Smart Charging Strategy for Electric Vehicles Using an Optimized Fuzzy Logic System

M. Gholami (1,2), M. Mehrasa (1), R. Razi (3), K. Hajar (3), A. Hably (3), S. Bacha (1,4), A. Labonne (1)
1 Univ. Grenoble Alpes, CNRS, Grenoble INP*, G2Elab
2 Faculty of engineering, University of Kurdistan, Sanandaj, Iran
3 Univ. Grenoble Alpes, CNRS, Grenoble INP*, GIPSA-Lab
4 SuperGrid Institute
*Institute of Engineering Univ. Grenoble Alpes

Acknowledgments

This work has been supported by the aVEnir project of the PIA operated by ADEME.

Keywords

≪Electric vehicle≫, ≪Energy management≫, ≪Optimized Fuzzy system≫, ≪Genetic algorithm≫, ≪Smart charging≫.

Abstract

The increasing growth of electric vehicles (EVs) may arise as a challenge of increasing the load. Therefore, energy management in microgrids, including renewable energy resources such as PV systems, would be essential. Moreover, providing a smart charging pattern can optimize the overall cost of energy in a microgrid. In this paper, a genetic algorithm-based optimized fuzzy technique is developed, which has simple implementation such as rule-based methods and provides the optimal operation. The proposed scheme is simulated in MATLAB/Simulink environment for a case study. Results show the effectiveness of the proposed approach in comparison to conventional models.

Introduction

Concerning environmental issues and the tendency to reduce fossil fuel consumption, the number of electric vehicles (EVs) is growing significantly [1, 2]. Despite their advantages, it can lead to a challenge by increasing the grid load, especially during peak hours [3, 4, 5]. Therefore, managing and shifting them to the light-load times would be not only effective but also essential. Since EVs are stayed at parking lots for most of the time, a flexible bidirectional operation including vehicle to grid (V2G) and grid to vehicle (G2V) modes can be considered to minimize the microgrid cost [6, 7, 8]. Moreover, concerning the variable market, charging planning has become very important and has been conducted in many studies as an interesting topic called smart charging [9, 10, 11]. In addition, with the increasing penetration of renewable energy resources, and the emergence of microgrids, the tendency to manage energy at the micro-grid level has increased [12, 13]. One of the solutions proposed in previous studies is the formation of microgrids including charging stations, local loads, and renewable resources such as wind and PV [14, 15, 16].

There are a variety of strategies have been proposed for smart charging implementation. The use of rule-based algorithms such as fuzzy systems [17, 18, 19], the use of optimization programming methods [20, 21, 22, 23], and also predictive optimization methods [11, 24, 25, 26] to implement the smart charging pattern have been presented in various studies. The efficiency of these methods can be compared based on two criteria, including model complexity (cost of calculations) and model flexibility in the presence of system uncertainties such as load, solar system power, and energy price. Rule-based methods, although simple to implement and the rules can be used in different uncertainty conditions do not necessarily create the optimal situation. While methods based on programming and predictive optimization, despite providing optimal solutions, to manage system uncertainties, model calculations must be repeated over consecutive periods to ensure an optimal solution. Therefore, these models have a high computational load, and their implementation is problematic.

In this paper, we proposed a smart strategy based on an optimized fuzzy system that has both the benefits of fuzzy systems simplicity and providing an optimal solution. In this method, Fuzzy system parameters are obtained using genetic algorithm-based optimization. This method does not require repetitive calculations. Once in the beginning, the optimization is performed to find a suitable fuzzy system, and then the control is performed in a rule-based manner. Furthermore, to ensure the requested state of charge (SOC) at the time of departure, a supporting controller is provided to decide according to the time remaining and the maximum rated power of the EV. The rest of the paper is organized as follows. In Section II, the system model is described. Then, in Section III, the proposed model is presented. In Section IV, the simulation results for a case study are shown. Finally, Section V is devoted to the conclusions.

System model

The studied system is shown in Fig 1. This grid-connected the system includes local loads, a charge station, and a PV system. In this study, we followed the cost minimization of the microgrid by participating EVs in the energy management process. Since EVs usually stay for a long time at the station, they can experience not only the charging mode but also the discharging mode in a smart strategy to achieve the maximum benefit.

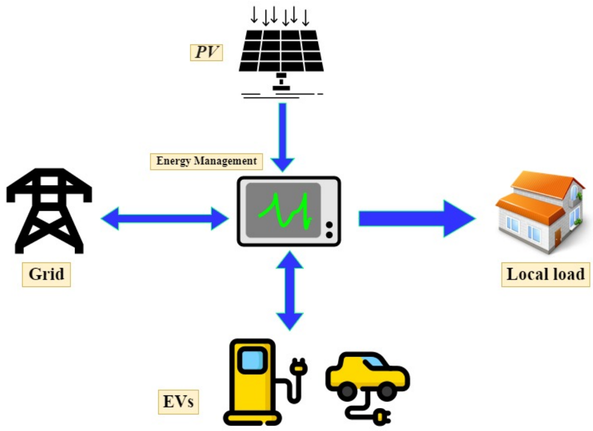

Fig. 1: The studied microgrid.

The objective function is defined based on the total cost for exchanged power with the grid, which is expressed in (1).

$$\begin{aligned} Cost = \sum_{k=1}^{N} [\Delta T * (\frac{P_{grid(k)} + |P_{grid(k)}|}{2}) * Price_{pos}(k) \\ - (\frac{P_{grid(k)} - |P_{grid(k)}|}{2}) * Price_{neg}(k)] \end{aligned} \tag{1}$$

In which, $P_{grid}(k)$ is the exchanged power with the grid at the instant k, ΔT is the duration of each interval, N is the number of intervals during the stopping in a parking lot. Also, the prices of positive and negative exchanged powers with the grid ($Price_{pos}, Price_{neg}$)are considered different. The constraints of the problem includes the rated power of EVs, the state of charge (SOC) of EV's batteries, and the microgrid power balance as bellow:

$$\begin{aligned}
&subject\ \ to \\
&\qquad\qquad P_{load} + P_{PV} + P_{EV} = P_{grid} \\
&\qquad\qquad P_{EV} \le P_{EV,n} \\
&\qquad\qquad SOC_{min} \le SOC \le SOC_{max}
\end{aligned} \tag{2}$$

The uncertainty in the load and PV power profiles and using the forecasted profiles is the main challenge for this problem where the optimization result will be affected by the prediction error. Although using some methods such as the predictive method can be useful to reduce the effect of prediction error, they need to be performed during subsequent intervals which leads to a high computational burden. The fuzzy inference system (FIS) method can deal well with the uncertainty so that it makes a decision based on the current information rather than forecasting data. A FIS system including membership functions and rules is designed based on the knowledge of the system. In addition to the knowledge, parameters of member functions and rules can affect the results of a FIS. Therefore, it is needed to optimize the FIS system based on the objective function. In this paper, we proposed an optimized FIS which is discussed in the next section.

Proposed smart charging strategy

The system given in Fig.1 is studied. In this paper, we consider one EV which can be extended to several EVs. An optimized fuzzy system is developed to perform the smart charging algorithm in this paper. First, the fuzzy system design is described and then the optimized fuzzy approach is presented.

Fuzzy system

The fuzzy system is used to obtain the power of EVs based on the status of the microgrid in terms of the energy price, the SOC of EVs, and the power of PV. Therefore a fuzzy system including three input variables and one output variable is designed. A Mamdani fuzzy inference system with triangular membership functions is used. Furthermore, rules are defined based on an overall view of the desired operation to achieve more benefit. According to these rules, the EV is charged during times with low energy price and high PV power and it is discharged vice versa. The intensity of charge/discharge power is determined through the fuzzy system. The membership functions for input and outputs are shown in Fig.2, and rules are given in Table I.

Optimized FIS

As mentioned the fuzzy system is designed based on an overall view and selection of parameters for membership functions are intuitive. In this paper, an optimized fuzzy system is presented and parameters are obtained based on minimizing the microgrid cost function as below:

$$\begin{aligned}
&min\{Cost(x,u)\} \\
&S.t. \quad g(x,u) = 0 \\
&\qquad\ \ f(x,u) \le 0
\end{aligned} \tag{3}$$

In which, u is the set of decision variables including three parameters for input membership functions and three ones for the output membership function, x is the set of independent variables, g and f are equality and inequality constraints mentioned in eq(2).

Due to the nonlinear and complex relationship between the cost function and the parameters of fuzzy variables, we use the Genetic algorithm (GA) optimization technique.

Obtaining the final SOC

To ensure the required SOC at the departure time, a support controller is provided which does not allow the SOC to be lower than the allowable level at any time. The allowable level at any time is determined based on the time remaining until the exit and the maximum rated power of the EV. It is defined in Eq(4).

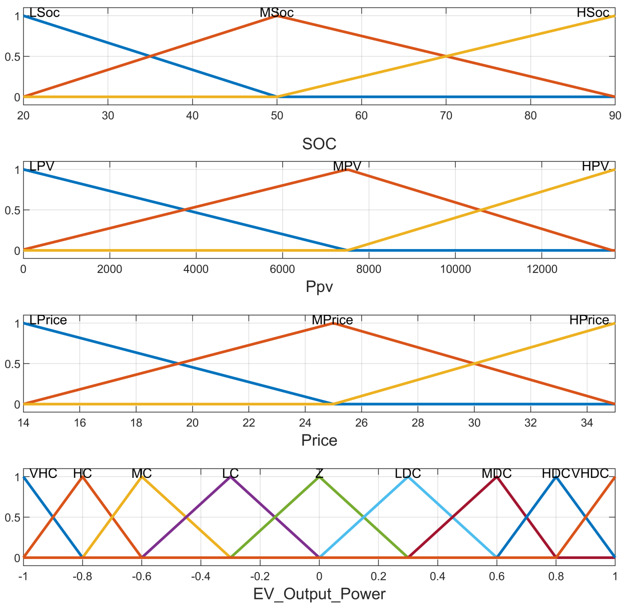

Fig. 2: Membership functions for normal-fuzzy system.

Table I: Fuzzy system rules.

SOC	P_{PV}	Price	EV	SOC	P_{PV}	Price	EV
L	L	L	HC	M	L	L	HC
L	L	M	LC	M	L	M	Z
L	L	H	Z	M	L	H	HDC
L	M	L	VHC	M	M	L	VHC
L	L	M	HC	M	M	M	LC
L	M	H	MC	M	M	H	MDC
L	H	L	VHC	M	H	L	VHC
L	H	M	HC	M	H	M	MCH
L	H	H	MC	M	H	H	MDC
H	L	L	LC	L:Low, M:Medium, H:High, Z:Zero			
H	L	M	LDC	LC:Low Charging			
H	L	H	VHDC	MC:Medium Charging			
H	M	L	LC	HC:High Charging			
H	M	M	LDC	VHC:Very-High Charging			
H	M	H	VHDC	LDC:Low Discharging			
H	H	L	LC	MDC:Medium Discharging			
H	H	M	MDC	HDC:High Discharging			
H	H	H	VHDC	VHDC:Very-High Discharging			

$$
\begin{aligned}
&SOC-Line = \begin{cases} SOC_{min} + m*(t-t_0), & \text{if } t \geq t_0 \\ SOC_{min}, & \text{otherwise.} \end{cases} \\
&m = \frac{(SOC_f - SOC_{min})}{\Delta T} \\
&\Delta T = ((SOC_f - SOC_{min}) * E_r/P_{max}) * 3600 \\
&t_0 = t_{out} - \Delta T
\end{aligned} \tag{4}
$$

where, SOC_f is the final SOC, E_r is the rated energy capacity, P_{max} is the maximum (rated) power of EV, and t_{out} is the departure time. Whenever the SOC level reaches the support line, the EV power is set to the maximum value.

Case study

The simulation result for one EV is given in this section to verify the proposed method. The characteristics of the microgrid are shown in Table II.

Table II: Microgrid characteristics.

Rated power of PV Array (P_{PV})	10kW
Rated power of load (P_{PV})	6kW
Rated power of EV (P_{EV})	15kW
Rated energy capacity of EC (E_{EV})	50kWh
SOC_{min} and SOC_{max}	0.2 - 0.95

The load, PV power ,and energy price profiles are shown in Fig. 3 and Fig. 4 for 24 hours. The same profiles are also considered for the next day in the simulation.

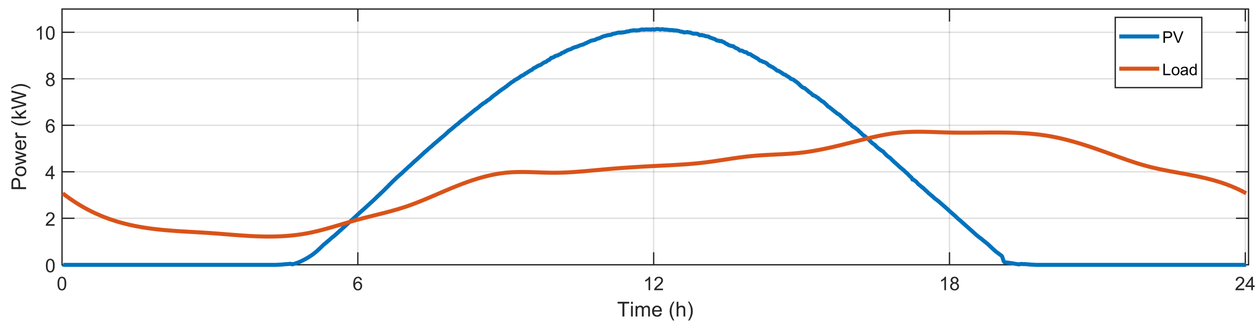

Fig. 3: Load and PV power profiles for 24 hours.

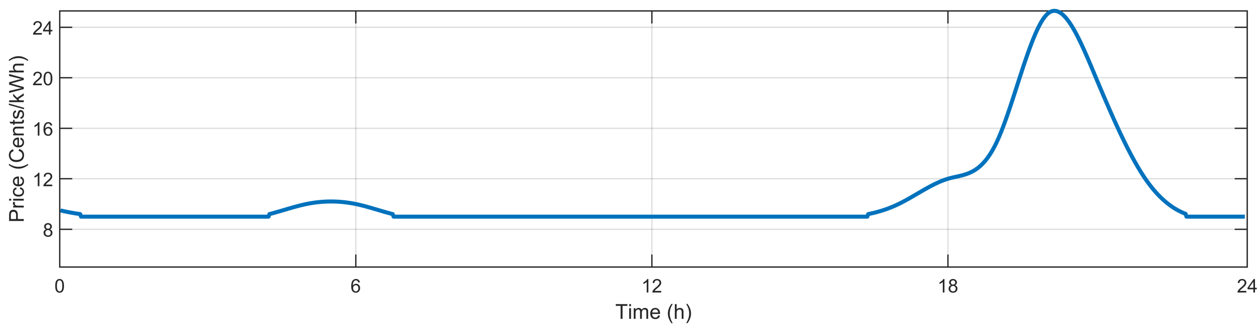

Fig. 4: Energy price profile for24 hours.

The studied scenario is defined as follows:

”The Ev is assumed to arrive at the parking lot at 4 p.m with the 60% of initial SOC and stays there until 8 a.m next day. The requested SOC at the time of departure is 90%.”

The support line for this scenario is shown in Fig. 5.

The simulation has been done in three cases. In the first case, there is no smart charging, and the EV just is charged to get the final SOC. In the two other cases, the smart charging is followed with normal fuzzy system and optimized fuzzy system. The fuzzy system is optimized using the GA technique in MATLAB, the new membership functions for the optimized fuzzy system are shown in Fig. 6. As can be seen, they are different than the normal system (Fig. 1).

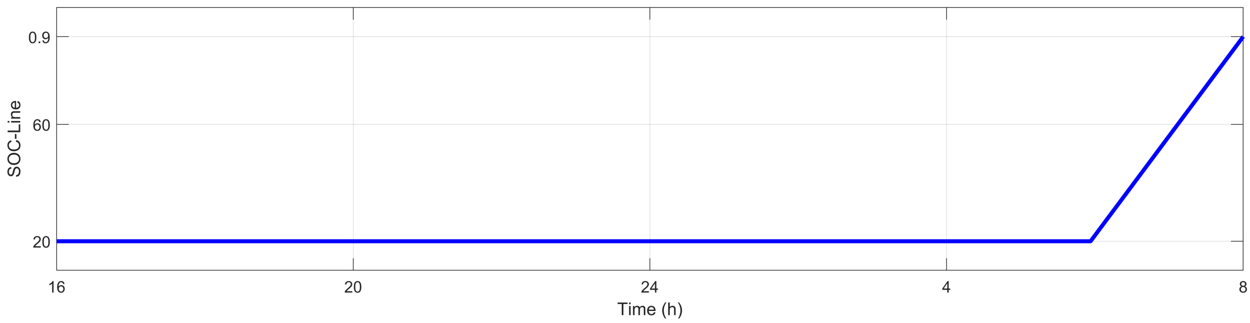

Fig. 5: Protective SOC Line.

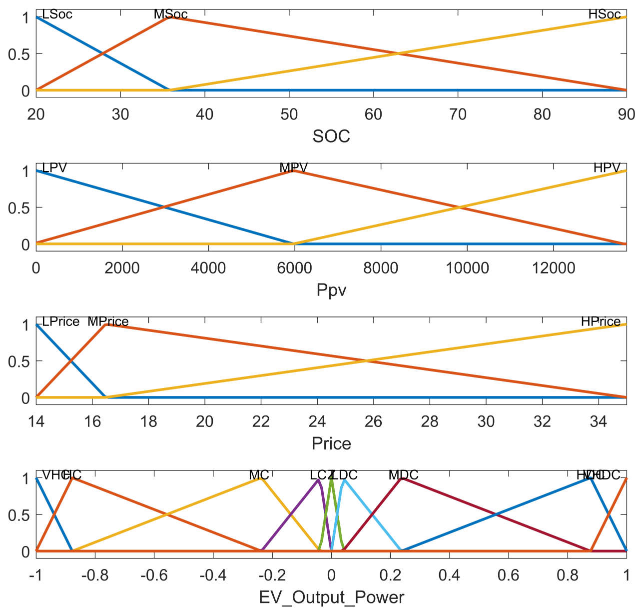

Fig. 6: Membership functions for optimized fuzzy system.

The simulation results including the power and SOC of EV and the cost of microgrid for three cases are shown in Figures 7, 8, 9.

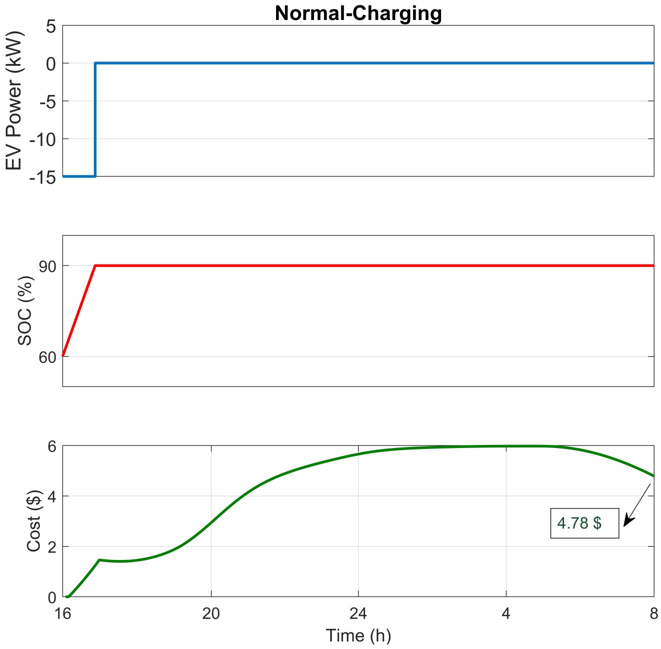

Fig. 7: Results for Normal-Charging mode; EV power, SOC, and microgrid cost.

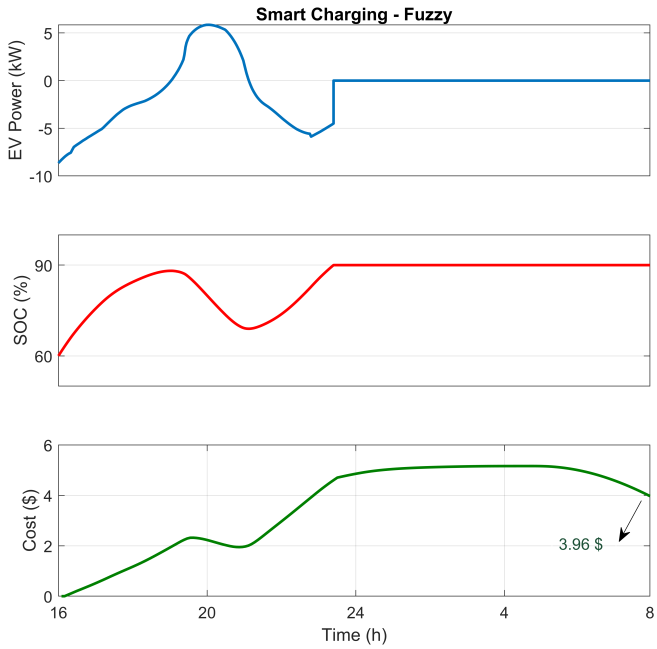

Fig. 8: Results for Smart-Charging mode, Normal-Fuzzy; EV power, SOC, and microgrid cost.

In the first case, the EV does not participate in the energy management and is charged with the nominal power to get to the final SOC. The final cost, in this case is 4.78$ which is much more than other cases. While the fuzzy controller has a significant effect in case II. The final cost is significantly decreased to 3.96$, which is 18% less than that of case I. Furthermore, the optimized fuzzy controller has much more effect in case III. In this case, the final cost is just 2.55$ which the final cost has been reduced to 50%. A comparison is given in Table III. As mentioned earlier, optimization in this method is done only once at the beginning of the EV entering the parking lot, so the implementation of this algorithm is much faster than other methods that require online optimization.

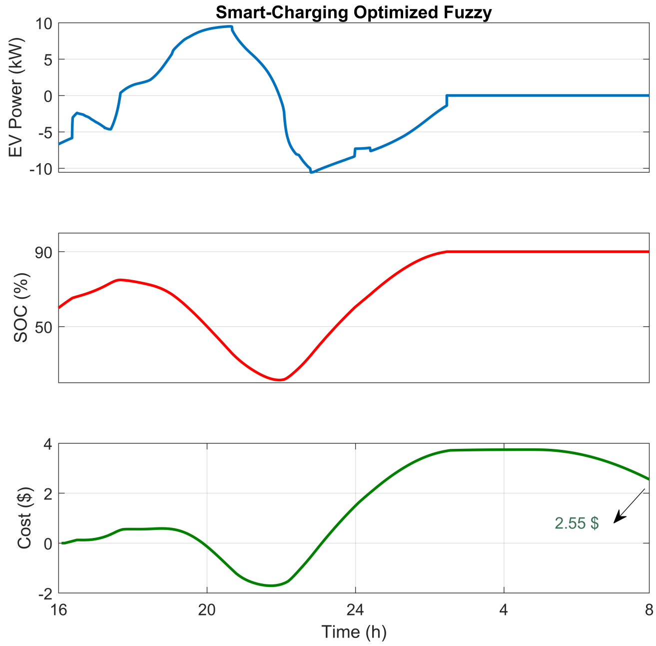

Fig. 9: Results for Smart-Charging mode, Optimized-Fuzzy; EV power, SOC, and microgrid cost.

Table III: Comparing the results.

	Case I Normal-Charging	Case II Fuzzy	Case III Optimized Fuzzy
Energy Cost ($)	4.78	3.96	2.25
Reduction percent (%)	0	18	53

Conclusions

The involvement of electric vehicles in the energy management of microgrids, including renewable and intermittent energy resources, can significantly reduce energy costs. In this process, charging of EVs is postponed to times when we have renewable production and energy price is low. In addition, when the energy price is high, they can discharge to provide some of the energy of local loads. Therefore, an algorithm is needed that can determine the power profile of EVs by considering the stopping time in the parking lot and their requested SOC at the departure. This paper presents an intelligent charging algorithm using an optimized fuzzy system that is both easy to implement and ensures an optimal response. In this method, the parameters of the fuzzy system membership functions are obtained based on the optimization of the cost function and using a genetic algorithm. The advantage of this method is that the optimization operation is performed only once when the EV enters the parking lot, and then, like the fuzzy method, it operates on a rule-based basis. Therefore, there is no need for optimization calculations during successive intervals. The next step in this strategy is to implement the algorithm in the presence of other vehicles, which will be examined in future studies.

References

[1] K. Hajar, B. Guo, A. Hably, S. Bacha, Smart charging impact on electric vehicles in presence of photovoltaics, in: 2021 22nd IEEE International Conference on Industrial Technology (ICIT), Vol. 1, IEEE, 2021, pp. 643–648.

[2] R Razi, M Mehrasa, K Hajar, M Gholami, A Hably, S Bacha, A Labonne: Predictive smart charging of plug-in electric vehicles for parking fleet scenario with modular converters. CIRED Porto Workshop 2022 E-mobility and power distribution systems.

[3] A. Gerossier, R. Girard, G. Kariniotakis, Modeling and forecasting electric vehicle consumption profiles, Energies 12 (7) (2019) 1341.

[4] H. Turker, S. Bacha, D. Chatroux, A. Hably, Modelling of system components for vehicle-to-grid (v2g) and vehicle-to-home (v2h) applications with plug-in hybrid electric vehicles (phevs), in: 2012 IEEE PES Innovative Smart Grid Technologies (ISGT), IEEE, 2012, pp. 1–8.

[5] M. Mehrasa, R. Razi, M. Gholami, K. Hajar, A. Labonne, A. Hably, and S. Bacha: A Dynamic Real-Time Optimization Algorithm for the Revenue Assessment of a Vehicle-To-Grid System in Presence of Wear Cost Model. Electrimacs 2022: 14th International Conference of TC-Electrimacs Committee, 16-19 May 2022 Nancy (France).

[6] Q. Hoarau, Y. Perez, Interactions between electric mobility and photovoltaic generation: A review, Renewable and Sustainable Energy Reviews 94 (2018) 510–522.

[7] V.-L. Nguyen, T. Tran-Quoc, S. Bacha, B. Nguyen, Charging strategies to minimize the peak load for an electric vehicle fleet, in: IECON 2014- 40th Annual Conference of the IEEE Industrial Electronics Society, IEEE, 2014, pp. 3522–3528.

[8] H. Turker, S. Bacha, Optimal minimization of plug-in electric vehicle charging cost with vehicle-to-home and vehicle-to-grid concepts, IEEE Transactions on Vehicular Technology 67 (11) (2018) 10281–10292.

[9] Y. Cao, H. Wang, D. Li, G. Zhang, Smart online charging algorithm for electric vehicles via customized actor-critic learning, IEEE Internet of Things Journal (2021).

[10] Y. Deng, Y. Mu, X. Dong, H. Jia, J. Wu, J. Zhang, S. Li, Hierarchical operation management of electric vehicles for depots with pv on-site generation, IEEE Transactions on Smart Grid (2021).

[11] R. Razi, K. Hajar, A. Hably, S. Bacha, A user-friendly smart charging algorithm based on energy-awareness for different pev parking scenarios, in: 2021 29th Mediterranean Conference on Control and Automation (MED), IEEE, 2021, pp. 392–397.

[12] M. Gholami, M. Mehrasa, R. Razi, A. Hably, S. Bacha and A. Labbone, "An Efficient Control Strategy for the Hybrid Wind-Battery System to Improve Battery Performance and Lifetime," IECON2021 – 47th Annual Conference of the IEEE Industrial Electronics Society, 2021, pp. 1-6.

[13] K. Hajar, R. Razi, M. Mehrasa, A. Labonne, A. Hably, and S. Bacha: Photovoltaics at the electric mobility's service: French case study. Electrimacs 2022: 14th International Conference of TC-Electrimacs Committee, 16-19 May 2022 Nancy (France).

[14] Y. Yang, M. Wang, G. Geng, Q. Jiang, Energy management of microgrid considering ev integration based on charging reservation information, in: 2021 IEEE/IAS Industrial and Commercial Power System Asia (I & CPS Asia), IEEE, 2021, pp. 609–614.

[15] A. Alsharif, C. W. Tan, R. Ayop, K. Y. Lau, C. L. Toh, Sizing of photovoltaic wind battery system integrated with vehicle-to-grid using cuckoo search algorithm, in: 2021 IEEE Conference on Energy Conversion (CENCON), IEEE, 2021, pp. 22–27.

[16] P. K. Ray, A. Bharatee, S. Panda, I. N. W. Satiawan, Modeling and power management of electric vehicle charging system, in: 2021 International Conference on Smart-Green Technology in Electrical and Information Systems (ICSGTEIS), IEEE, 2021, pp. 100–105.

[17] Y. Lu, S. Liu, M. Wu, D. Kong, Energy management of dual energy sources pure electric vehicle based on fuzzy control, in: 2021 IEEE International Conference on Internet of Things and Intelligence Systems (IoTaIS), IEEE, 2021, pp. 228–233.

[18] M. Mehrasa, R. Razi, K. Hajar, A. Labbone, A. Hably, S. Bacha, Power management of a smart vehicle-to-grid (v2g) system using fuzzy logic approach, in: IECON 2021–47th Annual Conference of the IEEE Industrial Electronics Society, IEEE, 2021, pp. 1–6.

[19] D. Sharma, B. Faujdar, B. S. Surjan, Fuzzy logic based power management of electric vehicle with battery and ultracapacitor energy storage system, in: 2021 4th International Conference on Recent Developments in Control, Automation & Power Engineering (RDCAPE), IEEE, 2021, pp. 246–250.

[20] Y. Lin, K. Wang, M. Quan, Z. Zhang, X. Dong, Optimal allocation method for microgrid system capacity with electrical vehicles, in: 2021 6th International Conference on Power and Renewable Energy (ICPRE), IEEE, 2021, pp. 1181–1185.

[21] N. Korolko, Z. Sahinoglu, Robust optimization of ev charging schedules in unregulated electricity markets, IEEE Transactions on Smart Grid 8 (1) (2015) 149–157.

[22] A. Pal, A. Bhattacharya, A. K. Chakraborty, Allocation of ev fast charging station with v2g facility in distribution network, in: 2019 8th International Conference on Power Systems (ICPS), IEEE, 2019, pp. 1–6.

[23] S. Bacha, A. Hably, A. Ovalle, Grid Optimal Integration of Electric Vehicles: Examples with Matlab Implementation, Springer, 2018.

[24] C. Diaz, F. Ruiz, D. Patino, Smart charge of an electric vehicles station: A model predictive control approach, in: 2018 IEEE Conference on Control Technology and Applications (CCTA), IEEE, 2018, pp. 54–59.

[25] M. Yousefi, A. Hajizadeh, M. N. Soltani, B. Hredzak, Predictive home energy management system with photovoltaic array, heat pump, and plug-in electric vehicle, IEEE Transactions on Industrial Informatics 17 (1) (2020) 430–440.

[26] F. Luo, G. Ranzi, C. Wan, Z. Xu, Z. Y. Dong, A multistage home energy management system with residential photovoltaic penetration, IEEE Transactions on Industrial Informatics 15 (1) (2018) 116–126