. The driving time when considering congestion on the road can be modeled by the latency function $t_{ij}(\eta_{i})$ [14], which is shown as follows:

$$
t_{ij}(\eta_{i}) = t_{ij}^0 \left[ 1 + 0.15 \frac{\eta_{i}}{c_{ij}} \right]^l, \quad \forall l \in E
$$

where the $t_{ij}^0$ is the travel time with no traffic on the link $l_{ij}$, i.e. the length of $l_{ij}$ divided by the speed limit, and $\eta_{i}$ is the current arriving rate on the link $l_{ij}$ and $c_{ij}$ is the capacity of link $l_{ij}$.

Assume the optimal driving route to the chosen FCS is represented as follows:

$$
\text{Route}(O \rightarrow D) = O \rightarrow l_1 \rightarrow l_2 \rightarrow \ldots \rightarrow D, l_k \in OD
$$

where the $O$ represent the original position of the driver and the $D$ represent the destined FCS, $OD_i$ is the link set of the driver $i$’s navigated route.

The total drive time of the guiding route is calculated as follows:

$$
T_{i,j} = \sum_{l_k \in OD_i} t_{ij}(\eta_{i}^k).
$$

#### 3.1.3. Waiting time $t_{i,tw}$

The queuing EVs waiting to recharge at an FCS can be represented by the $M/M/s/K$ model [15]. The arriving process follows the pattern of Poisson distribution, the number of the charging poles at an FCS is $s$, the waiting room in an FCS is $K$. The real-time service rate of the FCS can be expressed as:

$$
\rho(t) = \frac{\eta(t)}{\mu}
$$

Where the $\eta(t)$ and $\mu$ represent the real-time arriving rate and the service rate of the vehicles. The possibility of no EV at the FCS is:
\[ p_0(t) = \left[ 1 + \sum_{i=1}^{K} \rho(t)^i \right]^{-1} \]  
(7)

The customer loss rate is:

\[ p_k(t) = \frac{\rho(t)^K}{s^k \alpha} \cdot p_0(t) \]  
(8)

Then, from (6)–(8), the average waiting time can be expressed as:

\[ EW(M / M / 1 / K) = \frac{\text{Num}(t)}{\eta(t)[1 - P_k(t)]} - \frac{1}{\mu} \]  
(9)

where the \( \text{Num}(t) \) is the number of EVs at FCS at the time slot \( t \).

Then, the waiting time for the driver \( i \) is:

\[ T_{i,w} = EW(M/M/1/K). \]

3.1.4 Charging time \( t_{ic} \).

Direct current fast charging is conducted at FCS. The commonly used charging method is the one with current as constant and the voltage as constant (CCCV). The charging process can be categorized into two stages: the first is the charging stage under the constant current, when the battery voltage reaches the threshold voltage value; the charging mode then turns to the constant voltage charging. The former stage is when the battery is charged at rated power, while the later stage is when the charging is gradually completed with a continuously decreasing charging power. Tesla has recommended its consumers to charge EVs only at the first stage, i.e. charging to about 80% SoCs, to avoid the time-consuming charging process in stage 2 [16]. Therefore, the charging power function modeled as follows:

\[
P(E) = \begin{cases} 
P_{\text{max}}, & E < E_{\text{SoC}} \\ b - aE, & \text{otherwise} \end{cases}
\]  
(10)

where the \( P_{\text{max}} \) is the rated charging power at first charging stage; parameter \( a \) and \( b \) are the charging parameters of the second charging stage [16]. \( P(E) \) represent the charging power of the battery with energy level \( E \).

Then, the charging time \( T_{i,c} \) can be modeled as follows:

\[
T_{c,i} = \begin{cases} 
\frac{E_{\text{SoC}} - E_i}{P_{\text{max}}}, & E_i \leq E_{\text{SoC}} \\
\frac{E_{\text{SoC}} - E_i}{P_{\text{max}}} + \frac{1}{a} \ln\left(\frac{b - aE_{\text{SoC}}}{b - aE_i}\right), & E_i > E_{\text{SoC}} 
\end{cases}
\]  
(11)

where the \( E_i \) is the current energy of the EV \( i \)'s battery, \( E_i \) is the energy when EV is fully charged and the \( E_{\text{SoC}} \) is the energy that the battery reaches 80% SoC. Since a near-full SoC would lead to a longer charging time, which would lower the utilization efficiency of the charging poles. It is assumed that the drivers only charge to the 80% SoC and then would leave the FCS.

3.2 Locational marginal price recalculation

There would be a certain amount of charging demands updated by the EV drivers in the same time slot and the FCSs would receive these charging demands. However, the drivers tend to be changeable on their charging decisions, for example, one might decide to charge at the FCS with cheaper electricity price and then the driver might decide to charge at the FCS with less queuing time. In other words, the electrical load of each FCS is changeable and the LMP would not be settled until the charging choice of EV driver would not change anymore, then each FCS could confirm the number of EVs and recalculate the LMPs at a certain time slot. For example, if there are 5 charging requests received by one FCS in the time slot \( s \), and after confirmation there are only 3 EVs choose to charge at this FCS, then the new loading level of this feeder is only increased with these three charging demands for the time slot \( s \). As shown in the Figure 2, the EV driver updates the power demand and receiver the relative information of each FCS, the driver first chooses the FCS 2. At the second confirmation, the driver changes it to the FCS 1, and then the FCS 1 is confirmed for the rest few time confirmations, and then the recalculated LMP of that time slot of the FCS 1 is offered to the driver. Noting that the times of confirmation is
limited, such as the EV driver has to confirm the FCS within 4 times confirmations, so the convergence problem of the LMP calculation can be avoided.

![Diagram](image)

**Figure 2.** The charging decision confirmation process.

The LMPs of each FCS might be different because they tend to be connected to different feeders of the distribution system. The electricity price of each FCS is determined by the load condition of that time slot. Without the loss of generality, the optimal power flow model is implemented in the distribution network [17]. The LMPs change according to the loading condition of the corresponding feeders. If there are massive fleets of EV arrives at an FCS, which means the power demand of this bus would increase and thus the LMP should also increase for the additional power generation. The increased LMP act as a feedback signal and react upon on the EV driver’s charging choice and thus changes the traffic flow in the transportation system.

### 3.3. Rapid charging station model

As soon as the charging request updated to the agent, the agent would broadcast the power demand to its nearby agents gradually reach all the agents. Agents at each intersection would collect and exchange the traffic information and calculate the driving time on each road segment. Each driver would be confirmed several times of their charging decision, and then the FCSs would provide the final LMPs, waiting time and queuing time for the driver. With the three terms settled, the total cost is minimized by minimizing the driving time.

Assume the current time slot is \( t \), the time cost of the driver can be estimated as follows:

\[
TC = T_{i,td} + T_{i,tw} + T_{i,tc}
\]

Where the \( T_{i,td} \), \( T_{i,tw} \) and the \( T_{i,tc} \) are the driving time to the FCS, the waiting time at FCS and the charging time for the driver \( i \), respectively, which are calculated by using the transportation data at the time slot \( t \). The financial cost is modeled as follows:

\[
FC = \lambda(t) \cdot \Delta E
\]

where the \( \lambda(t) \) is the recalculated LMP at the time slot \( t \), \( \Delta E \) is the energy charged for the EV. The total cost of the driver is then modeled as follows:

\[
C(t) = TC(t) + FC(t).
\]

By letting the driver chooses the desirable FCS, the term FC and the term \( T_{i,tw} \) and \( T_{i,tc} \) can be settled.

### 3.4. Optimal routing discovery

The optimal guiding route is obtained by the distributed biased min consensus algorithm. For the agents at road intersections, the utilized form of the algorithm is:
Where the $S_1$ is the set of the FCSs and the $S_2$ is the set of the agents at road intersections.

4. Simulation Studies

In this section, case studies are performed to demonstrate the effectiveness of the proposed distributed guiding method.

4.1. 24-Intersection transportation system and 108-bus power system

The effectiveness of the proposed guiding method is tested on a 24-intersection transportation network and a 108-bus distribution network coupled system [17], [18] as shown in Fig. 3 and 4. Assume there are 2 FCSs located at intersection 2 and intersection 13, which are connected to bus 5 and bus 22 respectively. The charging vehicle has a charging demand of 50kWh. The driving speed of the EV is set as 60km/h. In this study case, it is assumed that each FCS has 50 charging poles and there are only 8 and 9 charging poles are available in the two FCSs, respectively. At current time, the FCS operation data is shown in the Table I.

| FCS | Connected bus | LMP ($/MVA-hr$) | Updated LMP ($/MVA-hr$) | Arriving rate (per hour) | Charging poles | Waiting time (min) |
|-----|---------------|----------------|-------------------------|--------------------------|----------------|-------------------|
| 2   | 5             | 28.87          | 30.25                   | 10                       | 30             | 4.5               |
| 13  | 22            | 40.25          | 43.33                   | 11                       | 30             | 3.2               |

Suppose there are charging demands arise and are collected by the agents at intersection 4, 7, 10, 15, 18, 19, 20, 22 and 23, the road agents then update the charging demand to the FCS agents. The agents at intersection calculate the driving time according to the traffic data and the agents at FCS calculate the economic cost and waiting time. Then the distributed biased min consensus algorithm is activated to search for the optimal routing with minimum charging cost for each charging demand. The minimum charging cost is then broadcasted to the corresponding driver by implementing the distributed min
consensus algorithm and finally obtained the routing strategies by searching for the parent nodes in a recursively manner.

| Intersection | Navigated FCS | Optimal routing | Total cost |
|--------------|---------------|-----------------|------------|
| 4            | 2             | 4→3→1→2        | 10.23      |
| 7            | 2             | 7→8→6→2        | 14.73      |
| 10           | 13            | 10→11→12→13    | 27.52      |
| 15           | 13            | 15→14→11→12→13 | 31.53      |
| 17           | 13            | 17→19→15→14→11→12→13 | 33.63 |
| 18           | 2             | 18→7→8→6→2    | 17.23      |
| 19           | 13            | 19→15→14→11→12→13 | 36.00      |
| 20           | 2             | 20→18→7→8→6→2 | 35.95      |
| 22           | 13            | 22→15→14→11→12→13 | 43.43      |
| 23           | 13            | 23→14→11→12→13 | 36.03      |

4.2. Dynamic transportation topology scenario

In general, the topology of transportation network is more dynamic because of the road construction and maintenance, or the road congestion caused by massive fleets in the rush hour of a day. On the other hand, however, the access to the charging service is also influenced by the traffic flow, for instance, the massive fleets of the EV charging may bring the FCS a long waiting queue and heavy electrical load to the connected bus. Under the overloaded situation, the FCS needs to quit the charging service so as to avoid road congestion.

Suppose the three topology changes occurred when the agents are planning the guiding routes for the EV drivers, at the rush hours, FCS 2 is fully loaded roads and there is road congestion occurred on the road segment $E_{10,17}$ and $E_{18,20}$ at iteration 8, 10 and 12, respectively. The dynamic changes in the transportation network require the guiding method can be adaptive to the topology changes. The real-time traffic information is gathered and shared by the MAS with each iteration the optimal charging path is searched with the real-time transportation network information, thus the EV driver can always obtain the guiding path to the accessible FCS. The parameter settings are the same as in the case A. The guiding results are shown in the Table III.

Figure 5 shows that despite frequent topology changes occur during the guiding process, the proposed guiding method can well adapt to these changes and converged within 21 iterations. The optimal routings which suitable for the topology changes are listed in Table III. Notice that the guiding process for the driver 23 converged firstly within 9 iterations, it is because that the optimal path for the EV driver 23 is not influenced by any topology changes, the guiding path in this case is the same as that of the Case A. By contrast, the recharging guiding for EV driver 18 takes 21 iterations to reach convergence, since guiding path for the EV driver at 18 has to be rescheduled since the FCS 2 is no longer available for charging service. For the EV driver at 20, the guiding path has excluded the edge $E_{18,20}$ and replaced with accessible edges. On the other hand, because of these topology changes, the charging cost for each EV driver also changes. Some drivers need to drive longer distance to reach the FCS 13 while the electricity purchasing cost in FCS 13 is higher. To be concluded, the proposed guiding method can react to these topology changes very fast and the offer the driver with newly planned routing strategy.
Figure 5. Updating process of the charging cost under the dynamic topology scenario

Table 3. Result of total time charging at the fcs with minimum driving time of case a.2

| Intersection | Navigated FCS | Optimal routing | Charging cost |
|--------------|--------------|-----------------|---------------|
| 4            | 13           | 4→3→12→13      | 18.70         |
| 7            | 13           | 7→8→6→2→1→3→12→13 | 40.36     |
| 10           | 13           | 10→11→12→13   | 27.52         |
| 15           | 13           | 15→14→11→12→13 | 31.53         |
| 17           | 13           | 17→19→15→14→11→12→13 | 46.08     |
| 18           | 13           | 18→7→8→6→2→1→3→12→13 | 42.86     |
| 19           | 13           | 19→15→14→11→12→13 | 43.71         |
| 20           | 13           | 20→19→15→14→11→12→13 | 46.2        |
| 22           | 13           | 22→15→14→11→12→13 | 48.51         |
| 23           | 13           | 23→14→11→12→13 | 36.03         |

5. Conclusion
A distributed guiding method for real-time EV charging is proposed in this paper. The guiding problem is constructed as an optimal routing searching problem in the transportation network. The proposed guiding method is based on the multi-agent system and wireless communication technology, which can achieve data processing very fast. The road congestion and the queuing time in the fast charging station are considered in the model while the electric vehicles are viewed as electrical load and can affect the locational marginal price, which then can react upon the choice of the drivers. Numerical simulation has been performed on both small and large scales transportation network and power network coupled system. The results demonstrate effectiveness, extendibility and robustness of the proposed guiding method. Future works will focus on a more accurate way to calculate the LMPs under the varied load conditions caused by the EVs.

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