Distributed Coordination of Electric Vehicle Charging in a Community Microgrid Considering Real-Time Price

Li, Chendan; Schaltz, Erik; Quintero, Juan Carlos Vasquez; Guerrero, Josep M.

Published in:
Proceedings of the 18th European Conference on Power Electronics and Applications (EPE'16 ECCE-Europe), 2016

DOI (link to publication from Publisher):
10.1109/EPE.2016.7695693

Publication date:
2016

Document Version
Early version, also known as pre-print

Distributed Coordination of Electric Vehicle Charging in a Community Microgrid Considering Real-Time Price

Chendan Li, Erik Schaltz, Juan C. Vasquez, Josep M. Guerrero
Aalborg University
Department of Energy Technology
Aalborg, Denmark
E-Mail: che@et.aau.dk; esc@et.aau.dk; juq@et.aau.dk; joz@et.aau.dk
URL: http://www.microgrids.et.aau.dk

Keywords

«community microgrid», « Electric Vehicle charging», «optimization », «distributed coordination», «real-time price»

Abstract

The predictable increasing adoption of EV by residential users imposes the necessity of Electric Vehicle charging coordination, in order to charge effectively while minimizing the impact on the grid. In this paper, a two-stage distributed coordination algorithm for electric vehicle charging management in a community microgrid is proposed. Each local EV charging controller is taken as an agent, which can manage the charging to achieve the optimization of the whole community by communicating in a sparse network. The proposed algorithm aims at optimizing real-time, which manages the charging activity based on the real-time price, while meeting the requirement of technical constraints of the distribution system.

Introduction

With awakening environmental awareness trigged by extreme weather and global warming, electric vehicles (EV) are increasingly considered as a promising technology to replace the traditional fuel-base vehicles, so as to curtail the dependence on the traditional fossil fuel and reduce the green gas emission [1]. Due to the declining of batter prices and the advance of related technology, plug-in electric vehicles are witnessed a steady increase in the market. Since the first introduction of modern electric cars in Denmark in 2009, sales have increased steadily over the years, from the 100 electric cars sold per year in 2009 and 2010, to 2014 in which there were 1575 new electric cars registered in Denmark [2].

The increasing EV charged by the residential user at home will certainly add more stringent requirements to the distribution grid, and how to minimized the impact of this new kind of load is a challenge that distribution network need to address. With the concept of microgrid, it offers an alternative angle to solve the problem, in which a part of distribution network can be deemed as an autonomous grid which coordinates the load and generation autonomously and collaboratively. In this aggregated way, the new kind of load is controlled to be not only user-friendly in term of economics, but also grid friendly in term of demand response.

For the coordination of electrical vehicle (EV) charging, researchers did many works to optimize this process with different objectives. In [3] and [4], authors use droop control to autonomously achieve charging coordination. However, whether it can achieve optimum is highly depended on whether droop parameters is optimally set and it is not flexible if the system is changed. A coordination algorithm is proposed in [5] considering the customers benefit and the revenue of the aggregator, but it only make the schedule which has the limitation in tackling the changes during real-time operation. In [6], convex quadratic programming is used in charging management to reduce the cost under time-varying electricity price signal, but it didn't consider the technical constraints of the grid. In [7], a multiagent system is implemented to meet the requirement of the distribution network both during the normal operation period and special cases. To balance the supply and demand, a complex prediction algorithm is used which is not easy to implement. In [8], a distributed algorithm is proposed, but the algorithm is not taking the real-time pricing into consideration.

In terms of implementation architecture, most of the works are based on a centralized controller [3]-[6], which gather all the information of the system and set the optimal signal to the EV charger to act. In this kind of implementation, it needs communication between all the EV charging and the centralized controller which brings heavy communication overload and make the system susceptible to single point of failure. Although others like [7] and [8] used the distributed methods, still have some limitation as mentioned above.

In this paper, a two-stage distributed coordination algorithm for EV charging management in a community microgrid is proposed. The proposed algorithm aims at optimizing in real-time, which manages charging activity based on the real-time price, while meeting the requirement of demand and supply balance and the limitation from the grid.

System description

In a community microgrid as in Fig.1, each residential user has level 1 EV charging at home (normally the maximum charging power is under 10kW). Each local EV charging controller is an agent, which can manage the charging to achieve the optimization of the whole community by communicating with sparse network. The communication network of EV charging agents is shown in Fig. 2.

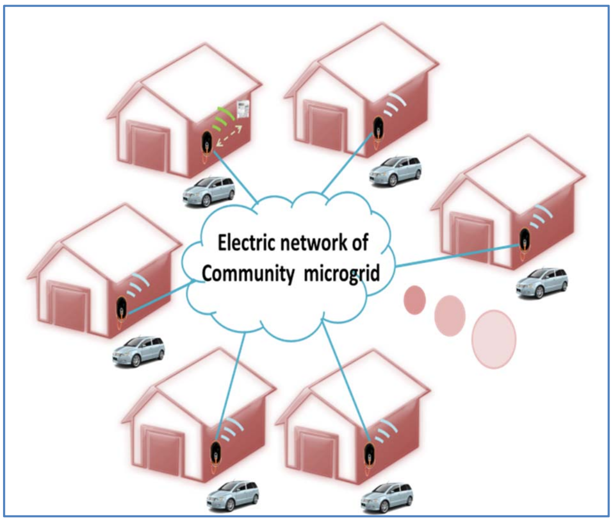


Fig.1: Community microgrid with EV charging

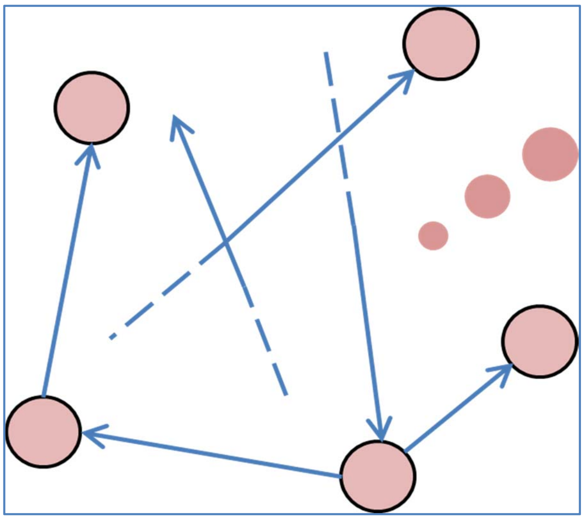
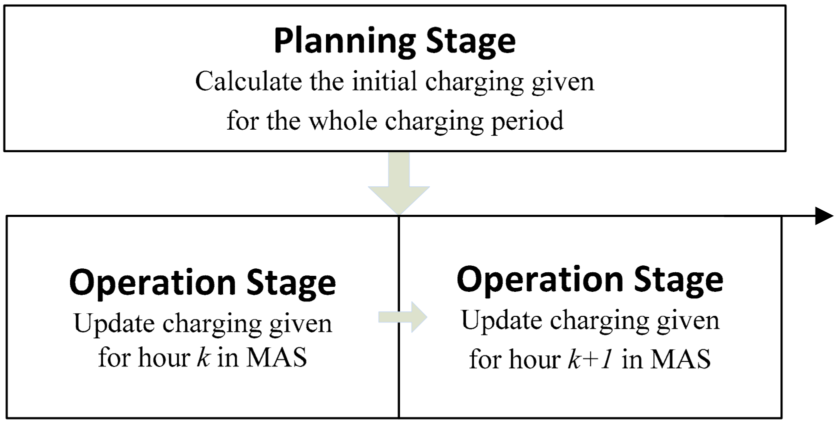


Fig. 2: Communication network of EV chargers

The local charging controller in the each residential home manages the charging process in a two-stage method as is shown in Fig. 3. In the first the stage, the local EV charger schedule the hourly charging power based day ahead market price, which gives the ideal optimal charging power. In the operation stage, due to the limitation of the total available charges power, the ideal optimal charging power might not be achieved, so that all the EV charging need to coordinate to get the optimum. The operation stage is based on consensus algorithm, in which no centralized controller is needed; each local EV can coordinate by communicating through sparse connections.

Problem formulation for the planning stage

To cope with the growth of domestic EV, utility launches new policies to encourage the end user to participate proactively in the demand response. One of the most promising is the introduction of the market mechanism, in that many pioneer distribution system operator (DSO) offer time varying price to the residential control [9].Fig. 3 show the day-ahead price and real-time price from Hourly Pricing Program provide by a US local utility and an energy delivery company ComEd’s in Illinois [9].



Decision making process of each EV of the MAS

Fig. 3: Two-stage charging management process

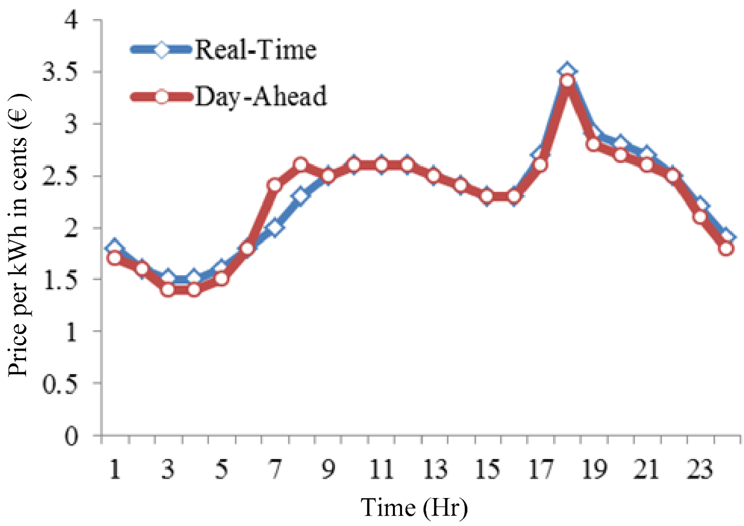


Fig. 4: Hourly price on 15/11/2015 day ahead and real-time

In the planning stage, the local EV charger schedule the hourly charging power based day ahead market price, which gives the ideal optimal charging power. The model of the EV batteries is using the equivalent circuit in [8].

$$V_i(\mathrm{k}) = \mathrm{V}_{oc,i} + R_i I_i(\mathrm{k}) \tag{1}$$

$$SOC_i(k+1) = SOC_i(k) + \frac{\Delta T}{E_i} I_i(k) \tag{2}$$

where V_i, $V_{oc,i}$, R_i, I_i, SOC_i ,and E_i are the output voltage, open circuit voltage, equivalent internal resistance, charging current, charging capacity of the battery *i*, respectively, ΔT is time slot of charging and *k* is the numbering of the charging time slot.

The charging power of each EV is defined as

$$P_i(k) = V_{oc,i} I_i(k) + R_i I_i^2(k) \tag{3}$$

where P_i denotes the charging power of EV *i*, To minimize the cost from the consumers' point of view, which is also complied with the demand response from the utility, the objective is to minimize the charging cost given the real-time price of the electricity.

$$\begin{aligned} & Min\sum_{k=0}^{k_i} p_i(k)P_{EV,i}(k)\Delta T \\ & s.t. \quad 0 \le P_i \le P_i^{\max} \\ & \qquad SOC_i(K_i) = SOC_i(0) + \sum_{k=1}^{k=K_i} \frac{\Delta T}{E_i} I_i(k) = SOC_i^* \end{aligned} \tag{4}$$

where SOC_i^* is the reference of the SOC after the whole charging process.

Distributed optimization in operation stage

In the operation stage, the ideal power command might not be followed due to the constraints of the grid and the individual EV charger. To adjust the charging power set in real-time which maintains the optimum, a consensus based distributed algorithm is proposed for the optimization in the operation stage. The objective of the optimization in the operation stage is to minimize the deviation between the ideal charging power command and the real charging power consider the constraints of the power balance of the load and supply, which can be shown as:

$$\begin{aligned} & Min\ L(k) = \sum_{i=1}^{n} L_i(k) = \sum_{i=1}^{n} \omega_i(k)[I_i(k) - I_i^*(k)]^2 \\ & = \sum_{i=1}^{n} \omega_i(k) \left\{ \frac{P_i(k)}{R_i} - \frac{V_{oc,i} + 2R_i I_i^*}{2R_i^2}\sqrt{4R_i P_i(k) + V_{oc,i}^2} + \frac{V_{oc,i}^2}{2R_i^2} + \frac{2I_i^*(k)V_{oc,i}}{R_i} + I_i^{*2}(k) \right\} \\ & s.t. \quad \sum_{i=1}^{n} P_{EV,i}(k) \le P_C(k) \\ & \qquad 0 \le P_i(k) \le P_i^{\max} \end{aligned} \tag{5}$$

where ω_i is the priority weight for EV i at time slot k, and I_i^* is the optimal charging current without considering the practical limitation during operation which obtained from the planning stage.

The incremental cost λ_i will be achieved when the equation (6) for all the EV chargers reach the same value;

$$\lambda_i(\mathrm{k}) = \frac{\partial L_i}{\partial P_i(\mathrm{k})} = \omega_i(\mathrm{k})\left(\frac{1}{R_i} - \frac{(\mathrm{V}_{oc,i} + 2\,\mathrm{R}_i \mathrm{I}_i^*(\mathrm{k}))}{R_i\sqrt{4R_i P_i(\mathrm{k}) + \mathrm{V}_{oc,i}^2}}\right) \tag{6}$$

The updating rule is as follows:

$$\lambda_i[t+1] = \sum d_{ij}\lambda_i[t] - \varepsilon \cdot P_D[t] \tag{7}$$

$$P_i[t+1] = \frac{(V_{oc,i} + 2 * R_i I_i^*(k))}{4R_i\left(\frac{\omega_i - R_i\lambda_i[t+1]}{\omega_i(k)}\right)^2} - \frac{V_{oc,i}^2}{4R_i} \tag{8}$$

$$P_D^{'}[t] = P_{D,i}[t] + (P_i[t+1] - P_i[t]) \tag{9}$$

$$P_{D,i}[t+1]=\sum d_{ij}P_D^{'}[t] \tag{10}$$

where $d_{ij}=\begin{cases} \dfrac{2}{(\mathrm{n}_i+\mathrm{n}_j+1)} & j\in N_i \\ 1-\sum\limits_{j\in N_i}\dfrac{2}{(\mathrm{n}_i+\mathrm{n}_j+1)} & i=j \\ 0 & otherwise \end{cases}$, and N_i is the set of the neighbours of the EV i,

and n_i is the number of agents connected with EV i.

The optimal charging power is:

$$P_i^{opt}=\begin{cases} \dfrac{(V_{oc,i}+2R_iI_i^*(k))^2}{4R_i(\dfrac{\omega_i-R_i\lambda_i(k)}{\omega_i(k)})}-\dfrac{V_{oc,i}^2}{4R_i}, & while\ P_i^{\min}<P_i^{opt}<P_i^{\max} \\ P_i^{\max}, & \dfrac{(V_{oc,i}+2R_iI_i^*(k))^2}{4R_i(\dfrac{\omega_i-R_i\lambda_i(k)}{\omega_i(k)})}-\dfrac{V_{oc,i}^2}{4R_i}>P_i^{\max} \\ P_i^{\min}, & \dfrac{(V_{oc,i}+2R_iI_i^*(k))^2}{4R_i(\dfrac{\omega_i-R_i\lambda_i(k)}{\omega_i(k)})}-\dfrac{V_{oc,i}^2}{4R_i}<P_i^{\min} \end{cases} \tag{11}$$

Case study

A community microgrid with 12 EV residential users is taken as an example in this study. The communication network topology is shown as in Fig. 5. The initial parameters of the EV batteries are listed in Table I. The real-time price is taken real data from the day ahead market data on the data 15/11/2015 in ComEd's in Illinois.

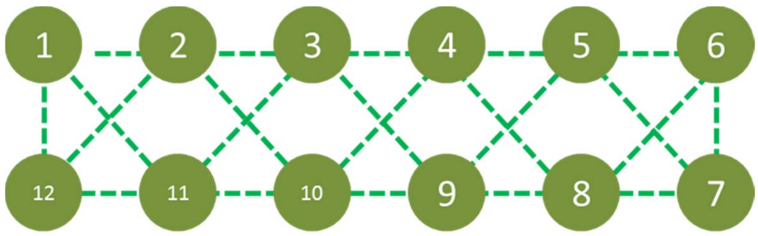


Fig. 5: communication topology of system studied

Table I: Parameters of EV batteries in the system

EV unit	R (ohm)	E (KWh)	Voc (V)	I EV max (A)	SOC(0)	SOC(K)
#1	1.05	28	312.5	15	0.25	0.8
# 2	1.12	30	308.4	15	0.4	0.9
# 3	1.14	24	294.5	15	0.3	0.85
# 4	1.03	29	304	15	0.36	0.9

# 5	1.09	21	280.3	15	0.24	0.8
# 6	1.38	32	285.4	15	0.21	0.8
# 7	1.23	30	291.4	15	0.35	0.9
# 8	1.26	20	288.4	15	0.2	0.8
# 9	1.32	26	305.6	15	0.4	0.9
# 10	1.09	27	293.1	15	0.26	0.8
# 11	1.16	21	285.4	15	0.32	0.85
# 12	1.15	26	277.6	15	0.22	0.75

Assuming the charging happens in during the evening and night in this study, the results of planning stage is shown in Fig. 6.

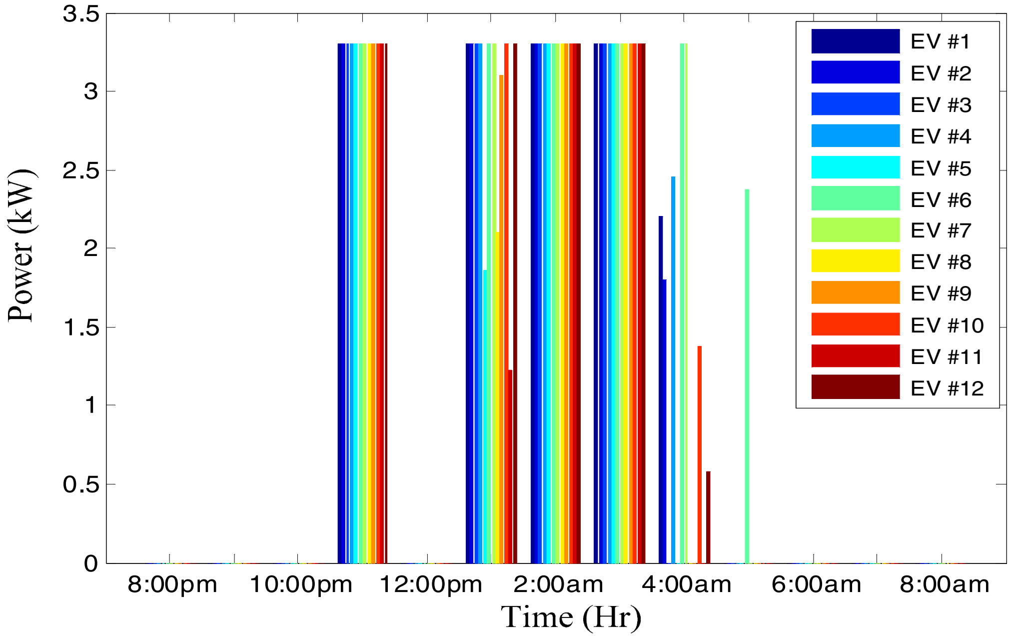


Fig. 6: planning stage results

In the operation stage, the charging process is managed by the distributed algorithm. The convergence process of the incremental cost, the power mismatch between the charging power and available power in one optimization step are shown Fig.7 (a) and Fig.7 (b), respectively. The optimal charging power is shown in Fig.7 (c). The whole optimization charging during the assumed charging period is shown in Fig. 8. The maximum charging power exposed by the DSO due to the technical constraints of the network or the substation transformer capacity is set to be 30.6kW.

Conclusion

In this paper, a distributed coordination algorithm is proposed for optimizing the EV charging in the context of community microgrid. By taking each local EV charging controller as an agent, the charging process is coordinated through a two-stage optimization via a sparse communication network. Case study shows that in the first stage the optimization is achieved considering only the real-time price, and in the second stage, the constraints occurred during the operation is addressed in a distributed way through consensus. The proposed EV charging network coordination is valuable in that the real-time optimization can handle the uncertainty of the load and power supply, as well as the limitation of the component capacity of the utility grid, and therefore can be a promising technology for regulating the increasing adoption of the residential EV.

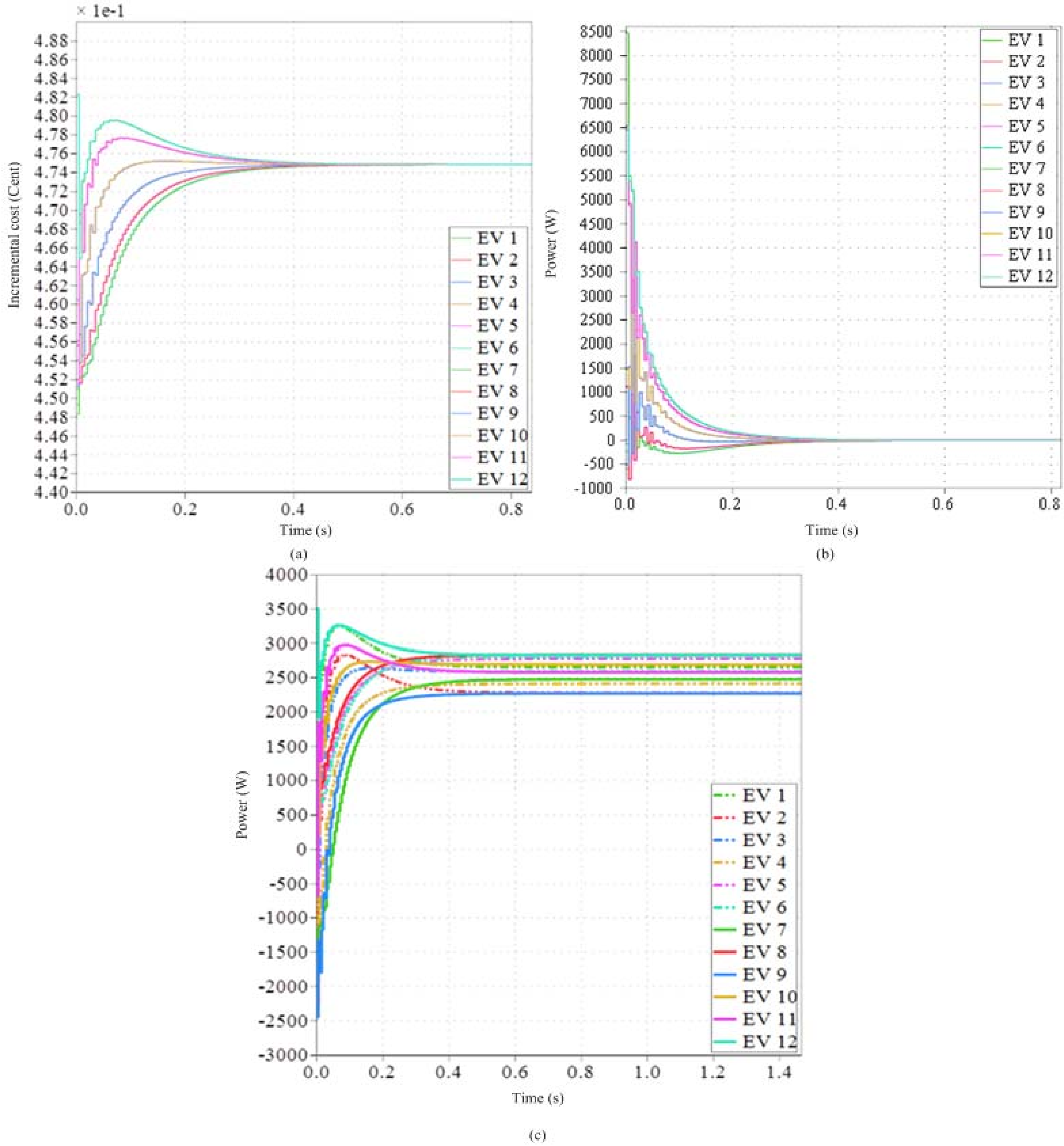


Fig. 7: Convergence process during operation stage (a) convergence of incremental cost (b)convergence of mismatch charging power and (c) Convergence of optimal charging power

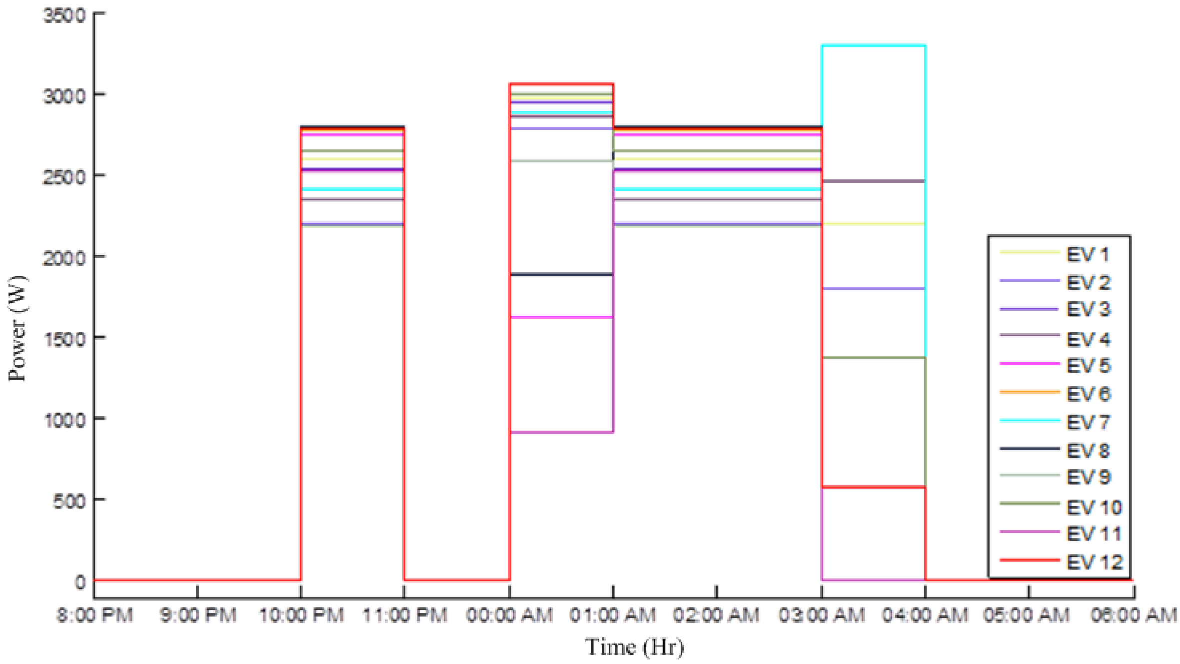


Fig. 8: EV charging coordination result

References

[1] http://mobi.vub.ac.be/

[2] http://www.danskelbilalliance.dk/

[3] Y. Ota, H. Taniguchi, T. Nakajima, K. M. Liyanage, J. Baba, and A. Yokoyama, “Autonomous distributed V2G (vehicle-to-grid) satisfying scheduled charging,” *IEEE Trans. Smart Grid,* vol. 3, pp. 559–564, 2012.

[4] H. Liu, Z. Hu, Y. Song, and J. Lin, “Decentralized vehicle-to-grid control for primary frequency regulation considering charging demands,” *IEEE Trans. Power Syst.,* vol. 28, pp. 3480–3489, 2013.

[5] C. Jin, J. Tang, and P. Ghosh, “Optimizing electric vehicle charging: A customer’s perspective,” *IEEE Trans. Veh. Technol.*, vol. 62, pp. 2919–2927, 2013.

[6] P. Papadopoulos, N. Jenkins, L. M. Cipcigan, I. Grau, and E. Zabala, “Coordination of the Charging of Electric Vehicles Using a Multi-Agent System,” *IEEE Trans. Smart Grid*, vol. 4, pp. 1802–1809, 2013.

[7] S. Bashash and H. K. Fathy, “Cost-Optimal Charging of Plug-In Hybrid Electric Vehicles Under Time-Varying Electricity Price Signals,” *IEEE Trans. Intell. Transp. Syst.*, vol. 15, pp. 1958–1968, 2014.

[8] Y. Xu, “Optimal Distributed Charging Rate Control of Plug-In Electric Vehicles for Demand Management,” IEEE Trans. Power Syst., vol. PP, pp. 1–10, 2014.

[9] https://hourlypricing.comed.com/