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TOPICAL REVIEW

Artificial Intelligence Application in Demand Response: Advantages, Issues, Status, and Challenges

AMIRA NOOR FARHANIE ALI[1], MOHAMAD FANI SULAIMA[1], (Member, IEEE), INTAN AZMIRA WAN ABDUL RAZAK[1], AIDA FAZLIANA ABDUL KADIR[1], AND HAZLIE MOKHLIS[2], (Senior Member, IEEE)

[1]Faculty of Electrical Engineering, Universiti Teknikal Malaysia Melaka, Melaka 76100, Malaysia
[2]Faculty of Engineering, University of Malaya, Kuala Lumpur 50603, Malaysia

Corresponding author: Mohamad Fani Sulaima (fani@utem.edu.my)

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ABSTRACT In recent years, there has been a significant growth in demand response (DR) as a cost-effective technique of providing flexibility and, as a result, improving the dependability of energy systems. Although the tasks associated with demand side management (DSM) are extremely complex, the use of large-scale data and the frequent requirement for near-real-time decisions mean that Artificial Intelligence (AI) has recently emerged as a key technology for enabling DSM. Optimization algorithm methods can be used to address a variety of problems, including selecting the optimal set of consumers to respond to, learning their attributes and preferences, dynamic pricing, device scheduling, and control, as well as determining the most effective way to incentive and reward participants in DR schemes fairly and effectively. The implementation optimization algorithm needs proper selection to mitigate the cost of energy consumption. Due to that reason, this paper outlines various challenges and opportunities in developing, utilizing, controlling, and scheduling the DR scheme's optimization algorithm. In addition, several issues in applications and advantages of optimization techniques in artificial intelligence approaches are discussed. The importance of implementing demand response mechanisms in developing countries is also presented. In addition, the status of demand response optimization in demand-side management solutions is also illustrated congruently.

INDEX TERMS Artificial intelligence (AI), demand response (DR), demand side management (DSM), optimization algorithms.

I. INTRODUCTION

It is becoming increasingly challenging to meet the growing demand for electricity due to the widespread use of electricity-powered appliances in homes, offices, hospitals, commercial plazas, and manufacturing facilities. Distribution companies compete for electricity prices in modern, deregulated power systems to maximize profits [1]. The power price fluctuates based on the electricity used at any given moment. To put it another way, power prices grow as demand increases [2]. Because the electricity demand is increasing, it is necessary to control the electricity demand. DSM is a comparatively recent approach to managing energy demand in the context of constrained electrical capacity, rising fuel costs, and environmental pollution concerns [3]. Dynamic pricing, improved metering, and supporting technology are only some of the programmes and initiatives that are part of DSM [4]. Several benefits to reducing the total load on an energy network include reducing electrical system issues and minimizing blackouts. Under this definition, DSM becomes increasingly advantageous as energy demand persists in rising significantly, outperforming the level of growth in power systems [5]. Other authors have indeed researched the advantages of DSM in terms of economic benefits of DSM [6],

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the consequences of DSM on the industrial and residential sectors [7], [8], the interaction between DSM and other smart grid technologies [9], the important concepts of DSM [10], the influence of DSM on power systems [11], the optimal power flow procedures of DSM [12], [13], and the forecasts [14]. Furthermore, DSM has been implemented in several countries, including the United Kingdom [15], India [16], China [17], Italy [18], North America [19], India [20], Kuwait [21], Korea [22], Turkey [23] and Denmark [24] with promising results. With such a rapid growth rate, DSM activities perform a significant function in the electricity-powered energy system to manage power demand, which eventually influences the reliability and economical operation. Demand response and energy efficiency are the two components of DSM.

Demand Response — Using this method, they can reduce or stabilize their energy consumption by using any proactive or reactive strategy. There are many ways to respond to demand, including peak clipping, valley filling, or load shifting [4]. Demand response is also known as ''flexible load shape'' because of its ability to respond to change [20]. In this scheme, utility companies encourage consumers to change their power consumption based on supply by giving them financial considerations [25], using schemes such as futures price, real time price and time of use rate [26]. Furthermore, this earns money for participants and helps the broader community by ensuring that energy remains reliable and affordable in the region. To date, DR programmes are classified into two parts: (1) incentive-based programme (IBP) and (2) price-based programme (PBP). The IBP mainly applies to utility programmes, which involve direct load control. The utilities and consumers control the loads used in the total electricity market design. The energy market design also involves capacity market, demand bidding, and emergency demand response. In addition, the interruptible programme exists as an incentive for the energy provider to provide a better electricity supply, where the stakeholder's commitment involves providing government tax incentives.

Accordingly, this study aims to provide a comprehensive overview of the optimization in demand response schemes that have been applied and the main specific application/tasks in energy DR to which these techniques have been adopted. The goal of this paper is two-fold: 1) providing a comprehensive overview of the area's evolution and future research directions, as well as giving some insights into the start-ups and more established sectors applying these techniques. As this is a very active field and offers a broad perspective of the field's evolution and potential future research path; 2) serves as a valuable reference for academics and experts in the area, outlining the benefits and downsides of implementing optimization techniques in various contexts. More specifically, this means informing them, for example, which optimization technique has been found to work best for their specific DR problem or application area, including the advantages and drawbacks of using optimization technique in each application domain. Therefore, as a result, the paper is divided into several parts: section II includes overview AI in demand response; section III discusses advantages of application; section IV outlines issues in application; section V illustrates the status of optimization, and section VI summarizes the challenges and opportunities in demand response.

II. OVERVIEW AI IN DEMAND RESPONSE

On a broad scale, demand response in the energy sector is regarded as one of the strategies of demand side management [27]. In an effort to encourage more people participating in the energy market, several demand response (DR) systems have been put into place, with the support of power system operators [28], [29], [30]. Meanwhile, the authors [31] state that in order to determine the economic potential of residential demand response, it is necessary to estimate the reductions in short-term demand predictions using machine learning algorithms [32] during demand response hours [33]. In [6], [34], and [35] involved in Artificial Intelligence (AI) focused on theory and background, optimization, algorithm, and various techniques such as control theory, statistics, and psychology [36]. Keywords for artificial intelligence refer to the study and design of intelligent entities or agents [37]. Thus, an AI-capable agent can consist of the ability of a machine that is truly capable of reasoning in discovering the algorithm used [38].

Optimization problems are classified according to their nature and determined by the optimization objective [39]. A variety of AI technologies are being used. Still, some techniques are more suitable for use. For example, ANNs, typically using multi variable functional approaches and regressions, are used rapidly for short-term load and price forecasting and supervised learning to achieve accurate forecasts [37]. In contrast, to the algorithms often used by RL to capture human feedback, which integrate the DR solution [40] in making it suitable for controlling HEMS. Unsupervised learning is used for grouping when there is no prior knowledge related to the category, which is often the case for DR clients who group tasks in an aggregator [41]. Aggregators schedule the activation of DR participants [30], [42], [43], and design their incentives and punishments by classifying DR consumers and forecasting their use [44]. There are several strategies for completing these tasks, such as those the authors in [27] and [45] discussed by employing nature-inspired optimization techniques [46], swarm intelligence. Multi-agent systems [47] may be used in the game theory context to determine the accuracy of schedule and pricing strategy [48]. An example of a nature-inspired optimization technique such as PSO has been used in various engineering fields. It can undoubtedly search for the best load curve with fast convergence.

In [49], provides an overview of demand response's benefits and challenges, while authors in [50] and [51] have been involved in highlighting and analyzing the challenges of home demand response systems, load-scheduling methodologies, and the most up-to-date information and

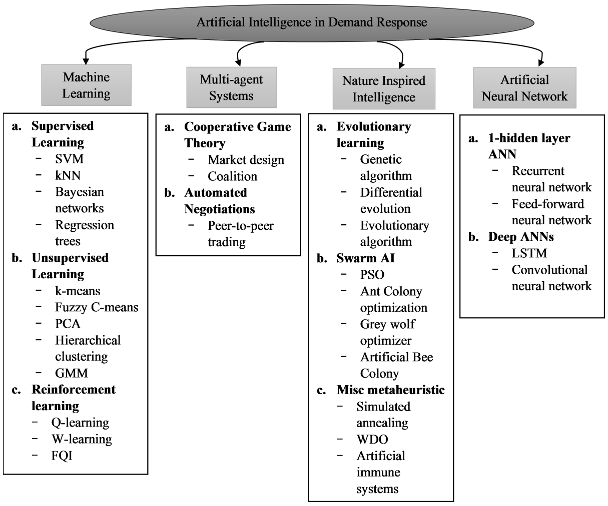

FIGURE 1. Classification of AI in demand response [27].

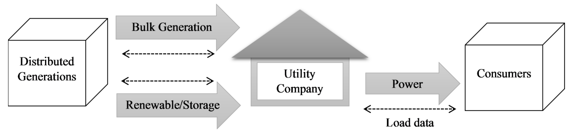

FIGURE 2. Demand response abstract picture [13].

TABLE 1. Summary advantage of machine learning algorithm.

Machine learning algortihm	Advantages
Supervised ML	Allows to collect data or produce a data output from the previous experience
Unsupervised ML	Solves the problem by learning the data and classifying it without any labels
Reinforcement Learning	Maximizes performance and sustain change for a long period of time

communications technology (ICT) that enables residential demand response applications. Aside from that, authors in [52] and [53] concentrated on a customer's intrinsic activeness, which reduces the impact of practical value on AI product demand while increasing the effect of symbolic value on AI product demand. Sustainable industries will be revolutionized by payload intelligence (AI) by empowering product AI in terms of user and state technical variances in how demand for user products is established [54]. For example, the sustainable phrase industries are related to sustainable developing industrial processes. The phrase refers to the green energy-intensive sectors such as the textiles, steel, cement, and paper industries. A variety of classification of AI strategies, as seen in Figure 1.

III. ADVANTAGES

Each frame of the DR issue has distinct inputs and outputs in order to attain the same goals. Appliances and other assets provide a variety of input signals to the optimization issue. The user may get the price signal from the utility. The DR optimization issue considers various user-specific inputs, including existing scheduling slots, device conditions, comfort preferences for electricity usage, time of day, power control signals, and data from motion sensors [55]. Energy generation is one of the asset's input parameters [56], along with temperature and humidity [57]. The nature of the optimization problem, for example, and the influence of demand volatility on the issue's solution [58], classification [59] and methods needed to make use of the approaches' applicability are scrutinized. Figure 2 depicts the demand response abstract picture, are employed in demand response (AI approach used for energy demand response). Only the power grid's distribution side implements a demand response system [60]. Energy generation at various scales, such as that from renewable sources [61], conventional and distributed generators, is available on the supply side [62]. In contrast, various household equipment functions are included on the demand side [63] such as battery storage systems and electric vehicles [64]. Since the 1950s, many methodologies and approaches have been used to develop thinking machines in artificial intelligence. In addition, symbolic and logic-based reasoning, statistical learning, and even soft computing are in this category.

A. MACHINE LEARNING

Machine learning has recently been a prominent issue in academia. A demand response firm may better understand how customers behave by using machine learning to get insight into consumer behavior and generate better projections [65]. With the recent advances in machine learning, it is now possible to create models that are both well-suited to nonlinear data and highly accurate. In machine learning, the subject of how to design machines that can learn from their own experiences is addressed. According to [66], artificial intelligence and data science rely on machine learning, which is a nexus of statistics and computer science. Machine learning algorithms fall into four categories: supervised, unsupervised, and reinforcement learning.

1) SUPERVISED MACHINE LEARNING

Data in supervised machine learning are labeled, including comprehensive input features and outputs that correlate to those features [65]. For example, k-Nearest Neighbors, Nave Bayes, Decision Trees, Support Vector Machines, Logistic Regression, Multiplayer Perceptron, and Random Forest are examples of supervised machine learning algorithms that are extensively employed in the field. In machine learning, ''supervised learning'' refers to gathering or developing data output based on prior experience — the ability to draw on prior experience to enhance performance standards. Machine learning under supervision helps users deal with a wide range of practical computing difficulties.

In simpler terms, the goal is to find a mapping that works well with new data. In DR, forecasting the demand for energy and the price of electricity has mostly been accomplished through the use of supervised learning techniques. These techniques include Kernel-based, tree-based, and linear regression models. Support vector machines (SVM) and Gaussian processes (GPs) are two common kernel-based algorithms that encode the input data into a new feature space and then discover a suitable hypothesis in this feature space. In references [67] and [68] have utilized Support Vector Regression (SVR) for the purpose of price forecasting. On the other hand, in [69] utilized SVR for STLF, even for non-aggregated loads.

In addition, there are a couple of articles that have made use of Gaussian Copulas in DR, primarily for the purpose of load forecasting. This method was used by [70] to predict the charging demand of electric vehicles for day ahead DR strategies and in [71] used to estimate the aggregate power demand of particular household appliances for the day ahead, while in [72] used it to forecast non-controllable loads for day-ahead DR.

2) UNSUPERVISED MACHINE LEARNING

Unsupervised machine learning tries to discover new patterns that may be utilized to enhance the decision-making process by evaluating data structure [65]. Unsupervised machine learning methods such as clustering and rule-based learning are often employed [66]. An unsupervised machine learning algorithm has the advantage that it doesn't need to know anything about the image area, there is less human error, unique spectrum classifications are made, and the process is quick and easy to do.

The most common application of unsupervised algorithms in DR has been for the purpose of clustering, which is when users create groups of objects (for example, load pro files) in such a way that objects within the same cluster are similar to one another, while objects in other clusters are different from one another. Users have been divided into groups, and typical load profile shapes have been identified, all through the use of various clustering methods. In turn, this categorization can be used to select consumers for DR schemes, pay consumers for participation in DR programmes, and identify households who might benefit from DR schemes. In addition to the segmentation of customers, unsupervised methods have been used to find out whether or not there are heating appliances in a home [73].

3) REINFORCEMENT LEARNING

As it moves through its issue area, reinforcement machine learning learns by its interactions with a dynamic environment. Through a process of trial-and-error, reinforcement machine learning enables machines and software programmes, generally known as agents, to independently select the best behaviors to achieve a goal. Reinforcement learning can increase performance and sustain change over time [66].

The RL framework has been utilized in a variety of fields, with robotics [74], resource management in computer clusters [75], playing video games via pixel input [76], and automated ML frameworks [77] being among the most significant. Tasks involving scheduling and controlling different units (such home appliances and electric vehicles) in DR have seen extensive use of RL due to its ability to factor in user preferences (via interaction with them). At the level of the consumer (as part of an EMS) and at the level of the service provider, RL has been provided as a data-driven alternative to model-based controllers for DR. This has been done on both levels. In further research [78], [79], and [80] the RL framework has been used to learn the DR pricing mechanism for service providers, and [81] it has been utilized to construct a demand elasticity model for an aggregate of consumers.

B. MULTI-AGENT SYSTEMS

A multi-agent system (MAS) is a system that is created around an indivisible feature called an agent [82]. Essentially, according to Wooldridge, an agent is "a software (or hardware) entity that is situated in a particular environment and is capable of autonomously reacting to changes in that environment; an intelligent agent possesses three fundamental characteristics, which are reactivity, pro activeness, and social ability" [83]. Because of the decentralized nature of the demand-side in power systems, there is a need for approaches that can learn, plan, and make decisions in a complex environment involving a large number of interconnected intelligent agents [84]. One of the most promising areas of research right now is multi-agent systems (MAS), a sub-area of distributed artificial intelligence that provides the capability to examine these challenges. The three sub fields of MAS that were looked at in this review are automatic negotiations, cooperative/coalitional game theory, and mechanism design [85]. These three sub fields are:

1) COOPERATIVE GAME THEORY

In recent years, it has been revealed that game theory may be used in the analysis of energy management and price-based demand response strategies [86]. According to the authors [87], a demand response model built on a game-theoretic framework was introduced. Coalitional game theory, often known as cooperative game theory, is a foundational concept in game theory. Rather than focusing on individual player strategies, cooperative game theory instead considers the coalitions that players might form with one another. The goal is to predict which coalitions will develop in the future based on the assumption that each alliance has the ability to acquire certain advantages (and hence the payoffs the agents will obtain). Instead of focusing on the actions taken by individuals to get rewards, the cooperative game theory focuses on how benefits are distributed among those who participate [88].

As a result, cooperative game theory has seen extensive use in the field of demand response, particularly in cases where parties have achieved binding agreements (i.e., incentive-based DR). In demand response, cooperative game theory is used to pick the best set of energy consumers to participate in DR schemes and distribute the coalition's dividend among DR participants (known as the solution concept). The DR flexibility members' money is distributed among themselves as the aggregator strives to meet specified requirements. Following this distribution is a notion for a solution Banzhaf Index (core), Nucleus (depending on deficiency), Kernel and Stable Set are often used in most solutions. The Shapley Value (SV) is the most often used solution strategy in DR to assure a fair distribution of payoffs [89]. For the time being, the SV's allocation of effort, reward, and punishment in a DR programme is a unique and fair approach to do so. It is suggested that each participant get a prize based on their performance in the programme [90], [91].

2) AUTOMATED NEGOTIATIONS

When assigning resources that may be utilized to distribute goods, negotiation is the procedure to use [92], or tasks [93], among of agents [94]. Automated negotiation research focuses on creating software systems that can negotiate on behalf of users or owners in a wide range of settings [95]. These programmes are called software agents, or just agents, for short. In the broadest sense, automated negotiation is primarily concerned with developing high-level procedures for the interaction of agents. A purchaser representative (customer or aggregator) will interact with a seller agent (provider or retailer) on a variety of topics during the day in automated discussions connected to energy demand response. The issues that are the subject of the negotiation are, for example, the price or the amount of energy.

TABLE 2. Advantages of multi-agent systems algorithm [83].

Multi-agent algorithm	Advantages
Cooperative Game Theory	Used to ensure team cooperation by considering a combination of individual costs as a team cost function
Automated Negotiations	Can be employed for many tasks human negotiators regularly engage in, such as bargaining and joint decision making

C. NATURE INSPIRED INTELLIGENCE

When developing novel computer-based analysis and computing methods, scientists have long-drawn inspiration from natural and biological systems. Researchers in the field of artificial intelligence have established the sequence of activities that an agent must do in order to achieve its goals by using nature-inspired algorithms for searching and planning [96]. Meta-heuristics are based on evolution, biological swarming, or physical events rather than pure algorithms are widely seen in the literature on DR. To define an array of workflows that employ intelligent learning strategies for exploring and exploiting the search space, the term ''meta- heuristics'' refers to a category of stochastic algorithms that are both randomized and methodologically random. Additionally, the term ''iterative processes that optimize heuristic techniques'' has been used in the literature [97]. A nature-inspired algorithm implemented in a home energy management system (HEMS) might be used to plan con-sumer loads and appliances, or aggregators and retailers could utilize the algorithm to optimize the prices of their customers who participate in demand response schemes. Because meta-heuristics can help find an answer in a certain amount of time, it has been used frequently in the DR situation when the design process might be too expensive.

1) EVOLUTIONARY ALGORITHM

Computational methods that mimic the evolution of life's most fundamental processes, including reproduction, mutation, and the recombination of DNA, are known as Evolutionary Computation (EC) or Evolutionary Algorithms (EA). The architecture of an EC algorithm consists of three basic steps. At this point, a few suitable solutions are selected from a pool of potential options. After that comes evolutionary iterations, including fitness evaluation and selection as well as population reproduction and variation as operational components (also known as population reproduction and interpretation). When determining a new population, it is necessary to evaluate the initial population's objective functions for fitness evaluation purposes. At the same time, selection criteria are used to select those individuals who perform best to determine a new population through reproduction crossover, replacement, and variation or mutation methods. In this step, a fresh population is analyzed to deter-mine whether the individual's judgment of the optimization function meets a termination criterion. Learning classifier systems (LCS), differential evolution (DE), and estimation of distribution algorithms (EDA) are some of the examples of evolutionary learning algorithm [98].

Evolutionary algorithms have several benefits, such as not requiring gradient information, being able to run in parallel, and the capacity to be exceedingly exploratory. This strategy, unlike conventional ones like optimizing an unknown function that specifies a user's utility for energy consumption or anticipating future prices on the power market, is useful when structures can't be accurately characterized in advance. Evolutionary techniques have inherent limits regarding convergence, interpretation ability, and selecting the best solution [99]. Many sectors have embraced EC algorithms because of their advantages [100].

2) SWARM ARTIFICIAL INTELLIGENCE

As a sub field of AI, ''swarm intelligence'' explores how biological hordes act in concert and how it might be used to solve various issues in other domains by mimicking this behaviour [101]. Particle Swarm Optimization (PSO) [102], Ant Colony Optimization (ACO) [103], Artificial Bee Colony

TABLE 3. Advantages of nature-inspired intelligence algorithm [98], [102].

Nature-Inspired Algorithm	Advantages
EA	The flexibility of the procedures, as well as solves problems through processes that emulate the behaviors of living organisms
PSO	Simple concept, easy implentation, robustness to control parameter, and computational efficiency
ACO	Inherent parallelism, positive feedback accounts for rapid discovery of good solutions, efficient for TSP and similar problem and can be used in dynamic applications
ABC	Self-organizing and collective intelligent data, simplicity and proper exploration ability
GWO	Easy to implement due to its simple structure, less storage and computational requirements, faster convergence due to continuous reduction of search space

(ABC) [104], and Grey Wolf Optimizer (GWO) [105] are the most widely cited swarm intelligence algorithms in the literature. These algorithms are discussed in further depth in the author's reviews [106], [107], [108]. Like evolutionary techniques, swarm AI can get stuck in local optima when used in conjunction with swarm intelligence. Rather than rejecting ''poor'' particles in GA, swarm AI systems use all histories to search [109]. Because there are fewer variables to modify when using technologies like swarm artificial intelligence, it requires less calibration and customization. Aggers and retailers deploy swarm artificial intelligence algorithms for energy demand response to discover the most cost-effective scheduling and pricing schemes. Many variables, quadratic functions, and limitations derived from AC power flow calculations are frequent features of the non-convex issue in DR. In this circumstance, heuristic optimization may be able to quickly find a solution close to the optimum while using fewer resources than other mathematical techniques. This one is one of the most extensively used, but also the most complex to execute, heuristic optimization strategies. To put it another way, each person in the group (referred to as a particle) seeks an objective (for example, food) while considering other people in the group's findings. This is an example of ''swarm dynamics'' (also referred to as particles) [103]. Advantages of swarm intelligence shown in Table 3 such as PSO, ACO, ABC, and GWO.

D. ANNS

On the right is a representation of an artificial neural network (ANN) that is based on biological nerve systems, especially the human brain. For an ANN, the input (independent variables), the hidden layer, and the output layer (dependent variables) are all three layers that make up a network. The input layer receives data that will be processed by the hidden layer, while the output layer provides the result [110]. An ANNs is a computer model of the brain. A natural brain can earn and adapt to a dynamic environment. ANNs is a branch of the AI family, including Fuzzy Logic, Expert Systems, and Support Vector Machines.

Multiple fields have made use of ANNs for tasks like classification, clustering, pattern recognition, and prediction [111]. In DR, ANNs of varying architectures and depth (number of layers) have mostly been employed for forecasting purposes. ANNs are used in the majority of DR applications to predict the future consumption of an asset (building, appliance, consumer group), the flexibility of a load, or the short-term pricing of power (from several minutes to one day ahead). As it turns out, ANNs can do the job of nonlinear regression tools quite fine.

1) SINGLE HIDDEN LAYER ANN

The feed-forward ANN, which has only one hidden layer, is the most widely employed model in the NDR domain. In addition, auto regressive feed-forward models are used in a variety of contexts [112]. A convolutional neural network and an Elman neural network were the only two RNNs that could discover, both in works by [113] and [114] (non-linear auto regressive with external inputs, RNN). There has been a lot of research in DR using single-hidden-layer ANNs. As well as using ANNs to classify customers based on their propensity to participate in a demand response programme [115], consumers' thermal discomfort or their capacity to utilize their utilization [116] has been modeled using single-hidden-layer ANNs, which are highly dependent on factors such as temperature, time of day and week, and price. The global approximation theorem states that all a fully connected FF-ANN needs are one hidden layer to learn a specific operation. Evidence suggests that utilizing concepts with more hidden layers (deep ANNs) can result in smaller architectures with fewer generalization errors [117].

2) DEEP LEARNING

Deep learning is a branch of machine learning algorithms that is capable of digesting raw data as well as developing the structures required for analysis to detect patterns in an automated way [118]. However, despite the fact that the phrase ''deep learning'' may be applied to ML frameworks that are not necessarily neutrally inspired is most commonly used to describe an ANN with two or more hidden layers. In some instances, deep learning algorithms have approached human or even superhuman levels of performance [119]. Deep neural networks come in a wide variety of architectural forms. People use feed-forward neural networks [120] and convolutional neural networks [118] in supervised learning, as well as RNNs [121] and auto encoders [122]. Deep reinforcement learning may also be achieved by combining deep learning with RL. DR's major application of deep architectures, like in the case of single hidden layer ANNs, has been for load and pricing forecasting jobs. The deep architectures are used by merchants to predict how people will react to DR events [34], manage home appliances based on DR events [123], find

TABLE 4. Advantages of ANNs algorithm [123].

ANNs Algorithm	Advantages
Single hidden layer ANN	Discovering various relationships between different inputs and perform multiple tasks in parallel without affecting the system performance
Deep Learning	Offer better and more effective processing models and ability to learn unsupervised drives continuous improvement in accuracy and outcomes

socio-demographic information about customers, and cluster customers using deep auto encoders.

IV. ISSUES

Numerous issues must be considered for DR programmes to be implemented successfully; these range from forecasting load and power rates to selecting appropriate customers to engage in DR initiatives and developing algorithmic tools to perform demand-side opportunities. DR has seen the use of artificial intelligence methodologies throughout the range of DR, providing forecasting capabilities, effective real-time operation of distributed systems, and selection while also responding to a changing environment and learning through human nature [124]. The highlighted issues such as forecasting, scheduling and controlling, incentive mechanism and pricing design, and segmentation customer and load.

In demand response scheme, AI approaches have been used to estimate power costs and various load forms. Real-time power scheduling and long-term system and service provider planning can be aided by forecasting techniques [125]. Accurate long-term projections can helps service providers and operators understand flexibility, which users should be targeted for DR, and how to establish DR signals in compensation/pricing. DR forecasting includes load and price predictions. Besides in controlling and scheduling, a fundamental difficulty for services providers and end-users is the wide selection of devices employed in DR. Without automated scheduling and control processes, it is impossible for a provider to efficiently manage a portfolio of demand response units. It is also critical to automate the scheduling and control of demand-side appliances to increase the number of consumers participating in DR schemes; otherwise, customers may suffer from response fatigue and eventually drop out of the DR programme [126]. Both the service provider (aggregator) and customer levels are available for scheduling and controlling the different DR units. The primary distinctions between the two levels are the size and scope of units. The algorithms used by the aggregator to schedule and control devices must be more adaptable and scalable than the algorithms used by consumers.

In incentive mechanism and pricing design might affect demand response program profitability and performance. Fair and attractive remuneration helps DR programs recruit and retain participants. Hierarchical energy market papers often employ optimization algorithms to find the optimal dynamic scheme for the day ahead to maximize service provider profit. However, they must consider market constraints and consumer dissatisfaction when markets shift [127], [128], [129]. The novel DR mechanism proposed by Meir et al. [130] also uses Vickrey-Clarke-Groves pricing to give a flexible set of contracts for DR to reduce consumption, reliable customer subsets are chosen. Ma et al. [131] add unknown preparation costs and multiple effort levels to their previous work [88]. This study recommends reward-bidding over penalty-bidding. DR prioritizes incentive-based. contract design. Lopes and co-authors [132] study store-commercial customer bilateral contracts. Like Haring and colleagues [133], they create incentive contracts for auxiliary services that involve service providers in the wholesale ancillary service market and retail consumer interest [69].

In addition, for segmentation of customer and load, grouping electricity users into distinct categories is a major use case for DR. Service providers may use it to help build disaster recovery programmes, aggregate resources, and analyze the potential burden of participating in multiple DR programmes. Based on their load profiles, customers are categorized into demand response schemes [134], [135], [136], [137]. Peak loads of [96], the average load of five consecutive weekdays [69], and specified factors such the mean relative standard deviation and seasonal score. Customers can be grouped without load statistics. Customers can be categorized by a variety of variables, including bid-offer data in an incentive-based demand response scheme [138] and the behaviour of EVs participating in demand response [139]. In addition, new research uses clustering algorithms to create DR application flexibility envelopes. Iria and Soares employed clustering techniques to determine energy market aggregator asset flexibility [140].

V. STATUS OF OPTIMIZATION

Artificial intelligence helps demand response methods overcome many of its problems, but it also comes with its own set of drawbacks and limitations. There are numerous ways for consumers to participate in the power market on the demand side. In addition, customers can take a more active role in reducing their energy consumption. As a demand-side management option, the author [27] investigated demand response in conjunction with energy efficiency as a smart grid solution that also included advanced systems, control, monitoring, and communication networks. AI and energy efficient ventilation systems ave also been a significant focus for the author [141]. As the AI method's DR application field, many issues need to be addressed, as well as the successful implementation of DR programmes. A focus on demand side management and a deeper exploration of AI is the focus of this investigation, which aims to ensure the Sustainable Development Goals can be adequately achieved. Based on different load classes, such as residential, commercial, and industrial, Table 5 compares other goal functions in the context of demand response and energy efficiency approaches

TABLE 5. The comparative analysis of techniques used in demand side management.

Ref.	Technique used in DSM	Objective	Concerned Field/Area
[142]	DR based building algorithm	To improve grid capacity	Industrial
[143]	DR programs	To examine how DR affects the distribution of network reliability benefits	Residential, Industrial
[144]	Binary PSO	To schedule Demand side resources	Commercial, Industrial
[145]	Home energy management (HEM)	To minimize household appliances from consuming excessive amounts of electricity	Residential
[146]	Game energy theory	In order to decrease energy use and consumption shifting	Residential, Commercial
[147]	Optimal power scheduling	To arrange power for DR	Residential
[148]	Demand response (DR) programmes	In order to examine the impact of DR on electricity market	Residential, Commercial
[149]	Game theory based & proximal algorithm	To study distributed DSM	Residential, Industrial
[150]	Appliance commitment algorithm	To schedule household load	Residential
[151]	DR based smart grid techniques	To investigate DR as a potentially profitable resource	Residential, Commercial
[152]	Transactive market mechanism	To investigate the use of DR in the regulation of commercial buildings.	Commercial
[153]	Score based intelligent HEM	To determine how the HEM's operation involves balancing the interests	Residential
[154]	Dynamic DSM techniques	To control the amount of electricity used in a home	Residential
[155]	Load management technologies	In order to examine the DSM idea for electricity providers	Residential, Industrial
[156]	Stochastic pricing Analysis	To examine the stochastic pricing capacity-controlled DSM and its implications	Residential
[157]	Mathematical model & approaches	To research DR in smart grids	Residential, Commercial
[158]	Co–ordinated scheduling	In order to improve the efficiency of smart home energy services	Residential
[159]	DSM &Multipronged approach	To investigate the application of DSM for electricity distribution.	Commercial, Industrial

utilized for the DSM under different load classifications. The objective function is similar in all these techniques; however, each is defined for other purposes with various constraints and operating conditions.

This analysis revealed that numerous artificial intelligence approaches are employed and that certain strategies are more appropriate for specific tasks than others. As a result, it is demonstrated that ANNs, which are regularly utilized for multi-variable function optimization and structural equation modeling, have become widely employed for short-term load forecasting and price forecasting, including supervised learning, to accomplish precise forecasts. Algorithms based on RL are frequently utilized to gather user feedback, making them particularly well suited for implementations of HEMS that incorporate a DR approach. On the other hand, clustering problems at the aggregator stage are often handled using unsupervised learning, given there is no background knowledge of classifications. When clients are categorized and actual demand is forecast, the aggregator schedules the formation of DR members and sets rewards and penalties for consumers. Alternatively, pricing and scheduling strategies can be optimized by utilizing multi-agent systems in game theoretic environments. Nature-inspired approaches such as PSO and ACO have been emphasized for these challenges, which can demand the employment of these techniques. Because of its widespread application in fields like technology and science, this optimization technique has earned high praise in the field. Furthermore, computer and AI advancements have greatly improved demand response and energy efficiency implementations in the DSM configuration. A wide range of AI approaches are now being implemented to implement these demand-response and energy-saving strategies. For AI-driven energy efficiency applications, Table 6 gives a detailed look at and evaluation of the current state of the art in the field.

VI. CHALLENGES AND OPPORTUNITIES

This section focuses on the fundamental AI methodologies used in energy consumption response, the main development fields of focus, and the ongoing industry involvement and investment in this field. A summary of the challenges and opportunities of each method will be shown in Table 7.

A. FORECASTING TASKS

One of the most frequently used approaches is artificial neural networks, primarily used for forecasting. The researchers employed ANNs for load and price prediction, employing single-hidden-layer and multi-layer structures. Demand response forecasting jobs, where prophecies might be linked to several inputs in a relatively non-linear form, have found favor with ANNs because of their flexibility in learning arbitrary, non-linear, complicated functions. Nonetheless, the effectiveness of the proposed variables is not guaranteed by any one method; rather, it can vary widely depending on the meta-model used as sources, the training process, and the configuration of multiple sets of parameters. Furthermore, ANNs may be prohibitively costly and generally involve a large amount of data in order to challenge other, less flexible techniques, which must be recognized. Because of the

TABLE 6. Comparison of the AI in DSM.

Ref.	AI Techniques used	Purpose	Finding	Devices/Appliances
[160]	ANN	A method for modelling and predicting solar energy has been presented	the ANNs can process noisy and missing data and that means they have a high fault tolerance	Photovoltaic Panels
[161]	ANN, PSO	The use of non-intrusive load monitoring (NILM) to model and identify equipment for DMS in a home energy management (HEM) system is becoming increasingly popular	reductions in the size of drive units used to track the heliostat, and the foundations required to support these structures	Electric rice cooker, Electric water boiler, Steamer, Television e.g., smart home
[162]	Deep learning	Air conditioning power consumption decomposition using NILM	as a more general learning and decision making paradigm, will deeply in-deep fluence learning, machine learning, and artificial intelligence in general	Air conditioning (AC) unit (e.g., load disaggregation)
[163]	Fuzzy c-mean clustering, GA	Designed a smart grid approach to link renewable energy output (solar and wind) with HVAC load	Fuzzy clustering is a powerful unsupervised method for the analysis of data and construction of models. In some cases Fuzzy Clustering is more natural than K Means clustering	Load of heating, ventilation, and air conditioning (e.g., Energy management)
[164]	Machine learning; k-mean clustering, support vector machine	Disseminated data-driven burden disaggregation	Method can deal with imbalanced data sets effectively by alleviating the influence of dominant class	Washing machine, electric oven, dishwasher, clothes drier (e.g., load disaggregation)
[165]	Classical combinatorial optimization, Factorial-HMM, Latent Bayesian melding, Super-state HMM	Evaluated NILM assisted appliances' anomaly detection approach	real-world energy disaggregation data set, show that the use of SACs dramatically improves the original AFHMM, and significantly improves over a recent state-of-the-art approach	AC and refrigerator (e.g., appliance anomaly detection)
[166]	GA	A approach for sizing wind-solar (hybrid) systems was presented in order to optimize the configurations of the systems	The performance of GA is better compared to PSO and ACO to archieve the objectives under TOU and IBR	PV modules, Wind turbines (e.g., optimal sizing)
[167]	Meta-heuristic optimization, i.e., Harmony search algorithm, Bacterial foraging optimization, and enhanced deferential evolution	A domestic load control method was designed with the goal of lowering total costs, energy demand, and the peak-to-average ratio in homes	The comparison is based on the quality of the results obtained, the computational demands and the sensitivity on the algorithmic parameter	Cleaner, water management heater, water pump; dishwasher; refrigerator; air conditioner; oven; washing machine; and fabric dryer are all examples of household appliances (e.g., HEMS)
[168]	Hidden Markov model (HMM), Log-Gaussian Cox process	An innovative NILM-assisted strategy to monitoring the health of older persons was provided	approaches effectively captured the nonlinear and multimodal relationship in process variables and showed superior process monitoring performance compared to those conventional process monitoring approaches	Kettle (e.g., NILM assisted health)
[169]	Conventional multivariable grey theory model, PDO	Predictions for solar power generation in the short term	forecast results at various resolution levels yield the overall forecast and reveal that this procedure is suitable for modeling the rainfall–runoff process	PV panels (e.g., prediction)
[46]	ACO	To reduce electricity cost and mitigate the MD, improved LF	cost electrcity reduction up to 5.8% when applied load shifting method	Scheduling Smart Home Appliances
[38]	SVM	to predict annual energy consumption of dairy farms	improved the relative prediction error of electricity consumption	microwaves, dishwashers or washing machines
[33]	GA	cost reduction of electricity and PAR reduction	performance of GA is better compared to ACO and PSO to achieve the objectives under TOU and IBR	Financial markets Manufacturing system

generally low acceptance rates of DR programmes, it is vital to consider this while employing DR programmes.

Supervised machine learning techniques are another class of technologies that have been employed mainly for forecasting purposes in the past. Suppose users compare these techniques to artificial neural networks. In such situation, users will find that the latter are typically less flexible, deploy more skewed approaches, and tend to depend on feature

TABLE 7. Summary of the challenges and opportunities of each method.

	Load Forecasting	Price Forecasting	Segmentation Tasks	Schedulling & Control (consumer)	Schedulling & Control (aggregator)	Pricing/Incentive Design
Supervised	14	2	2	2		1
Unsupervised	1		24	1	1	
Reinforcment Learning			1	11	4	5
Swarm AI			1	3	9	2
Evolutionary Algorithm				11	2	3
Deep Learning	6	5	2	2		
ANN (single hidden layer)	23	6	1	3	1	3
Coooperative Game Theory						6
Automated negotiotion						2

architecture to attain effective outcomes. Supervisory techniques like regression trees [170], [171] and gradient boosting [67], on the other hand, perform better when dealing with missing data than unsupervised approaches such as ANNs and require fewer samples to train. That has advantages from the standpoint of demand response. Using a forecasting model that produces a distribution rather than a point estimate makes it possible to make better decisions in DR while also paying participants more fairly because of more accurate baseline estimates. A further reason for this growth is that intelligence forecasting systems have the ability to develop forecasts that encompass several spatial and temporal boundaries and the capability to include ambiguity in the estimates, resulting in better-informed future predictions, artificial intelligence systems use a high-computational method. The systems' reliability may be affected by the excitable tuning and feature design used to make the system more accurate.

B. MULTI-AGENT METHODS AND PRICING MECHANISM

There are many more devices in the existing DR systems than in the traditional ones, which means that the interests of the various parties involved are not always aligned with the needs of the demand response system operator. Examples include HVAC systems in buildings, electric vehicles, and water tanks. Traditional DR approaches assume that the devices being managed are under direct control. Increasingly relevant in these systems are multi-agent systems techniques, such as those based on game-theoretic mechanism design [172]. Few exceptions can be found in the research that has studied the use of multi-agent systems in developing pricing and incentive mechanisms. A technique called mechanism design has been utilized to develop demand response systems with certain favorable qualities while also meeting requirements [173]. Even though these approaches can provide valuable insights into the performance of decentralized demand response structures, which natural individuals form, users are frequently primarily dependent on assumptions made throughout the modeling process. If these assumptions are not met in practice, the resultant schemes will not necessarily possess the desired characteristics. Coalitional game theory has been used to design incentive-based DR systems and distribute participants' expected payoffs. Since it is based on contractual agreements between providers and consumers in a demand response scheme, it is frequently utilized in incentive-based demand response schemes. On the other hand, challenges like computing complexity and intractability must be solved before these approaches may be made more broadly applicable. Combining function approximation techniques like those developed in [90] and [174] with fast search techniques might be a promising approach to tackling these issues.

C. DYNAMIC CONTROL AND SCHEDULING

As part of the machine learning methodology, reinforcement learning techniques have been mainly used to control problems. HEMS are necessary due to the need for automated consumer scheduling duties and control of the various demand response structures, especially in the residential sector. In addition, at the provider scale, particularly in specific load control demand response schemes, where a certain majority and variety of devices and equipment throughout the aggregator's offering render the operation of control and scheduling impractical without mechanizing a substantial amount, if not the entire process, control systems for DR are required to learn from customer contact and operate following their preferences. As previously mentioned, Q-learning is the most extensively used reinforcement learning algorithm in DR. When the set of possible actions and environmental conditions get huge; it might be challenging using tabular approaches such as Q-learning, even though it is an online method with convergence guarantees. The use of an ANN [175] or a FQI [77] to approximate the action-value function has been attempted to alleviate this problem in certain studies. When dealing with vast state paces, the literature has also used multi-agent real-time approaches. When dealing with large state fields, multi-agent real-time techniques have also been used successfully in the literature.

D. SCHEDULING TASKS

Algorithms derived from natural phenomena are far more frequently used to plan work schedules. In reality, it becomes more challenging to find a workable solution to a scheduling problem as the problem's complexity, non-linearity, and non-convexity rise. Because of its exploration and exploitation abilities, this collection of algorithms can identify promising solutions in a fair amount of time. Other important features are their resilience and flexibility to changing situations and environments, the fact it is parallelism, the ability to combine anti-local-optimization strategies, and speed make these algorithms particularly appealing. This class of algorithms often has ''anytime'' properties, meaning it can re-generate interesting responses if the computation is halted. Regarding actual applications, this is a crucial characteristic while there are usually physical limitations in terms of the equipment and computing capacity that can be utilized. Alternatively, nature-inspired techniques may not always result in finding the optimum route, and various methods may have their own limitations that must be considered while developing a solution. Participants may have to deal with premature convergence and unpredictable results if GAs are not correctly tuned. In contrast, PSOs can get locked into early convergence and slow convergence speed if they are not adequately tuned [97].

Artificial intelligence derived from nature-inspired is often used in developing pricing schemes, in which the supplier aims to predict the rates for demand response that will maximize their return while still considering the user interests and system constraints, among other things. Concerning DR, the NSGA method as well as its variants have already been employed in multi-objective to optimum scheduling of demands, as well as other applications [176], [177]. Over the years, a few traditional techniques for tackling DR scheduling issues have been created. These methods include nonlinear and linear programming, mixed-integer nonlinear, and mixed-integer linear programming, depending on how the scheduling problem is exposed. Linear programming is the most used approach [178]. Compared to typical DR scheduling techniques that are deterministic, population-based, stochastic, and nature-inspired AI systems can manage challenges with more decision factors and adapt to changes in scheduling much more quickly and effectively. These capabilities are significant because it allow adaptive DR systems to respond rapidly to shifts in the schedules of appliances and other pieces of equipment. Mathematical optimization/scheduling approaches frequently rely on implicit assumptions like linearity or convexity. A nonlinear control problem is frequently encountered in real-world demand response systems due to the increasing presence of heterogeneous equipment such as battery packs, HVAC units, production equipment, and electric vehicles (EVs). Regarding non-linear optimization issues, GAs, NSGAs, and PSOs routinely beat conventional techniques in most cases.

E. LOAD CLUSTERING AND CUSTOMER SEGMENTATION

In the existing demand response system, there is only a small amount of labelled data to use as a foundation for user classifications, which makes it difficult to properly assess customers. In order to address the problem of segmenting electricity consumers, clustering (unsupervised) models are the only practical option currently available. Research that supports the study's findings and is consistent with them indicates that clustering methodologies to build customer groups are consistently used across publications evaluated. Even though clustering algorithms are effective in this application, it also presents several challenges. These algorithms have a number of drawbacks, one of which is that their methods are affected by the high dimensional. It is tough to analyze their results because of a scarcity of labeled data, to name a few of the issues.

VII. CONCLUSION

The increased usage of electric vehicles (EVs), heat pumps, and distributed energy resources (DERs) are straining the electricity infrastructure. DR solutions are gaining popularity because they allow grid operators to maintain grid balance while avoiding or postponing costly network enhancements or backup production. Initially targeted at a few significant industrial and secondary clients, demand reduction (DR) programmes are increasingly expanding to include residential and secondary loads. The user must not only select the responsible end-users but also plan their usage, put up DR controls, and decide on incentive and penalty schemes. Researchers have used optimization algorithm solutions to achieve these goals. Because traditional methods were inefficient and unreliable, they turned to these new methods.

Artificial intelligence (AI) has recently been a hot topic in research to business, with numerous start-ups springing up in response. Even though these patterns are well-established, further study is required to uncover the optimal AI-DR solutions. Many proposed remedies have not been subjected to large-scale experimentation and trials. More research, industry ventures, and large-scale experiments are needed to produce more accurate models and AI solutions. This technology will make optimization strategies routine in the energy demand response market.

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AMIRA NOOR FARHANIE ALI was born in Terengganu, Malaysia, in 1998. She received the bachelor's degree (Hons.) in electrical engineering from Universiti Teknikal Malaysia Melaka (UTeM), in 2021, where she is currently pursuing the M.Eng. degree. Her research interests include demand response, demand side management, load management, energy efficiency, energy audit, and optimization algorithm.

MOHAMAD FANI SULAIMA (Member, IEEE) received the bachelor's degree from Tokai University, Japan, in 2010, the master's degree from the University of Malaya, and the Ph.D. degree in electrical engineering with a specialization in energy demand side management from Universiti Teknologi Mara (UiTM), Malaysia, in 2020. He is currently working as a Senior Lecturer with the Faculty of Electrical Engineering, Universiti Teknikal Malaysia Melaka (UTeM). Upon joining UTeM, he worked as a Coordinator and the Head of the Energy Management Division, Centre for Sustainability and Environment, before being appointed as the First Internal University Energy Manager, in 2015. He is also the Head of the Research Laboratory for Power and Energy System. His research interests include power systems, demand-side management, demand response, energy efficiency, measurement and verification, and artificial intelligence. As a result of his research interest, he has published more than 100 articles, including high impact journals, and academic articles.

INTAN AZMIRA WAN ABDUL RAZAK received the B.Sc. degree in electrical engineering from Universiti Teknikal Malaysia Melaka (UTeM), Malaysia, in 2006, the master's degree (engineering) in electrical power from Universiti Teknologi Malaysia (UTM), in 2008, and the Ph.D. degree from The National Energy University (UNITEN), Malaysia, in 2017. Currently, she works as a Senior Lecturer at the Faculty of Electrical Engineering, UTeM. Her research interests include load and price forecasting, artificial intelligence, and optimization algorithm.

AIDA FAZLIANA ABDUL KADIR received the B.Eng. and M.Eng. degrees in electrical from Universiti Teknologi Malaysia, in 2000 and 2003, respectively, and the Ph.D. degree in electrical engineering from Universiti Kebangsaan Malaysia (UKM), Malaysia. She is currently an Associate Professor at the Department of Electrical Engineering, Universiti Teknikal Malaysia Melaka, Malaysia. Her research interests include power system and power quality, distributed generation, and energy efficiency. She is also a Registered Professional Member of the Board of Engineers Malaysia (BEM) and a member of the Institute of Engineering and Technology (IET), U.K.

HAZLIE MOKHLIS (Senior Member, IEEE) received the B.Eng. and M.Eng.Sc. degrees in electrical engineering from the University of Malaya (UM), Malaysia, in 1999 and 2002, respectively, and the Ph.D. degree from The University of Manchester, Manchester, U.K., in 2009. He is currently a Professor with the Department of Electrical Engineering, University of Malaya (UM). He is also the Head of the UM Power and Energy System (UMPES) Research. His research interests include fault location, distribution automation, power system protection, and renewable energy. He is also a Chartered Engineer in the U.K. and a Professional Engineer in Malaysia.