Blockchain-Based Electric Vehicle Incentive System for Renewable Energy Consumption

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***Abstract*—The rising proportion of renewable energy (RE) penetration with high variability introduces immense pressure on the stability of power grids. At the same time, a rapid increase in electric vehicle (EV) penetration level leads to uncoordinated charging loads, which poses significant challenges to operators. By properly guiding and scheduling the charging behaviors, EV may no longer be a burden, but a valuable asset to mitigate the RE integration problem. In this brief, we first propose a prioritization ranking algorithm of EV drivers based on their driving and charging behaviors, and then we propose a blockchain-based EV incentive system to maximize the utilization of RE. The proposed system is secure, anonymous, and decentralized. By incorporating the utilities, EV drivers, EV charging service providers, and RE providers into the proposed incentive system, this brief provides a plan to guide the EV users to charge at the desired time frames with higher RE generation. The market mechanism of the incentive system is discussed. The effectiveness of the system is verified by simulation.**

***Index Terms*—Electric vehicle, blockchain, renewable energy, smart grids.**

I. Introduction

OVER the past decade, renewable energy (RE), such as solar energy and wind power, has experienced significant performance improvement and huge cost reduction. The electric grid is in the midst of a remarkable shift as it integrates increased RE into the system to mitigate climate change and energy shortage. However, due to the intermittent nature of RE, this remains a challenging task for grid operators. In the meantime, use of EV is becoming a mainstream consumer offering. While the EV load growth reduces fossil energy consumption, this could also prove to be burdensome for power grid operators and utilities, because EV load introduces harmonic currents and raises power quality issues due to its nonlinear characteristics and uneven distribution [1], [2]. In the future, more advanced electric vehicle supply technologies (EVSE), such as extreme fast charging and larger capacity battery charges, are expected to further amplify the EV load problem in the future [1], [3].

We believe through proper guidance and scheduling, the grid operator need no longer treat EV as a burden to the grid operators; rather, it can be a valuable asset that stabilizes the intermittency of RE and shifts its peak load. The premise for such an assumption is that once the load of all individual EVs is aggregated and controlled, it can lead to greater controllable conformity. The aggregation of the EV loads could be used as an energy buffer to store surplus RE produced during sunny and windy hours, which is then fed back to the grid during the peak load periods. However, how to effectively guide the EV users to charge in a desired manner is a problem.

Many studies have been carried out on EV and RE coordination. Based on predicted customers' aggregate load, a real-time decentralized demand-side management system was designed in [4] to adjust the EV load. In [5], researchers studied the EV optimization problem by considering the EV arrival rate, RE injection, and the electricity price based on the Markov process. The authors developed a control scheme in [6] to coordinate the EV charging behaviors using RE generation. In [7] the economic studies of EVSE were carried out using stochastic modeling. Most works on EV dispatching require real-time pricing or time-of-use pricing scheme and vehicle-to-grid (V2G) capability, which is yet far from being industrialized.

Although research on dynamic price incentives has shown great effectiveness, it is noteworthy that the highly regulated electric pricing system still dominates. Yet, there are still many technical obstacles and regulations concerning real-time pricing: (a) The effectiveness of the monetary incentive varies from individual to individual. For those with tight business schedules, the impact of a monetary incentive scheme tends to be less effective. For those with more flexibility in their daily schedule, however, they may be more willing to adjust to the charging time and power, while paying less. (b) In reality, the electricity price is subject to government regulations, and the utility does not have full access to determine the price. Therefore, the dynamic price incentive is difficult to be implement. (c) Since there are monetary price incentives, the currency will remain as a minor function of guiding EV charging. Because the economic function of money is enormous, the monetary incentive of EV cannot accurately reflect the energy demand on RE, EV, and the electricity market. Such inaccuracy will ultimately lead to the failure and ineffectiveness of the monetary incentive system. (d) Monetary incentive transactions often rely on existing credit card or

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currency trading systems which may lead to a relatively higher cost.

Recently, blockchain, which is an emerging distributed database technology, has drawn great attention for wide applications in finance, healthcare, business management, and utilities. Blockchain is a decentralized, secure, and low friction alternative transaction technology that allows for secured data storage, synchronized information sharing, and trusted transactions executing in a peer-to-peer network, and yet provides an alternative solution to reward users without the involvement of the utility pricing scheme [8]. In [9], the authors proposed a solar power based optimization method for the incorporation of EV, energy storage, and cryptocurrency. An energy coin system is proposed to enhance the EV's information security that is stored in the cloud and edge computing environment [10].

In this brief, we first propose a prioritization ranking algorithm to differentiate the EV drivers and to guide their charging manner in a utility-desired manner without any monetary incentives involved. Then, we propose a blockchain-based EV incentive mechanism to further enhance the guiding capability. The proposed system does not require extra energy storage units and can be adopted at large-scale.

The remainder of this brief is organized as follows: Section II presents the system architecture design, the priority ranking algorithms, and the blockchain-based incentive system as well as its market mechanism. Section III shows the simulation results for the effectiveness verification of the proposed system, followed by the conclusion in Section IV.

II. System Architect Design

An EVSE, which contains one or more chargers, normally cannot control EV drivers' driving and charging behaviors, such as the arriving time at the EVSE, the time of plug-in and plug-out, the time of leaving the EVSE, the charging duration time, and the charging capacity demand. Nor can a utility do this. Therefore, it is necessary to develop and adopt a mechanism to effectively guide EV charging behaviors. This section presents the system design to encourage EV drivers to adjust their charging time toward a higher RE generation period without enforcing a dynamic pricing scheme.

A. System Infrastructure

A microgrid consisting of EVSE and RE sources is connected to the distribution power grid [11]. The energy storage unit is optional in the proposed system. An overview of system structure and its components is shown in Fig. 1, in which RE in the microgrid environment is first considered to be consumed by the local EV charging demand, and the remaining RE is then injected into the distribution grid.

There are two fundamental components in the system: one is the drivers' prioritization ranking scheme and the other is the EV-coin incentive mechanism.

B. Prioritization Ranking

The system assigns drivers with priority to differentiate those who are more aligned with the system guidance than those who are not. Charging prioritization is the basis of the proposed system. Each EV driver is given a prioritization ranking index, S, which represents the priority in charging. Users with higher priority scores are entitled to benefits of priority charging, shorter wait time, lower charging price, faster charging with higher charging capacity assigned, etc.

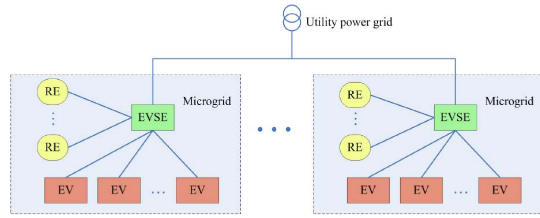


Fig. 1. The structure of EV charging networks with RE. The microgrids, which are formed by EV, RE, and EVSE and other units, are connected to the utility power grid. EV and RE are coordinated through EVSE in the local microgrid under the incentive scheme.

S is updated after each charging activity by (1).

$$S(i+1) = S(i) + \int_{t_{st}(i)}^{t_{et}(i)} \alpha(t)\mathrm{d}t, \tag{1}$$

where $\alpha(t) \in [-1, 1]$ is the charging reward factor at the time t, $t_{st}(i)$ and $t_{et}(i)$ are the starting time and the ending time of the i-th charging session, respectively. For simplicity of notation, in the rest of this brief, we use α_t to represent $\alpha(t)$.

In this brief, our goal is to guide the EV users to charge with more RE without the involvement of an electricity price scheme. Hence, we set α based upon the generation of RE and the consumption of RE by EV charging, as follows.

$$\alpha_t = \begin{cases} \frac{\min(P_{ev,t}, P_{re,t}-P_{mg,t})}{P_{re,max}-P_{mg,t}}, & \text{if } P_{re,t} > P_{mg,t}, \\ 0, & \text{if } P_{re,t} = P_{mg,t}, \\ -\frac{\min(P_{ev,t}, P_{mg,t}-P_{re,t})}{P_{evse}}, & \text{if } P_{re,t} < P_{mg,t}, \end{cases} \tag{2}$$

where $P_{re,t}$, $P_{mg,t}$ and $P_{ev,t}$ are the total power of RE generation, the total power of consumption of the local microgrid excluding EV charging load, and the total power of consumption of EV charging load at time t, respectively. $P_{re,max}$ is the capacity of RE generation in the microgrid. P_{evse} is the capacity power of all the EVSE in the microgrid. There are no limits of $P_{re,t}$, $P_{mg,t}$ and $P_{ev,t}$. However, we assume the microgrid will use RE first when it is available, and there will always be stable secondary power supply from the utility. $P_{re,t}$ and $P_{ev,t}$ are given as follows.

$$P_{re,t} = \sum_{m} P_{re,m,t}, \tag{3}$$

$$P_{ev,t} = \sum_{v} P_{ev,v,t}, \tag{4}$$

where m is the number of RE units, v is the number of EV charging sessions at the EVSE.

The prioritization ranking algorithm is shown in Algorithm 1. Based on the ranking index, EV users at EVSE are classed into different queue groups. Members with higher index scores than the threshold, $Q_{threshold}$, are grouped in the priority queue and are provided with better charging service. The priority queue does not affect the S score; rather, it is only a matter of better service experience, such as less queuing and waiting time. Charging with limited power

Algorithm 1: The Prioritization Ranking Algorithm

[1] **Input**: $P_{re,t}$, $P_{ev,t}$, $P_{mg,t}$, $P_{re,max}$, P_{evse}, $S(i)$, t_{st}, t_{et} and $Q_{threshold}$
Output: $S(i+1)$
if $S(i) > Q_{threshold}$ **then**
  Queue in the priority group;
else
  Queue in the normal group;
end
$reward_i = 0$,
for $t = t_{st}$ *to* t_{et} **do**
  if $P_{re,t} > P_{mg,t}$ **then**
    Charge EV with high priority and get EV-coin rewards;
  else
    if *EV user pay EV-coin* **then**
      Charge EV with designed power;
    else
      if *EV user Continuous to charge* **then**
        Charge EV with limited power;
      else
        Terminate the charging session;
      end
    end
  end
  Compute α_t based on (2); $reward_i$ += α_t,
end
$S(i+1) = S(i) + reward_i$.

means the charging current and power are being restricted and will result in longer charging time. Despite the longer charging time, limited charging power will pose less negative impact on the grid than the designed charging power.

When charging, if the EV is charging with surplus RE, $P_{re,t} - P_{mg,t}$, then α_t at that time will be positive, which represents that charging activity is encouraged. A zero α_t means the charging behavior is neutral, i.e., the activity does not benefit nor harm the grid. The S score of the user will not improve. However, a negative α_t will be assigned, and the EV users' ranking score will be harmed if the EV user charges at a time when the local load in the microgrid is larger than the RE generation, which means the microgrid is using the power from the distribution grid. If a charging activity is encouraged, not only will the charging process be with the factory designed power, which means the full charging capacity power of the EVSE, but also the user will be awarded cryptocurrency rewards. The currency is called an EV-coin, which is a cryptography incentive based on the consortium blockchain. In the EV-coin system, the content of the block, which is the ledger of EV-coin transaction, not only reflects the current states, but also the historical ones. Instead of a public blockchain where anyone can write blocks, EV-coin is a consortium chain, in which only approved participants, such as utilities and EVSE operators, can function as validators. To solve the security and trust issues in public chains, trade-off efforts are made, including limiting network throughput at about 100 transactions per second. In EV-coin, since all the participants' identities are known, a node that acts maliciously can be quickly apprehended and banned from the system. Therefore, superior performance can be achieved. The throughput in EV-coin can go up to 100,000 transactions per second.

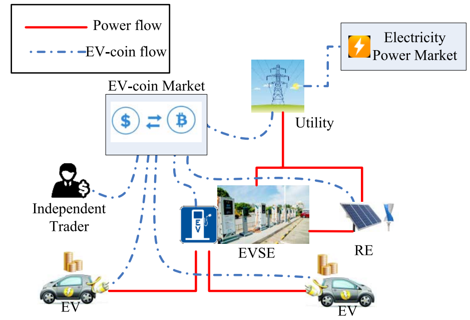


Fig. 2. Illustration of the EV-coin flow and the power flow associated with the market.

C. Market Mechanism

As shown in Fig. 2, the utility, EVSE, RE, and EV are all connected by power lines. In general, the utility provides energy to the distribution grid. The energy is then transferred to EV through EVSE. RE, on the other hand, injects the power flow to the utility through the distribution grid. If the system is V2G capable, the power flows can be bidirectional, which means the RE and EV may provide energy to the grid. Instead of transferring the RE to the utility through the distribution grid, the RE will be firstly used by local EVSE and EV. Guided by the incentive system, the usage rate of RE will be increasing, and the congestion of the distribution grid will be relieved.

Unlike the monetary incentive system, the EV-coin system provides the utility an additional dimension to optimize the power system and guide EV drivers to charge in the desired manner. The system is more effective with drivers who value time over a small amount of money.

The utility, EVSE, and EV drivers trade EV-coins in the online EV-coin trade market. Although the EV-coin system is a non-monetary, its effectiveness still follows the supply-demand relation. There are two ways for EV drivers to get EV-coin: One is to charge the EV with the desired charging behaviors and accumulated EV-coins, and the other is to buy EV-coins through the trading system. Since both the charging resources and time are limited, more EV drivers charge under the desired behavior, which means fewer people need to buy EV-coins, and thus the price of EV-coins remain steady. When there are fewer EV drivers charging at the desired time, i.e., an increasing number of users who charge at peak periods, then the EV-coin will become scarce, resulting in a rise in the price of the EV-coin. The cost of purchasing an EV-coin will increase, as more people intend to charge at peak periods until it reaches its equilibrium. In this way, the utility guides the EV drivers' charging behavior in a direct manner.

It is worth mentioning that EV-coin traders or independent operators can be profitable. The trader and the operator do not need to own EVSE, or a utility can still make profits by providing financial or operational service to other players in the EV-coin market. The price of the most well-known cryptocurrency, *Bitcoin*, has been suffering from voluminous fluctuations. Different from *Bitcoin*, the EV-coin system is an economic-based consortium blockchain.

We presume that there are four kinds of players in the EV-coin market: the utility, the EV users, the EVSE operators, and the operators of the microgrids and distribution networks, and all of them are rational. A utility's investment in an EV-coin system, such as the system operation cost, the incentives given to good behavior users, the payment for purchase of EV-coins from the market, etc., will not exceed the total gain it received from the EV-coin system. The utility benefits from the implementation of the EV-coin system, which properly guides the users' charging behaviors and results in consequences of higher RE usage rates and fewer energy requests from the distribution network and utility, by reducing or delaying the investment in the distribution networks. Although the short-term EV-coin price fluctuates with supply and demand and other market factors, in the long run, according to the rational expectations theory, the market will reach and stay its equilibrium, where the supply (investment) and the demand (gain) are equal as shown in (5). In other words, the total profits of EV users and EVSE made on EV-coin equals the total saving of the utility saved on the distribution network investment for EV charging because of the implementation of the EV-coin system.

$$\sum_{t=0}^{\infty} I_{u,t} = \sum_{t=0}^{\infty}\sum_{v} G_{ev,v} + \sum_{t=0}^{\infty}\sum_{n} G_{evse,n,t} + \sum_{t=0}^{\infty}\sum_{l} G_{mg,l,t}, \quad (5)$$

where I_u is the investment saved on the distribution grid by implementing the EV-coin system, $G_{ev,v}$, $G_{evse,n,t}$, and $G_{mg,l,t}$ are the earnings of the v-th EV, the n-th EVSE, and the l-th microgrid operator on EV-coin, respectively.

III. Effectiveness Verification

To verify the effectiveness of the system, we designed a simulation model to compare the performance of the EV charging system with and without the incentive. We assume that the solar energy is the only RE source and EV is the only load in the microgrid. EVSE charging will use RE when it is available and then use the energy from the utility grid. The solar energy data is collected from a 200 MW solar farm located with a latitude 34.35N and longitude 118.25W, at California, USA, from Jan. 01, 2006 to Dec. 31, 2006 [12]. To match the RE with EVSE and EV, we scale down the solar energy generation by 10^3, from 200 MW to 200 kW. The EVSE is Level-3 DC charging of 50 kW and is supported by local RE and the power grid with a topology shown in Fig.1. We assume that there is zero P_{mg} and the only load is the EV charging load, $P_{ev,t}$, which remains flat when working. Hence, $P_{re,t} \geq P_{mg,t} = 0$, and from (2) $\alpha_t \geq 0$. The setting of the simulation is shown in Table I.

It should be pointed out that Algorithm 1 is designed for a relatively large-scale system with market-driven and multiple game users, which enables the trading of EV-coin. To accurately evaluate the effectiveness, one should eliminate the influence of the different responses of diversified users and the dynamics of the market game. In the simulation, we take for a single EV system and introduce the arrival rate, λ_t, to reflect the user's charging behaviors. We will provide more details of λ_t in the next paragraph. In Algorithm 1, which aims for the ranking, λ_t has not been deployed and implemented. Because such deployment of λ_t in the large-scale ranking system is unnecessary and a waste of computation and storage resources. In Algorithm 1, the system rewards or penalizes the user with changing of EV-coin based on whether the charging action is encouraged or discouraged. The user will respond in their charging behaviors according to his sensitivity to the price of an EV-coin. In the simulation, instead of an EV-coin, the user is rewarded with an increase in the arrival rate when the charging behavior is appreciated. The two approaches may not be completely equivalent, but in the view of the economic mechanism underlying the EV-coin system and the differentiated service provision, the proposed incentive system may be more effective. Furthermore, the distribution of EV arrival at EVSE is very complicated and depends on many conditions. Studies show that the statistical distribution of EV arrival is close to the distribution of the solar power generation, and they both are scattered during the day [13]. Therefore, the assumptions of the uniform distributed arrivals that we made for the initial states are more stringent than the reality, and the proposed algorithm is more effective in reality.

TABLE I
PARAMETERS OF SIMULATION

Parameter	Setting
The capacity of the solar energy farm, $P_{re,max}$	200 kW
The power of EVSE, P_{evse}	50 kW
The power of EV charging, P_{ev}	50 kW
The number of EV	1
The days of simulation	365 day
Average charging duration time, μ_T	3 hour
Variance of charging time, σ^2	0.5 hour

To be compatible with the RE data resolution of 1 hour, we use 1 hour as the basic unit of time in the simulation. As only one EV, there will be no queue and a zero waiting time. At the i-th day, the EV arrives at EVSE for charging at random time t_{st}, which is given as follows.

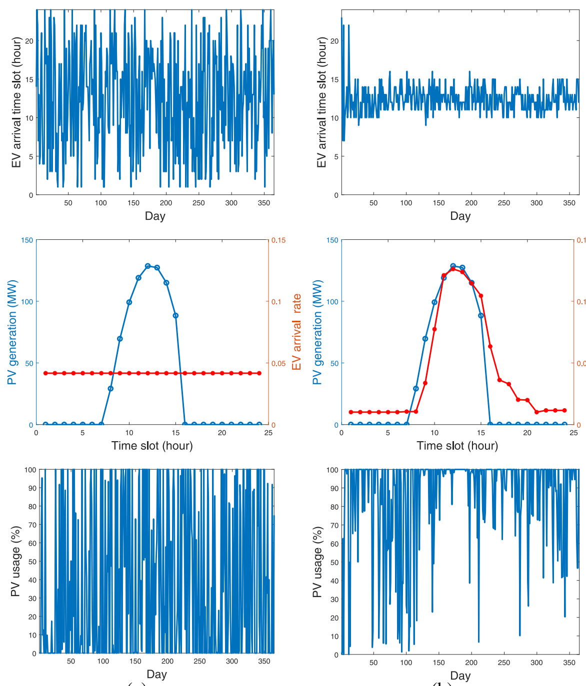
$$t_{st}(i) = \arg\max_{t} \quad \lambda_t(i)\boldsymbol{X} \quad (6)$$

$$\hat{\lambda}_t(i+1) = \lambda_t(i)(1+\alpha_t(i)), \quad (7)$$

$$\lambda_t(i+1) = \frac{\hat{\lambda}_t(i+1)}{\sum_t(\hat{\lambda}_t(i+1))}, \quad (8)$$

where $\lambda_t(i)$ is arrival rate at time t in day (i), $\lambda_t(i+1)$ is computed by normalizing $\hat{\lambda}_t(i+1)$, $\boldsymbol{X} \sim \mathcal{U}(0,1)$ is a random variable from uniform distribution, and α_t is the charging reward factor, which follows (2). Initially, the arrival rate of each hour among 24 hours is evenly equal. Hence, the The dynamics of charging duration time follows normal distribution, i.e., $\boldsymbol{T} \sim \mathcal{N}(\mu_T, \sigma^2)$.

Note that by following Algorithm 1, as time goes by, a user may accumulate an S score that diverges to infinity. It is intentionally designed as so. The system is predetermined to award preferential service to the well-behaved and loyal EV drivers. A newly joined EV driver, even with good charging behaviors, will still need time to accumulate higher S. After simulation of 365 days, the S score is 271.53 for the user under an incentive scheme, and 101.97 for the user without incentive.



(a) (b)

Fig. 3. Comparison of (a) original behaviors, and (b) behaviors under the incentive scheme. Top: The EV arrival time. Middle: The daily solar energy generation on Dec. 31, 2006 (left y-axis); The EV arrival rate, λ_t, on the day of 365-th (right y-axis). Bottom: The locally RE consumption rate used by EV.

The EV user that responded to the incentive accumulated more than 2.6 times more S points.

Fig. 3 shows the comparison results of the system behaviors over 365 days: (a) without incentive and (b) with incentive. The top two figures in Fig. 3 show the EV arrival time behaviors. It is clearly found that after a few days of training by the incentives, rather than arriving as evenly random during the 24 hours, the EV in the incentive system arrived around the middle of the days when there are higher $P_{re,t}$. The middle two in Fig. 3 show the hourly EV arrival probability, which follows very well with the daily solar energy generation curve $P_{re,t}$. The two figures at the bottom in Fig. 3 reveal the local RE consumption rate used by EV charging. The enhancement of the RE consumption rate is considerable. While the RE consumption rate in the bottom figure of Fig. 3 (a) shows fluctuation from 0 to 100% with a mean of 36.32%, it reaches much higher values with a mean of 85.13% over all 365 days in the Fig. 3 (b).

The simulation results demonstrate significant improvement in RE consumption by EV with incentives. There are still a few points to highlight. First, because of the dynamic nature of the output of RE, it is impossible and unnecessary to make EV charge fully comply with RE output, although one may predict the solar and wind energy with relatively high accuracy. Second, we only consider one EV, which can charge at any time when it needs to, so the advantages of the prioritization algorithm have not been shown. The behavior of a single-user system is more intuitive despite its simplicity. When there are more EV users, through differentiated services, the prioritization algorithm will be more effective. The system may exhibit greater robustness and more complex behaviors when there are more users who are competing with each other. Third, from the perspective of the EVSE operator, it is essential to maintain the EVSE utilization rate at a higher level to meet its own economic demands. When there are more EV users in the system, EVSE will become a kind of resource for competition, and EV users will have to minimize queuing time and charging costs based on their own economic conditions. The entire system is hence also optimized and balanced by local optimization of EVSE and EV.

IV. Conclusion

In this brief, we proposed a prioritization ranking algorithm of EV users based on their charging behaviors to differentiate drivers and thus to guide their charging patterns, which the utility appreciates without the involvement of monetary incentive. We also proposed a blockchain-based incentive, EV-coin, to further enhance the guiding capability by providing implicit monetary incentive. Simulation results showed that the proposed system effectively increases the utilization of RE from the local microgrid. The proposed system not only can reduce the transmission loads of distribution grids, but also can be a solution to the over-generation problem of RE by guiding local EV users to use more RE.

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