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Cao, Xihai; Engelhardt, Jan; Ziras, Charalampos; Marinelli, Mattia

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# Distributed control of electric vehicle clusters for user-based power scheduling

Xihai Cao

Department of Wind and Energy Systems  
Technical University of Denmark  
Roskilde, Denmark  
[xihca@dtu.dk](mailto:xihca@dtu.dk)

Charalampos Ziras

Department of Wind and Energy Systems  
Technical University of Denmark  
Roskilde, Denmark  
[chazi@dtu.dk](mailto:chazi@dtu.dk)

Jan Engelhardt

Department of Wind and Energy Systems  
Technical University of Denmark  
Roskilde, Denmark  
[janen@dtu.dk](mailto:janen@dtu.dk)

Mattia Marinelli

Department of Wind and Energy Systems  
Technical University of Denmark  
Roskilde, Denmark  
[matm@dtu.dk](mailto:matm@dtu.dk)

**Abstract**— The increasing penetration of electric vehicles (EVs) in the power system has raised concerns regarding the management of charging sessions to prevent systems from overloading. This paper proposes a distributed control method of EV clusters that enables controllers to make decisions independently, using only commonly broadcasted signals. Additionally, the method also includes a user-based power scheduling mechanism that prioritizes EVs based on their respective energy needs and time availability. A power-constrained system is considered for the case studies, where the system is only capable of charging one EV with maximum power. Simulation results demonstrate that the system effectively accommodates and schedules multiple EVs to charge simultaneously in a restricted environment without compromising user satisfaction. In instances of communication loss, the system demonstrates the capability to sustain the charging process through resource reallocation. The method is characterized by its distributed and autonomous nature, which ensures both robustness and effective operation.

**Keywords**— *electric vehicles, distributed charging, power management*

## I. INTRODUCTION

Electric vehicles (EVs) have gained much attention in recent years due to the urgent need to reduce carbon emissions from the transportation sector [1]. However, high EV penetration in the power system may cause overloading phenomena that can endanger the security of the system [2], [3]. Therefore, suitable coordination control approaches are needed to ensure the satisfaction of users while keeping the aggregated charging power within the system capability [4].

Compared to the commonly used centralized control [5], distributed charging control is gaining more attention in recent years since it localizes the decision-making process into each charging entity. Hence, system robustness and security can be improved [6], while user information privacy can also be protected [7]. On the other hand, distributed charging control mechanisms also bring some drawbacks due to the limited information being shared. Since each local entity only receives the common signal without the information of other local entities, the charging process usually suffers from reduced fairness and sub-optimal conditions in terms of charging power levels. Wang *et al.* [8] propose a distributed scheduling strategy for EV clusters, where each cluster only receives a common signal from distribution system operator (DSO). However, the decision is

still made in a centralized manner inside each cluster. Yan *et al.* [9] focus on distribution system with multiple EV clusters and develop a distributed coordination method where each cluster only exchanges the information of aggregated charging power. However, the method proposed assumes that the aggregated charging power is always within the cluster limit, and all connecting EVs can receive the requested power, which is uncommon for EV clusters. Other research works concentrate on limited EV charging cluster including a semi-distributed charging approach introduced in [10], where the authors eliminate the existence of the central control entity by enabling one local controller to make charging decisions for all EVs, whereas the power allocation process is still settled in a centralized manner. An autonomously distributed control approach for EV parking lots management is described in [11], [12], where each charger controller operates independently with the common signal, yet only one plug of each charger controller can be activated, then forcing the rest EVs to cease charging. In practice, it is challenging for some EVs to restart the charging process once being interrupted. Therefore, reliable charging service cannot be guaranteed for them.

The current research work on distributed charging control methods presents different limitations: some exhibit a certain degree of centralization in the decision-making process. Others either assume a sufficient charging cluster limit or fail to provide reliable charging power to users under limited scenarios, which results in less applicability in terms of system robustness and user satisfaction in realistic charging cases. Furthermore, practical EV batteries commonly experience ongoing charging power limitations due to high state of charge (SOC). However, the current body of research rarely accounts for this aspect. To tackle the above concerns, this paper proposes a fully distributed charging control strategy that allows power to be scheduled among EVs according to user-based priorities inside a cluster. Charging power limitation is also included as part of the smart charging algorithm based on experimentally tested results. In this case, the system is aligned with real-world charging situations that can be applied to public charging places.

This paper is organized as follows: The charging system functionality, user-based scheduling logics and EV charging power limitation nature are explained in Section II. The

results and EV behaviors analysis of case studies are presented in Section III, and Section IV concludes the paper.

## II. METHODOLOGY

### A. Distributed Charging System

Fig. 1 shows the developed distributed charging system. It allows four EVs to charge simultaneously with two charger controllers. Each controller contains two plugs, which enable two EVs to connect separately. There is a virtual aggregator (VA) assigned to every plug, acting as the local intelligence that determines the charging power for the corresponding EV.

The system point of common coupling (PCC) is the connection point between the charging system and external grid. Measurement at PCC will be sent out as common signals, including the reference power level  $P_{Ref}$  and the total charging power  $P_{Charging}$  of the system. In this paper, the reference power level is set as the fuse limit of the PCC transformer, implying the available charging power for the whole system. User inputs indicate the charging need specified by EV owners. The external input from PCC measurements and users is all transferred to a cloud aggregator (CA) that broadcasts the corresponding information to individual controllers. Consequently, the VA determines the specific charging power using the received information.

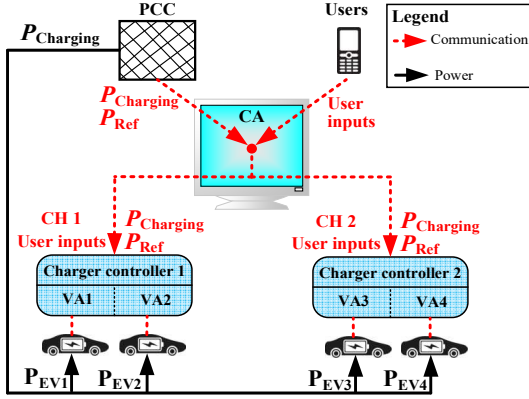


Fig. 1 The proposed distributed charging system – CA distributes the common information to controllers, and charger controllers make decisions individually.

In this system, CA, as the central operator, only collects and delivers the common information without any decision-making process. Each controller only receives the user data related to itself for power determination, while the information of other charger controllers is not provided. Therefore, this system is working in a distributed manner where charging power is settled locally. In situations where communication between the CA and charger controllers fails, unaffected controllers continue to operate normally. This method improves the robustness of the system by ensuring that the malfunction of one charger controller does not impact the operation of the others.

### B. User-based Power Scheduling and Priorities

Due to the PCC fuse limit, it is challenging to allow four EVs to charge at the maximum level. Therefore, power allocation is essential to ensure that the collective charging power does not trip the whole system. Additionally, the charging need varies among different users, thus charging all connected EVs at equal power level cannot guarantee fairness in the cluster. Hence, the available charging power needs to be

allocated within the system according to the charging priorities based on user information. In this system, each charger controller enables power scheduling between the two connected EVs.

Fig. 2 depicts the power scheduling mechanism within charger controller 1 as an illustration, while charger controller 2 employs the same pattern. Before each individual VA, the charger controller calculates the system power error and feeds the error into a PI controller to reserve the amount of power  $P_{CH}$  for connected EVs. Then the reserved power is scheduled to each of the two EVs according to their priority factor  $\beta$ .

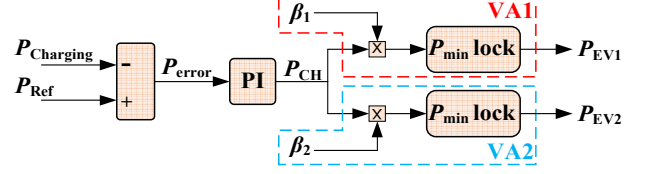


Fig. 2 Power scheduling mechanism for charger controller 1 – priority calculation and EV power signal are calculated inside each VA.

Eq. (1) shows how priority is calculated. The user input consists of the requested energy  $E_r$  and charging time  $t_r$  specified by the users.  $E_c$  and  $t_c$  denote the charged energy and corresponding time. Therefore, priorities also represent the average power each EV needs to achieve the energy goal. In this study, energy and charging time are specified in the units of kWh and seconds, respectively. The priority is dynamically adjusted as the charging session runs.

$$\alpha = \frac{E_r - E_c}{t_r - t_c} \quad (1)$$

Priority factor indicates the weighted priority between the two EVs inside the same charger controller. Eq. (2) presents the determination of the priority factor, where  $i$  and  $j$  indicate the plug number, and  $k$  indicates the charger controller number, in this paper  $i, j, k \in [1, 2] \cap \mathbb{Z}$ .

$$\beta_{i,k} = \frac{\alpha_{i,k}}{\alpha_{i,k} + \alpha_{j,k}} \quad (2)$$

Since priority factor varies while charging, the scheduled power also constantly changes. Finally, a minimum charging power lock logic is implemented in the VA to guarantee a minimum charging power for each EV in case the assigned power is too low to initiate the charging process.

### C. Charging Power Limitation

This system also considers the charging power limitation of the EVs. It is common for EVs to reduce the charging power when SOC is high enough, to protect the battery [13], [14]. To truly reveal the functionality of the distributed charging method, an experimental test was carried out at Technical University of Denmark Risø campus, for capturing the realistic charging curve of an EV. The test took place on 25<sup>th</sup> May 2023 with the ambient temperature at around 15 °C.

Fig. 3 shows the charging curve of a Renault Zoe with 42-kWh battery capacity. The starting SOC is 7%, and the charging power reaches the maximum saturation immediately. Hence it can be assumed that the charging power is also kept at the highest level with a lower SOC. The maximum observed charging power remains at around 21 kW even though the rated power is 22 kW. More importantly, the charging power starts to significantly decrease when SOC is above 83%, and

eventually reaches 0 kW when the battery is full. This characteristic is also accounted for in the case study.

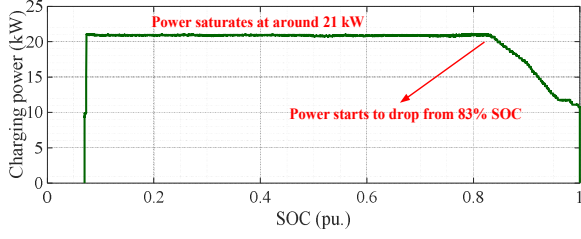


Fig. 3 Charging curve of a Renault Zoe with a 42-kWh battery.

#### D. Case Studies

Two case studies are conducted in MATLAB/Simulink environment to investigate the distributed charging method. The first case study lasts for one hour, with three Renault Zoes from above, the information is presented in table I. Note that EV1 and EV2 are both connected to the first charger controller, while EV3 is separately connected to another one. The fourth VA stays idle for simplicity.

The PCC fuse limit is input as power reference, which is set at 22 kW, thus the system can only afford one EV to charge with maximum power. Likewise, each charger controller is also limited with a maximum power of 22 kW. Therefore, a power scheduling strategy is needed to accommodate multiple EVs both in each charger controller and the system.

TABLE I. EV INFORMATION

	Attach time (s)	Detach time (s)	Desired energy (kWh)	Max/min power (kW)	VA	Initial SOC
EV1	400	3600	8	22/4.14	VA1	80%
EV2	200	2500	7	22/4.14	VA2	20%
EV3	1200	3600	5	22/4.14	VA3	70%

The second case study, on the other hand, investigates the robustness of the system by adding a communication failure scenario to charger controller 1 at 1800 seconds, shown in Fig. 4. As charger controllers are constantly receiving  $P_{\text{charging}}$  and  $P_{\text{Ref}}$  from CA for making scheduling decisions, the loss of communication affects its charging behaviors and the overall charging resource, thus bringing an impact to the decision-making process of each participant.

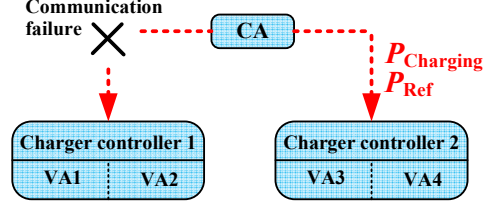


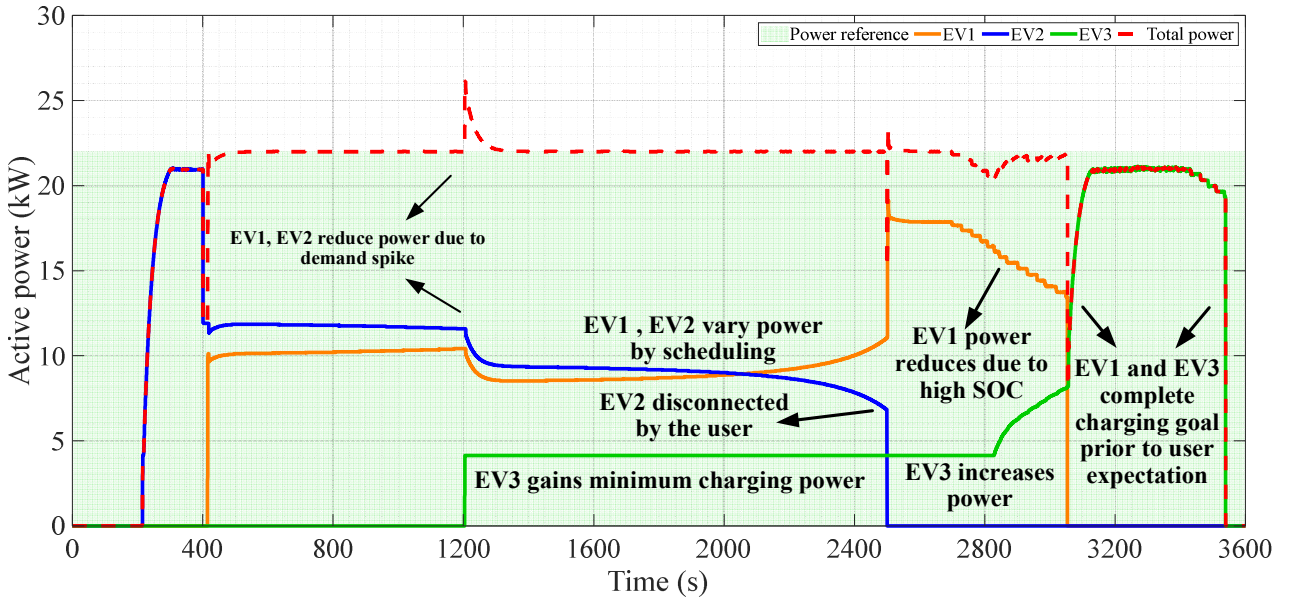
Fig. 4 System communication failure – charger controller 1 loses input from cloud aggregator, while charger controller 2 operates normally.

### III. RESULTS

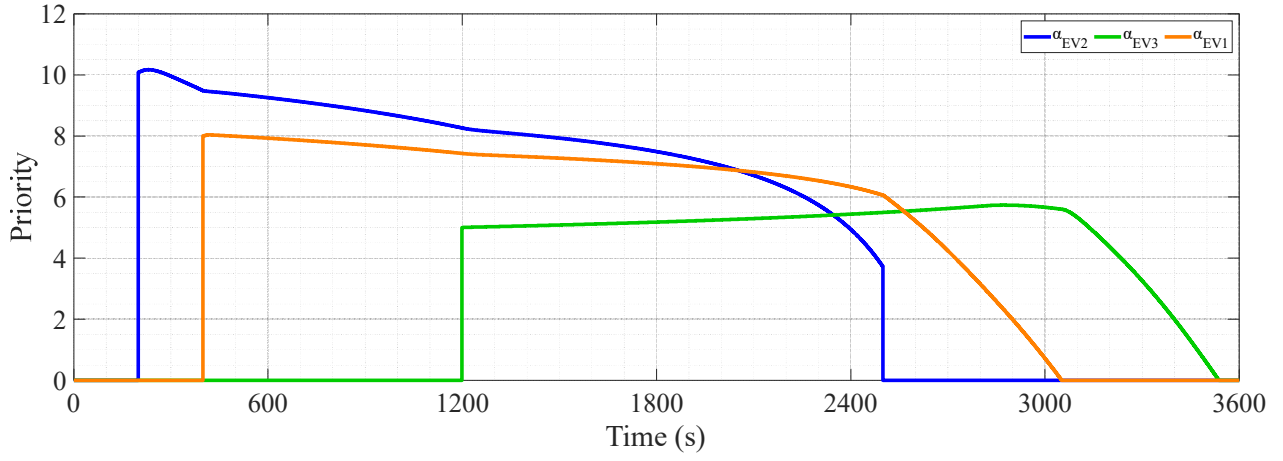
#### A. Case Study 1

Fig. 5 shows the simulated charging power, priorities and priority factors of the three EVs, where the EVs are connected consecutively. EV2 is the one firstly connected, and the power reaches observed maximum level according to the charging curve in Fig. 3. Afterwards, EV2 starts to reduce the power from 400 seconds, thereby creating the space for the charging of EV1. The difference in charging power allocation between EV1 and EV2 highlights the power scheduling capability of the charger controller via user-based priorities, which is also reflected in Fig. 5 (b), (c).

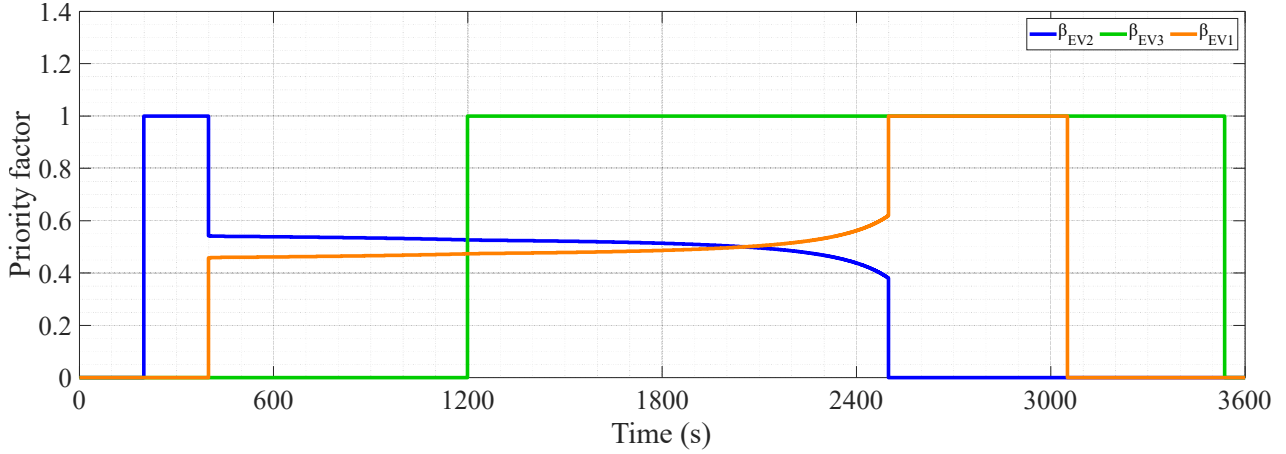
The charger controller dynamically adjusts the priorities during the charging process, leading to a gradual increase in the priority factor of EV1. Consequently, from 2000 seconds onwards, EV1 surpasses EV2 in terms of priority, resulting in a higher charging power allocation for EV1.



(a) Charging power



(b) Priorities



(c) Priority factors

Fig. 5 Simulated performance of EVs - case study 1. (a) shows the charging power levels of EVs; (b) shows the priority of EVs; (c) shows the normalized priority of EVs

From 1200 seconds, EV3 commences its charging process when there is no available power in the system, hence it charges at minimum charging power as guaranteed. However, the charging power from EV3 induces a demand spike in the system, prompting a negative power error. The error indicates all EVs to reduce the power, in this case EV1 and EV2 take the responsibility.

EV2 is plugged out by the user at 2500 seconds, which makes the priority factor of EV1 to be 1 pu. Therefore, EV1 increases the power to full reserved power  $P_{CH1}$ . Notably, from 2700 seconds onward, the charging power of EV1 experiences limitations due to its high SOC, leading to a reduction in power. This reduction contributes to a positive power error within the system, subsequently prompting an increase in the reserved power  $P_{CH2}$  of charger controller 2. As a result, EV3 power starts to rise accordingly.

Finally, after EV1 disconnects, charger controller 2 becomes the sole recipient of the system power reference, enabling EV3 to fully utilize it. Consequently, EV3 experiences an immediate surge in charging power, reaching its maximum level.

It is noteworthy to mention that both EV1 and EV3 cease the charging operations before reaching the designated plug-out time. This discontinuation is attributed to the fulfillment of the desired energy levels, as visually depicted in Fig. 6.

Fig. 6 demonstrates the charged energy of each EV throughout the simulation, the dash lines represent the requested energy that is initially input by each user. EV1 and EV3 achieve a 100% fulfillment of energy request, while EV2 reaches a fulfillment rate of 97.08%. The reason is that EV2 is competing with other two EVs during the charging session because the low fuse limit can only afford one EV to charge at the maximum level. Besides, as the charging progresses, EV1 overtakes EV2 regarding the priority, and forces EV2 to reduce the charging power. Therefore, the distributed charging system manages to satisfy all participants with significantly limited resources.

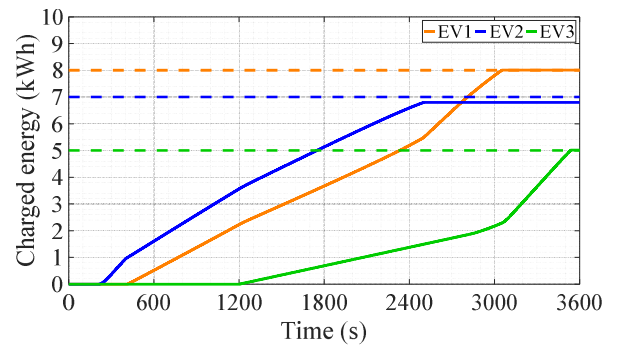


Fig. 6 Simulated charged energy of EVs – case study 1. Energy requests are fulfilled for 3 EVs.

### B. Case Study 2

The charging power levels of EVs in case study 2 are presented in Fig. 7, where charger controller 1 loses communication with CA from 1800 seconds. In such case, power scheduling is no longer offered to the connecting EVs (EV1 and EV2) due to the absence of  $P_{\text{charging}}$  and  $P_{\text{Ref}}$  in the decision-making process. Instead, the minimum charging power is provided for the continuation of charging process. As a result, the power drop from the two EVs creates a gap between  $P_{\text{charging}}$  and  $P_{\text{Ref}}$ , which is captured by the neighboring charger controller. Hence, EV3 starts increasing its charging level correspondingly.

It's important to highlight that EV3 halts its charging procedure at 2861 seconds, preceding the termination observed in case study 1. This is caused by the increased charging power of EV3 as the available power is shifted from charger controller 1 to charger controller 2 when facing communication failure. This feature is beneficial for the overall charging process as the early completion of EV3 allows the impacted EVs to be moved to undisturbed charger controllers in practice.

Fig. 8 and table II shows the charged energy and energy fulfillment rate of the three EVs. Since only minimum

charging power is offered to EV1 and EV2, the energy variation rate significantly reduces from 1800 seconds, resulting in a limited scenario for user satisfaction. However, table II presents that the energy fulfillment rate of EV1 and EV2 still reaches 71.76% and 84.82% even in a faulty situation. The system provides an additional 25.89% and 11.52% energy fulfillment rate for EV1 and EV2 after the loss of communication, and accordingly expedites the charging process of EV3. The model demonstrates its ability to counteract occurring errors to satisfy the charging needs.

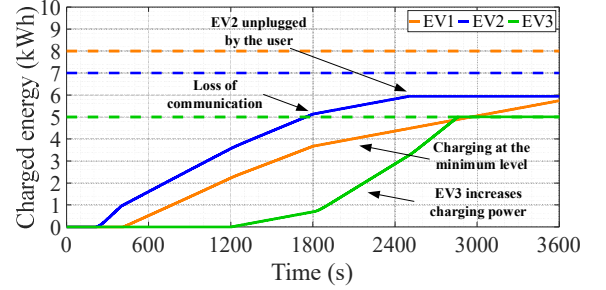


Fig. 7 Simulated charged energy of EVs – case study 2. EV1 and EV2 achieve additional energy fulfillment rate after communication failure.

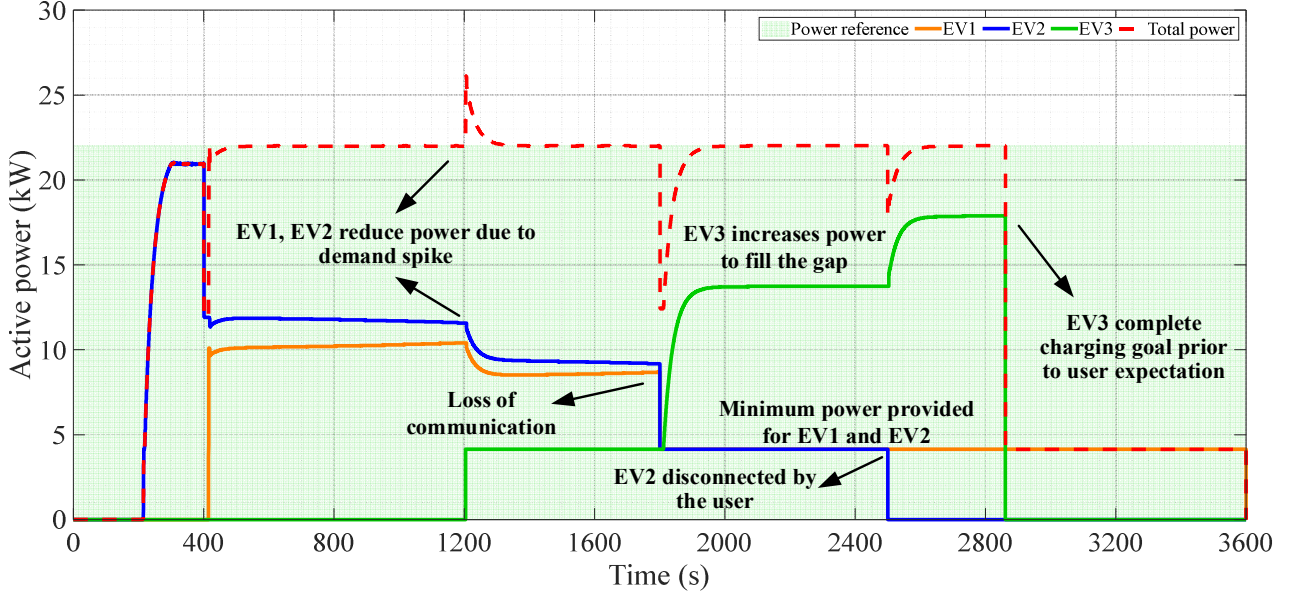


Fig. 8 Simulated performance of EVs - case study 2. EV1 and EV2 are provided with minimum charging power when charger controller 1 loses communication with CA, and the power gap is captured and filled by EV3, resulting in an early completion of charging.

TABLE II. EV ENERGY FULFILLMENT RATE – CASE STUDY 2

	Energy fulfillment rate at 1800 s	Energy fulfillment rate in the end
EV1	45.87%	71.76%
EV2	73.30%	84.82%
EV3	13.71%	100%

### C. Overall assessment

The system is working in a fully distributed manner, where each charger controller only has the information of its own connected EVs. The behaviors of EVs present the characteristics of the system:

- 1) **User-based power scheduling:** as the charging progresses, the charging power varies based on priority factors.
- 2) **Minimum power guarantee:** all EVs get at least minimum charging power in all cases.
- 3) **System protection:** when facing a demand spike that exceeds the fuse limit, all EVs reduce the charging power if possible.
- 4) **System robustness:** the charger controller is able to keep the charging process when encountering communication failure and to shift the resource to the unaffected ones.

Overall, the system is more resilient compared to centralized control, as no information is communicated among charger controllers. The distribution of decision-making process is capable of scheduling charging power and ensuring fairness among users, while keeping the system within the limit.

#### IV. CONCLUSION

This paper introduces a distributed charging method that allows charger controllers to independently make decisions without relying on central intelligence instructions. The method incorporates user-based power scheduling functionality to prioritize EVs with higher energy needs, while also accounting for EV charging power limitations due to high SOC. To validate the approach, a constrained system with three connected EVs is investigated in two case studies. The results demonstrate that the method ensures user satisfaction even under significant restrictions. When coming across loss of communication, the two affected EVs still achieve the energy fulfillment rate of 71.76% and 84.82%. By implementing a distributed control architecture, the method enhances system robustness when charger controllers face loss of communication, while the user-based scheduling of charging processes adds smartness. This showcases the practicality and applicability of the approach in real-life scenarios. Experimental testing of the system will be conducted in future work.

#### ACKNOWLEDGMENT

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