Fuzzy Logic-Based Online Energy Management System for Residential Microgrids

Wu, Jingxuan ; Li, Shuting ; Gui, Yonghao ; Cvetkovic, Milos; Vasquez, Juan C. ; Guerrero, Josep M.

DOI
10.1109/IECON51785.2023.10312171

Publication date
2023

Document Version
Final published version

Published in
Proceedings of the IECON 2023- 49th Annual Conference of the IEEE Industrial Electronics Society

Citation (APA)
Wu, J., Li, S., Gui, Y., Cvetkovic, M., Vasquez, J. C., & Guerrero, J. M. (2023). Fuzzy Logic-Based Online Energy Management System for Residential Microgrids. In *Proceedings of the IECON 2023- 49th Annual Conference of the IEEE Industrial Electronics Society* (Proceedings of the Annual Conference of the IEEE Industrial Electronics Society). IEEE. https://doi.org/10.1109/IECON51785.2023.10312171

Fuzzy Logic-based Online Energy Management System for Residential Microgrids

Jingxuan Wu[a], Shuting Li[a], Yonghao Gui[b], Milos Cvetkovic[c], Juan C. Vasquez[a], Josep M. Guerrero[a]
[a] Department of AAU Energy, Aalborg University, Aalborg, Denmark
[b] Electrification and Energy Infrastructures Division, Oak Ridge National Laboratory, Knoxville, Tennessee, United States
[c] Department of Electrical Sustainable Energy, Delft University of Technology, Delft, The Netherlands
{jinwu, shuli, juq, joz}@energy.aau.dk, {guiy}@ornl.gov, {M.Cvetkovic}@tudelft.nl

IECON 2023- 49th Annual Conference of the IEEE Industrial Electronics Society | 979-8-3503-3182-0/23/$31.00 ©2023 IEEE | DOI: 10.1109/IECON51785.2023.10312171

***Abstract*—A fuzzy logic based online energy management system (FLEMS) is designed in this paper to achieve the optimal electricity cost in a residential Microgrid (MG). The proposed FLEMS is combined by a local energy price model (LEPM) and a fuzzy-logic strategy. The LEPM will preprocess the sampling data to estimate the electricity market and local MG status. The fuzzy-logic mimics the artificial intelligent assessment to economic issues and make decision for the charging and discharging operation for energy storage system (ESS). In the FLEMS, not only electricity price and supply-demand balance, but also ESS state of charge are considered for the efficient and stable operations. The proposed method does not relay on the accurate prediction of renewable energy source and local loads. Historical experience of the system is involved by the LEPM and guides the ESS operation in the fuzzy-logic. A real-world data based household-level residential MG model is established to validate the performance of the FLEMS. A hourly-resolution-Particle swarm optimization (PSO) with perfect day-ahead prediction is implemented as the baseline to verify the superiority of the proposed method.**

***Index Terms*—EMS, energy storage, electricity cost, fuzzy logic, microgrid**

I. Introduction

The renewable energy develops rapidly during last decade due to the raising desire of environmental-friendly energy structure [1]. The wind energy and solar energy, superior for the extreme low greenhouse gas emission, bring intermittence and uncertainty to power system as well as flexible energy price to energy market. Energy management system is a widely accepted solution to Microgrids (MGs) with high proportion of renewable energy sources (RES) [2].

In residential MGs, EMS is regarded as an optimization problem in plenty of research works. To decrease the electricity cost and improve the energy efficiency, numerous optimization methods are designed to appropriately plan the working schedule of local loads [3] and energy storage system (ESS). Particle swarm optimization (PSO) is one of the typical look-ahead optimization strategies [4]. The operation mode of building MG could be optimized to achieve minimum electricity cost and maximum stability [5]. PSO could also collaborate with other methods, for instance, artificial neural network, to increase the reliability and energy efficiency [6]. However, the description of PSO problems meets more challenges as the development of controllable loads due to the nonlinear factors introduced by them. Mix-integer linear programming (MILP) is usually deployed to schedule the flexible loads, energy source [7] or electrical vehicles in MGs [8]. Besides, MILP is a effective solution to environment uncertainty in look-ahead optimization tasks [9]. In MGs with high proportion of RESs, the EMS has to optimize the operation of ESS against uncertainty caused by wind, solar irradiation, temperature, etc [10]. Given the impact of uncertainty, there is a growing interest in conducting additional research on real-time optimization as a means of reducing its influence [11].

The online optimization could be regarded as a decision problem in EMS. The efficacy of look-ahead optimization is hindered by real-time uncertainty in MG implementation [12]. The online EMS take real-time data into account to schedule the ESS against the uncertainty [13]. The short-term prediction results and the uncertainty model are utilized for the online parts, hence, the model predictive control (MPC) could be deployed for EMS [14]. Reinforcement learning (RL)-based methods also receive more attentions when considering MGs with multi RESs or ESSs [15]. Agents, including DQN [16], DDPG [17], SAC [18], PPO [19], are verified effective in various applications. However, the model of MPC and training of RL also bring cost of data acquisition and computation resource.

This paper proposes a fuzzy-logic-based online EMS (FLEMS) for household-level residential MGs (HRMGs). Fuzzy logic (FL) is good at nonlinear system compensation [20]. In residential MGs, the operation of ESS [21] and the coordinator of the energy sources [22] is a typical application for FL. To achieve the optimal electricity cost, a local energy price model (LEPM) is designed to involve the historical experience, and FL is built to make decision for ESS operation. The contribution of the proposed method includes, 1) the proposed FLEMS works within a minute resolution and without the requirement additional prediction method, increases the optimization precision and computation efficiency; 2) the online FLEMS considers the uncertainty from not only the energy supply and demand side, but also the flexible energy price of the market; 3) the proposed economical LEPM involves the essential historical information of the MG system as the experience of the EMS, the proposed FL strategy make the global decision accordingly.

The remainder of the paper is organized as follows. The

This work was supported in part by the China Scholarship Council (CSC).

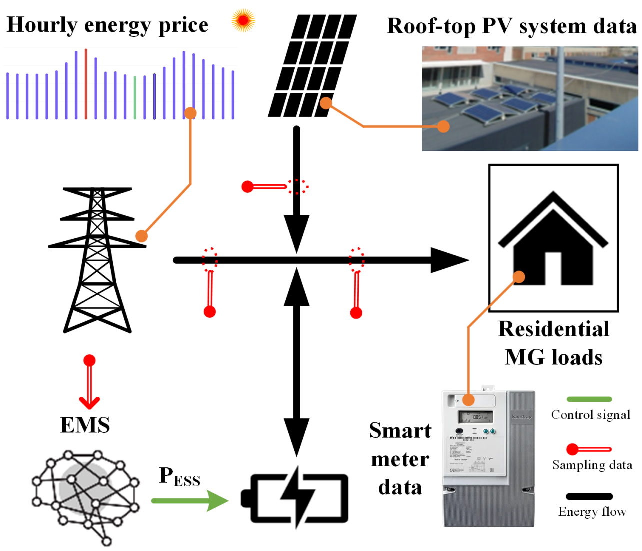

Fig. 1. Architecture of the household-level residential Microgrid.

structures of the HRMG and the LEPM are presented in Section II; Section III expounds the structure of the FL-based EMS; The case study using real-world data for Internet of Things Laboratory from AAU CROM is shared in Section IV; The conclusion is drawn in Section V.

II. Local Energy Price Model for Household-level Residential Microgrids

The architecture of the proposed HRMG is established according to the Internet of Things (IoT) Laboratory of AAU CROM. The statistical models of the devices in the HRMG are built using real-world data. The LEPM is embedded in the EMS as a data preprocessing and information mining method.

A. Architecture of the household-level residential Microgrid

The HRMG works on grid-connected mode, and the energy shortage and excess are compensated by the utility grid. The energy price is decided by energy supply company, the hourly electricity price of the coming day is updated at 1 p.m everyday. Hence, the electricity price prediction could be solved by reading the price data from website. The primary energy supply is a roof-top PV system, and the intermittence is mitigated by a battery ESS. The total load data is monitored by smart meter. The architecture of the HRMG is shown in Fig.1. The nominal power of the PV system is 3 kW. The capacity of the ESS is 5 kWh and the nominal charging and discharging power is 2.5 kW.

The loads of the HRMG include fridge, oven, coffee machine, TV, microwave oven and all the office stuffs like laptops, servers, etc. The total power is sampled by a smart meter and uploaded to IoT network. The power times series is stored in local database, the energy consumption is figured out through the integration of power data. The PV system, the ESS and the utility grid power are sampled and uploaded using wireless sensors.

The statistical models of the devices are established with 10-day time series, the EMS collects the energy price, device power data. The input signals are preprocessed by the LEPM and the power reference of the ESS is generated through the proposed FL strategy.

B. Real-time local energy price model

The proposed HRMG records the origin of local energy stored in ESS, and the State of Charge (SoC) of ESS are considered for future operation. The HRMG is superposed by an SoC estimation function and an local energy worth (LEW) function.

The SoC estimation function describes the status of ESS, which is shown as

$$\xi_{SoC}(t) = \lambda(SoC(t) - 0.5)^{2\tau+1} \tag{1}$$

the ξ_{SoC} donates the SoC estimation component of the LEPM, the λ affects the amplitude of SoC estimation function, and the τ decides the slope. The λ and τ are defined according to the electricity price. If the SoC is either extremely low or high, the SoC estimation function will have a significant impact on the LEPM. However, when the SoC is within the appropriate range, the SoC estimation function will have minimal effect on the LEPM. The function will promote charging when the SoC is low and facilitate discharging when the SoC is high to avoid excessive charging and discharging of the ESS.

The LEW function records the total value of the energy stored in local ESS. The energy value is defined by the electricity price at the mean time.

During the charging process, the total LEW is grown and the LEW component of the LEPM could be calculated by

$$\xi_{LEW}(t+1) = \frac{SoC(t)\xi_{LEW}(t) + \Delta SoC \cdot Pr}{SoC(t+1)} \tag{2}$$

where the ΔSoC represents the SoC change during the time interval, and the Pr donates the electricity price at the mean time. The equation (2) could be simplified as

$$\Delta\xi_{LEW} = \frac{\Delta SoC(Pr - \xi_{LEW}(t))}{SoC(t+1)} \tag{3}$$

If the ESS was discharging, the ξ_{LEW} should remain constant as

$$\xi_{LEW}(t+1) = \frac{(SoC(t) + \Delta SoC) \cdot \xi_{LEW}(t)}{SoC(t+1)} \tag{4}$$

$$\Delta\xi_{LEW} = 0 \tag{5}$$

In summary the ξ_{LEW} could be described by the combination of equation (3) and (5),

$$\xi_{LEW}(t+1) = \xi_{LEW}(t) + \Delta\xi_{LEW} \tag{6}$$

$$\Delta\xi_{LEW} = \begin{cases} \dfrac{\Delta SoC(Pr - \xi_{LEW}(t))}{SoC(t+1)}, & 0 < \Delta SoC, \\ 0, & \Delta SoC \leq 0. \end{cases} \tag{7}$$

The LEPM is the sum of the two components, not only the ESS status, but also the historical trading data are estimated.

$$\xi(t) = \xi_{SoC}(t) + \xi_{LEW}(t) \tag{8}$$

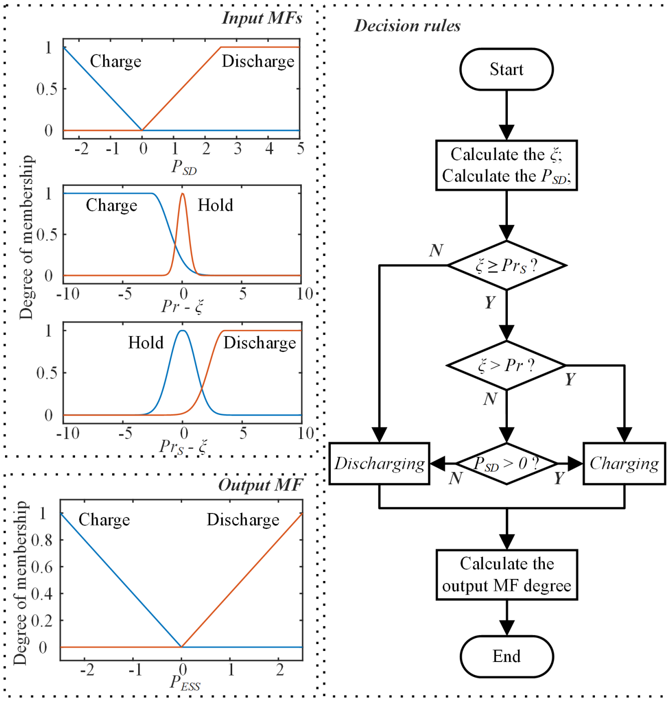

Fig. 2. MFs and decision rules of the FL strategy

In the proposed FLEMS, the LEPM preprocess the input signals and pass the judgement to the FL. The FL strategy is elaborated in Section III.

III. Fuzzy Logic-based Online Decision Strategy

The decision-making process based on FL emulates artificial intelligent assessment of economic issues. The decision is made according to the situations of local MG and electricity market. The condition of electricity market is represented by the comparison between electricity price and ξ_{LEW}, including the price of purchasing electricity and selling electricity. The purchasing price is the flexible hourly price and the selling price is set to zero. The status of local MG is estimated by the local supply-demand balance, which is defined by

$$P_{SD}(t) = P_{Load}(t) - P_{RES}(t) \tag{9}$$

in which, the P_{Load} donates the power demand, and the P_{RES} is the local power supply. $P_{SD} > 0$ indicates supply shortage, and $P_{SD} < 0$ manifests oversupply. The ESS has three operational modes: charging, discharging, and holding. The membership functions (MFs) and the decision rules are presented in Fig. 2. The input MFs decide the charging or discharging operations according to P_{SD}, ξ, Pr_S and Pr. After the essential parameters figured out, the market price and MG status are analyzed. If ξ is lower than Pr_S, the ESS injects power to the utility grid and local loads, and if ξ is higher than Pr, the ESS is set to charging. In other cases, the operation depends on the supply-demand balance, the energy shortage is compensated, and the energy exceeding is absorbed by ESS. The charging or discharging power is calculated through the output MF.

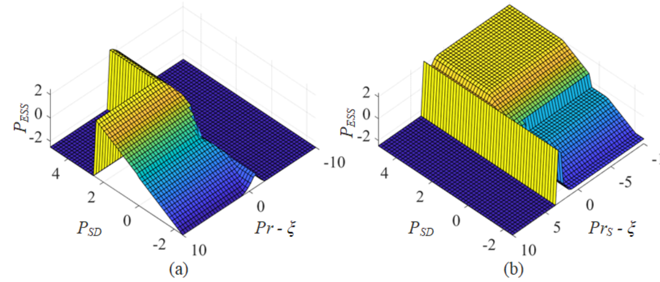

Fig. 3. Correlation of P_{ESS}, P_{SD}, ξ and (a) Pr, (b) Pr_S

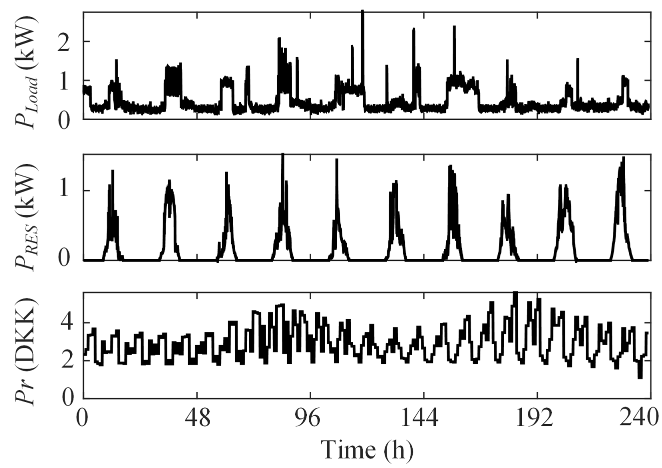

Fig. 4. Time sequence features of the HEMG scenario

The correlations of P_{ESS}, P_{SD} and the prices are shown in Fig. 3. The FLEMS updates the ESS output power reference every minute, and the LEPM is a real-time data preprocess method.

IV. Case Study

The proposed FLEMS is an online EMS and validated through the HEMG introduced in Section II. The scenario is based on the real-world data, including the PV output power, total load and electricity price over a period of 10 days. The time sequence features are presented in Fig. 4. The load power sequence records the total power consumption of IoT laboratory in AAU CROM, the appliances include an oven, two fridges, a microwave oven, several TVs, and office stuffs like laptops, lights, etc. The PV output power data contains different weathers. The power data updates every minute, the electricity price is in hourly resolution and the price of selling electricity is set to zero according to common situations in HRMG. A PSO-based hourly day-ahead EMS is designed as the baseline, in which perfect RES and load predictions are implemented. The results of the proposed FLEMS is presented in Fig. 5. If the ξ is higher than Pr, the ESS will compulsively set to charging mode, the HRMG will purchase energy from the utility grid. If the ξ is lower, the ESS will discharge to support the load demand. Benefit from the characteristic of the LEPM, the SoC of ESS could be detected. If the ESS is

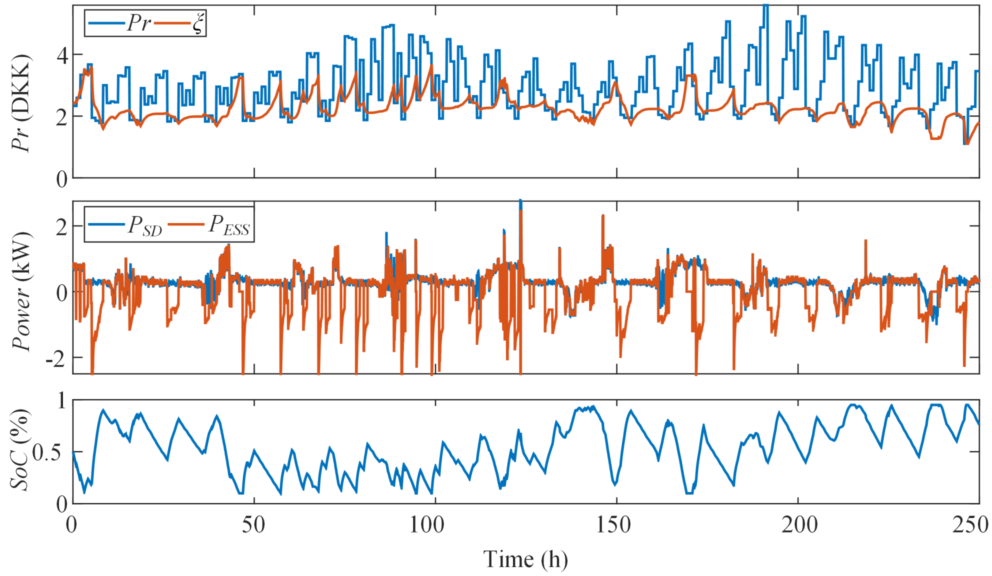

Fig. 5. The LEPM output and the ESS power time sequence for the HRMG with FLEMS

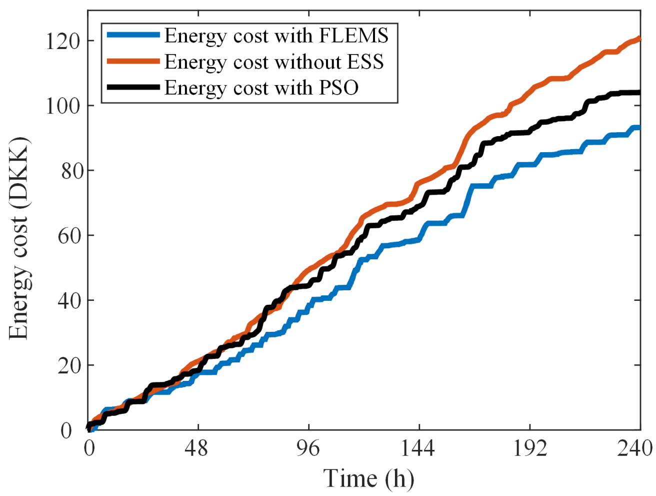

Fig. 6. The energy cost of FLEMS, PSO and traditional topology

either over charged or discharged, the output of LEPM will respond accordingly. From the figure, it is obvious than the SoC of ESS floats within appropriate range. The ξ reflects the overall trend of the electricity price and shows higher inertia, the effect of market price oscillation to the EMS is avoided.

The results of the proposed FLEMS and benchmarks are presented in Fig. 6. The energy cost of HRMG without compensation of ESS is 121 DKK. With the hourly day-ahead PSO, the cost is reduced to 104 DKK, saving 14% of expense. The proposed FLEMS decreases the cost to 93.2 DKK, with a 23% optimization.

In summary, the proposed FLEMS achieve best performance among the three methods. The PSO-based EMS could also provide good benefits to HRMG, but the performance is limited by the optimal resolution and the prediction precision.

V. Conclusion

.

This paper designed a FLEMS for residential MG to achieve efficient operation of ESS. Two main strategies are established for the minimum energy cost, LEPM and FL-based decision strategy. The main works of the paper are summarized into three aspects. 1) The FLEMS considers the flexible electricity price, the supply-demand balance and the SoC of ESS. The proposed LEPM involves the historical experience into the judgement for global decision. 2) The proposed FLEMS does not depend on prediction methods, the decision process simulates the artificial intelligent assignment to economical issues. 3) A real-world data-based HRMG platform is built to validate the performance of the proposed method, the superiority of the proposed method is verified through the comparison with tradition MG topology and PSO-based EMS.

References

[1] Z. Yang, W. Liao, H. Wang, C. L. Bak, and Z. Chen, "Improved euclidean distance based pilot protection for lines with renewable energy sources," *IEEE Transactions on Industrial Informatics*, vol. 18, pp. 8551–8562, 12 2022.

[2] J. M. Raya-Armenta, N. Bazmohammadi, J. G. Avina-Cervantes, D. Sáez, J. C. Vasquez, and J. M. Guerrero, "Energy management system optimization in islanded microgrids: An overview and future trends," *Renewable and Sustainable Energy Reviews*, vol. 149, 10 2021.

[3] A. Natarajan, V. Krishnasamy, and M. Singh, "Occupancy detection and localization strategies for demand modulated appliance control in internet of things enabled home energy management system," *Renewable and Sustainable Energy Reviews*, vol. 167, 10 2022.

[4] M. Manbachi and M. Ordonez, "Intelligent agent-based energy management system for islanded ac-dc microgrids," *IEEE Transactions on Industrial Informatics*, vol. 16, pp. 4603–4614, 7 2020.

[5] K. Thirugnanam, M. S. E. Moursi, V. Khadkikar, H. H. Zeineldin, and M. A. Hosani, "Energy management strategy of a reconfigurable grid-tied hybrid ac/dc microgrid for commercial building applications," *IEEE Transactions on Smart Grid*, vol. 13, pp. 1720–1738, 5 2022.

[6] J. Aguila-Leon, C. Vargas-Salgado, C. Chiñas-Palacios, and D. Díaz-Bello, "Energy management model for a standalone hybrid microgrid through a particle swarm optimization and artificial neural networks approach," *Energy Conversion and Management*, vol. 267, 9 2022.
[7] W. Violante, C. A. Cañizares, M. A. Trovato, and G. Forte, "An energy management system for isolated microgrids with thermal energy resources," *IEEE Transactions on Smart Grid*, vol. 11, pp. 2880–2891, 7 2020.
[8] A. Ravichandran, S. Sirouspour, P. Malysz, and A. Emadi, "A chance-constraints-based control strategy for microgrids with energy storage and integrated electric vehicles," *IEEE Transactions on Smart Grid*, vol. 9, pp. 346–359, 1 2018.
[9] Q. Sui, F. Wei, C. Wu, X. Lin, and Z. Li, "Day-ahead energy management for pelagic island microgrid groups considering non-integer-hour energy transmission," *IEEE Transactions on Smart Grid*, vol. 11, pp. 5249–5259, 11 2020.
[10] L. P. Raghav, R. S. Kumar, D. K. Raju, and A. R. Singh, "Optimal energy management of microgrids using quantum teaching learning based algorithm," *IEEE Transactions on Smart Grid*, vol. 12, pp. 4834–4842, 11 2021.
[11] X. Xing, L. Xie, H. Meng, X. Guo, L. Yue, and J. M. Guerrero, "Energy management strategy considering multi-time-scale operational modes of batteries for the grid-connected microgrids community," *CSEE Journal of Power and Energy Systems*, vol. 6, pp. 111–121, 3 2020.
[12] Y. Shan, J. Hu, and H. Liu, "A holistic power management strategy of microgrids based on model predictive control and particle swarm optimization," *IEEE Transactions on Industrial Informatics*, vol. 18, pp. 5115–5126, 8 2022.
[13] E. Kuznetsova, Y. F. Li, C. Ruiz, E. Zio, G. Ault, and K. Bell, "Reinforcement learning for microgrid energy management," *Energy*, vol. 59, pp. 133–146, 9 2013.
[14] H. Chen, R. Xiong, C. Lin, and W. Shen, "Model predictive control based real-time energy management for hybrid energy storage system," *CSEE Journal of Power and Energy Systems*, vol. 7, pp. 862–874, 7 2021.
[15] L. Langer and T. Volling, "A reinforcement learning approach to home energy management for modulating heat pumps and photovoltaic systems," *Applied Energy*, vol. 327, 12 2022.
[16] Y. Liu, D. Zhang, and H. B. Gooi, "Optimization strategy based on deep reinforcement learning for home energy management," *CSEE Journal of Power and Energy Systems*, vol. 6, pp. 572–582, 9 2020.
[17] L. Yu, W. Xie, D. Xie, Y. Zou, D. Zhang, Z. Sun, L. Zhang, Y. Zhang, and T. Jiang, "Deep reinforcement learning for smart home energy management," *IEEE Internet of Things Journal*, vol. 7, pp. 2751–2762, 4 2020.
[18] Y. Zhou, Z. Ma, J. Zhang, and S. Zou, "Data-driven stochastic energy management of multi energy system using deep reinforcement learning," *Energy*, vol. 261, 12 2022.
[19] C. Guo, X. Wang, Y. Zheng, and F. Zhang, "Real-time optimal energy management of microgrid with uncertainties based on deep reinforcement learning," *Energy*, vol. 238, 1 2022.
[20] T. A. Fagundes, G. H. F. Fuzato, P. G. B. Ferreira, M. Biczkowski, and R. Q. Machado, "Fuzzy controller for energy management and soc equalization in dc microgrids powered by fuel cell and energy storage units," *IEEE Journal of Emerging and Selected Topics in Industrial Electronics*, vol. 3, pp. 90–100, 6 2021.
[21] T. T. Teo, L. Thillainathan, W. L. Woo, and K. Abidi, "Intelligent controller for energy storage system in grid-connected microgrid," *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, vol. 51, pp. 650–658, 1 2021.
[22] M. Jafari, Z. Malekjamshidi, J. Zhu, and M. H. Khooban, "A novel predictive fuzzy logic-based energy management system for grid-connected and off-grid operation of residential smart microgrids," *IEEE Journal of Emerging and Selected Topics in Power Electronics*, vol. 8, pp. 1391–1404, 6 2020.