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A Blockchain Based Electric Vehicle Smart Charging System with Flexibility ⋆

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Abstract: The increase in development of electric vehicle(EV) will have a strong impact on the power distribution grid if adequate care is not taken on the high power demand required for charging EV. Consequently, there is need to create a platform to enable charging point operators to effectively manage the EV user's charging requests and ensure that there charging needs are satisfied while not exceeding the distribution grid capacity. If this is not done, there is no doubt that in few a years, EV owners will be faced with the problems of unavailability of charging stations and congestion in grid sequel to simultaneous charging of many EV's. This work proposes a smart EV charging infrastructure based on a blockchain platform. With the charging demand (kWh) and maximum duration of the charging event provided by the EV user, the EV load flexibility is determined and utilized through smart charging to achieve a stable grid. EV owners and charging stations are linked through the platform thereby reducing the actors in EV charging ecosystem from six to four. Flexibility (power and time) in charging of EV is traded within the blockchain platform. By this, additional investors will be attracted into the business of EV charging station and through flexible offers, EV loads are shifted from the peak load hours. Consequently, the simulations shows that the acceptance rate of EV users increased by more than 50% when our smart charging system was adopted compared to the normal charging scenario.

Keywords: Electric Vehicle, Blockchain, Smart Contract, Smart Charging, Charging Point, Distributed Applications, Smart grid.

1. INTRODUCTION

Smart charging of EVs is currently in its infancy. The power required for charging an EV is almost twenty times that of a typical household in North America (Wang et al. (2016)). Notwithstanding this high charging power, there is rarely grid congestion due to EV charging at the moment. This is as a result of low penetration rate of EV in many countries and charging points (CP) are installed in parallel with substation reinforcement. However, with the new emission rules (European-Council (2019)) in European countries and in trying to achieve zero emission for all new sold cars, there will be strong increase in penetration of electric vehicle in future. According to International Energy Agency (IEA), the global projected EV volume will be more than 30% of global market share by 2030 (IEA (2019)). Because of the large number of EV's that will be charged simultaneously from the same distribution grid, there is need to develop an optimal means for integrating EV's into the grid (Nour et al. (2019)).

Nour et al. (2019) in their work classified EV charging into three types namely; uncontrolled charging, delayed charging and smart charging. Uncontrolled charging is a type of charging where an EV user plugs their vehicle and it starts charging until it is fully charged or the owner disconnects it at a later time. This is a form of manual OFF- and ON-switching. Delayed charging is the type of charging where utility companies use the tariff to motivate EV owners to shift their EV load from peak load hours to off peak hours (Nour et al. (2019)). Smart charging is a type of charging in which the EV charging point is controlled by an algorithm. Smart charging can be induced by the distribution system operators (DSOs) if there is a communication channel linking DSOs to the charging station (Wargners et al. (2018)). It can occur in a centralized (via aggregators) or decentralized control architecture (Daina et al. (2017)). A centralized control architecture is when aggregators contract power demand from many EV owners and act as a middleman between them and ancillary service markets (Daina et al. (2017)). While in a decentralized control framework, EV owners through their charging preferences directly affect the flexibility of control that can be imposed on charging operation by responding to market information made available to them. It is therefore the work of the charging point operator (CPO) to create incentives for charging preferences that will allow for more flexibility operation (Daina et al. (2017)). This work will focus on creating incentives for charging preferences and will further show how this will result in an overall reduction of grid congestion while increasing the number of EVs charged at a charging station with several charging points.

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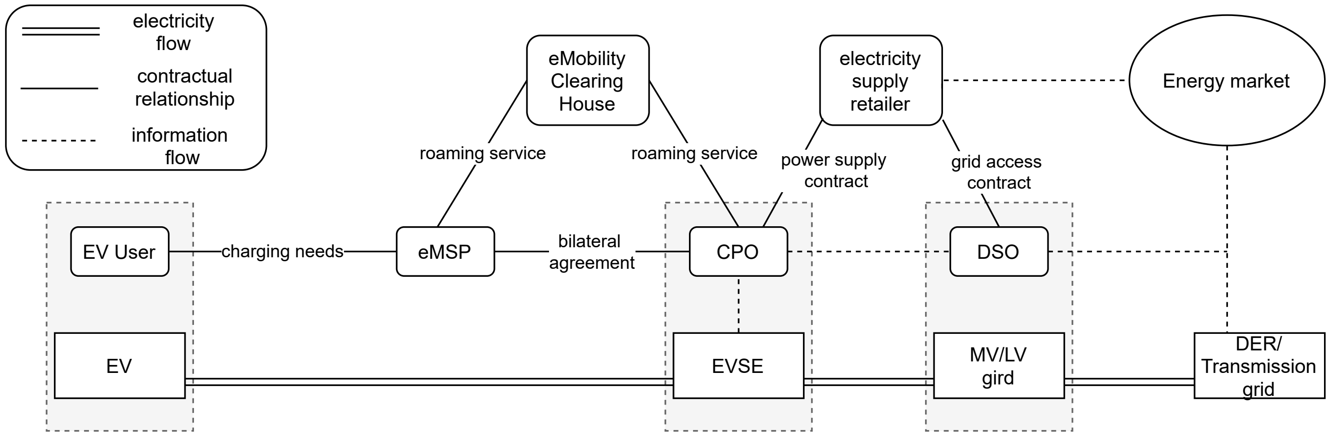

Fig. 1. EV charging market architecture

Fig. 1 shows the EV charging market architecture with the participants and how information and electricity flow among the actors. The actors within the charging ecosystem are EV user, CPO, E-Mobility service provider (eMSP), E-mobility clearing house, electricity supply retailer and DSO (Kirpes et al. (2019)). Electric power from the transmission grid or distributed energy resources (DER) is supplied to the medium or low voltage (MV/LV) distribution grid. EV supply equipment (EVSE) is powered from the MV/LV from which it supplies the EV.

- EV User: User or owner of an EV.
- CPO: Individual or firm that operates a charging station.
- eMSP: Firms that bridge the gap between EV users and CPOs by providing real time information of CPs. They help EV users to locate, reserve CPs and make payments.
- E-Mobility Clearing House: Entity that takes care of the payment transaction from EV user to CPO via eMSP.
- DSO: Utility company that operates low/medium voltage power distribution grid and delivers electricity to end users.
- Electricity supply retailer: Company that sells electricity to consumers and has grid access contract to buy from DSO .

Blockchain (BC) is a distributed data structure and computation network, secured by a combination of cryptographic signatures and consensus mechanism (Christidis and Devetsikiotis (2016), Munsing et al. (2017)). BC provides distributed, transparent and trustworthy access control in the internet of things (IoT) especially with the evolution of smart contracts (Zhang et al. (2018)). Smart contracts (SC) are code run on the Ethereum BC network that are used to enforce agreement among participating accounts or nodes and executed only when the predefined constraints are satisfied (Okwuibe (2019), Pop et al. (2018)). This paper proposes a model for giving incentives (rewards) to EV users for their charging preference and for payment for energy consumed from the CP. This reward is given in form of token (OLI Coin) and can be used by the EV user to consume further electricity from the CP. The remainder of this paper is structured as follows. Section 2 explains the design approach and simulation model. Section 3 discusses the results in details. Finally, section 4 concludes the paper giving information on how to further explore the topic.

2. APPROACH AND SIMULATIONS

2.1 Smart Charging Architecture

Fig. 2 shows the proposed BC-based EV charging system. The billing and payment functions previously executed by eMSP and the clearing house are done by SC deployed on the BC platform. The SC is also used to trigger smart charging of individual CPs. Furthermore, a SC is used to reward EV users for their flexibility offers to incentivise them to use smart charging.

2.2 Charging Algorithm and Flexibility Offers

Fig. 3 shows the decision diagram whenever there is a new charging request. EV users send their charge request by specifying the quantity of energy(E) they demand and the maximum time(T) they can spend charging the car. The duration of a time step is set to 15 minutes. By this, all charging requests that arrive at a particular time step are evaluated individually according to first come first serve principle. The accepted requests will start charging in the next time interval. Whenever a new charging request is received, the model checks if this will result in grid congestion if the request is accepted with all others continuing as before and the new one going in with full power. If this is not the case, the request will be accepted. Else, the model will check if the user added some flexible (Fle. Dem.) charging preference to enable smart charging and shift the congested load. If this is False (case of fast charge demand), the request will be accepted. Else, the model will do a fulfillment check to determine if the added flexibility can help in shifting the congested load and therefore satisfy the users energy demand within the time specified. If this is possible (Ful. check==True), charging will be accepted. Else, it will be rejected and be treated in the next interval if the user is still available.

In this context, flexibility is the charging time or power an EV user is willing to exchange for monetary benefits. Hence, its allocation should be done in a fair and transparent way. A proportionate allocation mechanism is used

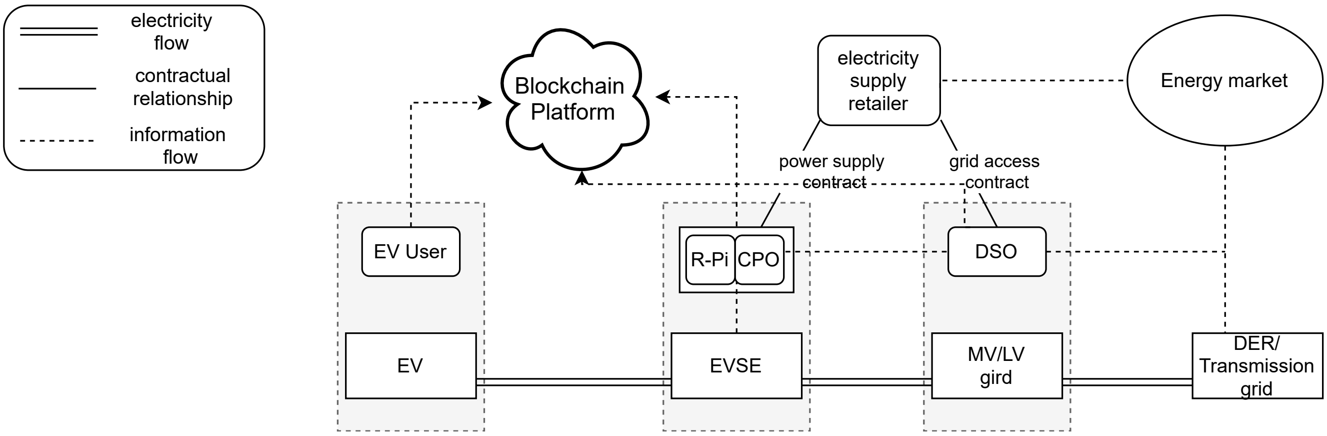

Fig. 2. EV charging market architecture using blockchain

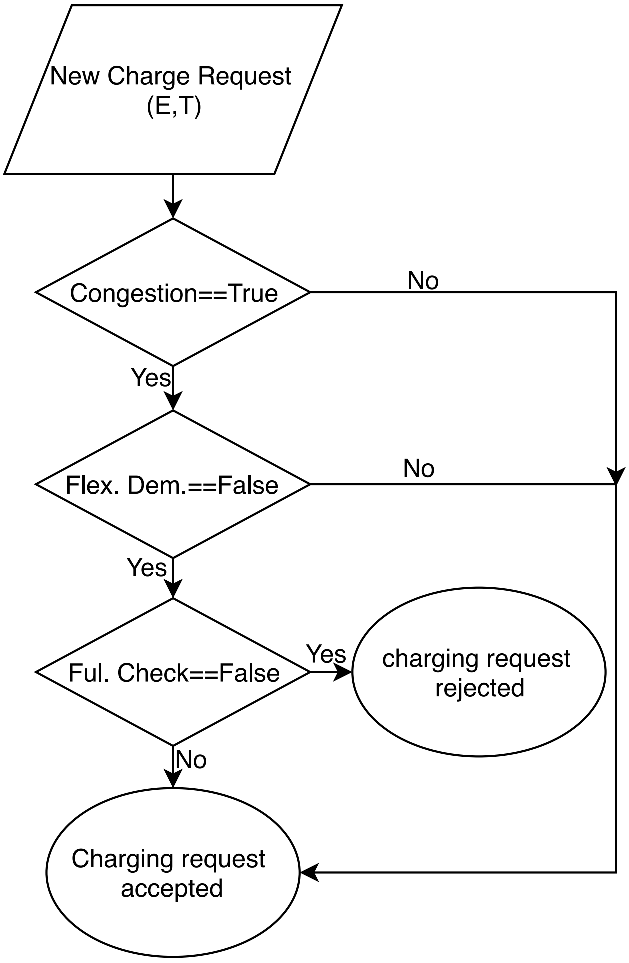

Fig. 3. Charging event decision diagram

to ensure that all charging processes with flexibility offers are involved. The method below is used to determine the potential of flexibility offer of an EV user for the next time step. For each charging activity (i) at a time step n, the energy supplied to the EV is denoted as $\mathrm{E}_{\mathrm{s(i,n)}}$ and the charging time as $\mathrm{T}_{\mathrm{s(i,n)}}$. Flexible time ($\mathrm{T}_{\mathrm{F(i,n)}}$) for charging activity (i) is calculated from equation (1).

$$T_{\mathrm{F(i,n)}} = T_{\mathrm{s(i,n)}} - \frac{E_{\mathrm{s(i,n)}}}{P_{\mathrm{N(i)}}}. \tag{1}$$

$\mathrm{P_N}$ is the nominal power of the CP. The flexible offer of the charging activity (i) for the next time step (n+1) is calculated from equation (2).

$$F_{\mathrm{l(i,n+1)}} = \begin{cases} P_{\mathrm{N(i)}} & \text{if } T_{\mathrm{F(i,n)}} \geq 15min \\ \frac{P_{\mathrm{N(i)}} * T_{\mathrm{F(i,n)}}}{15min} & \text{otherwise} \end{cases} \tag{2}$$

The flexible offer for any charging request is calculated whenever a new request is made and is used to determine how much power the user is willing to give and appropriate token rewarded accordingly.

2.3 Blockchain Integration

To integrate blockchain close to the hardware unit in order to achieve a fully secure trust chain, we installed the Ethereum blockchain client (Parity) in a Raspberry Pi (R-Pi). The R-Pi serves as a blockchain node and is installed on each of the CP's as shown in Fig. 2. The Python code for the smart charging algorithm and flexibility offers are deployed in the cloud. A SC is developed and deployed to the blockchain network and the SC Application Binary Interface (ABI) code copied to the Python script for interaction to the blockchain network. The Python script interacts with the blockchain network every 15 minutes through the SC ABI. At this time, the charging requests (E, T) from the EV users are received and used to calculate the flexible offers for the next time slot. The calculated results for accepted requests are stored in the blockchain using hash encryption. The CPO's backend interacts with the cloud in parallel to the blockchain node attached to it as a backup and for direct interaction with the cloud database and the Python Script. Upon completion of charging process and confirmation of providing the accepted flexibility offer from the EV users by the blockchain node installed on the CPO's node, token is awarded to the EV user to compensate for the flexibility offered. By this, EV users are paid for the flexibility they offered with their energy demand and time.

2.4 Simulation Data

The average daily travel distance of a German in 2017 was 39km (BMVi (2019)). The weekly driving range is 280km per person. The EV traction battery can support an average driving range of 7km/kWh (AUTOBEST (2018)). Consequently, an average EV user need to charge their car for 40kWh to satisfy their weekly mobility needs. Therefore, for our model, the energy demand for EV charging is within the range of 10 to 40kWh. According to the different charging behaviour of the EV user, the electricity demand is categorized as shown in table 1.

Table 1. Charging time categories

Category	Charging Time(h)	Charging Location
Category1	1-2	Shopping malls; Restaurants
Category2	2-4	Work place; Street parking
Category3	4-8	Home; Hotels

2.5 Simulation scenarios

The model was simulated for two different charging scenarios. Scenario1 demonstrates one charging request arriving at the charging pool every time step (15 minutes) while Scenario2 shows two charging request arriving per time step. All CPs are assumed to supply a maximum charging power of 11kW while the EV user's charging demand and available charging times are randomly generated. The charging demands are between 10 to 40kWh (equivalent to 50-200km) and the charging time between 1 to 4 hours. Charging plugs are not limited, which means all charging requests will be accepted as long as there are adequate amount of power supply from the grid. However, the power from the grid is limited and incremented by 11kW from 33kW. The simulations are executed by changing grid power limit, EV energy demand and available charging time. For all the simulation scenarios, the total electricity sold and overall acceptance of both the uncontrolled and smart charging are recorded and compared. The simulations were repeated a hundred times and the average results recorded.

3. RESULTS AND DISCUSSION

The results of Scenario1 for a charging period of ten hours with different power limit is shown in Fig. 4. The blue, orange and yellow bars represents the total electricity supplied (sold) to EV during uncontrolled charging scenario, during smart charging scenario and total utilized flexibility from EV's that contribute to smart charging, respectively. The difference between the length of the orange and blue bar is the electricity sold by adopting smart charging against uncontrolled charging for the power limit. The blue and green dotted lines represent the average acceptance rate of uncontrolled and smart charging, respectively. At a grid power limit of 33kW, the average acceptance rate for uncontrolled charging is 0.38 while that of smart charging is 0.7 which is 1.84% of the value for uncontrolled charging. Also, as the threshold power limit increases, the difference in the uncontrolled and smart charging acceptance rate decreases. This difference become zero from a threshold power limit of 120kW onwards. This is evidence that not more than 11 EV's were charged simultaneously and the utilized flexibility are electric power supplied to the EVs by using smart charging.

Fig. 5 shows the simulation results of Scenario2 with all other parameters remaining the same as the previous scenario. By doubling the charging requests in each time step, the acceptance rate for uncontrolled and smart charging dropped to 0.23 and 0.43, respectively, at a power limit of 33kW. Also, as the threshold power limit increases, the difference in the uncontrolled and smart charging acceptance rate decreases and become zero from a threshold power limit of 143kW onwards. For the 33kW threshold power limit case of Fig. 5, only 309kWh of electricity is supplied to the EV for the uncontrolled charging. However, the electricity supplied (603kWh) is 1.95% of the value for uncontrolled charging when smart charging was adopted. This quantity supplied during smart charging is equivalent for uncontrolled charging when the power limit is 66kW. Hence, adopting smart charging is equivalent to expanding the grid capacity by 33kW. The utilized flexibility (yellow bars) increases from the beginning (at 33kW threshold power limit) until it reaches a peak value of 364kWh at 88kWh. Afterwards, it decreases even as the threshold power limit continue to increase and finally drops to zero at 220kW power limit. At this point, the grid capacity is large such that smart charging adds no more advantage compared to uncontrolled charging. To explain this; at the beginning (from 33kW threshold power limit) the power to enable extra charging of the EV comes from flexibility offers as a result of grid power limitation. As the grid power limit increases, the extra needed power of the EVs is supplied from the grid rather than flexibility offers. Hence, flexibility offers are considered only when the power from the grid is not enough to supply the needed power of the EVs.

4. CONCLUSION

Flexible EV charging has a great potential of reducing load congestion resulting from restricted grid capacity in electric power distribution grid while providing all EV users with their desired energy demand. Our model identified the major challenges EV users will be confronted with in the near future which are insufficient grid capacity and unavailability of charging points. The combination of EV smart charging and blockchain architecture brings about more bussiness opportunities. In future work, the market mechanism will be developed and evaluated. Laboratory testing will be conducted before the final stage which will be field test. In summary, blockchain technology is very promising in EV charging business and joint efforts from EV users, CPOs and DSOs are required in order to achieve a decentralized and effective EV smart charging system. Furthermore, the proposed software solution can cut costs significantly if grid expansion needs to be paid instead.

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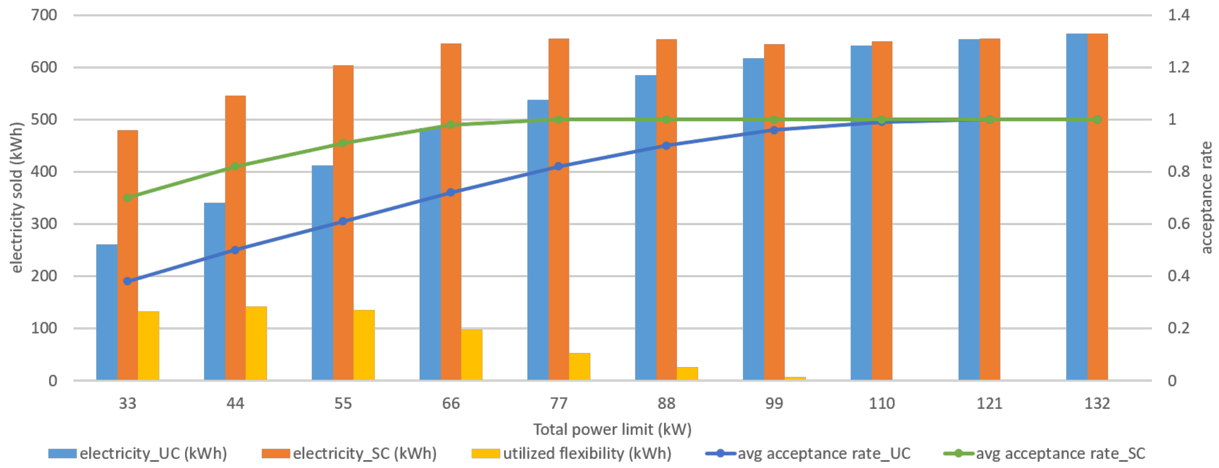

Fig. 4. Simulation results for Scenario1

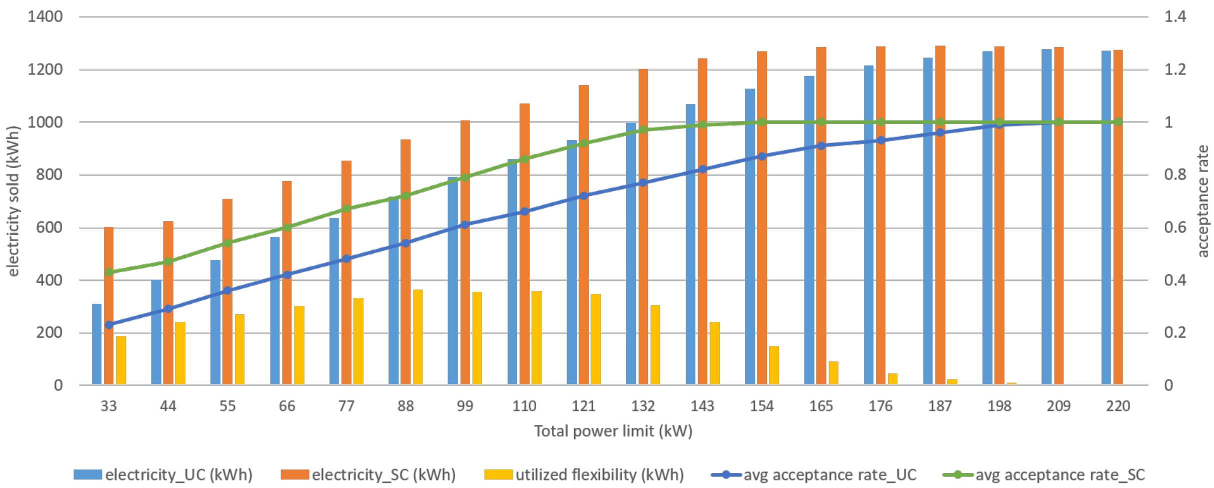

Fig. 5. Simulation results for Scenario2

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