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Editorial

Electricity Demand Side Management

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Demand-side management is a resilient concept. It was coined in 1984 by Clark Gellings, from EPRI, long before the wave of liberalization of the electricity industry occurred in many parts of the world. The extraordinary track record of DSM in terms of the efficient use of energy resources was not enough to avoid its crossing of the desert as market liberalization took its course. Nevertheless, it re-emerged as an inevitable toolbox component to tackle climate change and achieve carbon neutrality.

The MDPI Electricity DSM topic attracted many contributions, covering a wide spectrum of themes that show the vitality of scientific research in this area. Demand modelling and load forecasting represent instrumental issues in policy design. Behavioural aspects are considered, in terms of investment behaviour, consumer behaviour, or dealing with strategies to implement flexible load dispatch as a crucial tool for network management in view of the growing penetration of renewable generation. End-uses are thoroughly covered, both in the residential and industrial sectors, identifying opportunities for energy efficiency improvements and network flexibility management through the load shifting of appliances, electric vehicle charging, or energy storage management. The demand response is the theme of a substantial portion of the contributions to this topic. This is approached from several perspectives: the need to adopt DR strategies that are adapted to the preferences of consumers to maximize their effects, the role of DR in the seamless integration of renewable generation in the network operation, and the importance of DR in peak demand limiting, energy price containment and network frequency control.

Berbesi and Pritchard [1] focused on modelling energy data, incorporating spatial and temporal components, using generalized additive models with one-dimensional and two-dimensional smoothers. The inclusion of spatial data was expected to improve the representation of the socioeconomic characteristics of the regions under study. The proposed method was applied to model energy demand in Colombia.

Kanté et al. [2] aimed to forecast and understand the long-term electricity demand of the Taoussa area for the sustainable development of the regions of northern Mali, using the Model for Analysis of Energy Demand (MAED) from the International Atomic Energy Agency. Candela Esclapez et al. [3] developed an algorithm to estimate the accuracy of forecasts, aiming to determine the best schedules to produce accurate forecasts with a limited computational burden. Dejamkhooy and Ahmadpour [4] applied a Gaussian process model to forecast electricity prices in a restructured power system. Shaqiri et al. [5] uses a dynamic regression model for a short-term forecast of the electricity consumption of industrial and institutional customers of an electricity provider.

Turdaliev [6] focused on behavioural aspects by analysing the purchase of major electrical appliances in regions with Increasing Block Rates (IBR) for electricity pricing in Russia, finding significant effects when shaping the behaviour of households using price-based policies. Huang et al. [7] used psychological research to find a direct connection between users' herd mentality (HM) and their decision-making behaviour towards participation in demand-shaping actions. Manandhar et al. [8] applied machine learning methods to study the energy consumption changes resulting from the COVID-19 pandemic and lockdown measures in Dubai.

Senchilo and Ustinov [9] analysed energy storage at the end-use level, applying a novel algorithm to determine the optimal storage capacity for a specific consumer, minimizing the costs of levelling the load schedule when participating in a demand response program. Obi et al. [10], studied communication-enabled water heaters to shift electric load off the peak and move toward periods when renewable resources are more prevalent. Goh et al. [11] applied an orderly electric vehicle (EV) charging approach based on optimal time-of-use pricing and studied the effect of varied degrees of responsiveness on charging strategies for EVs. Hua et al. [12] proposed a voltage control strategy by optimizing the limited regulation capacity of air-conditioners, finding significant potential to provide voltage regulation services to the distribution network. Rodrigues et al. [13] focused on the technological feasibility, economic viability and global impact of using domestic refrigeration and freezing appliances for electrical load shifting from peak to off-peak demand periods, aiming to achieve a greater penetration of renewable energy sources.

Regarding end-uses, Talei et al. [14] aimed to identify smart building inefficiencies using machine learning, applied to a single building's HVAC consumption data and building usage data in a highly efficient office building. Sanchez-Escobar et al. [15] reviewed the contribution of bottom-up energy models to support policy design for electricity end-use efficiency in residential buildings. Hummel et al. [16] measured the electric power demand of air compressors in industrial facilities, finding key influencing factors for the compressed air electric ratio. Zhang et al. [17] analysed aluminum smelters' role as a possible flexibility supplier, helping to manage maintenance schemes for the electric power grid. Köberlein et al. [18] also targeted industrial use-cases of energy-flexible manufacturing, identifying challenges and solutions for the simulation of these processes.

Focusing on demand response, Kaczmarski et al. [19] studied how utilities should design direct-load control programs to improve participation. Binyet et al. [20] analysed barriers to participation in demand response programs. Schöne et al. [21] assessed the preferences in residential demand response in a small community on the island of Mayotte, a French overseas department located in the Indian Ocean. Santos et al. [22] applied a mixed-integer linear programming formulation to model DR as a dispatchable resource in the day-ahead hydrothermal scheduling problem. Ming et al. [23] introduced a robust controller to coordinate the demand side with the supply side, aiming to improve the stability and robustness of the grid under large disturbances. Salazar et al. [24] developed combined price- and incentive-based DR models to manage consumer demand with data from a real San Juan's Argentina distribution network.

Finally, Mimi et al. [25] performed a systematic review of optimization approaches for demand-side management in the Smart Grid, covering publications between 2013 and 2022, revealing the growing use of hybrid approaches involving meta-heuristics and identifying the need for more accurate models of renewable sources and storage elements.

Demand response is the legitimate heir of the load–demand curve objective of the primal DSM, known as "flexible load shape". The concept already existed; the proliferation of renewable generation gave it great importance in contemporary network management. Demand-side management is here to stay as an invaluable concept for the evolution of the electricity industry and the sustainable development of the energy system as a whole, in view of the growing electrification of the economic activities and the decarbonization strategies adopted by many energy policies around the world. Scientific research on DSM will undoubtedly accompany this trend.

Conflicts of Interest: The authors declare no conflict of interest.

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