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Editorial

Optimization Trends in Demand-Side Management

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The electrical system is undergoing a structural change, dissolving into a new concept of a distributed environment, based on renewable energies, demand management and resource sharing [1]. This new structure poses a challenge for administrations and infrastructure managers, who must act as facilitators of the active role of distributed users. This new development will only be possible thanks to the development of optimization techniques for the new distributed concept of prosumers, agents with both production and consumption capabilities distributed along the electrical network [2].

A fundamental aspect in electrical systems is the fact that energy cannot be stored in large quantities, and therefore, there must always be a balance between the generated and consumed power. Historically, electricity power systems have been designed by following a vertical integration scheme: large power generators supply energy to multiple consumers through a hierarchical transport and distribution network. In this scenario, management was carried out by controlling the generation of electrical energy in large manageable plants, allowing their production to follow the consumption demand curve. This management was simple because the number of large power plants to control was relatively low.

However, we are currently witnessing a paradigm shift in the electricity sector. This change has caused the traditional centralized structure of generation, transport and consumption to be diluted in a new concept of distributed environment, where users can generate their own energy and use it in internal micro grids [3]. Therefore, the role of the consumers in this new environment must be much more active and flexible, also assuming the role of producer. In this context, the users will play an important role in the so-called Smart Grid [4], helping to manage their demand towards both local and global energy efficiency, based on demand response (DR) [5] and demand-side management (DSM) [6] strategies.

In recent years, several works have focused on the optimization of DR and DSM for the residential, industrial or commercial sector, with the objective of saving costs and reduce carbon emissions. In this editorial, we refer to five specific strategies, which focus on the optimization of the energy produced and stored. The highlighted manuscripts address the multi-objective problem form different perspectives: model-based or model-free, with local generation or local storage and based on traditional optimization tools, machine learning or deep learning techniques. However, they all share a common objective, to increase the efficiency of the electric networks by means of powerful and up-to-date optimization techniques.

Specifically, in [7], the authors propose a home energy management system that optimizes the load demand and distributed energy resources. The system is presented as a multi-objective optimization problem. The multi-objective function is defined as a fitness function that consists of the electricity cost and the customer dissatisfaction. Both objectives are weighted and combined into a single objective function, which allows users to select the best optimization according to their economic interests. Simulations analyze the impact of dissatisfaction, distributed energy resources and cost, with the aim of minimizing consumption cost while considering users' comfort and lifestyle. The

Citation: Gutiérrez, Á. Optimization Trends in Demand-Side Management. *Energies* **2022**, *15*, 5961. https://doi.org/10.3390/en15165961

Received: 12 August 2022
Accepted: 16 August 2022
Published: 17 August 2022

proposed algorithm showed a reduction in the electricity consumption cost and in the aggregated peak demand, when compared to the same scenario without the optimization.

In the same direction, [8] proposes an energy optimization method for a local energy community. The authors propose a DSM algorithm for electrical energy optimization, where the operating costs are reduced by incorporating the users in the DSM program. At the same time, they analyze the tradeoff between the users' comfort and their participation. This tradeoff is typically not taken into account when developing algorithms, but it is an important aspect to warranty users' adhesion to DR or DSM programs. Authors plan a day-ahead scheduling optimization model for the community, where they show that operating costs are reduced when the users are involved in DSM programs

A similar approach, but relying on energy storage, is presented in [9]. The authors propose an optimization method based on a hybrid genetic ant colony optimization algorithm. Besides the real-time pricing and the local generation, a battery system is included for local energy maximization, with the objective of reducing the electricity import, the peak load demand and the carbon emissions simultaneously. Different scenarios with and without local generation or batteries are compared. The proposed hybrid algorithm outperforms the state of the art of genetic algorithms [10], ant colony optimization [11] or particle swarm optimization [12] tested for the same scenarios and conditions.

Although storage capabilities are desirable to damp energy consumption with DSM techniques, excessive loading and unloading could be harmful to the electrical system. This is something already perceived when observing the effects of a high penetration of electric vehicles, because peak demand can be transferred to unusual time periods and create a generation–consumption mismatch. Therefore, optimization must also focus on how to improve DSM when electric vehicles are present. Specifically, in [13], the authors propose a machine learning-based approach for energy management in microgrids, with renewable energy penetration where a reconfigurable structure is considered for modeling and estimating electric vehicles' demand. The prediction model forecasts the charging demand of electric vehicles with higher accuracy than standard autoregressive models or artificial neural networks.

Previous approaches require accurate forecasts of the energy price, PV generation based on weather prediction or users' consumption. Therefore, the quality of the forecasts can deteriorate the excellence of the results obtained. On the contrary, in [14], the authors focus on a model-free approach. Specifically, they propose a system based on the twin delayed deep deterministic policy gradient (TD3) method [15], which outperforms previous model-free approaches that overestimate the expectations, thus avoiding sub-optimal policies and obtaining better convergence properties. Simulations with real data demonstrated that the developed algorithm converges to a near-optimal solution and reduces the energy cost compared to previous approaches.

All the manuscripts presented in this editorial point to the direction of improving the electrical network behavior, with the aim of reducing electricity costs and carbon emissions. Moreover, this new concept based on optimization will continue growing until a new complete concept of multi-agent self-organization emerges [16]. Therefore, in the following years, a new smart-grid paradigm will arise, where a high number of heterogeneous optimization algorithms will coexist to improve energy efficiency and distributed control.

Funding: This research received no external funding.

Conflicts of Interest: The author declares no conflicts of interest.

References

1. Abdella, J.; Shuaib, K. Peer to Peer Distributed Energy Trading in Smart Grids: A Survey. *Energies* **2018**, *11*, 1560. https://doi.org/10.3390/en11061560.
2. Rodríguez-Molina, J.; Martínez-Núñez, M.; Martínez, J.-F.; Pérez-Aguiar, W. Business Models in the Smart Grid: Challenges, Opportunities and Proposals for Prosumer Profitability. *Energies* **2014**, *7*, 6142–6171. https://doi.org/10.3390/en7096142.
3. Liang, H.; Zhuang, W. Stochastic Modeling and Optimization in a Microgrid: A Survey. *Energies* **2014**, *7*, 2027–2050. https://doi.org/10.3390/en7042027.
4. Lobaccaro, G.; Carlucci, S.; Löfström, E. A Review of Systems and Technologies for Smart Homes and Smart Grids. *Energies* **2016**, *9*, 348. https://doi.org/10.3390/en9050348.
5. Hussain, I.; Mohsin, S.; Basit, A.; Ali Khan, Z.; Qasim, U.; Javaid, N. A Review on Demand Response: Pricing, Optimization, and Appliance Scheduling. *Procedia Comput. Sci.* **2015**, *52*, 843–850. https://doi.org/10.1016/j.procs.2015.05.141.
6. Rabl, V.A.; Gellings, C.W. The Concept of Demand-Side Management. In *Demand-Side Management and Electricity End-Use Efficiency*, De Almeida, A.T., Rosenfeld, A.H., Eds.; Springer: Dordrecht, The Netherlands, 1988; Volume 149. https://doi.org/10.1007/978-94-009-1403-2_5.
7. Amer, A.; Shaban, K.; Gaouda, A.; Massoud, A. Home Energy Management System Embedded with a Multi-Objective Demand Response Optimization Model to Benefit Customers and Operators. *Energies* **2021**, *14*, 257. https://doi.org/10.3390/en14020257.
8. Li, Y.; Zhang, J.; Ma, Z.; Peng, Y.; Zhao, S. An Energy Management Optimization Method for Community Integrated Energy System Based on User Dominated Demand Side Response. *Energies* **2021**, *14*, 4398. https://doi.org/10.3390/en14154398.
9. Ali, S.; Khan, I.; Jan, S.; Hafeez, G. An Optimization Based Power Usage Scheduling Strategy Using Photovoltaic-Battery System for Demand-Side Management in Smart Grid. *Energies* **2021**, *14*, 2201. https://doi.org/10.3390/en14082201.
10. Holland, J.H. *Adaptation in Natural and Artificial Systems: An Introductory Analysis with Applications to Biology, Control, and Artificial Intelligence*; University of Michigan Press: *Ann Arbor*, MI, USA, 1975.
11. Dorigo, M.; Stützle, T. *Ant Colony Optimization*; The MIT Press: *Cambridge*, MA, USA, 2004. https://doi.org/10.7551/mitpress/1290.001.0001.
12. Kennedy, J.; Eberhart, R. Particle swarm optimization. In Proceedings of the ICNN'95—International Conference on Neural Networks, Perth, WA, Australia, 27 November–1 December 1995; Volume 4, pp. 1942–1948 https://doi.org/10.1109/ICNN.1995.488968.
13. Lan, T.; Jermsittiparsert, K.; T. Alrashood, S.; Rezaei, M.; Al-Ghussain, L.; A. Mohamed, M. An Advanced Machine Learning Based Energy Management of Renewable Microgrids Considering Hybrid Electric Vehicles' Charging Demand. *Energies* **2021**, *14*, 569. https://doi.org/10.3390/en14030569.
14. Ye, Y.; Qiu, D.; Wang, H.; Tang, Y.; Strbac, G. Real-Time Autonomous Residential Demand Response Management Based on Twin Delayed Deep Deterministic Policy Gradient Learning. *Energies* **2021**, *14*, 531. https://doi.org/10.3390/en14030531.
15. Lillicrap, T.P.; Hunt, J.J.; Pritzel, A.; Heess, N.; Erez, T.; Tassa, Y.; Silver, D.; Wierstra, D. Continuous control with deep reinforcement learning. *arXiv* **2015**, arXiv:1509.02971. https://doi.org/10.48550/arXiv.1509.02971.
16. Castillo-Cagigal, M.; Matallanas, E.; Caamaño-Martín, E.; Gutiérrez, Á. SwarmGrid: Demand-Side Management with Distributed Energy Resources Based on Multifrequency Agent Coordination. *Energies* **2018**, *11*, 2476. https://doi.org/10.3390/en11092476.