ARTIFICIAL INTELLIGENCE-BASED DEMAND-SIDE RESPONSE MANAGEMENT OF RENEWABLE ENERGY

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ABSTRACT
Renewable energy (RE) sources will aid in the decarbonization of the energy sector, which would assist in alleviating the negative consequences of climate change. However, using RE resources for hybrid power generation has two technological challenges, uncertainty and variability owing to RE features, making estimating generated power availability difficult. Artificial intelligence techniques have been used in a variety of applications in power systems, but demand-side response (DR) is just lately receiving major research interest. The DR is highlighted as one of the most promising ways of providing the electricity system with demand flexibility; as a result, many system operators believe that growing the scale and breadth of the DR programme is critical. There are many different sorts of demand reduction programmes, and the most common classification is dependent on who begins the demand reduction. There are two types of DR schemes: (1) price-based programmes and (2) incentive-based programmes.
Keywords: demand response, renewable energy, artificial intelligence, machine learning.

1 INTRODUCTION

Demand response (DR) has grown in importance in recent years in endorsing energy systems' stability and efficiency as a result of smart metering infrastructure and current improvements in information and communication technologies. It has the ability to manage inconsistencies in power demand (D) and supply (S) by managing elastic loads on the D-side [1]. In Energy Management System (EMS), a well-planned DR structure has major positive benefits for society. This includes increasing human comfort, promoting the use of renewable resources, lowering global energy consumption, and decreasing dependency on fuel resources linked with high carbon emissions [2].

Consumers can participate in DR programmes by lowering or adjusting their energy use during peak hours as a result of time-based tariffs or other financial incentives [3]. The most energy-intensive segments of electricity systems are residential and industrial customers (CUs). Residential and industrial sectors consumed 58% of aggregate global power usage in 2018 (22% and 36%, respectively), according to the U.S. Energy Information Administration [4].

The Home Energy Management System (HEMS) is described in the residential segment as the best system for delivering services for energy management to efficient management and monitoring of power usage, and effective generation, and storage in smart homes [5]. The primary manageable residential appliances are divided into three classifications: (1) thermostatically controlled appliances, (2) non-thermostatically controlled appliances, and (3) electrical energy storage.

Increasing urbanization, the integration of additional RE generation resources, and the outlook of electric vehicles introduce new challenges for the control of the power grid. The effects of these problems can already be observed in places like California, where rolling blackouts are becoming increasingly frequent, especially during the summer, when consumers need electricity the most and D is at its highest. Some of these problems can be tackled through additional capital investments to oversize the power grid at the transmission and distribution levels and create a buffer for D/S volatility. However, proper control

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techniques can reduce the need for such investments significantly. In the U.S., buildings represent about 70% of the total power usage, and it is estimated that DR has the potential to reduce peaks of electricity D by roughly 7% to 27%, depending on the region [6].

The value of energy storage and DR can be assessed as a function of multiple factors, including the energy mix, how volatile the loads are, the costs of different energy generation and storage technologies, and what control systems are leveraged. Similarly, there are multiple tradeoffs between using centralized or distributed energy resources, which depend on the incremental unit costs of distributed energy resources and the incremental locational value of electricity [7]. Thus, there is a need for more simulation tools that can help in such kinds of assessments under diverse sets of conditions.

This paper is organized in five sections. Section 2 is a survey of literature on renewable energy demand-side response (DR). The applications of Artificial Intelligence (AI)/Machine Learning (ML) in the renewable energy sector are covered in Section 3. Section 4 discusses the problems of AI applications in DR management, followed by conclusions in Section 5.

2 RENEWABLE ENERGY DR

Price-based programmes and incentive-based programmes are the two categories of DR programmes. CUs in price-based schemes modify their energy use patterns as a response to changes in power prices. Unlike price-based programmes, control equipment is installed at the CU's location in incentive-based programmes. The Load Servicing Entities (LSEs) can use this technology to switch particular electric appliances at specific periods.

In price-based programmes, these members can save money by limiting their power use during peak hours or by receiving incentive payments in incentive-based programmes. Gathering DR resources to compete for ancillary services in the marketplaces can assist LSEs. DR, by actively participating in the power balance, adds to the overall dependability and stability of the power system. Furthermore, it aids in the avoidance or postponement of the building or implementation of distribution and transmission infrastructure [8]. By providing required information about individual consumers, such as their electricity consumption habits, load profiling plays a critical role in the formulation of lucrative D programmes.

2.1 Price-based DR programs

CUs alter their power use in accordance with the price set by LSE in price-based schemes, such as (1) Time Of Use (TOU), (2) Critical Peak Pricing (CPP), and (3) Real Time Pricing (RTP). Only the overall electrical use of a day, month, or even more extended period is sent to the LSE without smart meters. Consumers with similar overall consumption but varying peak consumption are charged the same amount. Load profiling may be done with the use of smart meters to help the LSE establish time-variant pricing in order to optimize profit and increase DR.

Creating an optimization model and solving it based on load profiling is the basic approach to pricing design. A three-stage technique for TOU design was developed by Mahmoudi-Kohan et al. [9]. Various rates are optimized for CUs belonging to different clusters independently after determining the CUs' eagerness to purchase power. A simulation with 300 clients revealed that clustering with a lower CDI might result in higher profits. Conditional Value at Risk (CVaR) is applied by Mahmoudi-Kohan et al. [10]. The stochastic programming model was used using the same clustering approach and acceptance function as shown by Mahmoudi-Kohan et al. [9].

Mahmoudi-Kohan et al. show that load profiling was performed to discover CUs with comparable peaks in the overall curve [11]. CUs with high elasticity are given priority in a cost reduction model. The limitation states that the overall load decrease must equal or exceed the retailer's power shortfall. Panapakidis et al. used load profiling to extract typical load curves and then determined the pricing for each standard curve [12]. For an industrial CU, a comparison was made between yearly load profiling and seasonal load profiling. The findings revealed that taking into account the impact of seasonal pricing variations in the pool market might boost earnings. Maigha and Crow offered load profiling-based optimum TOU structures instead of pricing design [13]. A performance parameter for clustering algorithms is the granularity of the cluster's sensitivity, that relates to a scenario in which clusters comprise fewer than two hours and are scattered throughout the day. A case study confirmed that among the examined strategies, Gaussian mixture models performed the best.

2.2 Incentive-based DR programs

In incentive-based schemes, the residential CU has a contract with the programme administrator (such as an "aggregator" or "service provider") under which the programme administrator may be authorized to execute various control measures aimed at lowering power prices. The following DR programmes are often accessible in this category: (1) Direct Load Control (DLC), (2) Interruptible Tariffs, (3) Demand Bidding Programs, and (4) Emergency Programs [14]. Since it invades the CU's privacy, the DLC technique is deemed intrusive.

The administrator has authority over the operation of the client's appliance until the CU gets the agreed-upon payment in DLC. Interruptible tariffs are available to both "industrial" and "residential" consumers, and they basically provide multiple pricing layers according to the agreement between the energy provider and the client. The quantity of energy utilized is not reduced by load interruption, but it does shift load operation to off-peak hours [15]. CUs can take part in the electricity trading market by proposing to adjust their patterns of consumption, reschedule their loads, or reduce their usage through D-bidding. During times of high D or when the grid is disrupted by unanticipated occurrences, emergency programmes are implemented. Participants in these programmes limit their consumption to relieve grid stress in emergency circumstances, and they are compensated with compensation depending on the required amount of load reduction [16].

Furthermore, the temperature sensitivity of home power was the subject of Albert and Rajagopal's research while segmenting electrical consumers [17]. A novel probabilistic graphical model was used to simulate each CU's thermal regimes, with each concealed state representing the usage of heating or cooling equipment. Effective duration and effective thermal response sensitivity were used to classify the consumers. Because of the large potential for the usage of heating and/or cooling equipment, the thermal profile of consumers is critical for DR.

3 AI AND ML APPROACHES

The capacity of a smart grid with integrated RE to decrease CU suffering while maintaining fair power costs is critical to its future success. In order to balance the energy generation and delivery options, and AI/ML-enabled DR program may incorporate CUs into the decision-making process. The ever-increasing need for energy has dramatically widened the gap between D/S during rush hours, resulting in a huge increase in the financial worth of grid-connected electricity.

3.1 Artificial neural network based DR management

Artificial Neural Network (ANNs) are computer models that are based on the biological nervous system. It is divided into two categories: (1) “single hidden layer ANN” and (2) “deep learning”. In the case of DR, a “single hidden layer ANN” is used to classify consumers, loads, and prices, whereas deep learning aids in predicting consumer reaction behavior, controlling household equipment, clustering consumers, and so on. Table 1 summarizes recent developments.

Table 1: ANN based DR management.

Reference	Year	Technique(s)	Objective(s)
Shirsat and Tang [18]	2021	Linear regression, MD-RNN	Determine the CU’s heat sensitivity
Ruan et al. [19]	2020	NNLMS model	Speed up the distributed DR mechanism
Hafeez et al. [20]	2020	ANN-based forecast engine, a DA-GmEDE-based HEMC	Lower power bills, relieve the PAR
Lu and Hong [21]	2019	RL, DNN	Stimulate D-side involvement, boost SP and CU profitability, and enhance system dependability
Lu et al. [22]	2019	ANN, multi-agent RL	Determine the best judgments for diverse appliances

Shirsat and Tang proposed a system for determining distinct CUs’ consumption reduction potential and generating mixed distributions to assess their reduction capabilities [18]. They utilize these distributions to create simulations for a stochastic knapsack problem with risk aversion. The stochastic CU selection issue has been addressed for the first-time employing mixture distributions and CVaR as an empirical risk metric. To predict the load decrease during a DR event, their suggested model relies on the sensitivity of consumers’ consumption to external temperature.

The delayed convergence of existing distributed DR systems makes it difficult to develop dependable smart grid applications. To deal with this problem, Ruan et al. present a novel distributed procedure, the neural-network-based Lagrange multiplier selection, that significantly reduces iterations while avoiding oscillation [19]. The major enhancement is in an LSE forecast technique, which uses a specifically developed neural network (NN) to record consumers’ pricing reaction attributes.

In the smart grid, Hafeez et al. presented a unique framework for effective HEMS to lower power bills, relieve the Peak-to-Average Ratio (PAR), and get the desirable balance between energy costs and user discomfort [20]. For efficient energy management, the forecasting software anticipates price-based DR signals and usage of energy trends. The home energy management controller (HEMC) timetables home equipment based on the anticipated energy usage patterns and pricing signals. For performance validation, the suggested day-ahead grey wolf modified enhanced differential evolution algorithm (DA-GmEDE) based approach is compared to two benchmark strategies: day-ahead genetic algorithm and day-ahead game-theory.

Lu and Hong developed a real-time incentive-based DR algorithm with Reinforcement Learning (RL) and Deep Neural Network (DNN) for smart grid systems, with the goal of assisting the Service Provider (SP) in acquiring energy resources from its various CUs to balance energy variations and improve grid dependability [21]. To address future uncertainties, the SP can only access the price from the wholesale power market and energy D from its CUs for the present hour due to the intrinsic nature of real-time electricity markets.

Lu et al. suggested an hour-ahead DR method for HEMS, based on AI, with the goal of reducing the user's energy bill and level of discomfort [22]. A stable price forecasting model based on ANN is proposed to overcome future pricing uncertainty. Multi-agent RL is used in conjunction with anticipated pricing to make the best selections for various appliances.

3.2 ML based DR management

ML is a set of techniques for identifying patterns in empirical data and turning them into useable models. supervised learning, unsupervised learning, and RL are the three basic forms of ML used in DR algorithms, as shown in Table 2.

Table 2: ML based DR management.

Reference	Year	Technique(s)	Objective(s)
Yang et al. [23]	2022	KELM, APVMD, CSCA	Power price forecasting tool
Pallonetto et al. [24]	2022	LSTMs, SVM	Load data forecasting comparison
Wicaksono et al. [25]	2021	DNN, LSTM, CNN, Hybrid	Estimating DR program's dynamic electricity pricing
Uimonen et al. [26]	2020	RF, NNMs	Power curtailment at a low cost
Pallonetto et al. [27]	2019	ML approaches for data modeling and optimization algorithm	Deployment of DR techniques

Yang et al. created an enhanced electricity price forecasting model using adaptive data pretreatment, sophisticated optimization, kernel-based model, and optimum model selection technique [23]. An Adaptive Parameter-Based Variational Mode Decomposition (APVMD) method is developed to achieve appropriate data preprocessing outcomes. The Chaotic Sine Cosine Algorithm (CSCA) is used to design and implement a leave-one-out optimization strategy for developing effective Kernel-Based Extreme Learning Machine Models (KELM) and APVMD.

Pallonetto et al. assess and evaluate the two most often used short-term load forecasting methods [24]. They teach the basics of Long Short-Term Memory Networks (LSTMs) and Support Vector Machines (SVM), as well as the typical techniques of short-term load forecasting. Preprocessing of data and feature selection are then performed based on the features of the electrical load dataset. One-hour ahead load forecasting and Peak and valley load forecasting one day ahead are done using the LSTMs and SVM models.

Wicaksono et al. create a system that uses pricing and incentive-based DR programmes to engage manufacturing power CUs [25]. Instead of centralized data integration, the system uses data from heterogeneous systems on both the D/S sides, which are linked by semantic middleware. The semantic middleware uses an ontology as its integrated information model.

ML algorithms are being developed to anticipate the power provided by RE sources as well as the electricity consumed by manufacturing users based on their operations.

Uimonen et al. offered a solution to the problem of selecting acceptable escalators from a vast pool in order to meet the aim of power curtailment at a low cost, and they highlighted the escalator attributes that make the best DR candidates [26]. They examine four different calculating methods that differ in computation speed and accuracy. The primary answer is the simulation-based model that was previously created and improved. The random forest (RF) and neural network models (NNMs) give a solution based on the simulation-based model's output, with the goal of increasing computation speed.

Pallonetto et al. evaluated the performance of control algorithms in the residential sector for the deployment of DR techniques [27]. A calibrated building simulation model was constructed and used to evaluate the effectiveness of DR techniques in combination with thermal zone management under various time-of-use power tariffs. Two DR algorithms were used to manage an integrated heat pump and thermal storage system, one based on a rule-based approach and the other on a predictive-based ML method. A common DR pricing scheme was used to compare the two algorithms.

3.3 Nature-inspired algorithm based DR management

In search processes, nature-inspired algorithms (NIA) are used to forecast the sequence of activities required to attain the stated goals. Evolutionary algorithms, biological swarms, and physical processes are all frequent DR methods, as shown in Table 3.

Table 3: NIA based DR management.

Reference	Year	Technique(s)	Objective(s)
Singh et al. [28]	2021	Black Widow Optimization, Technique for Order of Preference by Similarity to Ideal Solutions	Improves the load factor and system dependability
Bui et al. [29]	2020	SI, ABC	Optimize power costs of smart HEMS
Makhadmeh et al. [30]	2019	GA, GWO	Minimize the electricity bill and PAR
Ullah and Hussain [31]	2019	GA, MFO, TG-MFO	Lower energy costs
Silva and Han [32]	2019	ACO	Overall cost reduction

To overcome the uncertainty associated with solar and wind power output, Singh et al. used a stochastic-based scenario development and reduction strategy [28]. Unlike other techniques, the flexible load responsive model is developed for each DR programme in order to quantify the sensitivity of consumer engagement. TOU, CPP, RTP, and a mix of both TOU and CPP are used to modify predicted load D. The suggested problem is analyzed on a three-feeder microgrid (MG) test system, and Black Widow Optimization is used to find the best scheduling configuration for DR programmes.

By incorporating the notion of swarm intelligence (SI) into connected devices, Bui et al. offer a computational intelligence model for IoT applications [29]. Decentralized management of smart HEMS is taken into account, in which linked appliances make individual decisions for optimizing power costs of smart HEMS by exchanging information with one another. They are divided into two primary categories: (a) they propose a framework for decentralized management in smart HEMS; and (b) the artificial bee colony (ABC) algorithm, a typical SI technique, has been applied to connected appliances in terms of communication and collaboration with one another to optimize the EMS' performance.

For the Power Scheduling Problem (PSP), Makhadmeh et al. used the Multi-Objective Grey Wolf (GWO) optimizer [30]. PSP is handled by setting household equipment to a certain time horizon to reduce power bills and PAR while also improving user comfort. To produce an optimal schedule, the multi-objective function is formalized and used in GWO. The suggested multi-objective GWO is evaluated using seven consumption profiles and seven real-time energy prices with distinct features. The suggested algorithm's performance is evaluated using three criteria: electricity bill, PAR, and user comfort level.

Ullah and Hussain suggested two bio-inspired heuristic algorithms for an EMS in smart homes and buildings: the Moth-Flame Optimization (MFO) method and the Genetic Algorithm (GA) [31]. The performance of these devices in terms of energy cost reduction, PAR minimization, and end-user discomfort minimization is examined. Then, to meet the aforementioned goals, a hybrid version of GA and MFO called Time-constrained Genetic-Moth-Flame Optimization (TG-MFO) is presented. To provide optimal end-user comfort, TG-MFO not only combines GA, and MFO, but also integrates time limitations for each appliance. In the literature, many energy optimization strategies have been presented.

Appliance scheduling using heuristic algorithms is being studied as a possible option for managing the energy D/S gap during peak hours. However, because of the potential for early convergence, the validity of Ant Colony Optimization (ACO) based scheduling has been questioned. As a result, Silva and Han suggested a mutation operator integrated ACO scheduling method with pre-defined consumption limits to reduce energy costs and waiting time while addressing ACO's contested shortcoming [32]. The comparative study verifies the suggested work's superiority in terms of cost reduction, peak load reduction, waiting time reduction, and PAR reduction, indicating its potential to become a mainstream solution for D-side management challenges.

3.4 Multi-agent based DR management

A multi-agent system (MAS) is a "computerized system" that is composed of multiple intelligent agents that communicate with each other. Multiple interacting intelligent agents can be used in DR projects to enable successful planning, choices, and methods for RE resources. "Coalitional game theory", "mechanism design", and "automated negotiation" are the three subsections of MAS. They also help with DR programmes, as shown in Table 4.

A three-layer MAS optimization model including Distributed Management System (DMS) agent, MG Central Controller (MGCC) agent and MG Controllable Element (MGCE) agent are built by Li et al. [33]. Then the DR power and heat load mechanism is constructed, with the real-time production of new energy generation and the Energy Storage System (ESS) as optimization objects and the operational cost, environmental cost, and wind and solar abandonment cost as optimization targets. They suggest an improved particle swarm optimization approach based on an adaptive-weight and chaotic search to solve this problem. Finally, three scenarios are presented to demonstrate that the ESS and DR may lower the cost of MGs while also encouraging new energy use, as well as the superiority of the enhanced algorithm.

Vázquez-Canteli et al. introduced CityLearn, which is an OpenAI Gym environment, and a simulated framework for the implementation of RL for DRM and urban energy management [34]. CityLearn guarantees that, at any time, the heating and cooling energy D

Table 4: Multi-agent based DR management.

Reference	Year	Technique(s)	Objective(s)
Li et al. [33]	2020	DMS agent, MGCC agent, MGCE agent	Encompass the DR of electrical and heat load, as well as the ESS
Vázquez-Canteli et al. [34]	2020	Multi-agent, single-agent RL algorithms	Customize the incentive function and select reward modes (central-agent or multi-agent)
Golmohamadi et al. [35]	2019	DRP, IDRA, RDRA	Provide up/down-regulation for the power system in case of a deficiency or excess of generation
Li et al. [36]	2018	Stackelberg–Cournot game model with two stages	Integrate RE and DR into the wholesale power market
Leo et al. [37]	2018	JADE in Eclipse IDE	Stabilize and optimize the MG

of the building are satisfied regardless of the actions of the controller. The actions of the RL controller are automatically overridden to satisfy such constraints of thermal energy D. This allows the controllers to focus on shaping the curve of electricity consumption without running the risk of interfering with the comfort of the occupants or the desired temperatures.

Golmohamadi et al. provide a unique market-based strategy for integrating the flexibility potential of diverse, responsive CUs, such as the residential and industrial sectors, into a power system with substantial intermittent power penetration [35]. The ultimate goal was to offer up/down control for the power system in the event of a generating deficiency or surplus. The complex challenge was divided into a multi-agent framework to achieve the goal. As a result, three types of agents were studied: DR Provider (DRP), Industrial DR Aggregators (IDRA), and Residential DR Aggregators (RDRA). The time-oriented DR programme was developed to optimize the overall cost of energy and regulation by allowing the DRP to trade DR opportunities in three consecutive floors of the electricity market, namely the day-ahead, adjustment, and balancing markets, in order to ensure power system flexibility. Instead of subsidizing D-side flexibility, the DRAs might exchange DR values in a competitive framework based on D bids.

Li et al. propose a novel RES and DR programme integration architecture to increase energy efficiency and system resilience [36]. They propose a two-stage Stackelberg–Cournot game model to describe energy trading behaviors among power utilities, RES-based MGs, and DR players. In the suggested paradigm, the power utility is the leader, while RES-based MGs and DR participants coordinated via an aggregator are the followers. Furthermore, using a risk-controlled game model, a CVaR assessment is used to quantify the intermittency of RES and the uncertainty of DR, which might lead to a more dependable energy trading strategy for both the forwards and spot markets. Finally, they provide a computational approach that accelerates the optimal reaction dynamics on the follower side.

Leo et al. create a simulation model for dynamic energy management that takes into account the intermittent nature of solar power, randomness of load, dynamic grid pricing, and variation of critical loads, and chooses the best possible action every hour to stabilize and optimize the micro-grid using Java Agent Development Environment (JADE) in Eclipse IDE [37]. Additionally, environmental factors are detected by an Arduino Mega microcontroller and sent to MAS agents. MAS improves responsiveness, stability, adaptability, and fault tolerance, resulting in increased operational efficiency and cost and environmental savings.

4 DISCUSSION

DR indicates changes in energy consumption patterns, such as through financial incentives or improved consumption optimization, in order to better match the power supply in power systems [1]. It has complicated impacts on integration costs in general, making it significant for various cost components in addition to profile costs [2]. DR can reduce profile costs in the long run by decreasing peak D and boosting capital utilization while deferring the need for network improvements, hence affecting grid-related integration costs. In the short term, it has an impact on power markets, which might affect balancing costs.

Rocha et al. describe a novel energy planning methodology based on AI methods for smart homes [38]. This study takes into account power price variations, equipment priority, operational cycles, and a battery bank to anticipate distributed generation. When smart houses with and without distributed generation and battery banks were examined, the method's efficiency revealed a 51.4% cost savings.

The majority of the research on DR programmes for residential CUs focuses on developing a model of household loads that may be used to identify an electric usage pattern. This is accomplished by using either a grid-oriented approach, which models end-user consumption as a whole in terms of general characteristics such as gross domestic product and unemployment rate, or a scenario-oriented approach, by Appling a bottom-up technique, in which the load profile is created by aggregating the electric consumption of numerous domestic appliances or a variety of families [39]. Such research uses a simulation-based optimization analysis to estimate the advantages of providing disaster recovery services to residential clients [40].

According to several stakeholders, the primary challenges to DR are inadequate programme design and low CU engagement. Because better programme design may enhance client engagement, there is a strong link between these two obstacles. The bulk of currently used DR systems, which are based on highly centralized control ideas, need the collection and processing of a considerable quantity of local data from a central location. This demonstrates a great deal of complexity at the central coordinating point, which has an impact on the scalability of such DR methods. As a result, in all DR deployments, the majority of the controllable D concerns large commercial or industrial clients who fail to include a significant number of modest residential CUs.

We discovered that RL could adapt to its surroundings and acquire CU preferences through a feedback control loop throughout the review process, which appears promising for MG planning. When a large amount of data is available, RL algorithms can be effective, and system control is based on real-time judgments.

Modeling and computation processes are growing significantly more challenging as issue sizes become larger. Market operators must hedge against the more complicated structure in today's restructured energy markets by providing market players with adapting tools to the new market structure. To deal with such a challenge, MAS is a way to break down a large problem into smaller pieces. In this method, different agents may simply replicate the market model, which can then be expanded by additional entities.

MAS is particularly effective at solving complicated issues. A wide range of applications employs MAS. Gazafroudi et al. describe a MAS for the intelligent use of power in a smart home, resulting in increased energy efficiency [41]. MAS method has been widely embraced in the bottom-up approach because of its scalability and capacity to mimic the stochastic nature of household consumption as well as the dynamic interactions between residences and the grid. The power system literature has various MAS-based applications, including (1) electricity market, (2) voltage regulation, (3) load restoration, (4) load shedding, and (5) the smart grid area.

Pallonetto et al. examined the implementation of D-side management methods in the residential sector using a rule-based and predictive ML algorithm [42]. The rule-based system saved 20.5% on electrical end-use expenditures compared to the baseline scenario, while the predictive algorithm saved 41.8%. For utility generating costs, both strategies are saved in the same range.

5 CONCLUSIONS

Through price modifications or incentives, a DR programme encourages end-users to modify their power consumption habits to match RE sources' availability. The adoption of DR systems is a steady but sluggish trend aimed at maximizing the usage of RE in residential homes and many industries, including manufacturing. We analyzed four AI approaches, namely (1) ANNs, (2) ML, (3) NIAs, and (4) MAS, which have been utilized in DR programs to support RE dissemination. We discovered a DR program based on ANN that helped to reduce load shedding, enhance the PAR, engage in energy management schemes, and optimize load D, among other things. ML techniques were used for clustering, to reduce peak consumption, and for optimal bidding strategy to reduce the uncertainty of consumer's D and flexibility. The NIA was employed to optimize the scheduling of distributed energy resources, provide incentive-based DR management, control smart devices, and benefit the aggregator. For optimization purposes, a multi-agent-based DR program enabled bidding strategy, energy management, and power trading.

REFERENCES

[1] Yu, M., Lu, R. & Hong, S.H., A real-time decision model for industrial load management in a smart grid. *Appl. Energy*, **183**, pp. 1488–1497, 2016.

[2] Li, Y.-C. & Hong, S.H., Real-time demand bidding for energy management in discrete manufacturing facilities. *IEEE Trans. Ind. Electron.*, **64**(1), pp. 739–749, 2017.

[3] Department of Energy (DOE), 2022. https://www.energy.gov/.

[4] U.S. Energy Information Administration, 2022. https://www.eia.gov/.

[5] Zhou, B. et al., Smart home energy management systems: Concept, configurations, and scheduling strategies. *Renew Sustain Energy Rev*, **61**, pp. 30–40, 2016.

[6] Gils, H.C., Assessment of the theoretical demand response potential in Europe. *Energy*, **67**, pp. 1–18, 2014. DOI: 10.1016/j.energy.2014.02.019.

[7] Burger, S.P., Jenkins, J.D., Huntington, S.C. & Pérez-Arriaga, I.J., Why distributed? A critical review of the tradeoffs between centralized and decentralized resources. *IEEE Power and Energy Magazine*, **17**(2), pp. 16–24, 2019.

[8] Connell, N.O., Pinson, P., Madsen, H. & Malley, M.O., Benefits and challenges of electrical demand response: A critical review. *Renewable and Sustainable Energy Reviews*, **39**, pp. 686–699, 2014.

[9] Mahmoudi-Kohan, N., Parsa Moghaddam, M., Sheikh-El-Eslami, M.K. & Shayesteh, E., A three-stage strategy for optimal price offering by a retailer based on clustering techniques. *International Journal of Electrical Power and Energy Systems*, **32**(10), pp. 1135–1142, 2010.

[10] Mahmoudi-Kohan, N., Parsa Moghaddam, M. & Sheikh-El-Eslami, M.K., An annual framework for clustering-based pricing for an electricity retailer. *Electric Power Systems Research*, **80**(9), pp. 1042–1048, 2010.

[11] Mahmoudi-Kohan, N., Eghbal, M. & Moghaddam, M.P., Customer recognition-based demand response implementation by an electricity retailer. *21st Australasian Universities Power Engineering Conference (AUPEC)*, IEEE, pp. 1–6, 2011.
[12] Panapakidis, I.P., Simoglou, C.K., Alexiadis, M.C. & Papagiannis, G.K., Determination of the optimal electricity selling price of a retailer via load profiling. *47th International Universities Power Engineering Conference (UPEC)*, IEEE, pp. 1–6, 2012.
[13] Maigha & Crow, M.L., Clustering-based methodology for optimal residential time of use design structure. *North American Power Symposium (NAPS)*, IEEE, pp. 1–6, 2014.
[14] Haider, H.T., See, O.H. & Elmenreich, W.A., Review of residential demand response of smart grid. *Renew. Sustain. Energy Rev.*, **59**, pp. 166–178, 2016.
[15] Kostková, K., Omelina, L., Kyčina, P. & Jamrich, P., An introduction to load management. *Electr. Power Syst. Res.*, **95**, pp. 184–191, 2013.
[16] Chen, C., *Demand Response: An Enabling Technology to Achieve Energy Efficiency in a Smart Grid. Application of Smart Grid Technologies*, Elsevier: Amsterdam, pp. 143–171, 2018.
[17] Albert, A. & Rajagopal, R., Thermal profiling of residential energy use. *IEEE Transactions on Power System*, **30**(2), pp. 602–611, 2015.
[18] Shirsat, A. & Tang, W., Quantifying residential demand response potential using a mixture density recurrent neural network. *International Journal of Electrical Power and Energy Systems*, **130**, 106853, 2021.
[19] Ruan, G., Zhong, H., Wang, J., Xia, Q. & Kang, C., Neural-network-based Lagrange multiplier selection for distributed demand response in smart grid. *Applied Energy*, **264**, 2020. DOI: 10.1016/j.apenergy.2020.114636.
[20] Hafeez, G. et al., An innovative optimization strategy for efficient energy management with day-ahead demand response signal and energy consumption forecasting in smart grid using artificial neural network. *IEEE Access*, **8**, pp. 84415-84433, 2020. DOI: 10.1109/ACCESS.2020.2989316.
[21] Lu, R. & Hong, S.H., Incentive-based demand response for smart grid with reinforcement learning and deep neural network. *Applied Energy*, **236**(C), pp. 937–949, 2019.
[22] Lu, R., Hong, S. & Yu, M., Demand response for home energy management using reinforcement learning and artificial neural network. *IEEE Transactions on Smart Grid*, **10**(6), pp. 6629-6639, 2019. DOI: 10.1109/TSG.2019.2909266.
[23] Yang, W., Sun, S., Hao, Y. & Wang, S., A novel machine learning-based electricity price forecasting model based on optimal model selection strategy. *Energy*, **238**, 121989, 2022. DOI: 10.1016/j.energy.2021.121989.
[24] Pallonetto, F., Mangina, E. & Jin, C., Forecast electricity demand in commercial building with machine learning models to enable demand response programs. *Energy and AI*, **7**, 2021. DOI: 10.1016/j.egyai.2021.100121.
[25] Wicaksono, H., Boroukhian, T. & Bashyal, A., A demand-response system for sustainable manufacturing using linked data and machine learning. *Dynamics in Logistics*, eds M. Freitag, H. Kotzab & N. Megow, Springer: Cham, 2021. DOI: 10.1007/978-3-030-88662-2_8.
[26] Uimonen, S., Tukia, T., Ekström, J., Siikonen, M. & Lehtonen, M., A machine learning approach to modelling escalator demand response. *Engineering Applications of Artificial Intelligence*, **90**, 2020. DOI: 103521. 10.1016/j.engappai.2020.103521.

[27] Pallonetto, F., De Rosa, M., Milano, F. & Finn, D., Demand response algorithms for smart-grid ready residential buildings using machine learning models. *Applied Energy*, **239**, pp. 1265–1282, 2019. DOI: 10.1016/j.apenergy.2019.02.020.
[28] Singh, A.R., Ding, L., Raju, D.K., Kumar R.S. & Raghav, L.P., Demand response of grid-connected microgrid based on metaheuristic optimization algorithm. *Energy Sources*, *Part A: Recovery, Utilization, and Environmental Effects*, 2021. DOI: 10.1080/15567036.2021.1985654.
[29] Bui, K.-H.N., Agbehadji, I.E., Millham, R., Camacho, D. & Jung, J.J., Distributed artificial bee colony approach for connected appliances in smart home energy management system. *Expert Systems*, **37**, e12521, 2020. DOI: 10.1111/exsy.12521.
[30] Makhadmeh, S.N. et al., Multi-objective power scheduling problem in smart homes using grey wolf optimiser. *J. Ambient. Intell. Human Comput.*, **10**, pp. 3643–3667, 2019. DOI: 10.1007/s12652-018-1085-8.
[31] Ullah, I. & Hussain, S., Time-constrained nature-inspired optimization algorithms for an efficient energy management system in smart homes and buildings. Applied Sciences, **9**(4), p. 792, 2019. DOI: 10.3390/app9040792.
[32] Silva, B.N. & Han, K., Mutation operator integrated ant colony optimization based domestic appliance scheduling for lucrative demand side management. *Future Gener. Comput. Syst.*, **100**, pp. 557–568, 2019.
[33] Li, C., Jia, X., Zhou, Y. & Li, X., A microgrids energy management model based on multi-agent system using adaptive weight and chaotic search particle swarm optimization considering demand response. *Journal of Cleaner Production*, **262**, 121247, 2020. DOI: 10.1016/j.jclepro.2020.121247.
[34] Vázquez-Canteli, J., Dey, S., Henze, G. & Nagy, Z., CityLearn: Standardizing research in multi-agent reinforcement learning for demand response and urban energy management. Cornell University, 2020.
[35] Golmohamadi, H., Keypour, R., Bak-Jensen, B. & Pillai, J., A multi-agent based optimization of residential and industrial demand response aggregators. *International Journal of Electrical Power and Energy Systems*, **107**, pp. 472–485, 2019. DOI: 10.1016/j.ijepes.2018.12.020.
[36] Li, C., Liu, C., Yu, X., Deng, K., Huang, T. & Liu, L., Integrating demand response and renewable energy in wholesale market. *27th International Joint Conference on Artificial Intelligence (IJCAI)*, Stockholm, Sweden, 2018. DOI: 10.24963/ijcai.2018/53.
[37] Leo, R., Morais, A.A. & Milton, R., Advanced energy management of a micro-grid using arduino and multi-agent system. *Proceedings of ICIEES'17*, 2018. DOI: 10.1007/978-981-10-4852-4_6.
[38] Rocha, H.R.O., Honorato, I.H., Fiorotti, R., Celeste, W.C., Silvestre, L.J. & Silva, J.A.L., An artificial intelligence based scheduling algorithm for demand-side energy management in smart homes. *Appl. Energy*, **282**, 116145, 2021. DOI: 10.1016/j.apenergy.2020.116145.
[39] Grandjean, A., Adnot, J. & Binet, G., A review and an analysis of the residential electric load curve models. *Renew. Sust. Energy Rev.*, **16**, pp. 6539–6565, 2012.
[40] Zhanle, W. & Sadanand, A., Residential demand response: an overview of recent simulation and modelling applications. *IEEE 26th Canadian Conference and Computer Engineering*, Regina, SK, pp. 1–6, 2013.
[41] Gazafroudi, A.S. et al., Organization-based multi-agent structure of the smart home electricity system. *Evolutionary Computation (CEC)*, IEEE Congress, pp. 1327–1334, 2017.

[42] Pallonetto, F., De Rosa, M., Milano, F. & Finn, D., Demand response algorithms for smart-grid ready residential buildings using machine learning models. *Applied Energy*, **239**, pp. 1265–1282, 2019. DOI: 10.1016/j.apenergy.2019.02.020.