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TOPICAL REVIEW

Artificial Intelligence Enabled Demand Response: Prospects and Challenges in Smart Grid Environment

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ABSTRACT Demand Response (DR) has gained popularity in recent years as a practical strategy to increase the sustainability of energy systems while reducing associated costs. Despite this, Artificial Intelligence (AI) and Machine Learning (ML), have recently developed as critical technologies for demand-side management and response due to the high complexity of tasks associated with DR, as well as huge amount of data management to take decisions very near to real time implications. Selecting the best group of users to respond, learning their attitude toward consumptions and their priorities, price optimization, monitoring and control of devices, learning to engage more and more consumers in the DR schemes, and learning how to remunerate them fairly and economically are all problems that can be tackled with the help of AI techniques. This study presents an overview of AI approaches used for DR applications. Both the Artificial Intelligence and Machine Learning algorithm(s) are employed while discussing commercial efforts (from both new and existing businesses) and large-scale innovation projects that have applied AI technologies for energy DR. Different kind of DR programs implemented in different countries are also discussed. Moreover, it also discusses the application of blockchain for DR schemes in smart grid paradigm. Discussion of the strengths and weaknesses of the evaluated AI methods for various DR tasks, as well as suggestions for further study, round out the work.

INDEX TERMS Artificial intelligence, blockchain, demand response, demand side management, demand response, Internet of Things (IoT), smart grids, machine learning.

I. INTRODUCTION

Power grid operators face significant new hurdles due to the emerging growth of renewable energy sources (RES). There must be a quick adjustment in energy infrastructure to meet the growing diversity of integrated energy sources. RES in general are notoriously hard to estimate when it comes to their power production because of their inherent instability and intermittent nature (i.e. they are totally dependent upon variable solar and wind energy). Because of the requirement for flexible power system to ensure the continued and safe functioning and stability of power systems, they possess greater challenges to operation and management [1]. Integrating fast-response electrical power production system, demand-side management, and other energy storage devices are the primary methods for offering flexibility [2]. Also, the digitalization converts conventional grids to modern smart grids to manage electrical grids. Power systems may be made more efficient, secure, dependable, robust, and sustainable with the use of new technologies like the IoT, real-time management and control of power at different level and smart contracts [3]. Several nations have set ambitious goals for the widespread implementation of advanced metering infrastructure (AMI) [4], [5]; for instance, the UK's Ofgem has mandated the installation of 53 million smart meters for electricity monitoring and control

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2020 [6]. There has to be automated methods for analyzing the enormous amounts of data produced by this infrastructure (IoT, AMI). The evolution into faster, decentralized, and intricate power systems [7] also brings forth new challenges that may eventually become unmanageable for manual control system. Artificial intelligence techniques have been suggested as an important method for dealing with these issues in power grids. More stable and efficient power system may be achieved via the application of AI to forecast power demand and production, optimize the maintenance and use of energy assets, get a deeper understanding of energy consumption patterns, and more. AI play its crucial role in human life because it makes decision making process easier and very near to the actual/real-time decision also automatically schedules different appliances being used for different purposes at domestic and industrial level.

A. MOTIVATION AND SCOPE OF THE REVIEW

Although AI methods have long been studied and utilized in many power system applications in different areas, but currently researchers paid attention about the application of AI in the context of demand response. Increasing the scale and scope of DR initiatives is an important factor for power system operators as it has been highlighted as one of the potential techniques to allow more demand flexibility to the power system. For DR schemes to perform better, an automated framework that can be more flexible and learn about its context (such as customer preferences) is necessary. In reality, it is becoming clearer that AI may contribute significantly to the future success of DR schemes by automating the process while learning the preferences of end-use customers. This framework is only possible with inculcating AI techniques for demand side management.

The dramatic uptick in study within this field is indicative of the growing need for AI-based solutions within the DR industry. As can be observed in Figure 1, between 2011 and 2021, the number of scholarly articles on this topic increased dramatically. As a result, there is a growing need for a comprehensive evaluation of the many artificial intelligence (AI) algorithms now in use throughout DR's many different application domains. While many of these papers make important contributions, they typically only examine one AI/ML method and one application area at a time. Based on the body of information presented so far in current publications, we believe there is a pressing need for an in-depth analysis that charts the growth of the field and serves as a guide to the most promising AI approaches utilized in certain sub-areas of DR. Because of this, the goal of this study is to give a comprehensive analysis of the different AI data-driven methodologies for DR applications. Our evaluation has three main purposes:

At first, we want to provide a thorough review of the artificial intelligence (AI) methods underlying this field, as well as the primary particular applications/tasks in power DR in which these methods have been applied. Therefore, providing a holistic view of the development of the area

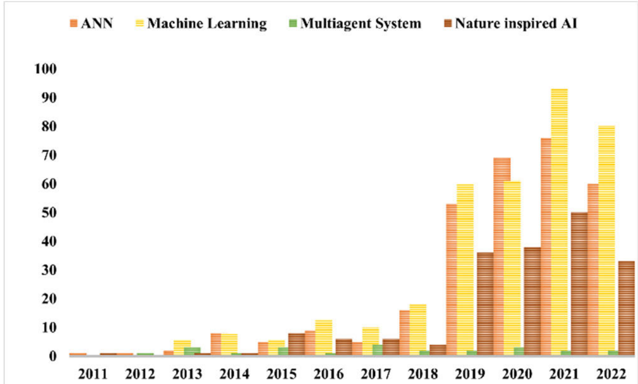

FIGURE 1. Number of articles published related to different AI techniques used in DR.

and directions for future study. In addition, we believe our evaluation will be a valuable resource for future scholars and professionals in the subject. Specifically, this entails educating them about the AI strategies that have proven effective in solving problems similar to theirs in terms of DR. Specifically, this involves a methodical evaluation of the pros and cons of using a certain AI method in each particular field of use. Finally, we wanted to provide more context than is provided by just reviewing academic publications by discussing some of the research efforts in this field that are supported by industry. Our investigation reveals a total of forty businesses/commercial efforts and twenty-one major projects in this space, demonstrating the high level of activity and investment in this area. To the authors ' knowledge, this is the most extensive analysis to date of the use of artificial intelligence (AI) in the field of energy demand side response.

B. RELATED REVIEWS ON DEMAND RESPONSE (DR)

The literature on energy-demand-response reviews is abundant. In [8] looked at the Several advantages of DR in smart grids which consists of different smart sensors used for control, monitoring, and communication systems. Innovations in DR systems, load forecasting approaches, and communication channels are studied in [9]. Long-term, less obvious effects of DR, such as its influence on energy market pricing and on customers, were investigated in [10]. In [11] looked at the technical side of DR for frequency regulation, while economic effect of DR are investigated in [12]. In addition, the optimum management of DR techniques and DR pricing schemes were improved in [13].

Particularly in [14] there is a literature analysis on different Artificial Intelligence (AI) techniques for DR, discussing how AI might be used to create a scheduled monitoring system for a Smart home that is being monitored under DR. For example, [15] compared and evaluated several self-organizing optimization algorithms for demand response in smart buildings while in [16] author used clustering technique to mitigate the load profile and managing load demand intelligently and [17] narrowed their attention to the use of reinforcement learning for DR specifically.

In addition, [18], explored the use of smart meter and its data analysis for DR application while [19], [20] examined AI based load prediction, concentrating mostly on deep learning and artificial neural networks (ANNs) [21]. aggregation of thermal inertia, particularly from district heating networks is emphasized in [22] and [23] highlights the emerging concept of integrated demand response, which integrates multiple energy types and vectors (including electricity, natural gas, and heat). Our main focus, on the other hand, is on electricity demand and demand side management that goes into further detail on the artificial intelligence methods that make this possible.

While the above-mentioned assessments of AI technologies for DR applications have proven helpful, it is worth noting that they are often limited in scope. They often focus on one particular facet of artificial intelligence, such reinforcement learning [17] or one area of application, like home energy management systems [14]. The goal of this research is to present a more all-encompassing and global perspective on the AI methods now used in DR schemes to facilitate power system function. To identify possible research gaps and propose future study directions in this rapidly expanding domain, we believe that a systematic review of this size and breadth is necessary and desirable.

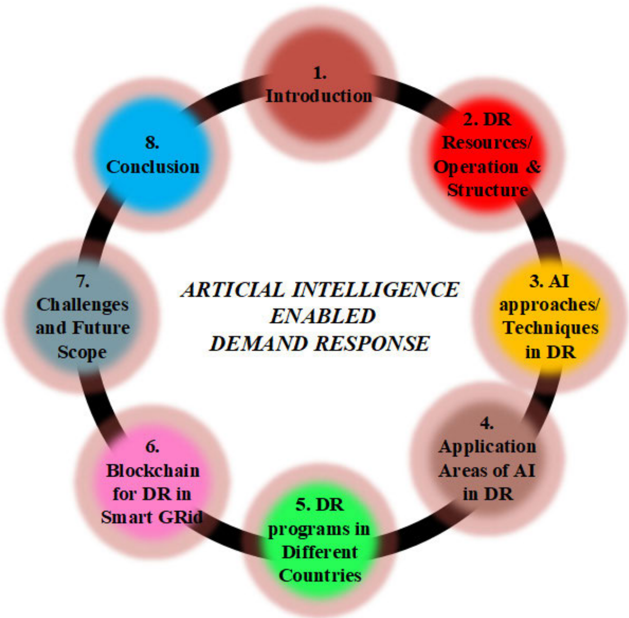

FIGURE 2. Layout of the paper.

C. STRUCTURE OF THE REVIEW

This paper's structure is given in Figure 2 and is organized as follows. Section 2 will first introduce DR and its connection to the electrical grid and energy markets. The next Section3 introduce AI and its different techniques like machine learning, deep learning and other techniques under AI and its fundamental ideas before classifying the evaluated literature. Section 4 describes the applications of AI techniques in demand side management specially for DR like for forecasting techniques, Load management or Energy management. DR programs being implemented in different countries are explained in section 5 while blockchain application on DR in smart grid is explained in detail in section 6. While challenges and future scope is given in section 7 which followed the conclusion in section 8.

II. DR RESOURCES, OPEARTION, AND MARKET STRUCTURE

The conventional design of the power grid is based on a one-way flow of energy from generation end to consumer end. High voltage generators under centralized control are employed to provide this supply. Demand side management and notably demand response have emerged as viable options for the efficient and reliable operation of the electric grid as a result of the proliferation of grid service markets and the inclusion of DER in recent years. However, a DR model, in contrast to conventional power grids, calls for a two-way communication system and intelligent algorithms to analyze the produced data. Because of this, smart meters are a crucial part of a smart grid and play a pivotal role in DR models [24]. Information gathered may also be used by AI-based solutions to improve DR initiatives. The purpose of this section is to provide an overview of DR services and define their place in the existing framework of the electrical market.

Demand side management is a broader area in electrical power system of which demand response is a subset, and is achievable because of emerging technologies and innovations in conventional grids i.e., due to smart grid operations [25]. When we talk about "Demand Response" in this article, we're talking to the ways in which commercial and industrial consumers of electricity alter their consumption patterns. Customers agree to modify their typical load profile as required from the utility provider in order to get maximum possible benefits for both sides by decreasing or shifting their energy usage away from peak hours [25]. Although DR encompasses a wider range of energy sources (such as thermal energy, gas, etc.), this study will just discuss electrical power aspects of the generation side. Figure. 3. Shows the classification of DR, where DR programs based on motivation offered to customers are further divided into two distinct categories, which corresponds with the classifications provided by [9], [26], and [27].

A. PRICE BASED DR PROGRAMS

With the goal of getting end-use consumers to shift their energy consumption habits, the electricity price in this scenario fluctuates over different time intervals. Time-of-use pricing, critical-peak pricing, and real-time pricing are all examples of such schemes [10].

B. INCENTIVE BASED DR PROGRAMS

End-use customers are incentivized to lower their power use via these programs by providing them with offers to

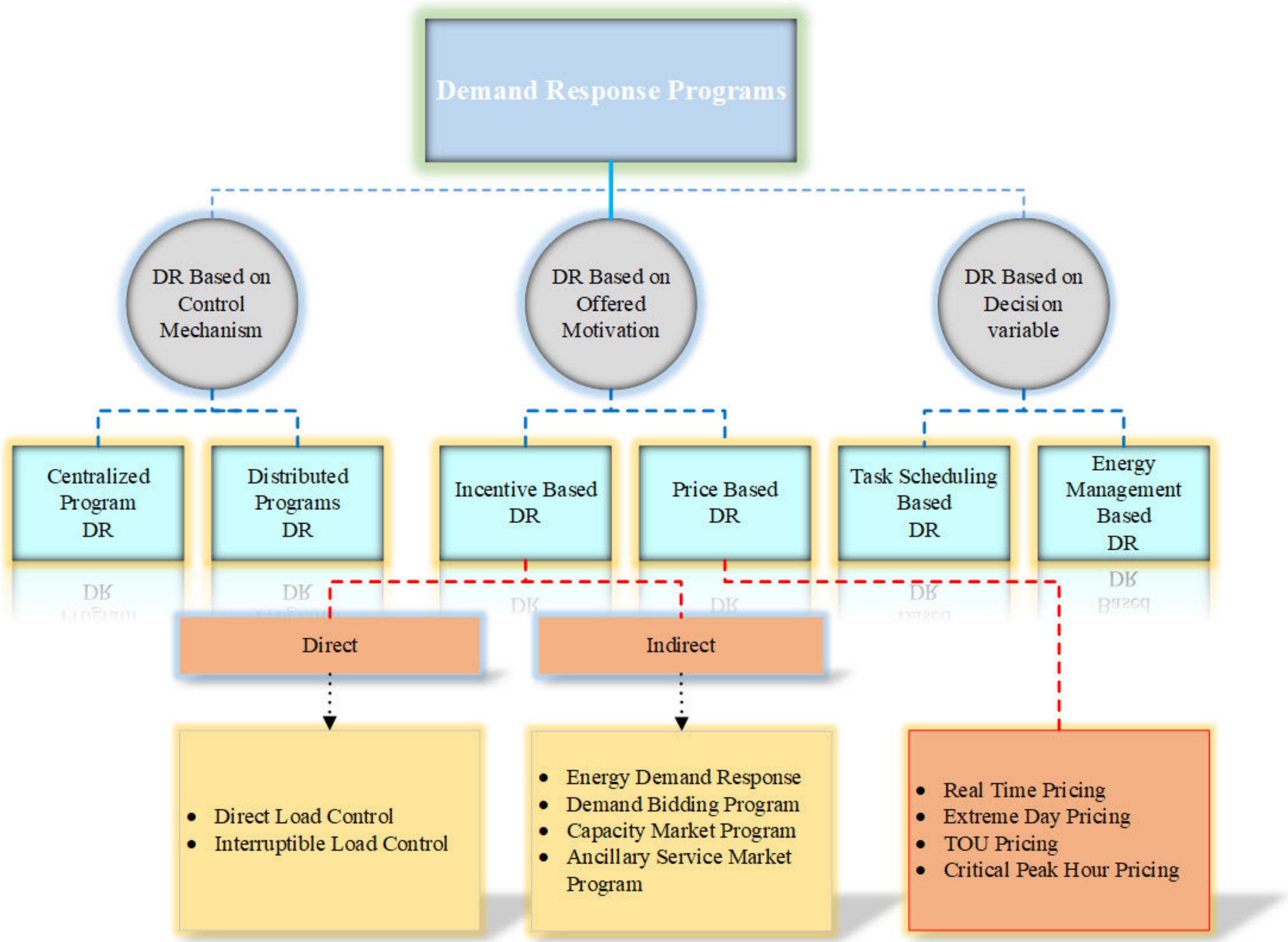

FIGURE 3. **Classification of DR resources, operation and structure.**

do so upon request or in accordance with a contractual agreement. Direct-load controls (DLCs), interruptible tariffs, and demand-bidding programs are all examples of this kind of scheme [28].

Each of these methods of management calls for tailoring the incentives or contracts offered to customers in light of their actual behavior. There are also two distinct types of markets for electricity: retail, where electricity retailers directly contract with end-users for electricity delivery, and wholesale, where retailers, suppliers, producers, grid operators, and third-party aggregators all work together to ensure that retailers can deliver power to their customers without jeopardizing the reliability of the grid. Three distinct markets—the energy market, the capacity market, and the ancillary services market—make up the wholesale electricity market and work together to incentivize various parties to contribute to the nation's power distribution and the grid's efficient operation and reliability. The energy and auxiliary service sectors are linked with demand-side responsiveness. Contracts between market participants may be conducted bilaterally (over the counter (OTC)) or by a proper broker company, depending on the national policy. The items may be exchanged on the spot market (day ahead and/or intra-day) in both circumstances and for ancillary service in spot market. If a resource provider makes a definite promise to provide a particular quantity of electricity into the grid, they must fulfil that promise or face financial consequences. Therefore, it is crucial for DR monitoring companies to agree the end consumer and offer power flexibility.

As distributed energy resources (DER) become more integrated into power networks, innovative approaches are needed to meet the technological constraints of a smart grid (mainly frequency and local voltage regulation). DR is one of the best options. Smart DR plans may be built upon the infrastructure that is being put in place with the usage of smart meters for homes and commercial buildings along with IoT-enabled smart appliances being deployed in smart homes. Furthermore, in order to effectively regulate demand without adversely impacting end-user comfort, these tactics will use AI-based smart algorithms.

In the next part (Section 3), we describe different artificial intelligence (AI) methods offered and researched in literature in the interest of automating DR. Section 4 then discusses the applications of AI and ML to various DR services.

III. AI APPROACHES/TECHNIQUES IN DEMAND RESPONSE

AI, or artificial intelligence, is the study and development of intelligent entities (agents) [29]. These smart agents are computer programs that can analyze their surroundings and take appropriate action to accomplish certain objectives. Computer science, neurology, economics, information theory, statistics, psychology, control theory, and optimization are just few of the many disciplines that contribute to AI.

Hence Agents with artificial intelligence (AI) may vary from robots with true thinking capabilities to search algorithms utilized in board games. Different methods have been used since the advent of AI in the 1950s to develop intelligent computers. Among these methods are statistical learning [30], [31] soft computing [32] and knowledge-based systems [33] In this work, we will examine the data-driven, soft-computing, non-symbolic approach to AI. This study also examines AI methods in both the single-agent and multi-agent contexts in order to provide a more complete picture. Figure 4 shows many types of AI approaches that have been used to DR and how they have been classified.

A. MACHINE LEARNING AND STATISTICAL METHODS

In the age of big data and the Internet of Things, automated analysis of the "data tsunami" that is variable constantly being generated is crucial. Machine learning is an essential part of artificial intelligence (AI) that consists of a collection of techniques that aim to learn from data. Methods that automatically recognize patterns in data and utilize these patterns to make predictions and other kinds of decision making in an uncertain environment fall under the umbrella of this set of AI approaches [34]. Machine learning is an interdisciplinary field that largely uses ideas from computer science, statistics, mathematics, and engineering. Murphy [34] lists supervised learning, unsupervised learning, and reinforcement learning as the three primary categories of machine learning.

With an already labelled collection of input-output pairings, the purpose of **supervised learning** is to learn a mapping between the input vector x and the outputs y. The inputs xi might range from a basic real number to a highly structured object, and this collection of data is known as the training set (e.g. an image, a timeseries, a graph, etc.). By using kernel-based and tree-based approaches in addition to linear regression models, supervised learning techniques have been largely employed in DR to anticipate the demand and power pricing. Supervised ANNs are also widely used for forecasting purposes.

Using **unsupervised learning** techniques, the system is merely provided with the inputs and is tasked with finding potentially relevant patterns of interest within them. Because the patterns that need to be recognized are unknown in advance and there are no clear error measures to employ, unsupervised learning is a less well-defined technique. Due to the scarcity of labelled data, this is useful in DR. Clustering has been the primary use of unsupervised algorithms in DR, whereby items (such as load profiles) are grouped together such that their members are similar to one another but different from those in other clusters. Consumers have been categorized, and typical load profile shapes have been identified, with the help of several clustering techniques. Therefore, this categorization may be used to choose consumers for DR programs, pay consumers for participation in DR programs, and identify families who can benefit from DR schemes.

The concept of "interactional learning" is central to almost all learning philosophies. To learn from experience, **Reinforcement Learning** (RL) is one of the most fascinating computer methodologies. RL is a method that considers the whole challenge of an agent learning to achieve a certain objective in the context of an unknown environment [35]. The two most distinguishing features of RL are the use of a trial-and-error search strategy and the provision of delayed reward. RL has been used from a very long ago for DR to monitor and control the various kinds of loads at domestic level or Electric vehicles while taking into consideration the customer preferences. RL technique proved to be on of the best and easiest model for DR to manage the complex data for both customer and service provider. Researchers have also utilized the RL framework in order to estimate the budget for utility [36], [37], [38] and to create a scalable and efficient model for a group of customers [39].

B. NATURE-INSPIRED ALGORITHMICS

When developing new computational methods, scientists have always looked to natural and biological systems for inspiration. Artificial intelligence (AI) researchers have used algorithms inspired by nature to perform tasks including looking for relevant information and figuring out the best course of action to achieve a goal [29]. Meta-heuristics inspired by evolution, biological swarming, and physical processes are the most common types of algorithms drawn from nature. The term "meta-heuristics" is used to describe a group of iterative processes that supplement heuristic procedures through the application of proper hieratical flow model to find the most optimum and efficient solution using different kind of nature inspired intelligent learning strategies [40].

Algorithms inspired by nature have been utilized extensively in the field of DR, mostly for consumer-level load scheduling (algorithm included in HEMS) and for assisting aggregators and retailers in optimizing the price of their DR service provider clients. In the DR setting, where the scheduling problem might be computationally costly, meta-heuristics have been widely used because they can discover solutions in a fair amount of time.

Evolutionary algorithms, also known as Evolutionary Computation (EC), are a heuristic-based technique that mimics key aspects of biological evolution in a computing setting, including different kind of biological processes

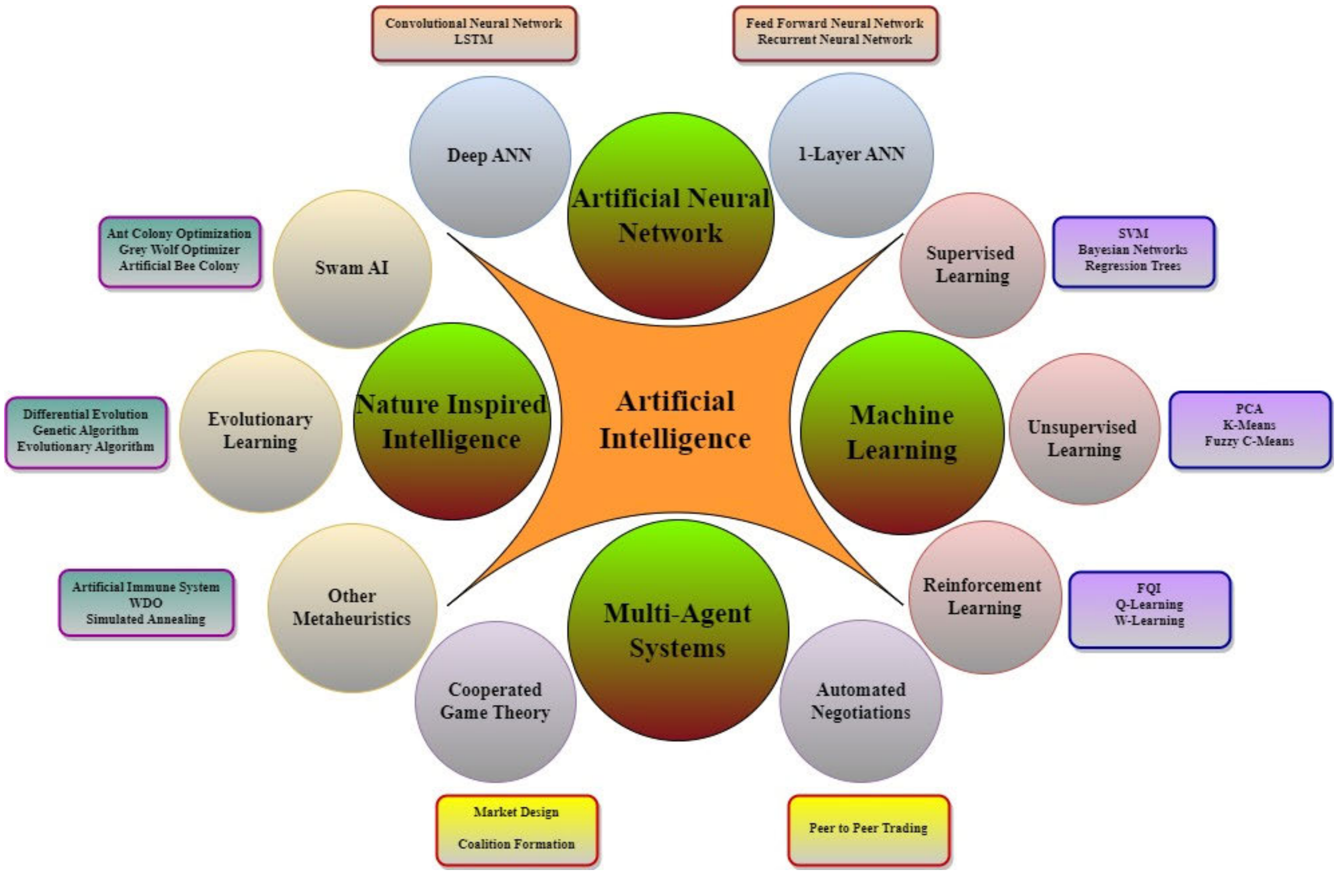

FIGURE 4. Different artificial intelligence techniques used for DR.

like reproduction, mutation, recombination, and selection. The process is evaluated for different number of iterations until the optimization function on an individual reaches a termination criterion. Genetic algorithms (GA) are biological model inspired by natural processes in humans, animals and birds according to Charles Darwin's theory of natural selection [41], [42], [43], [44], [45] and have emerged as the dominant approach from the evolutionary computation in the literature on energy DR [43], [44], [45], [46]. Implementing these meta-heuristic genetic algorithms gives maximum possible efficiency for turning different appliances ON/OFF at domestic and industrial level. For example, a differential Evolutionary Algorithm (EA) which is utilized in battery management system in order to manage the data of lithium-ion battery in datacenter [47], and a bi-level Evolutionary Algorithm (EA) which is used to find the maximum efficient electricity tariff for consumers under DR strategies [48] are all examples of evolutionary algorithms being used in the DR setting.

Swarm intelligence is a branch of artificial intelligence that studies how imitating the behavior of biological swarms might help with problem solving [48]. The Particle Swarm Optimization (PSO) method [49] and the Ant Colony Optimization (ACO) algorithm [50] are the two most popular examples of swarm intelligence algorithms in the research literature. For further details on these algorithms, see the reviews [51], [52], [53]. Swarm AI systems may become trapped in local optima and have a sluggish convergence pace, much as evolutionary approaches [40]. In contrast to GA, where "poor" particles are eliminated, all particles' histories are used in swarm AI systems to aid in the search [54]. In addition, swarm AI approaches often have fewer parameters that need fine-tuning before deployment. Swarm AI algorithms are often employed by energy aggregators and retailers to determine the best scheduling and pricing strategies to minimize costs associated with demand response. The optimization issues in DR are notoriously non-convex because they include a high number of variables, quadratic optimization functions, and limitations derived from the calculation of the AC power flow. Heuristic optimization is well-suited to this situation since it can quickly locate a near-optimal solution while requiring less effort than other mathematical methods. A most popular example of these heuristic optimization methods in DR is particle swarm optimization (PSO).

In addition to these algorithms, several nature-inspired meta-heuristics have been discovered, many of which defy easy categorization. With inspiration from the mechanisms present in biological immune systems [55], the CLONALG-based [56] Artificial Immune System (AIS) algorithm is utilized to set prices for the aggregators. The Wind Driven Optimization (WDO) algorithm [57], which is based on atmospheric motion, is used to find an optimum schedule of appliances at the household level, and the simulated annealing approach, which was developed on the annealing concept, is used for DR.

C. ARTIFICIAL NEURAL NETWORKS

Computer models called Artificial Neural Networks (ANNs) take cues from the structure and function of real-world neural networks. This study presents ANNs as a separate category because to their widespread use in DR applications; nevertheless, ANNs might technically be classified as either a machine learning method or a method inspired by nature in the field of artificial intelligence. Multiple fields have made use of ANNs for tasks such as classification, clustering, pattern recognition, and forecasting [58]. In DR, ANNs have used for load forecasting, and they have been of varying designs and complexity (number of layers). ANNs are used in the majority of DR applications to predict the future consumption of an infrastructure (building, appliance, consumer group), the flexibility of a load, or the short-term pricing of power (which can be for hours, minutes and even world is progressing towards seconds to one day ahead). In certain cases, ANNs may serve as a viable alternative to nonlinear regression methods. For instance, most load forecasting implementations takes inputs like previous consumptions, weather, day, hour and sometimes the price. Inputs for a price forecast are often prices from the past. A lot of literature has led to the identification of two primary classifications, single hidden layer ANN and Deep Learning.

Single hidden layer, feedforward ANN has wide range of application in the DR sector. For the most part, single hidden layer ANNs have been used in the DR literature for load and pricing forecasting. In addition to these applications, single hidden layer ANNs have been utilized to represent complicated functions like cooling system control algorithms [59] or urging users to manage and shift the load to the off-peak hours [60], But this can be directly linked to the day temperature, weather and electricity cost.

Deep learning is a kind of ML that processes data in its raw format and automatically discovers the data which is needed to be represented for detection or classification [61]. It involves learning several layers of representation and abstraction. Like single hidden layer ANNs, deep architectures have mostly been used for load and pricing forecast in DR. In addition, deep architectures have been used for customer response prediction [62], DR event-aware home appliance control [63], identifying consumer socio-demographics to inform targeted DR mitigation strategies [64], and customer clustering based on the estimated load curve which is already encoded in the system using deep learning based autoencoders [65].

D. MULTI-AGENT SYSTEMS

Because the demand side of power systems is often decentralized, there is a pressing need for methods that can learn, plan, and make choices in the context of a system comprised of various interacting intelligent agents. Multi-agent systems (MAS), a branch of distributed artificial

intelligence, give the analytical tools necessary to investigate such issues. This review focuses on the subfields of MAS known as automated negotiations, which focus on finding a common agreement between different participants in the game/scheme, cooperative/coalitional game theory, which focuses on the study of coalitions among these players and designed agreements.

One important idea of **Game Theory** is "game," which is represented by a mathematical model that "captures the essential aspects of the interaction between self-interest entities" [66]. Understanding what makes a result of a game logical is a central goal of game theory, and many solution ideas have been devised to help narrow down the possibilities. One such notion is the Nash Equilibrium.

A subfield of game theory known as "coalitional" or "cooperative" game theory in which the aim is to foresee which coalitions will emerge. As opposed to focusing on the strategies used by each player individually, cooperative game theory [66] instead divides the payout among the participants. Cooperative game theory has seen extensive use in the DR setting, particularly in instances where legally enforceable agreements have been established (i.e. incentive-based DR). Selecting the best group of power users to take part in DR schemes and dividing up the coalition's payout are two primary uses of cooperative game theory in DR (known as solution concept). Depending on the requirements that the aggregator is trying to satisfy, the solution idea relates to the method in which the income is divided in between the participants in DR for power demand flexibility.

Strategically speaking, **Mechanism design** is a subset of social choice theory which postulates that different kind of participants would act in a manner that maximizes their own utility. Since the ability to ensure specific qualities is crucial to the maximum possible optimum solution for DR schemes, mechanism design has been frequently employed in DR literature. Consumers are encouraged to submit accurate bids using incentive-based mechanisms designed with the help of mechanism design in DR. Several articles [67], [68], [69] suggest DR techniques that guarantee consumers will optimize their utility function by providing accurate reports of their preferences. Incentive compatible mechanisms (IC) are those that may be used in conjunction with incentives. Future pricing and end-user choices for various time periods throughout the day inform the scheduling and payment function proposed in [68]. Two "penalty-bidding" mechanisms based on a dominant-strategy equilibrium are presented in [69], whereas [68] offer a mechanism that takes the opposite, "reward-bidding," approach. Last but not least, [70] present a cooperative mechanism that is both efficient and incentive compatible, meaning that participants do not benefit from increasing their baseline consumption in order to demonstrate a false demand decrease. The aggregator chooses a selection of agents, submits bids on their behalf to the electrical flexibility market, and then splits the proceeds with them based on their pledge to cutting down on energy use, while punishing those who actually raised their usage.

Among a group of agents, products as in [71], resources as in [72], and tasks as in [73] may be divided up via negotiation. The existing research classifies allocation processes into two broad categories "Auctions" and "Negotiations" [74]:

- Auctions are systems wherein a group of people compete with each other in an automated process controlled by a third party. Here, the norms and the procedure are set in stone. Using concepts of mechanism design, the goal of auction theory is to arrive at an optimum auction model which ensures a set of desired qualities.
- The goal of any negotiation is to reach an agreement between two or more parties through an exchange of information that includes offers, counteroffers, and arguments [239]. Negotiations encompass a diverse and an unclear set of iterations which are used to distribute goods, resources, services, or tasks. More complicated and individualized agreements, as well as more decentralized and adaptable protocols, are all possible with the help of automated negotiating methods.

IV. APPLICATION AREAS OF AI IN DEMAND RESPONSE

Many electrical power system factors, including load and energy price forecasts, selecting the most appropriate customers for DR schemes, and developing automated systems for managing demand-side resources, must be considered for the successful implementation of DR programs. Forecasting, real-time management of networked infrastructure, taking best decision very near to optimal decision, adapting to a dynamic behavior, learning from load profile and many other areas where AI technologies have been used in DR [75]. Here, we categorize the different applications of AI in the field of DR that have been found in the published literature.

A. FORECASTING IN DR

Forecasting has been one of the primary applications of AI methods. It has been discovered that artificial intelligence (AI) techniques are being implemented for forecasting of power prices for different kind of loads in the DR environment. Schedules for delivering power in the near future may be influenced by forecasts, and longer-term plans for the system and service providers can also benefit from forecasts [76]. Improving power scheduling with short-term forecast helps aggregators provide better services and customers react more closely to appropriate DR signals. If service providers and operators have more accurate long-term estimates, they will be better equipped to make decisions about how much flexibility to provide, which customers to prioritize for DR, and how much to compensate or charge those customers.

1) LOAD FORECASTING

Load forecasting and estimate are crucial to the safe and effective functioning of any electricity grid. Proper demand forecasting is a crucial tool for addressing several DR concerns, such as ensuring adequate planning, compensating DR participants, and determining the capacity potential of DR resources [19]. Long-term load forecasting (>24 hours) and short-term load forecasting (24 hours) are commonly used to categorize demand forecasting. The publications included in this overview are those that focus specifically on the load forecasting issue in the DR context. The analysis in [19] provides a more comprehensive look of load forecasting in the smart grid setting for anyone interested in learning more.

There are a number of publications in the literature that attempt to predict demand, some of which account for potential changes in demand brought about by DR. Most of the studies [77], [78], [79], [80], [81], [82], [83], [84], [85], [86] focus on estimating demand for the next day or two, while others [87] look forward a week. Also, load forecasting has been done at many other aggregation levels, including for single-family homes [78], [88], [89], [90], commercial buildings [80], [83], [91] and individual appliances [92], [93] such as chillers, ice banks, and lights. The load forecasting for single consumer or a group of consumers for day ahead prediction depends on previous load profile and weather conditions as presented in [92] using ANN-based method for home load forecasting. Artificial neural networks may also be used for appliance-level load predictions. Deep neural networks with a principal component analysis (PCA) based feature selection strategy to estimate loads of home appliances is presented in [93], whereas [83] use ANNs to anticipate loads of HVAC systems.

Baseline load estimate describes the scenario when load forecasting is performed without considering DR. In the context of DR, the baseline load can be determined as the load that is feeding power in the absence of the DR programs. [94]. Rewarding DR participants requires accurate estimates of typical power usage, which may be obtained from the baseline consumption measurement of consumers [94]. Baseline load estimate research for homes [94], [95], commercial buildings [96], [97], and industrial plants [98] may be found in the aforementioned works.

In addition to the above, the practice of flexibility forecasting has been the subject of several research investigations. A flexible load is one that can be adjusted in response to changes in the time of day, the weather, and the smart-grid control signal [99]. Studies have estimated the DR heat-load flexibility of homogeneous [100], [101], [102] and heterogeneous [103] VPP heat-load clusters. Both the DA market and other energy markets are open to trading the estimated flexibility [100], [103]. Research in this area includes energy flexibility prediction, forecasting of smart homes air conditioning systems [98] and peak time DR capacity calculation [104].

2) PRICE FORECASTING

Electricity price forecasting has been done at both the aggregator and the end-user levels. In a multi-aggregator context, in which out of group of customers, only one consumer is implementing a DR scheme is described in [105] for predicting the regional wholesale energy price from the demand bids of the different aggregators to the SO. The ideal incentive rates for various customers are determined in part by a model employed by Lu and Hong [106] to anticipate the price of electricity on the wholesale market. The bulk of the publications [107], [108], [109] focus on the consumer level and attempt to predict the residential load a day before in order to manage the production under the influence of price incentives. In contrast [110] predict the hourly fluctuations in power costs for businesses.

3) GENERATION FORECASTING

The purpose of the generation forecasting is to anticipate the amount of power that will be generated or required to be generated from renewable sources. Better Renewable Energy Systems (RES) projections has grown with the inclusion of demand response by implementing proper DSM techniques to offer more flexibility to power system with the rising renewable energy resources. In [111], the authors discuss current research that assesses the efficacy of artificial intelligence (AI) approaches used to RES prediction models, considering a wide variety of forecasting horizons, and a wide variety of renewable energy generating sources. Results show that benchmark ML models can process big datasets and provide reliable forecasts; however, by integrating machine learning algorithm models can enhance the system reliability. Two reviews cover different aspects of solar power forecasting: [112] discusses PV forecasting using ML and metaheuristic techniques, while [113] zeroes in on time-series statistical, physical, and ensemble approaches. In [114], the authors examine the current status of SVM as it pertains to solar and wind forecasting. Although the SVM regressor is straightforward and accurate, it does not scale well to big data sets and performs poorly with high levels of noise.

In [115], a variety of ML techniques are investigated for use in the production of wind and solar electricity. In [116], the authors analyze several PV forecasting methods, from the most basic to the most complex, and draw the conclusion that certain methods work better than others in different climates. Models for PV forecasting one day in advance using deep learning neural networks are the subject of [117]. In [118], we take a look at how CNN may be used for multi-site PV forecasting. In [119], the most prominent ML techniques for predicting wind speed and power are reviewed. These techniques include data preparation, initialization of different parameters, their optimization, and at the final stage of error minimization. These hybrid methods often provide better results than using individual models alone. In [120], the authors examine the use of Artificial neural network for variable wind energy production, bringing together the primary techniques used in prediction techniques and noting their advantages and disadvantages. Wavelet transform is employed to convert the initial data into its small component to smooth out the peaks and valleys in the initial data [124]. Several research [121], [122], [123] have used this technique. The DSO and BRPs have a difficult time coping with distributed solar energy due to a lack of information on the prosumers' aggregated small-scale solar power. To get around this issue, [124] makes guesses about the total power output of unmonitored distributed solar installations on residential roofs.

4) FLEXIBILITY FORECASTING

Flexible loads, decentralized storage facilities, and (DERs) may all be combined into one large pool of potential flexibility, and the advent of aggregated flexibility prediction makes it possible to define the default area's share of this resource. Aggregated distribution grid flexibility may be used to lessen the demand for grid expansion and improve the efficiency of power system by improving power system operations [125]. The computation of aggregate flexibility is elaborated on in [126].

In order to (i) give flexibility facility to power system agents (ii) reduce end-user energy bills through Home Energy Management Systems, and (iii) participate in electricity markets by using optimal bidding strategies [127], [128] the aggregator is the service provider responsible for gathering and controlling its portfolio of flexibility sources [128] and develops new flexible business model methods. Demand-side flexibility aggregation becomes crucial for balancing the future power system due to the growing penetration of intermittent RES and the sizeable number of residential users with potential flexible sources [128], [129]. In [125], ML-based regression models are used to forecast residential customers' flexibility for real-time applications. [130] presents a framework for flexibility forecasting and how it can be managed across various energy sources and domains. [131] decides to construct a flexibility load forecasting model for DR capacity scheduling using the GBM ensemble technique.

The aggregator provides a financial incentive signal in [132] with the intention of encouraging a shift in demand-side consumption. [133] estimates the adaptability potential of wet appliances (dishwasher and washer machine) in France. Residential load flexibility projections are computed in [133] using the NILM method. [134] considers predetermined customer preferences, loads, and PV forecast uncertainty to define a workable flexibility space from controllable home resources. The proportion of end users who must be able to submeter in order to determine the aggregate demand composition is examined in [104]. According to the findings, only 5% of submetering coverage is necessary to accurately predict the aggregated load composition at the substation level. [135] proposes a scalable and non-intrusive methodology for determining the flexibility of thermal loads.

B. SCHEDULING AND CONTROL OF LOADS FOR DR

For service providers and their customers, the sheer variety and quantity of DR devices available presents a significant issue. It is not practical for service providers to manually schedule and control their DR units throughout their portfolio. Further, automating the scheduling and management of the many demand-side appliances is crucial for increasing consumer engagement in DR schemes, since otherwise customers would experience response fatigue [136] and stop participating in the DR program altogether. When it comes to DR, scheduling and management of the different units may be handled either by the service provider (aggregator) or by the individual user (consumer). The size and breadth of the units used distinguishes between the two tiers as the primary distinction between them. When it comes to scheduling and controlling devices at the aggregator level, the algorithms utilized must be more flexible and adaptable to a wider variety of circumstances than those used at the consumer level.

1) LOAD SCHEDULING AND CONTROL AT THE AGGREGATOR LEVEL

While DR unit control is intuitive, improving solution time efficiency requires careful consideration of how and when certain events will occur in a scheduling issue. The scheduling process may be seen as a multi-objective optimization problem with constraints. A huge amount of literature data is available on scheduling DR resources while considering no limitations [137], also including imposed network constraints [138] while keeping balanced system conditions [139] like [140] can be taken an example of planning the load a day before with proper monitoring of generation sources. Additionally, [141] perform proper management for the forecasted DR units for DA in order to increase utility provider benefit cost and users flexibility while minimizing fluctuation from variable resources (like wind and solar) on the grid. For utilization and monitoring of commercial and industrial loads flexibility [142] created a cooperative and decentralized agent-based platform that takes into consideration the dynamics of each building separately. Scheduling the charging of EV fleets is also the subject of study for the purpose of DR service provision [143].

2) LOAD SCHEDULING AND CONTROL AT THE CUSTOMER LEVEL

Energy management systems (EMS) [57], [144], [145], are composed of several systems that work together to automate the scheduling of the different consumers and their loads at residential and non-residential buildings. Automatic choices are made by EMS in response to DR signals, with consideration given to power costs, customers' lifestyle trade-offs, and the most efficient usage of appliances and equipment. The implementation of DR systems by households and small businesses and factories depends on automated EMSs. Load scheduling for DR under an EMS is investigated in [146] and [147], proposing a user-independent power scheduler for residential appliances that accounts for limitations across appliance classes.

Minimizing electricity cost [45], [57], [125], [148], [149], [150], [151], [152], energy consumption [57], [63], Peak to average ratio (PAR) [57], [150], and maximizing social welfare [153] and reducing environmental pollution [154] are common goals in the monitoring and control aspects of customers' loads. These goals must be achieved while taking into account the tastes of the consumers. There are two primary ways to determine what people want. An intelligent algorithm, which may be either predefined [144], [145] or learnt [155], [156], can be used to reflect human preferences for the operation of household appliances. The second strategy involves putting limits on what is considered a realistic timeline [149], [150], [151]. TCLs, such as heat pumps [144], [148], [157] and water heaters [144], [157], air conditioners [144], [158], [159], battery storage systems [144], [160] and electric vehicles [144], [160], [161], [162] are common examples of appliances that are controlled in a DR setting. Although most papers [150], [151], [155] focus on residential buildings as consumers, there is a lot of research literature focusing on scheduling like for scheduling of different loads at small commercial buildings level is presented in [162], while charging points for smart Electric Vehicles may got overloaded at peak hours, so they need to schedule their loads and customers while considering the customer level load scheduling in order to provide a better DR service [162], and also at industrial level optimization model which consisted of multivariable price function has been used to mitigate the load problems [163].

C. DESIGN OF INCENTIVE/PRICING SCHEME FOR DR

Both the aggregator's and retailer's bottom lines and the DR scheme's effectiveness are impacted by the pricing or incentive mechanism's design. A DR program's ability to recruit new members and keep current ones engaged depends in part on the quality of its reward system. When it comes to pricing mechanisms, the vast majority of papers utilize AI methods to determine the best interactive scheme a day in a meritocratic electricity market [66], [80], [107], [108], [138], [139], all while maximizing the profit of the service provider within the bounds of realistic market constraints and the discomfort of consumers for load reduction/shifting. Further, [164] use the numerical model relationship between real-time total cost and energy expenditure in a DR scenario for real-time pricing, and [110], [165] have constructed a model based on the cost elasticity matrix which is proposed for dynamic pricing. A novel tariff structure, dubbed prediction-of-use (POU), is proposed by [25], which determines the rate by comparing the end-use users expected and actual power consumption. Electricity prices, including upper and lower limits, are being investigated concurrently by [134] for a bi-level model of consumer pricing.

Several articles [24], [26], [27] discuss the topic of how to appropriately compensate a group of consumers who are collectively lowering or shifting demand during a load attenuation event via the use of incentive mechanisms. In addition, Lu and Hong [109] analyze the profitability of both users and service providers (aggregators) in a structured energy market to determine the appropriate incentive rates for various electrical users. A two-part reward function is developed by [135] to incentivize DR participation, with participants receiving rewards for their individual and collective efforts to achieve a reduction objective. One portion is the agent's compensation for its role in the reduction effort, and the other part represents any fees or fines it must pay. Money is offered (a reward) to customers in return for cutting down on consumption in a model developed by [115], which simultaneously learns the likelihood that consumers will take up the offer. To begin building a multi-round bidding model, [141] learn the interruption load compensation price. In [134] author also suggest a novel DR mechanism that uses Vickrey-Clarke-Groves pricing to provide a customizable suite of DR contract options. This novel system selects a selection of consumers to cut down on consumption while also factoring in the likelihood that the goal will be attained (reliability). By including variable preparation costs, different effort levels, and multi-unit consumption reduction, [132] generalize prior work [166]. This paper suggests a reward-bidding technique as an alternative to a penalty-bidding mechanism for achieving effective incentives. Other research focuses on the design of contracts for incentive-based DR. For example, [167] examine bilateral contracts (between a retailing agent and a business client) in a multi-issue negotiation context. In a similar way, [58] devise incentive agreements for ancillary services, in which service providers engage in the commodity supplementary service market and coordinate engagement with end users at the retail level. Other than the two-way dialogue between the service provider and the customer, their work also considers the interaction amongst customers.

D. LOAD/CUSTOMER SEGMENTATION

Segmenting/Grouping power users into categories is a crucial application for DR which is an assistance to utility providers in creating DR programs, pooling services, assessing the load capabilities of joining various DR programs, etc. [168]. The produced groups of consumers are created in the study literature to carry out various tasks in the DR context. A significant portion of the evaluated works classify customers to find potential participants for DR programs [77], [169], [170], [171], [172] and identify the best group of consumers who are already enrolled in DR programs to contact in order to reduce demand during DR programs [173], [174]. According to [64], load profiles can be used to extract socio-demographic data, and the characteristics of these consumers can be used to choose potential DR participants. The typical daily load profiles that are created for each group are then used in [175] to create customized power price plans for price-based DR programs. DR resources are grouped in [176] to determine compensation rates. The most effective resources are well-compensated in this way, which encourages them to take part in the DR programs which provide them maximum possible benefits. The creation of DR programs and demand control strategies [168], the gathering of DR resources [177], [178], the evaluation of a DR project's potential benefits, and the identification of hourly loads for carrying out DR programs [179] are other uses of classifying consumers. In a number of works, customers are categorized based on their quotation data [188], behavior [180] for EVs engaging in DR, predicted effects of the DR program [181], number of residence occupants, building size, building type, and terrain type. While [182] partitioned the flexibility of EVs for DR services by clustering EV charging sessions, in [183] author designed flexibility envelopes of TCLs for DR. For DR, [184] combined the flexibility of batteries and modest non - dispatchable loads using a unique clustering approach. The overall flexibility of an aggregator's portfolio of assets has been calculated using clustering approaches in the more general situation of energy markets, such as the work in [185].

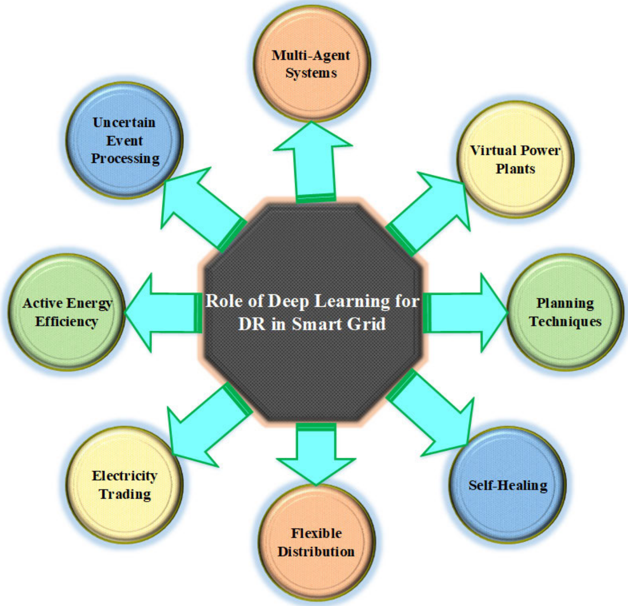

FIGURE 5. Role of deep learning techniques for DR programs in smart grid.

E. ENERGY THEFT DETECTION

Theft of energy, or tampering with one's electric power data, is done so that one may pay less for their electricity. This is one of the biggest crimes ever committed in the USA. Several methods exist to steal power in an SG. As shown in Fig. 5, some of the methods include wiping recorded events, altering stored demand, manipulating the meter, disconnecting the meter, and so on. In the past, public reports would prompt power companies to dispatch teams to inspect electrical infrastructure. Smart meters and other developments in the metering infrastructure have made it simpler to identify instances of energy theft. This resulted in the development of AMI (Advanced Metering Infrastructures) [186]. AMIs, however, bring a number of drawbacks, including the possibility of manipulated meter readings. Because of this, a new feature engineering framework has been developed, whose primary purpose is to prevent energy theft from smart power networks. For market segmentation purposes, there is a suggested framework in [187] that uses both genetic programming and finite mixture model clustering. The purpose of this was to produce a collection of features that effectively communicates the relevance of demand over time. In addition, the ability to compare results from different houses gave it a high degree of accuracy for spotting irregularities and fraud. Many distinct ML algorithms were used. The amazing result may be attributed to the computationally extremely practical nature of this approach. The Gradient Boosting Machines outperformed all previous ML classification models with respect to the classification method. This may be explored more thoroughly in future studies, and it has important practical implications for power utilities.

If energy is distributed but never invoiced or paid for, this is known as non-technical loss (NTL) in SGs. This has become an international crisis in the electricity supply sector. In [188] there is a suggestion of a concept based on a power distribution network, the intermediate monitor meter, to simultaneously detect bypassing of the meter and NTL of meter manipulation (IMM). For a thorough analysis of the power flow and efficient NTL detection, this model separates the network into finer and more autonomous networks. The energy balance between the IMMs and the collector is analyzed, and a suggested method for NTL detection is created to solve the resulting linear system of equations (LSE). The authors also described the IMMs' underlying hardware layout. This structure was time-effective and robust enough to endure a detection accuracy of 95%. It was also confirmed that it detects energy wasted due to customers' lack of morals and circumventing of regulations, both of which are notoriously hard to track down using more conventional methods of investigation.

A newly proposed detection method, electricity theft detection using deep bidirectional RNN (ETD-DBRNN), which is used to capture the internal characteristics and the external association by analyzing the energy consumption records, thereby overcoming the shortcomings of existing ML based detection methods is presented in [189]. Validation of this strategy was shown by experiments using real-world data.

It was observed that this technique better captures the information of the power use records and the intrinsic characteristics between normal and abnormal electricity usage patterns than the currently available methods. In reality, energy thieves' meter readings should have a stronger correlation to the value of power theft loss than the readings of honest users. Due to this, [190] systematically formulated the issue of power theft identification as a time-series correlation analysis problem. Two coefficients were constructed to

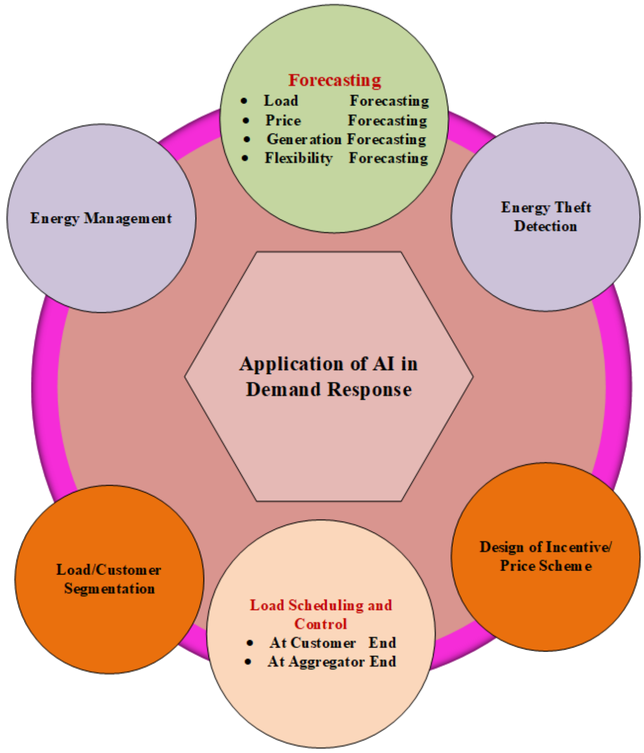

FIGURE 6. Application/areas of AI in DR.

assess the credibility of each consumer's claimed energy use pattern. The experimental results revealed that this strategy significantly enhanced the pinpointing accuracy in comparison to other recently existing methods. The Internet of Things (IoT) and artificial intelligence (AI) are two crucial enabling technologies for smart cities. For the purpose of identifying energy theft, [191] suggested a method that relies on SG energy privacy protection. By analyzing a long-term trend, they were able to utilize CNNs to spot any strange behavior in the metering data. In addition, the paillier algorithm was used to ensure the confidentiality of transmitted energy data. This solution demonstrated the concomitant success of data privacy and authentication. The experimental results showed that the modified CNN model was able to identify aberrant behaviors with an accuracy of up to 92.67 % [191]. Using the new method of multiple pricing (MP), [192] demonstrated a method of stealthy power theft (HET). As a means of building the HET assault, they suggested an optimization problem with the goal of maximizing attack revenues while evading existing detection mechanisms. Two algorithms intended to hack smart meters were also developed. In order to demonstrate the potential of HET attacks, the authors discovered and exploited a wide variety of new vulnerabilities in smart meters. To defend SGs against HET attacks, the authors recommend a number of defensive and detection techniques, including restricting the attack cycle, selective protection on smart meters, and an updated billing methodology. The recommended countermeasures successfully reduced the attack's effect with little effort or expense.

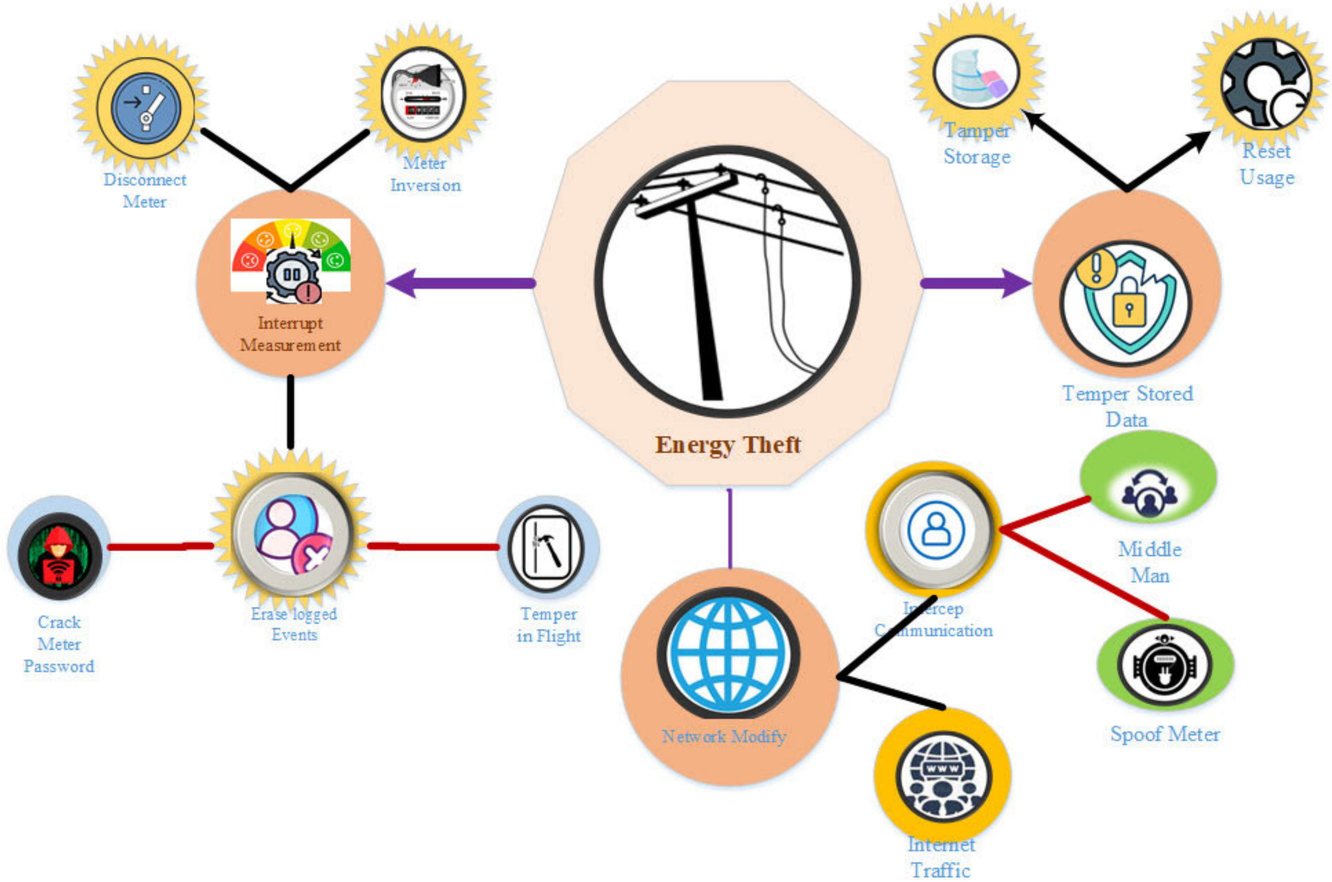

FIGURE 7. Possible energy theft techniques.

The reintroduction of old problems like energy theft necessitated the development of cutting-edge detection systems and architecture predicated on data analysis, machine learning, and predictive modelling made possible by the advent of digital power meters. To identify electricity meter manipulation in its early stages, [193] exhibited a multidimensional innovative detection technique and architecture by comparing a collection of energy demand time series. Newer monitoring systems can often only analyze one time series; thus, this approach was a welcome addition and improvement. Their goal was to find ways to spot electrical theft, and they offered three different approaches to preprocessing data to do so. This approach demonstrated the metric's robustness in the face of tampered data. With detection rates of over 90%, the authors demonstrated the primary advantage of combining numerous data sources at once, rather than relying on each one of them separately. This approach also demonstrated the usefulness of comparing data from several houses without first categorizing them into comparable groups.

F. ENERGY MANAGEMENT SYSTEM

In order to improve building energy efficiency and DR programs, the fast deployment of smart meters in recent years has created a large quantity of data (e.g., price-based, incentive-based and environmental-based. In this part, we will discuss the IA methods used in EMS on the building level. By using AI techniques, we can plan for and control numerous energy assets automatically via the EMS, therefore addressing a number of problems plaguing the field of energy management. There has been a noticeable growth in the use of AI techniques in DR programs since 2013. Price-based programs and domestic consumer types have seen the most use of these AI technologies, followed by small-scale industrial and commercial structures [8].

Numerous articles discuss the use of AI in energy DR initiatives. For a broader view, see [202], which explores the current status of DR applications and analyses the AI methodologies used across a variety of DR scheme types and customer types. In addition, a comprehensive overview of corporations, innovators, and European-funded commercial initiatives using AI for DR is offered. In particular, [194] examines the current AI-based approaches to cloud EMS and how blockchain technology may be incorporated into them. However, there is a significant number of unanswered questions about blockchain that need be investigated in the next years, including its expensive development and storage costs, the absence of uniformity in the field, and the scarcity of specialized knowledge.

The research examples below make use of Supervised Learning and Unsupervised Learning approaches. In [195], an MLP-based deep learning model is employed to improve load consumption and storage management in light of variable pricing. By optimizing the scheduling of domestic appliances and RES production, [196] a deep ANN and Genetic Algorithm help to lower energy consumption during peak hours. Loads for EMS may be identified by means of smart plugs using supervised learning algorithms like DT and Naive Bayes. Using regression trees and RF, the authors of [197] build a model of a heating system with the goal of controlling its operation. In [106], authors use an ANN-based stable price prediction model to address the problem of pricing uncertainty in EMS. After a demand response (DR) event mandated by the power company to minimize peak usage, [198] creates a household scheduling controller utilizing the hybrid lightning search algorithm ANN to forecast the best ON/OFF state for home electrical equipment. While [199] provides a prediction approach based on LSTM of the end-user reaction behavior to incentive-based DR program, [62] employs ANN to anticipate and plan building appliances energy consumption and genetic algorithms for job scheduling.

The articles under consideration in this area have one major flaw: they depend on the end user being completely familiar with the surrounding environment. Although price-based DR programs get the lion's share of attention in the literature, it is clear that a variety of incentive-based DR methods would benefit the distribution network greatly. To yet, only a few of papers have shown even somewhat accurate models of the appliances that can be controlled by EMS. The RL technique does not need any knowledge of the system model, unlike standard model-based approaches. Table 10 summarizes this whole process by dividing each source into three distinct categories: data-driven method, DR program, and client type.

V. DR PROGRAMS EMPLOYED IN DIFFERENT COUNTRIES

The present emphasis in Europe is on DR monitoring and SG-enabled monitoring systems, according to a study of scientific and applied sources. For the past 20 years, SG initiatives have been carried out; however, because of inconsistencies in implementation of DR in EU, current efforts may be difficult in case of transferring smart grid information data and across the border with nearby countries. Another issue is the lack of an EU-wide program or unified DR policy. Countries that create SG-based power supply networks can let their electrical users take part in DSM initiatives. Source [200] reports that while domestic appliances and commercial services shares for 30.9% and 30.4%, respectively, of the total electricity demand in Europe, industrial users account for 36.1% of that demand. Previous studies have shown that DSM is most advantageous when applied to larger consumption area as compared to lower one.

Only a small number of European nations have so far allowed aggregators and DR access to their marketplaces [201]. In Europe and the US, DR is seen as a crucial instrument for combining renewable energy sources with a consistent electrical supply [202], [203]. Similar issues, such a restrictive power market or a monopoly, are, however, virtually nonexistent in many developing nations [204]. One aspect influencing the creation and use of such a DR program is the nation in which it is implemented. The main reason for this is that every nation has unique energy resources, regulatory and policy frameworks, and power markets. As a result, the supply side needs for DR projects change. For instance, solar energy is more relevant in some nations than wind energy is in others, necessitating a different change in demand [205]. Numerous countries across the globe, such as Germany, Denmark, Finland, and others, have considerable levels of varying renewable energy in their power network and are battling various problems due to fluctuation while integrating at the grid station due to fluctuations and flickers which causes reduction in the stability of the grid [206]. Programs across the European countries are heavily depends on initiatives taken by each country its unique legislative environment because the unified European electricity market does not yet exist [207]. Cross-border connectivity would entail the transmission of power via high-voltage lines between nations, but it would need the right infrastructure and transactional procedures [208]. Any nation that has one or more network points is in charge of these connecting points. The balance-responsible party (BRP) must create scheme for power generation and load balanced system which is known as the balancing duty [200]. Day-ahead, capacity, next day, intraday, and balancing energy markets are currently available in each individual EU member state. Each of these markets has its own participation requirements [207].

The British Empire (UK): The UK's Office of Gas and Electricity Markets (OFGEM) was the first organization which is allowed to initiate a capacity market in 2013 when Energy Act was passed to encourage the development of DR [209]. The US began testing DR in the early 2000s. UK was one of the first market to implement DR in their power sectors and energy markets [210]. Short term operation service (STOR) like other initiatives were taken in order to make a balance between supply and demand [211], the UK market for DR in the electricity sector began to take off. In addition to Belgium and Switzerland, the DR analysis reveals that the UK was the leader among the European nations that would be the most useful for comparison [23]. The commercial and public sectors make up around one-third of the portfolios of aggregators, and the UK is one of the best nations to implement these schemes and participant got fully interested in participating more and more. [210].

Germany: Germany is frequently seen as a pioneer in the management of renewable energy [211] which separated its activities to liberalize its power sector. Additionally, it has the most trustworthy system available, ENTSO-E [200]. Energy-saving initiatives are far more prevalent in Germany than

TABLE 1. Different forecasting models and evaluation metrices for DR programs using AI techniques.

Type of Forecasting	Location	Highlights	Data-driven technique	Forecast horizon
			Aggregated demand forecasting	
Load Forecasting Models	US	Residential buildings' expected daily electricity use.	DNN, RF	Short-term
		The auto-encoders' features more precisely forecast day-ahead load forecasting	SVM	Short-term
		The suggested approach includes an optimal training algorithm consisting of PSO and ALO	MLP	Mid-term
		Prediction of the monthly total load during a time period of four years	Multiplicative error model (MEM)	Long-term
	UK	Based on two-terminal sparse coding and DNN, day-ahead aggregated load forecasting	CNN-LSTM	Short-term
		For one-week prediction, ELM outperforms SVM	SVM, ELM	Mid-term
	Australia	Advanced data preparation technique. Outstanding data learning and forecasting capabilities are possessed by DBN.	DNN	Short-term
		Predicted half-hour electricity demand for the coming week	Autocorrelation LSSVM	Mid-term
	France	To capture the many annual cycles in power load data, using wavelet decomposition with the proposition of new boundary treatments.	MLP	Short-term
	West Africa	Estimated hourly and annual electricity usage for 2030 in 14 different West African nations	MLR	Long-term
			Smart meter load forecasting	
	US	Aggregated household load predictions	DNN	Short-term
		For load and price forecasting, energy big data is employed as a data set.	LSTM, MLP	Short-term
	China	An industrial steel plant's demand predictions	LSTM	Real-time
		Probability density and power load forecasting	DNN	Short-term
	Australia	Forecasting household loads with probability in the presence of significant volatility	LSTM	Real-time
		Forecasting of individual and combined residential loads	LSTM	Short-term
	Honk Kong	Day-ahead cooling demand for office buildings, categorized by seasons	K-means-MLP	Short-term
	Cyprus	SVM and ANN achieve more reliable and precise outcomes	MLP, SVM, MLR	Short/Long -term
			Solar forecasting	
Generation Forecasting Models	China	More weather features are added to the prediction mode thanks to CNN's enhanced feature extraction.	CNN	Short-term
		Model built using SCADA and weather data	SVM	Short-term
		Focuses on the most important input features for forecasting using the attention mechanism.	LSTM	Short-term
	Australia	Forecasting horizons of five minutes. Model based on short-term multivariate historical data sets	LSTM	Real-time
		based on trained feed forward neural network and PSO	DNN	Short-term
	US	Forecasting for Multiple Solar Sites	CNN	Short-term
	South Korea	PV forecasting using simply weather and calendar information. For all seasons, the LSTM algorithm provides the best results.	MLP, DNN and LSTM	Short-term
	Cape Verde	Using weather forecasting information, an hourly day-ahead prediction of solar irradiance	LSTM	Real-time
			Wind speed/power forecasting	
	China	Wind power prediction for the very near future. Performance of a single CNN is enhanced with LightGBM	CNN-GBM	Real-time
		Wavelet transform-based probabilistic wind power forecasting	CNN	Real-time/ short-term
		It employs the wavelet transformation. Nine models are used to compare its performance.	LSTM-ElmanNN	Short-term
		By grouping wind power impact factors, the K-Means creates a new LSTM sub-prediction model.	K-Means-LSTM	Short-term
	Mongolia	Performs extreme optimization forecasting ten minutes and one hour in advance.	LSTM, SVM	Real-time
	Tunisia	The inputs are the spatial average of wind speed, wind direction, and previous power values.	RF	Real-time
	Europe	Uses transfer learning and a deep sparse auto-encoder for base-regressor training.	Ensemble DNN	Short/ Midterm

TABLE 2. *(Continued.)* **Different forecasting models and evaluation metrices for DR programs using AI techniques.**

Price Forecasting Models	USA	Compared to conventional ML, hybrid DNN performs better. models	CNN-LSTM	Real-time
		Precise and affordable in computing terms	GBM	Real-time
		DNN produces less errors. Greater precision was attained using many data sources	SVM, MLP, DNN	Real-time
		The effectiveness of neurofuzzy models against MLP is demonstrated in this study.	Neuro-fuzzy ANN	Short-term
		Results from Deep LSTM are superior to those from ELM. both NARX	LSTM	Short/ midterm
	Australia	Enhances the forecast's real-time accuracy during unexpected dynamic pricing changes.	ELM	Real-time
		Good results for prices with high volatility	DNN	Short-term
		When modelling time series with complex nonlinear properties and outliers, the model can be a reliable forecasting technique.	Hybrid outlier-ELM	Short-term
	Canada	Performance for the MKELM model is superior than that of the ELM and KELM.	ELM	Short-term
		Studies with a significant amount of input data are advised to use the proposed technique. The predicting outcomes are improved using the feature extraction tool and rough neurons.	Dimension reduction, DNN, SVM, LSTM	Short-term
		Dynamic Trees outperform RF and provide a suitable real-time and short-term solution.	Dynamic Trees	Real-time short-term
	Spain	When employing a limited number of input variables, inconsistent behavior was seen as the layer count increased. With more historical data, the model performs better.	DNN	Short-term
		The model's most important predictor is the hour feature.	GBM	Short-term
		This study demonstrates how using Tensor flow software improves convergence speed.	MLP	Short-term
		The factors that produce the greatest accuracy are the spot and futures prices for Brent crude oil, as well as the Spanish wind generation.	Co-integration and vector error correction	Long-term
	Germany	Due to their strong association with electricity prices, the forecasting model takes into account the price of oil and natural gas.	SVM	Short-term
		DNN performs better. Weighted KNN, a model based on data autocorrelations, provides accurate forecasts even 29 days in advance.	Weighted KNN, DNN	Mid-term
	Belgium	Compares the four proposed DNNs for electricity price predictions with 23 benchmark models. DNN, LSTM, and GRU perform better than research model.	DNN, LSTM, GRU, CNN	Short-term
		Performance is improved over SVM and univariate LSTM when hyperparameters are modified using the Jaya optimization multivariate LSTM algorithm.	Jaya-LSTM	Mid-term

DR [202]. The German demand reduction control is playing a key role in reducing imbalance of supply because it is based on broad, high-demand targets for the medium and long term, out of which few are longer-term and more ambitious than those outlined in the EU energy efficiency regulation [211]. The penetration of RES into the energy system and the dependability of the grid have a greater influence on the German DR's value [202]. The wholesale market in Germany has become too volatile because to the significant penetration of RES [212]. The technological capacity of German DR is 6.4 GW/h, from which 3.5 GW/h is attained within the present market and regulatory structure. DR might be as high as 10 GW [213] if a better market and regulatory environment are created. The nation requires a reliable system for establishing prices [211].

Finland: Finland is regarded as an innovator in the use of smart meters and a leader among European nations with a DR system [214], [215], [216]. The network's functionality is managed by Helsinki, Finland-based transmission company Fingrid Ltd., which also responds to customer demand using the market's established processes [217], [218]. Active retailers typically insistently offer price tariffs to end-users when the nation moves to commercial activities, prompting a change in consumption based on the market environment [219].

Switzerland: Typically, local governments design and administer DSM policies. Swiss utilities have been using ToU and ripple control, two DSM technologies, longer than other European nations. To maintain the stability of the electricity grid, fluctuation control is a common method of load control. The conventional power signal is switched to a higher frequency signal (50 Hz). Loads such as heaters, electric boilers, and public street lighting can all be turned on and off.

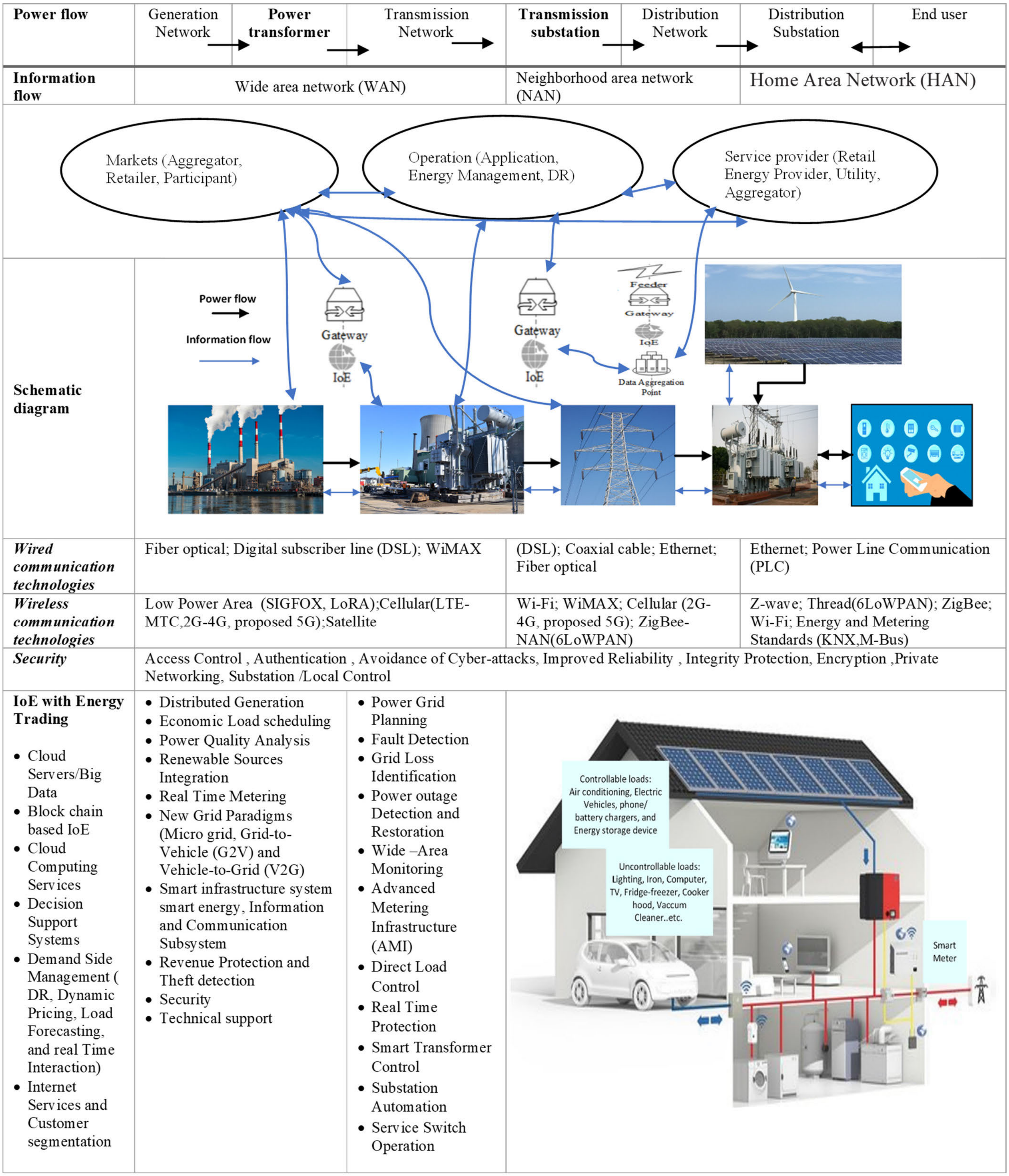

FIGURE 8. IoE sources with big data for energy markets at different level (generation, transmission, and distribution) at different consumer level (residential, commercial and industrial) for different function blocks (cloud, server, platform and HMI application) using different hierarchical network (HAN, WAN, NAN).

Belgium. DR projects are receiving more attention, particularly in the residential sector, as a result of the scheduled retirement of some nuclear power reactors and the constant development in RES capacity [40]. In order to encourage

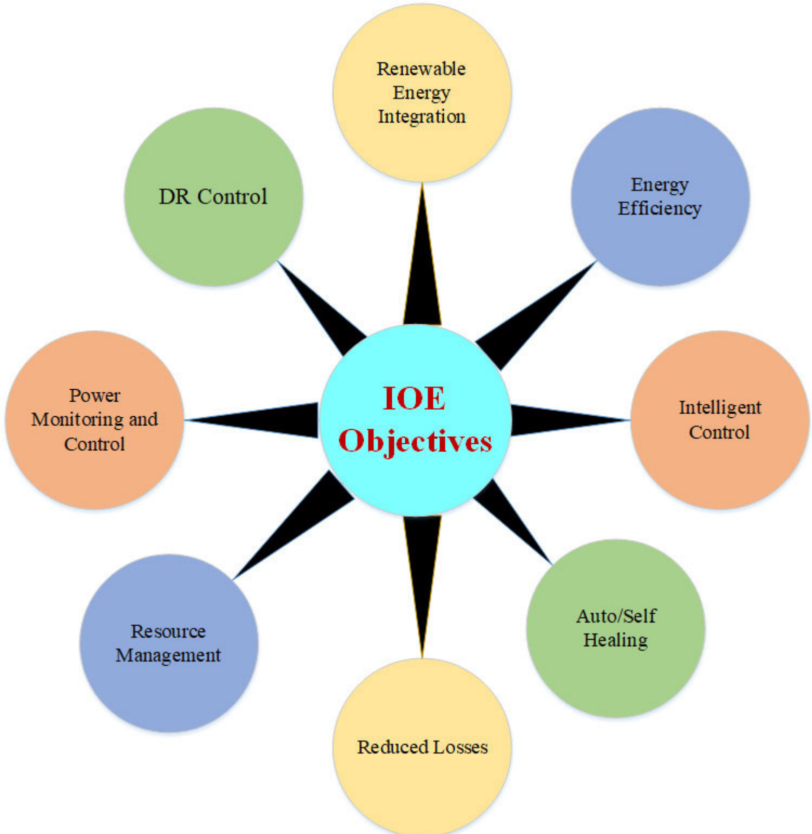

FIGURE 9. Different IOE objectives.

flexibility, the national transmission operator is searching for measures to reduce energy costs. Such flexibility is especially crucial during the winter, when demand for electricity peaks at around 12,000–14,000 MW, or around 2000 MW more than in the summer [220].

Baltic States. The balancing management of the Baltic power system is become more difficult for two reasons. First, similar to trends in Central and South-Eastern Europe, the power of easily regulated traditional major power plants is declining in the Baltics, while the output of less regulated, less foreseeable, and distributed sources, such as wind power, is increasing [221]. Second, by 2025, the Baltic states intend to cut their ties to Russia's single power grid, forcing the creation of additional flexibility sources to maintain electrical balance under both normal and unusual circumstances [222]. This will be made possible by a project that was endorsed by the Commission of the Connecting Europe Facility of the European Union Infrastructure Network, which aims to make the Baltic power systems independent with regard to frequency with Poland and other countries in continental Europe. Due to the underdevelopment of the energy-intensive industry in the Baltics, the DR potential is restricted to smaller consumer markets [223]. Consumers in Latvia and Estonia can now access implicit DR thanks to energy supply agreements where the retail price is linked to the spot price. A DR aggregation pilot program has been running in Estonia since the end of 2017 [224]. The main barrier for aggregators in Latvia at the moment is the lack of a legal framework defining the duties and responsibilities of aggregators as well as the compensation mechanisms amongst various energy system participants [221]. The Estonian start-up Fusebox and the Lithuanian transmission firm ''Ignitis'' began working together in 2020 with the goal of creating Lithuania's first independent power demand aggregator. In terms of energy security and efficiency, the power demand service is a recent development in the Lithuanian electricity market.

VI. BLOCKCHAIN BASED DEMAND RESPONSE IN SMART GRID

The production of power and economic losses of generated power must be reduced for which one strategy is to use smart energy solutions (SES) more frequently. However, the dissemination of SES should be promoted as a tool to achieve shared objectives rather than for its own sake [225]. Artificial intelligence (AI) and machine learning (ML) are appeared as one of the best recently emerged critical technologies for supporting DR. Due to the complex nature of DR operations, exploitation of bid data and the demand for near actual decisions the internet of energy (IoE), which uses the networks to integrate and communicate different transducers

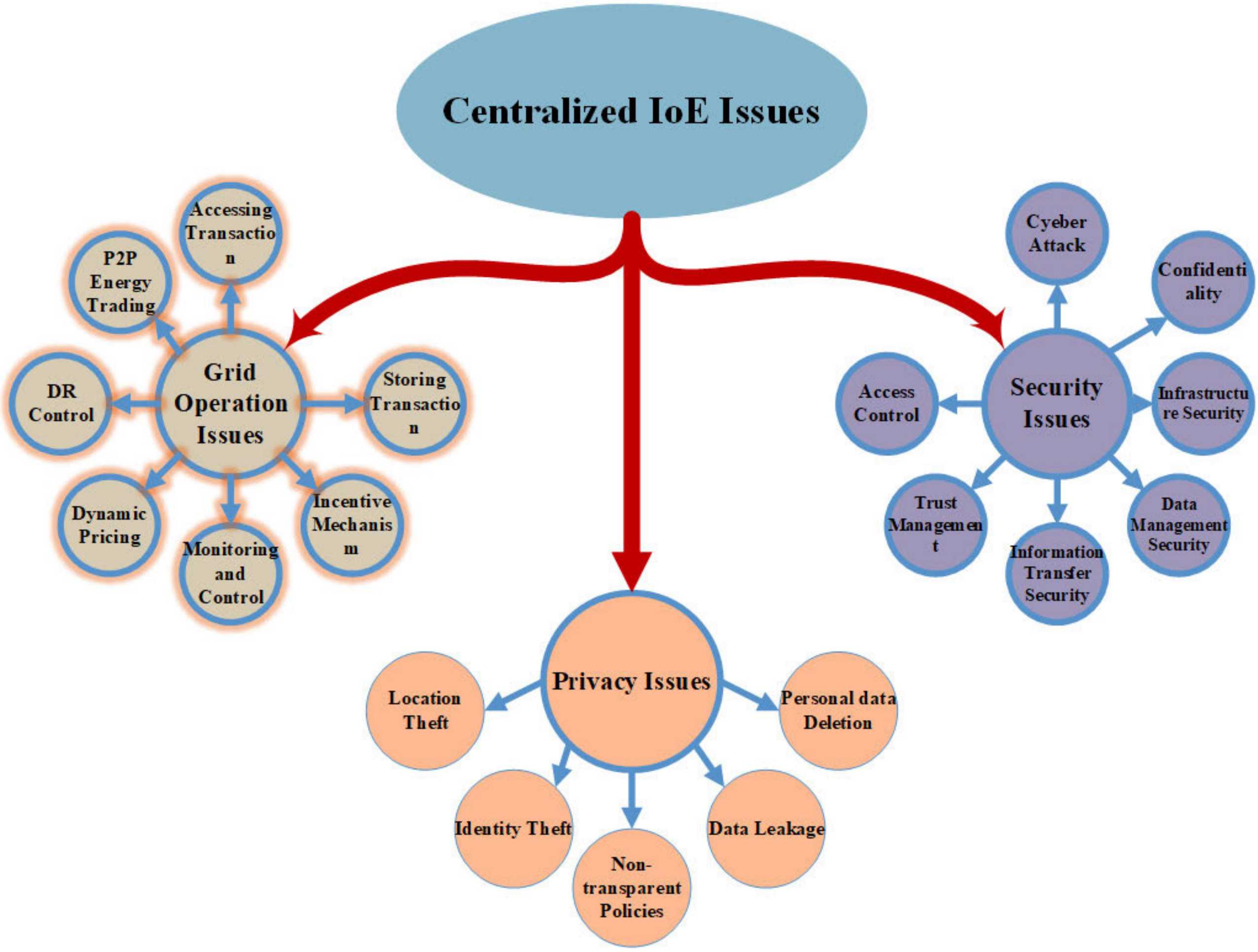

FIGURE 10. Centralized classification of different issues associated with IoE.

and sensors deployed for different measurements, integration of RES into smart grids, and several other techniques plays its crucial role and transformed power production and supply in to new era of technological development by implementing proper schemes. DSM programs are made up of energy saving and efficiency improvement consideration, DR programs, and domestic or commercial load monitoring programs. By changing the consumer electricity usage schedule, smart buildings can improve the adaptability of the power load and provide excellent opportunities for power DR's. However, there hasn't been much research done in this area, so it's unclear how big the potential effects of smart houses engaging in power demand response would be. Smart houses in particular can take part in power DR in two different ways: (a) By spreading out the load across a specific time period, smart homes can flatten the load curve by "peak shaving and valley filling." And (b) To reduce residential power costs, smart houses can move a load to a time period that is more affordable. Internet of Everything (IoE) is a term that emerged from the internet of things (IoT) to describe industrial applications that make use of big data processing, ubiquitous computing, and M2M communication [226]. The IoT extends the reach of the internet to include the devices deployed on the energy system by using standardized communication protocols [227]. IoE is characterized by a variety of energy sources, supply and demand coordination, centralization and decentralization, and extensive public involvement [228]. IoE promises a number of significant advantages, like power monitoring, energy demand management, expanding renewable energy integration, less wasted energy, fewer power failures, self-regulation, and resource management. In order to accomplish efficient, clean, and secure energy consumption, the Internet of Energy (IoE) is a grid that connects numerous distributed power harvesting technologies, electrical energy storage devices, and various types of loads [24]. To accomplish efficient, clean, and secure energy consumption, a variety of loads are used [228].

Smart Grids with IoE. In order to I lower electricity prices, (ii) control peak loads, and (iii) lower electricity costs for RES generation variations, which may disrupt energy systems [229], smart grids allow a two-way link between customers and operators. Contrarily, an SG facilitates a solution for energy production, supply, and storage, with the most up-to-date information on energy pricing attached [230]. When conventional methods of grid fortification are either impractical or too costly to implement, SGs in distribution networks need creative approaches to circumventing network restrictions [231]. Smart metering's widespread use and the potential to combine several decentralized small-scale RES [34] pose a significant threat to the limitations of traditional centralized power networks. These facts point to the need of a shift toward a decentralized and distributed energy system [230]. However, the high penetration rate and fast pace of variable RES and battery energy storage systems (BESS) make energy management in decentralized energy systems challenging [232].

However, we will discuss the major challenges that DR systems provide in the area of Smart Grids. The first source of power market interoperability is the plethora of utility providers, retailers, and hardware/software developers. Second, the number of agents and the complexity of their behaviors in power systems are both increasing due to widespread use of smart meters, IoT devices, and DERs. Finally, a decentralized architecture that at least offers the potential for a settlement agreement in energy transactions is required to entice buyers and diverse actors in the energy sector to engage in large-scale DR schemes and assist market expansion [233]. To capitalize on the expanding market for energy and the expanding set of stakeholders, businesses are turning to business-to-business (B2B) e-commerce platforms. Although standardized market processes serve as the backbone of such platforms, they may be modified to better serve their intended purpose. The provision of energy and supplementary services are only two examples of the kinds of significant tasks that may be balanced via market procedures. Providers may also provide ancillary services, which are customized solutions for problems like emergency power supply or energy conservation. An operator of the market commences the delivery of balancing services in accordance with internal/external norms and generator schedules [234].

The Internet of Things with renewable power sources like the sun. Solar photovoltaic (PV) farms have had access to AI methods for improving modelling, operational management, and output forecasting for over two decades [235]. Every DR system consists of two main parts: the controller and the electrical appliance. To rephrase, the DR program helps to maintain a healthy equilibrium between power manufacturing and utilization, and the two control loops (additional control and DR control) collaborate to maintain order in the system [236]. By facilitating real-time data sharing from PV sensors and allowing for remote controllability over the operation of solar units, IoT may aid in the identification of breakdowns and defects, as well as the performance of predictive and preventive maintenance [237]. The Internet of Things (IoT)-based smart PV monitoring systems are given in [238], [239], [240], and [241]. Using smart monitoring systems, PV modules may be tracked and controlled just like any other node in the Internet of Things [235].

Distribution system operators (DSOs) are anticipated to focus on the effect of PV intermittency on optimal power flow (OPF) and voltage regulation as solar power becomes more widely used. Using DR capabilities to their full potential is one effective technique for overcoming such PV integration challenges [242]. Technology developments have also allowed for a wider range of inverter control tactics to be included into systems. In addition, these inverters carry out a number of functions, including as regulating voltage, generating active and reactive power, and extracting energy from a photovoltaic (PV) module or array [243]. In terms of network reliability, frequency is considered crucial [234]. If the frequency of an object deviates from the usual, it means that either more power is needed or there is too much already [234]. Since the system frequency decreases when demand exceeds supply and increases when supply exceeds demand, DR is a useful tool for keeping the network's frequency stable [235]. Most DR equipment has fast on/off controls to provide a steady power supply from the consumer end [81].

In a dynamic distribution system, single-phase PV inverters may introduce power inconsistencies from dispersed generators. Single-phase devices such inverters, voltage regulators (VRs), and capacitor banks (CBs) may break the three-phase symmetry of voltages and currents when voltage control and DR are employed together, leading to an increase in imbalance levels. Distributed photovoltaic systems may be connected into the power grid using either a smart PV inverter or a regular PV inverter. Conventional PV inverters are unable of performing the complex control tasks required by PV systems (such as real power restriction, fixed power factor regulation, volt-var control, volt-watt control, and frequency-watt control), while smart PV inverters are capable of doing so. Therefore, smart PV inverters may reduce the number of voltage and frequency control devices required in an electric power grid, which in turn reduces the cost of both of these factors [244].

Technique of conveying messages. Recent advances in communication technology [89] have made it possible for modern SGs to transfer data and information swiftly and reliably in both directions. To increase power dependability and quality and stop electrical blackouts, DR's marketing and emergency signals may be sent utilizing a two-way communication system (wireless, wire, GSM, and the internet). Utility billing disputes may be resolved faster with the use of this technology, and customers who verify DRs can get incentive offers. Matching real-time supply and demand data, integrating, and dispersing demand, and generating energy transactions and DR are all possible thanks to the IoE. To save on transmission costs, energy data is stored locally or on a network at a designated node [236]. Through these protocols, the many nodes may exchange information with one another and the central control or decision nodes. Technologies such as LoRa or Sigfox (which provides the foundation for cloud-based services in future grids), ZigBee, Z-Wave, Bluetooth, Wi-Fi, and cellular technology such as LTE-4G and 5G networks are only a few examples [237]. Problems with data transfer rates, communication delays, security, and device connection may all be mitigated with the use of 5G technology [239]. 5G's reduced latency and high reliability make it a practical replacement for hardwired connections. When it comes to SG communication, it's rather uncommon to have stringent performance requirements, such as extremely low latency (usually less than 1ms) [240]. As 5G technologies continue to evolve, a demonstrably better DR infrastructure will emerge [239], raising the standard in transmission, reliability, safety, and connection. The latest standard for communicating DR signals via IP networks (like the internet) is called Open automated demand response (OpenADR v2.0). Smart meters, internet-connected devices, and distributed energy resources (DERs) have led to a growth in the number of agents and the complexity of activities associated to power systems [233]. For instance, the Enel Info +, Smart Demo Grid, and FLEXICIENCY projects have all built new smart meters with a dedicated communication channel at home area networks [239]. The need for outsourcing platforms is rising at the present time. When it comes to customer service, several platforms use employees to reduce customers' wait times [240]. Each DR installation must have online bidirectional connection with a national control center [239], and DR aggregators may employ new technologies to make it possible.

Issues with cyber security in smart grids. The use of smart grid technology to handle DERs and EVs necessitates enhanced sensing, communication, and control mechanisms [241]. Infrastructure failures may occur as a consequence of cyber assaults, cascade failures, blackouts, and other forms of attack on the electric grid [242]. In a residential home management system, for instance, the usage of heater or air conditioner data throughout the summer and winter seasons might provide insight about inhabitants' availability. The burglars might use this knowledge to plan an attack on the home. Because the regulators may access the central server at any time, which has all the information and data required from the utility suppliers, this is an extremely important problem to solve [243]. Smart grids have challenges from the huge variety of devices connected through wide area networks. Securing isolated devices within the context of a larger network is the biggest challenge [244]. More thought has been given to cyber security in the context of modern DR initiatives and the corresponding communication networks, such as OpenADR in the United States and China's reform of the management system for air conditioning in public buildings [239].

Protecting the smart grid using blockchain technology. The goal of creating a decentralized energy system using micro-grids, RES, and EVs necessitates a trading model that is robust, extensible, and effective. In addition, we need to upgrade our communication, transmission, and distribution networks so that we may take control of our networks' individual operations and services. With more and more vulnerabilities caused by the centralization of IoE, the adoption of innovative solutions is increasing rapidly. The use of smart contracts and encryption in blockchain technology serves as an example of how decentralization and autonomy may be achieved. [245] As renewable energy prices decrease and new technologies become more affordable, consumers are demanding a more efficient, greener, and long-term energy system. Through its decentralized trading mechanism, blockchain technology will promote sustainable electricity use and help bring about a circular economy [246]. The blockchain technology was first developed for the digital currency Bitcoin, and it guarantees secure transactions by connecting buyers and sellers directly. When Bitcoin was successful, the next generation of blockchain technology, the smart contract platform, was developed [233]. A new technology built on the same Bitcoin-inspired premise, blockchain for smart contracts allows the requisite distributed-operations-enabling techniques via its decentralized network architecture [13]. Power providers may utilize blockchain for smart contracts on DERs, such as to accept, fund, and sell electricity generated by renewable energy sources (RES) [233]. Due to its importance in facilitating the implementation and usage of RES and the smart grid, blockchain technology is poised to play a pivotal role in the expansion of the IoE market. Secure and efficient energy transactions are made possible by the widespread use of blockchain technology and the Internet of Things (IoT). Simultaneously, it enables the integration of electricity from distributed generation, utility grids, and other sources [79]. More work has to be done to establish potentially effective system protocols for blockchain-based power systems, and all promotional opportunities should be taken advantage of [240].

The analysis of current research that uses distinct indices to decrease the effect of DR technology on consumers reveals a number of particularly noteworthy studies. By generating consumer convenience and demand rebound indices and developing objective functions based on these indices, the authors of [247] provide a novel approach to lowering customer dissatisfaction, system capacity, and demand rebound. In [248], the authors propose a new linear discomfort index (DI) formulation that takes into account user preferences during normal appliance usage as part of a self-scheduling model for HEMS. Building a sustainable energy infrastructure requires a plethora of different strategies. As an alternative, the transition should be carried out carefully, with consideration given to all relevant technologies and approaches.

VII. CHALLENGES AND OPPORTUNITIES OF USING AI IN DEMAND RESPONSE

Artificial neural networks are one of the most widely used families of techniques and have mostly been used in forecasting applications. The researchers have implemented ANNs utilizing a single hidden layer as well as "deeper" multi-layer designs for both load and price forecasting. In contrast hand, the collection of chosen variables that will be used as inputs, the learning algorithm, and the optimization of their hyperparameters can all have a significant impact on how well they function, and there is no one approach that can ensure the best selection of these. Additionally, ANNs can be resource intensive and typically need a lot of data in order to perform better than other less flexible methods. Due to the current low adoption of DR programs, this may be a challenge for DR applications. Compared to ANNs, supervised machine learning approaches are less flexible, greater bias procedures, and primarily rely on feature engineering and selection to achieve effective results. On the other hand, supervised techniques like gradient boosting and regression trees [249], [250] can manage missing data effectively than ANNs. The benefit of AI forecasting algorithms to produce forecasts that span several horizons in time and space, as well as the ability to include uncertainty in the forecasts, results in predictions that are more useful. The performance of AI techniques for predicting, on the other hand, can vary depending on the hyper-parameter tuning and feature engineering they employ.

There are not so much labelled data points available in the current DR environment to categorize customers [251]. As a result, the only workable method to tackle the issue of segmenting electrical customers is to use unsupervised/clustering models. Although clustering algorithms are useful in this application, there are several difficulties with them. These algorithms, among others, suffer from the "curse of dimensionality," require data pre-processing to function, and it is extremely difficult to evaluate the results [34].

Reinforcement Learning (RL) techniques typically do not call for the use of an environment model, in contrast to more conventional DR control mechanisms like Model Predictive Control (MPC) [35]. This gives designers of DR control systems that consider consumer preferences an advantage. Deep RL has also been demonstrated to perform better in high-dimensional problems [35]. The design of reward signals, however, is a major problem for RL generally, with consequences for its proper application in DR [35]. There have been many instances where RL agents have discovered novel ways to manipulate their environments so that rewards are delivered but with unfavorable rules [35]. To the best of our knowledge, there is very little research literature on this subject in the energy DR.

Mostly, nature inspired algorithms are used for scheduling purpose. The scheduling problem, in general, can be extremely difficult, non-linear, and non-convex. Due to their capacity for exploration and exploitation, these group of algorithms can locate interesting solutions in a fair amount of time [40]. They are parallel algorithms, which are robust and adaptable to changing conditions and environments, among other major benefits [40]. On the other hand, nature-inspired approaches do not promise to discover the best solution, and certain algorithms have their own limitations. Like PSO, which can become stuck in local optima and have slow convergence rates, also GAs occasionally use sophisticated, occasionally unintuitive functions in selection and crossover operators and, if not correctly adjusted, can suffer from early convergence and unpredictable results [40].

Key obstacles in allowing AI approaches are the availability and access to high-quality data sources. There is a lack of high-quality data in the energy industry, making it difficult to create robust systems [10]. In addition, there is a need to enhance the freshness, integrity, correctness, and consistency of data used in energy AI applications [9]. Data management and data governance techniques will become more important as digital technologies advance so that these issues may be dealt with effectively.

Widespread adoption inside and across applications requires not just agreed upon methods, but also the accessibility of data points and computation solutions. Companies are wary of sharing data to protect proprietary information and keep their competitive edge. Distribution System Operators (DSOs) and Transmission System Operators (TSOs) may benefit greatly from an open and honest interchange of operational information from distribution and transmission grids. Because of this, TSOs and DSOs must establish what data they need, the data's quality, the data's owner, and how confidentiality and openness may be maintained [8]. However, optimization schemes and solutions can't be created or tested without access to public data sets. Green Button and OpenEI in the United States and the ENTSO-E Integrity Platform in the European Union are only two examples of the many projects that encourage energy data exchange among stakeholders. However, there is a need for a rise in publicly accessible data on energy, since doing so, together with opening up data from the public sector and adopting common data standards, may assist to spur innovation.

Data mining, machine learning, data analysis, data processing, and data visualization are just some of the cutting-edge methods that have been used to the energy industry. The utilization of Big Data has become more simpler because to the sophisticated technologies that have been steadily improving and are now more widely available. The development of new enterprises and the provision of new services is facilitated by these cutting-edge data analysis methods. For this reason, it is essential to discover untapped markets by analyzing current data and developing data-driven business models examines forty data-driven energy industry startups as case studies of these novel business models.

VIII. CONCLUSION

New demands, such as electric vehicles, heat pumps, and the rising penetration of distributed energy resources (DERs) provide new difficulties for electrical networks. Grid operators may keep the electrical grid in balance by investing low-cost on implementing proper DR schemes, while eliminating the need for expensive enhancements of the electrical network or investing in a great deal of expensive back-up generation, so DR providing a cost-effective response to these difficulties. There is a significant push to add domestic and commercial customers into the DR portfolio, despite the fact that DR programs were initially aimed for a selected group of major industrial and heavy commercial users. This shift demands to appropriately choose the end users contributing to a certain consumption hour, but also to plan their usage, control units for DR, and set the reward/ punishment schemes. Artificial intelligence (AI) solutions have been widely employed by researchers to accomplish these goals, particularly in cases when more conventional methods failed to provide acceptable outcomes.

To identify and explore the trends for AI techniques in the energy DR industry, the authors here investigated through more than 150 articles, as well as 35 plus businesses and commercial efforts, and 20 significant projects. According to the research that was analyzed for this paper, AI methods are a potential tool for DR. Artificial intelligence (AI) usage is crucial to the future success of DR programs. It is crucial for successful use in a DR context to have a better grasp of AI methodologies and their limits.

Our analysis revealed that many distinct AI methods are in use, but it is evident that certain methods are better suited than others for certain jobs. Using supervised learning, it was shown that ANNs are widely utilized for short-term load and price forecasting. ANNs are often used for multi-variable function approximation and regression. On the other hand, RL-based algorithms are typically employed to gather human input, making them well-suited for control tasks in HEMS that include a DR solution. For clustering problems at the aggregator level, such as those involving DR customers, unsupervised learning is often employed since it does not need any previous knowledge of the categories. After classifying and forecasting DR customers' usage, aggregators then set a date to activate DR participants and determine incentives and punishments. It has been noted that standard, stochastic optimization approaches are less accurate, and that alternative, nature-inspired optimization techniques (such as swarm intelligence) may be required for certain jobs. The ideal pricing and scheduling method may also be determined using multi-agent systems in game-theoretic situations.

Our findings also demonstrated that the industrial sector shares the increased enthusiasm of the research world for AI solutions in the DR sector, as seen by the proliferation of new start-ups in this area over the last several years. Although these AI-in-DR trends are well-established, further study is obviously required to determine the best solutions for various situations. Many of the suggested remedies have not been subjected to rigorous testing in the form of large-scale, real-world trials and experiments. More research is needed, together with industry projects and large-scale testing, to pave the way for the development of more precise models and AI-based solutions. Taking this road will enable AI/ML methods to become commonplace in the energy DR industry.

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