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Review on optimization techniques and role of Artificial Intelligence in home energy management systems

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ABSTRACT

Present advancements in the power systems paved way for introducing the smart grid (SG). A smart grid is beneficial to consumers which enables the bi-directional flow of information between the utility and customer. Demand-side management (DSM) techniques are crucial as load-side management techniques to attain the better stability of the grid. Home energy management systems (HEMS) play a indispensable part in the DSM. Countless traditional optimization techniques are utilized to implement HEMS, but the limitations of traditional Math heuristic methods gave rise to a concept-based optimization techniques called the Meta heuristic methods. Recent advancements introduced smart optimization techniques powered by Artificial Intelligence (AI). This article elucidates the applications of AI-based optimization techniques and their advantages over other methods. Various Machine learning (ML) and Deep Learning (DL) algorithms and their utilization for HEMS are discussed in brief.

1. Introduction

HEMS plays an important role in power flow control in the smart grid. Main aim of HEMS in SG is to optimize the energy consumption and reduce the electricity cost, this mechanism benefits both the user and the utility (Zafar et al., 2020; Serban et al., 2020). HEMS in smart grid broadly consists of three sectors, sensing, communicating and controlling. The energy consumption information is sensed and communicated to the controllers for energy optimization. Communication networks in the smart grid are categorized based on the area of their operation, Home area network (HAN), neighbourhood area network (NAN) and Wide area network (WAN) (Kumar et al., 2019). HAN network is established in the household territory where different smart devices are connected together and the energy usage information is transmitted to the smart meters which are located between central controller of HAN and utility. Smart meters become very important in the operation of smart grid to track the bidirectional floe of energy. The energy from consumer to utility through renewable energy sources (RES) and electric vehicles (EV) are tracked through smart meters along with energy consumption (Zhang et al., 2019). This data is then sent to the utility administrator, which helps them make decisions based on the system parameters. According to the communication medium, HAN's technology is classified into two categories. Power Line Communication (PLC) and Ethernet comes under the first category, whereas wireless networks like Bluetooth, Wi-Fi, a low-rate personal area and wireless cellular networks come under the second category. PLC is used for indoor power networks (Han et al., 2014b) and communication in Energy Management Systems (EMS) (Han et al., 2014a; Aslam et al., 2018). For operational use of HEMS, integrating Renewable En- energy sources (RES), Energy Storage Systems (ESS), Electric Vehicles (EV'S) and power electronic devices are essential in smart homes. For managing RES, ESS play a crucial role. ESS combination with power electronic devices ensures the stabilization of power generation and improves the power quality. Whenever a power imbalance arises, then RES is necessary, and their generation is based on weather conditions. Both RES and ESS are used during peak demand when there is a power surplus. On single RES cannot provide a reliable power supply (Ahmad et al., 2017). Therefore, multiple systems are to be integrated like wind, solar, biomass etc.,together called hybrid RES systems. Energy generation from different sources varies across countries. For example, the US generates about 20% of its energy using RES, whereas India generates 10% of its energy using RES, the remaining from fossil fuels. Even though the generation of power through green technologies is increasing,fossil fuels still play a keen role . The efficient use of electrical energy can be done by increasing EVs, demand-side management (DSM) solutions and HEMS. The new SG model enables bidirectional communication between the utility and user with advanced metering infrastructures and a wide area network.HEMS helps improve productivity in quality and capacity by power monitoring and controlling, which capitalizes on the smart grid. Communication protocols between the consumer and grid are used to exchange information about energy availability, which is helpful for HEMS in scheduling the appliances. Optimization techniques are used to balance the level of user comfort (UC).This paper

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Nomenclature

ACO	Ant Colony Optimization
AI	Artificial Intelligence
ANN	Artificial Neural Network
BBSA	Binary Backtracking Search Algorithm
BFA	Bacteria Foraging Algorithm
CP	convex programming
CPP	Critical Peak Pricing
CSA	Crow Search algorithm
DER	distributed energy sources
DL	Deep Learning
DP	Dynamic Programming
DR	Demand Response
DSM	Demand-side management
EDE	Enhanced Differential Evolution
ESS	Energy Storage Systems
FA	Firefly algorithm
GA	Genetic Algorithm
GSA	Gravitational Search Algorithm
GWO	Grey Wolf Optimization
HEMS	Home energy management systems
HSA	Harmony Search Algorithm
IBP	Incentive-Based Program
IBR	Inclining block rates
KNN	K-Nearest Neighbours
MILP	Mixed-integer linear programming
MINLP	Mixed-integer non-linear programming
ML	Machine learning
MSE	Mean Square Error
PAR	Peak Average Ratio
PBP	Price-Based Program
PLC	Power Line Communication
PSO	Particle Swarm Optimization
RL	Reinforcement Learning
RTP	Real-Time Pricing
SG	Smart grid
SL	Supervised Learning
SVM	Support Vector Machine
TOU	Time of Use
UC	user comfort
USL	Unsupervised Learning

discusses the architecture of HEMS in Section 1.1, explaining detail communication technologies in HEMS.Section 2 briefly explains the DR programs and their types used in HEMS. Section 3 illustrates optimization techniques,uses and their types for scheduling the appliances in HEMS. Section 4 contains the brief explanation of math-heuristic techniques,its classification and detailed view on literature survey.Section 5 elucidates the meta-heuristic techniques,its types which is discussed with equations and separate literature surveys.Section 6 exemplifies machine learning along with its types, theory and literature survey. Section 7 demonstrates deep learning technique,methods and literature survey. In Section 8 conclusion is presented.

1.1. Architecture of HEMS

The main components in HEMS are smart controllers, smart meters, Renewable Energy Sources, Energy storage devices and EVs, as shown in Fig. 1. The function of a smart controller is Logging, monitoring and controlling. It acquires real-time data on energy usage in scheduled and non-scheduled appliances to perform Demand side management (DSM) strategies. Another main component is the communication infrastructure, which transfers wired or wireless data. The essential measuring component in HEMS is Smart Meter. These smart meters act as bidirectional communication between utility and user. It enables users to manage the energy based on their requirement, i.e., using distributed energy sources (DER)N (Petreus et al., 2019; Ma et al., 2014). The smart meter will enable smart billing for all the users based on different pricing schemes like Real-Time Pricing (RTP) and Time of Use (TOU). The main features of the smart meter are:

- To measure the multi-power rates of reactive and active power usage (Lloret et al., 2016; Arif et al., 2013).
- To increase the reliability of the energy power supply, the smart meter interacts with DER and HEMS to provide electricity.

Integrating the smart meter with the HEMS will display the end-user energy consumption based on the user's comfort. All the home appliances are classified into non-schedulable and schedulable loads. Electric vehicles, AC and water heaters are the schedulable loads that can be turned on and off at any time. These schedulable loads are classified into interruptible and uninterruptable loads. Utility signals cannot shift the non-schedulable loads. Demand-response programs like Critical Peak Pricing (CPP) and TOU pricing are used for home appliances scheduling based on user comfort. HEMS has distributed generation sources, and renewable energy sources are a part of it. The most commonly used RES is PV and wind technologies. The generated energy from these sources is based on weather conditions that will affect the stability, reliability and quality. Therefore, Energy Storage Systems are used as a backup for stabilizing the system. EVs are also an essential component in HEMS. These will act like both loads as well as sources. During the peak load conditions, EVs act as a Vehicle to grid (V2G), and during non-peak time hours, they will act like Grid to Vehicle (G2V). The smart HEMS has the elements which include, for monitoring purposes, the use of sensors and microcontrollers. Actuators and microcontrollers are used to perform an action when the command receives. A server for data ingestion serves as a gateway for connecting the other networks, and remote control of data and appliances web applications are used.

2. Conventional methods

One of the essential elements of the SG is the Demand Response (DR) programme. Using these programs, some selective loads are limited to deal with sudden supply events like transmission line outages during peak hours (Zhao et al., 2013). Mainly these DR programs are used for industrial and commercial purposes. These programs are usually implemented using the Incentive-Based(IBP) and Price-Based Program (PBP). Fig. 2 represents DR program classification.

2.1. Price based program (PBP)

The average price fixed by the utility for user power consumption is not the same as the full sale price. To avoid this problem, different pricing mechanisms like Real-Time Pricing (RTP), Peak Time Pricing (PTP), Time of Use Pricing (TOUP) and Critical Peak Pricing (CPP) are envisioned. A brief introduction of these pricing schemes is given below:

Time of Use Pricing (TOUP). These have predetermined rates and pricing periods which are structured in a way that is beneficial for both user and utility. Customers are made aware of the prices and time of off-peak and on-peak periods a year in advance since TOUP rates are forecasted over a specific time frame (e.g., a year). The utilities must calculate their tariffs and transform their costing periods into rating periods while developing TOU pricing rates.

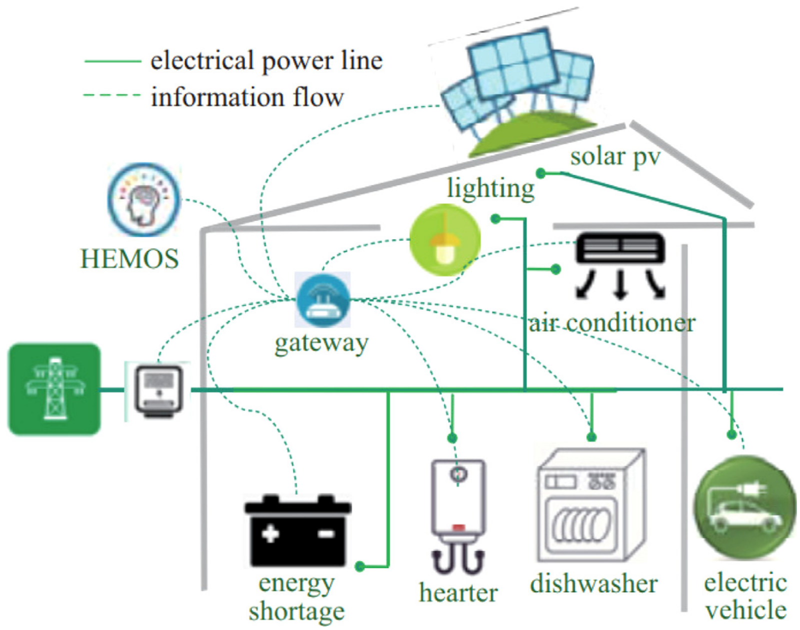

Fig. 1. Architecture of HEMS.

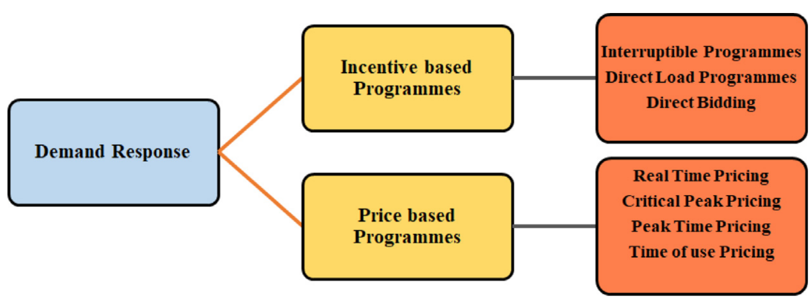

Fig. 2. Classification of DR programes.

Real Time Pricing (RTP). These rates are not predetermined but are predicted when they go into effect (e.g., One day ahead). The marginal cost of supplying electricity is used to calculate real-time rates. As a result, consumers can change their usage time hourly. Real-time rates improve economic efficiency by giving customers a "proper price signal", which represent the marginal costs.

Critical Peak Pricing (CPP). The utility will set the threshold limit for the user based on the amount of power consumption. The utility will charge new rates if the consumer exceeds the power consumption beyond the threshold limit. The new rates are intimated to the user beforehand. This scheme helps maintain supply and demand by confining the user's electricity consumption below the threshold limit, which will benefit the utility and the user. The fundamental goal of DR is to keep electricity demand low during peak hours while preventing increased power consumption when price of electricity (POE) is low. However, one disadvantage of RTP is, that demand will be high during low POE (Zhao et al., 2013), resulting in increased electricity consumption with a more prominent peak to the average ratio that results in Overload or blackout. As a result, RTP is integrated with inclining block rates (IBR), which improves the power consumption threshold limit when combined with POE.Yet, the safety and security of the system are neglected. A Lagrangian function has been used to improve the robustness of the subgradient technique and ensure reliable convergence (Zhu et al., 2018) which is unique in getting the optimal local solution. It demonstrates that RTP can lead customers' consumption behaviour and meet the primary goal of peak reduction, which improves the social community's energy-saving and emission reduction but fails to integrate renewable energy sources. The HEM testing is performed (Elma et al., 2017) in the Yildiz Technical University Smart Home Laboratory (YTUSHL), a real smart home. A forecasting algorithm is used to forecast the RES generation. Then the net power is calculated, which is helpful for proper decision-making using RTP, but this is used only for short-term EMS. Shinde et al. (Shinde, 2015) proposed HEMS to reduce households' total consumption below the specified limit by managing the loads based on user requirements. Users will be notified via SMS when the status of their appliance changes, resulting in low cost and highly secure architecture for deploying a HEMS. The performance of HEM operation and each load is analyzed using the intended DR algorithm in Kuzlu et al. (2012) which is regulated by the HEM unit. The average communication time delay between the load controllers and HEM unit is measured in milliseconds and rises significantly as the distance between them increases. The suggested system's real-world implementation will benefit electric power distribution operators by assisting them in avoiding distribution transformer overloads caused by new power-intensive loads such as EVs. Still, the limitation is the same as Zhu et al. (2018). In a real-time load profile, consumption data from 200 consumers are collected at half-hour intervals (Joseph and Jasmin, 2021). The load data from the user/consumers are clustered using ensemble clustering as the first stage in developing RTP. Three classes of homes are created based on this information and the load profile generated by the clustering algorithms. Results demonstrate RTP's good impact on DR programmes. The operation of the energy scheduling unit is augmented, depending on the scheduling horizon, by a price predictor unit, which forecasts future prices by applying a weighted average filter to historical prices (Mohsenian-Rad and Leon-Garcia, 2010). The best price prediction filter coefficients are identified for each day of the week to reduce household electricity bills assuming every house with a smart meter.

2.2. Incentive – based program (IBP)

IBP aims to decrease energy consumption at peak- hours, i.e., by reducing or shifting the load to off-peak hours. In this program, consumers permit the utility to manage their loads during peak hours, which affects their comfort level. In addition to the fixed/TOU pricing structure, the programme operator of an IBP gives its clients variable or fixed financial incentives to limit demand consumption. For incentive-based DR programmes, in the year 2006, direct load control, curtailable or interruptible service, demand bidding/buyback programmes, capacity market programmes and emergency DR programmes were all classified by the US Department of Energy. Three scenarios are compared regarding the consumers' daily financial benefits from engaging in the appropriate pricing method or DR programme (Abrishambaf et al., 2016). Case 1 is without DR programmes and PV system; Case 2 is with DR method, and Case 3 follows case 2 with 2kw PV installation. The amount of energy purchased from the generating station is minimized as the customer utilizes their own generated energy. Compared to case study 1, the user saved 44 per cent on costs but did not show the effect of Peak Average Ratio(PAR) using the proposed method.

3. Optimization techniques

DR referred as changes in demand-side power consumption from standard forms of responsible consumption, as well as changes in electricity pricing or incentives to decrease power use during periods of high-cost price. To achieve DR, various optimization techniques based on heuristic approaches are implemented and different case studies on heuristic approaches are discussed in Sections 4 and 5 . Optimization is the best strategy for finding solutions to problems after selecting a constrained objective function. Power consumed in the residential sector can be decreased by proper scheduling and optimizing the power, increasing consumer and supplier benefits. The objective is to maximize or minimize the power consumption, including integrating ESS with RES. To meet this objective, optimization techniques are used. A smart grid (SG) is grounded on Advanced Metering Infrastructure (AMI) and bidirectional or two-way communication. By conveying power consumption and availability to end-users, the user can switch between conventional and non-conventional or vice versa to reduce cost and increase efficiency. It maintains a perfect balance of dependency availability, efficiency and cost. The multi-objectives costs minimization, load management, PAR reduction, and peak load. The optimal solution for these multi-objectives is appliance scheduling, dynamic pricing, load forecasting, and demand response. Fig. 3 shows the optimization techniques classification where the techniques are classified into Mathematical Programming, Heuristic, Meta-Heuristic and Artificial Intelligence (AI).

4. Math-heuristic techniques

The goal of HEM is to control the user's power consumption within a HAN. This is not an easy task, though, because each HAN device responds differently, and measurements and forecasts are often inaccurate. Models estimate the appropriate schedule of devices within the home to simplify the scheduling process; nevertheless, there should be a balance between complexity and optimality. Three main approaches are typically used to schedule home energy usage, heuristic methods like math heuristic and meta heuristic and mathematical optimization methods. For mathematical techniques,Optimal scheduling is attained by selecting the organized input values (Petreus et al., 2019).

- The simplest form of mathematical optimization is linear programming, in which the constraints and objectives are linear functions.Though they may not accurately represent a household energy system, they can be solved in polynomial time.
- Quadratic programming (QP) problems are also easy, as the quadratic objective is the main difference between linear and quadratic programs. The solution to the optimization problem depends on the type of objective. If the objective is positive and definite, the solution will be in polynomial time. If the objective is indefinite, it is referred to as an NP-hard problem.
- A convex objective function, concave inequality constraints and linear equality constraints are present in convex programming (CP) problems. Compared to the previous two, this optimization problem is more complicated, but if a solution exists, it will converge.
- Problems with Dynamic Programming (DP) split significant complicated problems into smaller sub-problems and recursively solve problems by storing solutions to sub-problems. Variables in HEMS applications are often restricted to discrete values alone.
- Despite being non-linear, Mixed-integer linear programming problems (MILP)have integer variables and are NP-complete in complexity. These issues require branch-and-bound algorithms to solve because they require discontinuities in modelling for extra flexibility, such as binary variables.
- Mixed-integer non-linear programming (MINLP) and non-linear programming problems can be challenging to solve, and even if a solution exists, it does not guarantee accuracy.

Except for Dynamic and Quadratic Programming remaining optimization methods are implemented in HEMS and explained in detail as shown below: Two scenarios are investigated to validate the performance of the proposed algorithm: with and without the SG (Conejo et al., 2010). Use of the smart grid model allows the user to acquire a daily utility that is 15.86% more than that achieved without the smart grid this however focused mainly on cost minimization without considering the user comfort. ESTA is a certainty-equivalent control approach, which means it makes decisions as if the weather and pricing forecasts were certain (Constantopoulos et al., 1991). A real-time control method is presented utilizing a decision modelling approach designed for prescribing customer reaction to a fluctuating energy price in the case of space conditioning use. This technique is proven to save considerable amounts of money daily at the cost of minor interior temperature variations around its excellent value. The energy distribution layer of the home automation system (HAS) employs a linear programming method, whereas the reactive layer employs a dynamic programming strategy (Ha et al., 2007). The distributed power regulation adjusts the distribution of power for each home to maximize their satisfaction, but PAR performance is not considered. LP aims to increase the total coefficients of distributed power as much as possible. The GLPK solver is used to implement this linear programming, which communicates with the load management system simulator via Java interface.

The power consumption scheduling mechanism is an LP optimization problem to reduce the hourly peak load (Lee and Choi, 2014). This proposed technique is used for energy conversion from a PHEV to a home ESS via vehicle to grid (V2G) and optimizing the saved energy using LP. A 38 per cent reduction in the hourly peak load using the proposed strategy is shown but does not focus on cost minimization. The model in Escobosa Pineda (2018) comprises three different types of loads. The HVAC unit is the primary load, followed by a deferrable load and a non-interruptible load. The goal is to give a conceptual decomposition of the optimization issue into computationally tractable subproblems using the HEM device as an interface with the energy aggregator through real-time pricing and an economic incentive load profile. The proposed model predictive control technique reduces consumer discomfort levels subject to peak power, cost, and limitations

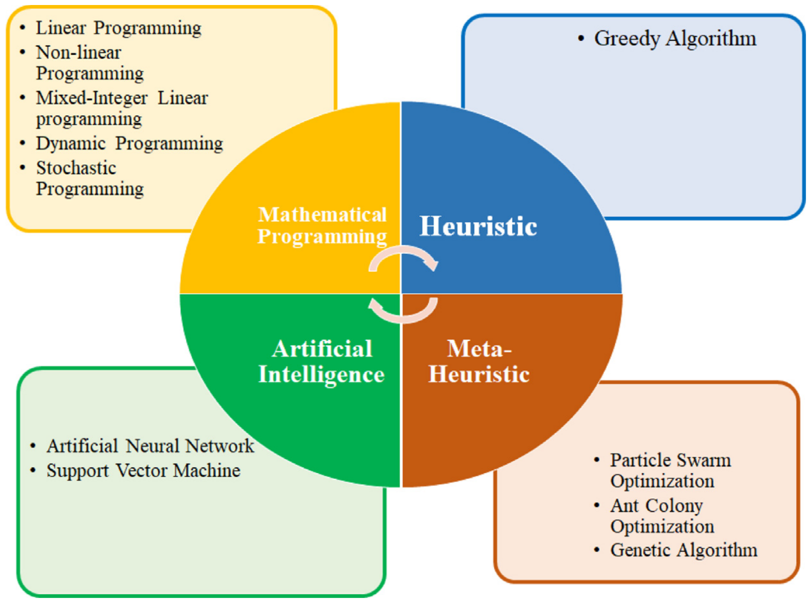

Fig. 3. Optimization methods in HEMS.

using a limited stochastic optimization that integrates temperature sensors, thermal dynamics, and the real-time pricing signal. In Jia et al. (2011), the HEM control problem formulates a multi-stage stochastic programming problem. HEM system optimizes the power allocation based on the measurements and numerical weather data to reduce user discomfort. The online thermal parameter estimates techniques and the first-order thermal dynamic model are evaluated using actual measures. A smart power system with a single energy source and multiple load subscribers is considered. The goal of the developed scheduler is not to modify the amount of energy consumed but to manage and move it systematically. The optimization issue is convex and may be handled centralized using CP techniques like the interior point method (IPM) (Yu et al., 2013). This method drastically reduced the PAR and the total energy cost in the system, but it considers only particular appliances and did not focus on discharging batteries. The single-house problem is formulated as an MINLP problem that calculates the energy plan for each household user (Mohsenian-Rad et al., 2010). The problem's purpose is to reduce the active householder's daily power bill. According to numerical calculations derived from actual energy consumption data, the system-wide peak absorption performed in a wholly distributed method can be lowered by up to 20% but not focused on user comfort. Based on these models, an MILP optimization problem for the optimal operating scheduling of home energy hubs was developed to reduce demand, the total cost of electricity and gas, emissions, and peak load of the hubs (Barbato et al., 2013). These models have been applied to a real household, with a discussion of various implementation elements and savings of up to 20% on energy bills and 50% on peak demand while maintaining the user's desired comfort level. The algorithm (Bozchalui et al., 2012) divides the time horizon into intervals, planning during each interval's start. The goal is to create a local controller that can react to signals from a global controller, allowing global optimizations to be supported. The results show that device control based on objectives has been achieved without energy shortages or surpluses while meeting most needs. Still, both (Barbato et al., 2013; Bozchalui et al., 2012) PAR and integration with RES are not considered. A novel decision model for energy household management based on MILP and a heuristic allocation method is proposed in Molderink et al. (2009). The model specifies how the consumer should change the daily consumption schedule to account for the aggregator's signal(s). The scheduling methods used in the selected methodology (Agnetis et al., 2013) for appliance load control are inspired by the scheduling strategy used in real-time computer systems. Electrical load scheduling is modelled as an MILP problem that seeks to reduce overall operational costs while considering capacity restrictions and appliance operating needs but failed to integrate with RES. An efficient home load control algorithm for DSM on the side of load uncertainty where just an estimate of future consumption is proposed in Costanzo et al. (2012) to reduce consumers' electricity payments. The use of real-time pricing in conjunction with IBRs to balance the home load and achieve a low PAR is examined. This proposed method is integrated with RES, but user comfort is neglected.

For large-scale residential demand response, a two-layer communication-based distributed direct load control system is proposed (Samadi et al., 2013). The goal is to distribute the overall control task among the EMCs of each building. According to numerical data, the system's capacity to match a prescribed load consumption profile with actual demand levels has improved significantly. The aim of this (Chen et al., 2014) is to present a new way for sizing optimal providing systems and managing residential energy. The results provide insight into the evolution of PV systems in the near and medium-term. Pham et al. (2010) proposes two household load models for optimizing energy usage in the residential sector network. When combined with the programming technique, these proposed models can ease peak load and electricity costs at the same time. Some algorithmic changes can be made to allow for a more efficient solution, but a linear software system like Solver will be adequate for most situations. In Dehnad and Shakouri (2013), optimization problems that can give schedule plans for home appliance usages are formulated and numerically simulated to reduce the electricity bill on the domestic side for time-varying electricity prices. The results show that optimization under the TOU pricing environment can reduce the residential electricity compared to the worst-case scenario.

MINLP, non-integer linear programming, CP and MILP are utilized to minimize cost and energy consumption. These techniques, on either hand, will not be able to handle many appliances. These methods are computationally intensive, and user comfort is not adequately considered. Due to the random nature of human behaviour, these strategies cannot handle many different home appliances with non-linear, unpredictable and complex energy consumption patterns. The capability of mathematical optimization techniques delivers exact solutions, although they are often time-consuming when dealing with complex optimization problems. Meta Heuristic optimization techniques are now usually used to overcome the drawbacks of mathematical optimization.

5. Meta-heuristic techniques

Heuristic methods are used for problem-solving using practical methods to obtain the solution for real-time problems. Complexity in the math heuristic methods leads to the practice of meta heuristic methods. Meta-heuristic methods are nature-inspired and are genetic algorithms. Few assumptions in the algorithm make the solution more accurate. Compared to the math heuristic methods, meta-heuristic methods are less computational and converge to the optimal solution in less time. As a result, they are effective methods for resolving optimization challenges and have the following features:

1. Independent of the objective function's nature, i.e., they can solve nonlinear, linear, discrete-time complex, persistent problems, which is usually impossible with traditional techniques.
2. Nature-inspired approaches efficiently explore and exploit the search space.
3. Can be fine-tuned to improve their performance, and they can be employed in complex scenarios as part of a hybrid with other algorithms.
4. Because such optimization techniques mature faster than traditional optimization techniques, the computing time for solution is reduced.

Because heuristic techniques frequently generate a random initial population, the solution obtained may be sub-optimal and may vary between tests to some extent. These algorithms are liable to becoming caught in a local optimum and failing to generate a viable solution. Typically, these flaws are addressed by

1. repeating the algorithm and selecting the best solution,
2. fine-tuning the heuristic algorithm parameters to avoid premature convergence and aid in finding near-optimal solutions with minimal computational effort.

The multi-objective household appliance schedule optimization problem is addressed by considering the benefits and resolving the drawbacks via iterative tuning. Every meta-heuristic technique is based on the theory inspired by nature, which helps solve the optimization problem. For example, a Genetic Algorithm (GA) is inspired by the genetic process of a living organism. Bacteria Foraging Algorithm (BFA) is on mine chemotactic shifting of virtual bacteria in the problem hunt space. Grey Wolf Optimization (GWO) population affects the leadership hierarchy and searching procedure of grey wolves, and Particle Swarm Optimization (PSO) is based on swarm intelligence. Other Meta-heuristics algorithms include Enhanced Differential Evolution (EDE) algorithm, Gravitational Search Algorithm (GSA), Ant Colony Optimization (ACO), Binary Backtracking Search Algorithm (BBSA) and Harmony Search Algorithm (HSA). Working of algorithms, their benefits and drawbacks are explained further.

5.1. Differential evolution algorithm (DEA)

This DEA algorithm was proposed by Price and Storn in 1995 (Zafar et al., 2017). Compared to other optimization approaches, it has several powerful features, such as simple coding, minimal control parameters, fast convergence, and the ability to solve real-world optimization problems. Differential evaluation performs two steps for achieving the optimization, one is a mutation, and the other is recombination. The set of solutions will undergo evolution called target vector (1). This target vector will undergo mutation to evolve into a mutant vector, and then recombination takes place to obtain the trailing vector.

$$M_i = X_{r_1} + C * \left(X_{r_2} - X_{r_3}\right) \tag{1}$$

where M_i is the mutant vector for the i^{th},variable and X_{r_1}, X_{r_1}, X_{r_1} are the target vectors that are calculated from the solutions r1,r2,r3 where $r1, r2$ and $r3 \in \left\{1, 2, 3, \ldots .N_p\right\}$, N_p being the population size. Selection of solutions must be random and the population size should be greater than or equal to 4. C is the scaling factor decided by the user. Recombination is performed to increase the diversity of the solutions, Recombination process is performed as shown in (2).

$$T^j = \begin{cases} M^j & if\, r \leqslant P_c \quad or \quad j = \delta \\ X^j & if\, r > P_c \quad\quad AND \quad j \neq \delta \end{cases} \tag{2}$$

A random variable r and Probability crossover P_c is defined by the user which are between 0 and 1. T^j is the jth trail vector generated by selecting the random variable δ, $\delta \in \{1, 2, 3, \ldots .D\}$ D is the number of decision variables. After obtaining all trail vectors for all the solutions, values are verified to be within bounding parameters, adjusting them to be within the upper and lower bound. Later, the fitness function is evaluated, and a greedy search is performed to obtain the population for the next iteration. A single household with nine appliances is considered, and DE (Storn and Price, 1997) approach is implanted. Home appliances are classified into three groups, i.e., A, B, and C. The electricity cost per hour using the algorithms EDE, BFA and HSA are compared by assigning the load from off-peak hours to on-peak hours. Due to this load shifting, the tariff paid during on-peak hours is lesser than the off-peak hours, of which HSA has the low price per unit, BFA has the high price per unit, and EDE has the low PAR. Based on multiple performance metrics, two stochastic population-based optimization algorithms (DE and EDE) are investigated and assessed in a home with seven smart appliances (Rehman et al., 2017b). These algorithms reschedule appliances to lessen the peak energy demand hours but failed to integrate with RES. Sixteen appliances consisting of automatic and manual operation, interruptible and non-interruptible types are scheduled by considering each time slot of 12 min, i.e., a total of 120-time slots, which is known as Shortest Length of Operation Time (SLOT) (Tariq et al., 2017). EDE reduces the cost of electricity by shifting the load from peak to off-peak hours, which also reduces PAR.

5.2. Harmony Search Algorithm

HSA is an evolutionary algorithm that imitates the actions of musicians. Memory-based play, random play and pitch adjustment are the three main processes of HSA. The problem of residential power load control is investigated in this study (Rehman et al., 2017a) to lower the electricity cost for home appliances. Based on electricity usage, home appliances are classified into three classes. Two meta-heuristic algorithms, Firefly algorithm(FA) and HSA, are used to reduce electricity costs, load management, and PAR.However, to achieve better outcomes, a hybrid model of HSA and FA can be implemented using RES. To evaluate HSA and BAT, MATLAB simulations are used. Eleven appliances were categorized into Elastic Appliances, Fixed Appliances, and Shiftable Appliances (Farooqi et al., 2017). Their LOT is set, but they can operate anytime during the day. The electricity cost is calculated using the CPP pricing methodology. HSAs have proven overall effectiveness compared to BAT. In the similar way Ali et al. (2017) divided 7 appliances into three classes. The main aim is to reduce PAR and energy consumption using HSA and Crow Search algorithm (CSA). The results show CSA performs much better than HSA in cost reduction and user comfort (UC), while in terms of PAR reduction and UC, HSA outperforms CSA.

5.3. Bacteria Foraging Algorithm (BFA)

BFA's working architecture is based on poor foraging methods (Passino, 2002). Because of the algorithm's statistics, the cell swarmed stochastically and collectively towards an ideal solution, which is why BFA is adopted. Zahra et al. (2017a) classified the significant appliances into three categories: fixed, elastic and shiftable. The main aim is to schedule the home appliances using BFA and strawberry algorithm(SBA) algorithms. Comparative results show that BFA outperforms SBA in elastic and shiftable appliances, but SBA outperforms BFA in fixed appliances. Similarly, the BFA algorithm for HEMS is proposed (Khan et al., 2017) to reduce the overall electricity consumption and PAR and considers the scheduling of appliances.

5.4. Ant Colony Optimization (ACO)

The drawbacks of Swarm intelligence and discrete combinatorial optimization problems are solved using ACO, a meta-heuristic technique. It has unique self-organization, self-healing and self-protection properties. The ACO algorithm is robust, a well-calculated mechanism and simple to combine with other approaches to perform well when addressing complex optimization problems. The inspiration for ACO comes from the behaviour of ants finding food in ant colonies. Finding a portion of food is an optimization task that should be achieved by spending the minimum amount of energy. Ants produce the pheromone chemical to communicate with other ants during this process of finding the shortest path. This analogy is adapted to solving the optimization problems for finding the minimization. This optimization technique is formulated as shown in (3).

$$\Delta\tau_{i,j}^{n} = \begin{cases} \frac{1}{S_n} \& n^{th}\, ant\ on\ edge\ i,j \\ 0 \qquad\qquad otherwise \end{cases} \tag{3}$$

$\Delta\tau_{i,j}^{n}$ is the amount of pheromone deposited by the ant while travelling through the edge i,j. S_n is the weight of the graph obtained from the cost matrix. Cost matrix and the pheromone matrix are defined to find the probabilities of the path. Total amount of pheromone on the path i,j by all the ants in this process can be obtained from (4).

$$\tau_{i,j}^{n} = \sum_{n=1}^{m} \Delta\tau_{i,j}^{n} \tag{4}$$

n represents total no.of ants. (4) is valid when there is no vaporization or no loss during the marking of shortest path. If a loss factor ρ is considered in the realtime scenarios that lies between 0 and 1, the (4) is modified as (5).

$$\tau_{i,j}^{n} = (1-\rho)\,\tau_{i,j} + \sum_{n=1}^{m} \Delta\tau_{i,j}^{n} \tag{5}$$

After obtaining the amount of pheromone on the respective paths, a probability of choosing the path is calculated by using (6).

$$\frac{\tau_{i,j}\left(\frac{1}{S_n}\right)}{\sum \tau_{i,j}\left(\frac{1}{S_n}\right)} \tag{6}$$

The path with the highest probability is chosen as the shortest path to faster optimization. For power bill calculations, ACO is used to solve objective functions and combined pricing models, IBR model and TOU tariff (Rahim et al., 2016a,b; Leo et al., 2021; Imran et al., 2020a). Based on the results, it is clear that the proposed strategy effectively minimizes electricity bills and improves PAR while considering user satisfaction. Still, in Rahim et al. (2016a,b) the security issues between the utility and user should be improved. This (Fatima et al., 2017) is based on a microgrid connected to a grid using a point of standard coupling (PCC). The proposed ACO technique has a low PAR by scheduling (with incentive mechanism and penalty) and high PAR without scheduling appliances. ACO for HEMS is applied in Ramalingam and Shanmugam (2021) and is compared with Knapsack. These results show that ACO effectively minimizes the electricity cost of energy consumption. The ACO algorithm was proposed and compared with GA (Diwekar and Gebreslassie, 2016) to minimize the electricity cost and maximize the UC. The results show that ACO is more efficient than GA.

5.5. Grey Wolf Optimization (GWO)

The GWO algorithm is grounded on the wolf pack hunting paradigm (Anwar ul Hassan et al., 2017). Wolves have a social hierarchy ad hunting patterns which decide who and how to down the prey. Wolves are categorized according to hierarchy as α the fittest, β second best and subordinates to α then δ lower grade compared to previous, finally ω weakest among all. In the optimization problems, the fittest and best solutions are considered α. All the solutions are graded according to their performance based on the wolves' hierarchy. Mathematical modelling is performed to solve the real-time optimization problems as shown from (7)–(13).

$$\vec{y}_{\alpha} = \left|\vec{m}_1.\vec{x}_{\alpha} - \vec{x}\right| \tag{7}$$

$$\vec{y}_{\beta} = \left|\vec{m}_2.\vec{x}_{\beta} - \vec{x}\right| \tag{8}$$

$$\vec{y}_{\delta} = \left|\vec{m}_3.\vec{x}_{\delta} - \vec{x}\right| \tag{9}$$

$\vec{y}_{\alpha}$, $\vec{y}_{\beta}$, $\vec{y}_{\delta}$ are the distances of α, β, δ from the prey and $\vec{x}_{\alpha}$, $\vec{x}_{\beta}$, $\vec{x}_{\delta}$ are the positions of α, β and δ respectively. whereas $\vec{x}$ is the position of the prey or optimal solution in the real world problems. $\vec{m}_1$, $\vec{m}_1$, $\vec{m}_1$ are the vectors of coefficient matrix $\overline{M}$.

$$\vec{x}_1 = \vec{x}_{\alpha} - \vec{n}_1.\vec{y}_{\alpha} \tag{10}$$

$$\vec{x}_2 = \vec{x}_{\beta} - \vec{n}_2.\vec{y}_{\beta} \tag{11}$$

$$\vec{x}_3 = \vec{x}_{\delta} - \vec{n}_3.\vec{y}_{\delta} \tag{12}$$

$$\vec{x}\,(t+1) = \frac{\vec{x}_1 + \vec{x}_2 + \vec{x}_3}{3} \tag{13}$$

$\vec{x}_1$, $\vec{x}_2$, $\vec{x}_3$ are the position change that α, β and δ must make to approach the prey, $\vec{x}\,(t+1)$ is the average moment made by all three wolves to approach the prey.$\vec{n}_1$, $\vec{n}_2$, $\vec{n}_3$ are the vectors of coefficient matrix $\overline{N}$, these values are reduced in each iteration generally from 2 to 0, this reduction is performed to ensure the convergence of the solution. In the SG with day-ahead pricing (DAP) model (Ghafar et al., 2017; Rahmani et al., 2013; Abdulgader et al., 2017), the GWO technique is used in a typical home with 16 appliances. It is then compared to BFA. In terms of cost reduction, the results suggest that GWO outperforms BFA. The same algorithms are applied to home appliances using CPP pricing to calculate electricity bills (Molla et al., 2019). Still, GWO performs better than BFA with 10% more savings in terms of electricity bills. In both cases (Ghafar et al., 2017; Molla et al., 2019) GWO takes more computational time but provides faster convergence than BFA but in Anwar ul Hassan et al. (2017), Molla et al. (2019) integration with RES and user comfort is not considered. The GWO is also applied in appliance scheduling and compared with PSO on two models of smart home (Jordehi, 2019). GWO has shown more savings compared to PSO in electricity bills and optimal appliance scheduling but neglected the PAR reduction. GWO and GA algorithms are compared (Naz et al., 2018; Kazemi et al., 2017) to reduce the PAR and cost, which shows better results than the proposed algorithm GWO.

5.6. Binary Backtracking Search Algorithm(BBS)

BBSA is at the front of the search for the most effective use of populations, and it works in the domain to achieve it, with powerful exploration abilities (Lin et al., 2015). Weekdays and weekends were used as the two scenarios for the DR in Latif et al. (2020). The predefined objective function of the BBSA and schedule controller implementation was to minimize energy usage. The BBSA is compared with binary PSO for weekdays to evaluate the accuracy of the HEM system controller, which shows the proposed BBSA outperformed the binary PSO controller in terms of the overall consumption of energy within the demand limit by minimizing peak loads and scheduling household appliances during the week while allowing homeowners to use their appliances as they like. The BBSA is utilized as a scheduling controller to the HEMS for weekdays to calculate the optimal schedule of household appliances to achieve the best energy savings for every device (Ahmed et al., 2017). The results showed off that BBSA schedule controller performs better than BPSO schedule controller in terms of energy savings and actively regulating loads while keeping the power demand of household appliances within the set demand limit. Still, both (Latif et al., 2020; Ahmed et al., 2017) failed to integrate with RES and PAR reduction. GA has given better results in terms of maximizing UC level, reduction of cost and peak load compared to Binary PSO (BPSO) in Rahim et al. (2016c), which overcomes all the limitations from Lin et al. (2015), Latif et al. (2020), Ahmed et al. (2017). These theories of different optimization techniques are used to solve the multi-objective problem. In Javaid et al. (2017a), the PSO algorithm solved the load scheduling problem in smart homes. A HEMS model using the PSO algorithm is presented (Javaid et al., 2017b) for appliance scheduling, and the simulation results show that it effectively reduces power consumption during peak load. Still, integration of RES is not considered in both (Javaid et al., 2017a,b). A Binary PSO is applied on HEMS with an optimized controller (Zhou et al., 2014) to minimize the overall power consumption, and the results show that 35% of the cost is reduced. Discrete Particle swarm optimization (DPSO) algorithm is proposed in Christobel et al. (2015) to reduce the computational time, yielding adequate power consumption. The results show the proposed DPSO reduces computational time compared to EDF, and the limitation is similar to Javaid et al. (2017b). For obtaining optimal scheduling problems and reducing the electricity cost, GA is proposed (Miao et al., 2012). A real-time HEMS using GA is presented (Rasheed et al., 2016) to minimize the cost and maximize UC. BFA algorithm for HEMS is proposed (Ishaq et al., 2017) to reduce the overall electricity consumption, and PAR and appliance scheduling are considered. To reduce energy cost consumption GWO & WFO are proposed (Khan et al., 2019) but neglected the appliance scheduling. Hybrid Genetic PSO (HGPSO) proposed to reduce electricity bills, minimize carbon emissions, ensure UC, and reduce PAR by neglecting both ESS and EV (Imran et al., 2020b). Table 1 shows comparative studies of different meta-heuristic techniques.

Due to premature convergence, the solution's optimality cannot be guaranteed. However, heuristic optimization approaches like PSO, which are widely used, have several limitations: They can easily get trapped in local minima solutions and have difficulties identifying optimal control parameters, resulting in inaccurate solutions due to their high computational cost and slow convergence. Machine learning technology is predominantly used in the field of HEMS for creating a smart home. In the smart grid environment, machine learning algorithms are usually applied for a lot of challenges such as energy management, reliability and prediction.

6. Machine learning (ML) techniques

Artificial Intelligence (AI) is a broader concept of machines being able to carry out tasks more innovatively. It enables machines to act like humans by replicating their behaviour and nature (Sarker, 2021). Machine learning (ML) is an AI subfield that focuses on designing systems that can learn from making decisions and predictions based on experience, which is the data in the case of machines (Ray, 2019; Dhall et al., 2020). These algorithms improve over time when they expose to new data. ML is classified into Unsupervised, Supervised, and Reinforced Learning (Rastrollo-Guerrero et al., 2020; Sah, 2020) as shown in Fig. 4.

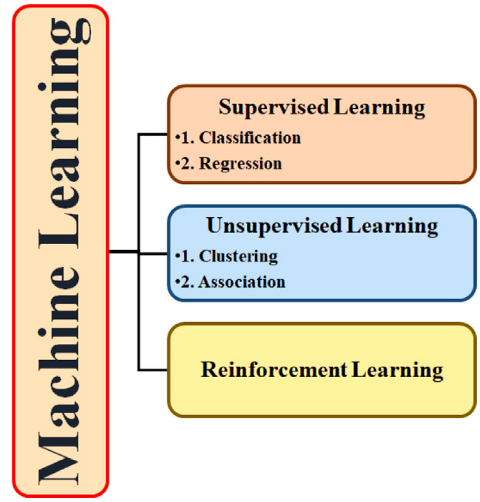

Fig. 4. Classification of ML techniques.

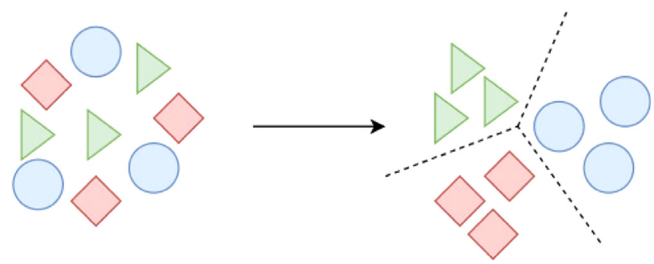

Fig. 5. Supervised learning.

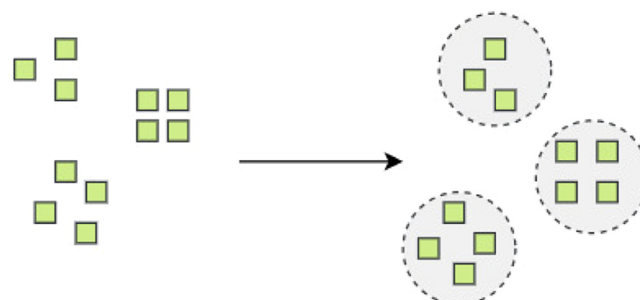

Fig. 6. Unsupervised learning.

1. Supervised Learning (SL): SL is a type of ML in which machines are trained using well-labelled training data and then used to predict output (Hastie et al., 2009). Some input data has already been labelled with the appropriate output, as indicated by the labelled data. The overview of SL is shown in Fig. 5. The training data presented to the machines act as a supervisor in supervised learning, by training the machines to predict the output correctly. It is based on how a student learns under the supervision of a teacher.
2. Unsupervised Learning (USL): It is a type of ML in which models are trained on unlabelled data before being let to act on it independently without supervision. On the other hand, models utilize data to find hidden patterns and insights. It is similar to the human brain's ability to learn new things. Unsupervised learning, unlike SL, cannot be applied to a regression or classification problem immediately because there is no output data for the input (Usama et al., 2019; Yan et al., 2019). As demonstrated in Fig. 6, USL aims to uncover a dataset's underlying structure, categorize data based on similarities, and display the dataset in a compressed way. Similar to SL, these are classified into two types: Clustering and Association.
3. Reinforcement Learning (RL) In RL, there are four main parts: reward, active, agent and environment. As shown in Fig. 7, RL is a mapping between actions and states to maximize support for agents and rewards in a dynamic and uncertain world. RL learns by interacting with the environment, unlike previous algorithms that learn from external supervisors' prior knowledge (Liu et al., 2020a).

Table 1
Comparison of different Meta heuristic techniques.

Ref	Optimization technique	Aim	Achievement	Drawbacks
Kumaraguruparan et al. (2012)	Knapsack	Minimize electricity bill	Consistency in users energy	Users satisfaction, PAR reduction
Rahim et al. (2015)	ACO,Knapsack	Cost minimization, Maximize users comfort	The proposed model achieved highly efficient	PAR neglected
Mahmood et al. (2016)	PSO, Knapsack	Cost minimization	Load categorization is improved	users' comfort is ignored
Talha et al. (2017)	GA, PSO	schedule appliances	Cost is improved and load balancing problem is solved	Complexity in GA become more and become slow convergence
Naseem et al. (2016)	GA, WDO, Binary PSO and BFOA	Cost minimization and PAR reduction	Within finite time horizon, the overall cost of system is minimized	User's comfort is neglected
Zahra et al. (2017a)	GA, BFA	Cost minimization and PAR reduction	Better load management strategies is provided	User's comfort is neglected
Rasheed et al. (2016)	GA	Minimize cost, maximize users comfort and PAR reduction	Considered Temperature, capacity limit and waiting time	Compression with other techniques is not done
Ansar et al. (2017)	BFA, EDE, GA and WDO	Schedule the appliances and minimize cost	To obtain optimum scheduling Optimization process is implemented	PAR is neglected
Zahra et al. (2017b)	BFA	Minimize cost, maximize users comfort and PAR reduction	The load is managed Efficiently	Ignored Integration of RES
Anwar ul Hassan et al. (2017)	BFO and GWO	To reduce cost of energy consumption	In particular scenario better algorithms are determined	Appliance scheduling is neglected
Rehman et al. (2017b)	ACO, EACO	Solving continuous and combinational mixed variable optimization problems	Efficiency encasement	Systems cost and efficiency is neglected
Fatima et al. (2017)	ACO, PSO	The forecasting output energy of wind turbine	The operational efficiency of a wind form is improved	Neglecting Cost of the system

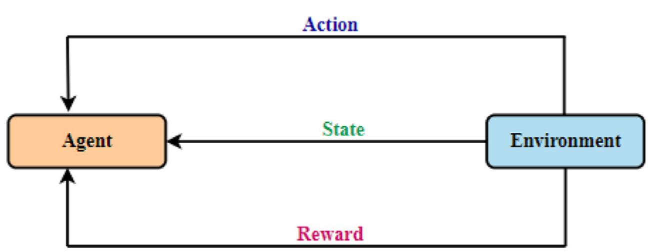

Fig. 7. Reinforcement learning overview.

6.1. Support vector machine (SVM)

A support vector machine is a machine learning algorithm that works for classification and regression tasks. Compared to other ML classification techniques, SVM is capable of producing the most generalized yet efficient classification. SVM has a unique feature of classifying the non-linear separable data points by projecting them into the higher dimensions to obtain separate plane (Angra and Ahuja, 2017). As shown in Fig. 8, SVM creates a hyperplane and two parallel planes. On either side of the hyperplane, the significance of these planes is to create an extra margin for classifying the samples to generate the generalized solution (Rambabu et al., 2016). The nearest data points passing through the margin lines are known as support vectors. The more the distance between margins, the more efficient the classification (Bhavsar and Panchal, 2012). The hyperplane is selected to satisfy the criteria as shown in (14).

$$y_i * \theta^T x_i + b_i \geqslant 1 \tag{14}$$

$$y_i = \begin{cases} +1 & \theta^T x_i + b_i \geqslant 1 \\ -1 & \theta^T x_i + b_i < 1 \end{cases} \tag{15}$$

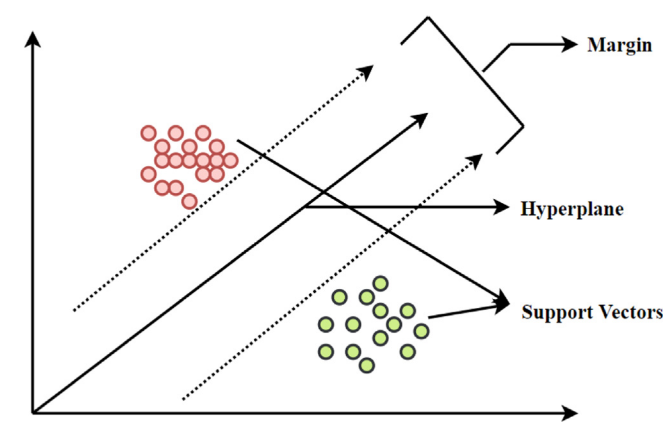

Fig. 8. Working of SVM.

y_i, is the value of the data point based on the classification, θ^T is the slope vector, x_i is the position of the datapoint in the plane and b_i is the bias value assigned to the datapoint. The optimization problem defined to obtain the best possible classification is shown in (15). The slopes and biases should be changed such that it satisfies (16).

$$\left(\theta^*, b^*\right) = min \frac{\|\theta\|}{2} + R \sum_{i=1}^{n} \zeta_i \tag{16}$$

R is the regularization parameter that decides the maximum number of misclassified samples allowed in the margin to avoid overfitting, ζ_i is the value of the misclassified samples. This optimization technique can also be extended to solve the regression tasks. In SVM, the learning problem is converted into an optimization problem of arched quadratic programming (Mohan et al., 2020), which can theoretically obtain the globally optimal solution, as shown in Fig. 9. $\phi_{(ai)}$ are the vectors

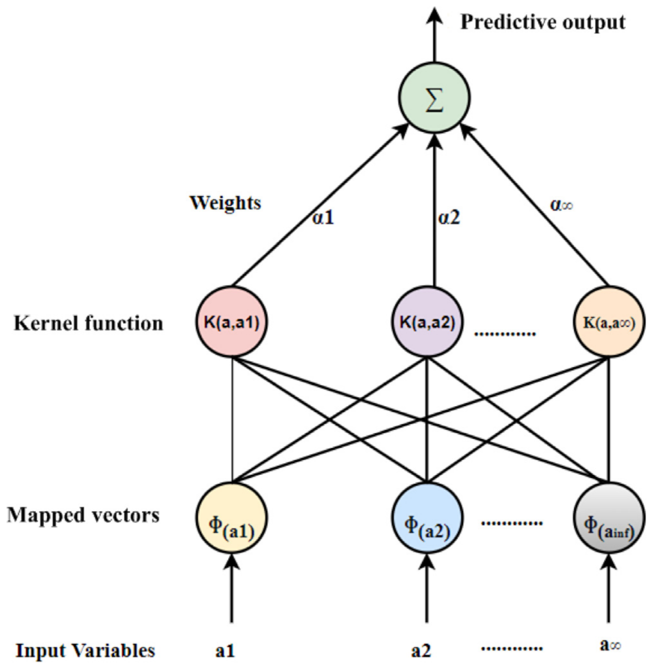

Fig. 9. SVM training model structure.

mapped in the original dimension whereas $K(a(i), a(i+1))$ is the value obtained when the data point is projected to the higher dimension. The efficiency of the classification in the higher dimension depends on the selected kernel performance. The primary goal of Zendehboudi et al. (2018) is to discuss how to make decisions about load management to reduce grid load. The house model is a local storage network battery with an integrated PV system. The parameters Grid, battery SOC, and day/night/type of load are evaluated. As a result, the controller can make decisions based on the status of the parameter. The SVM algorithm is proposed and compared to the Artificial Neural Network (ANN) algorithm for proper decision-making. The accuracy of SVM algorithm improves in the proper utilization of RES, reducing the load on the grid compared to ANN. SVM model named ("influencing factors - energy demand") is developed in Ma et al. (2018) for which the energy demand data of building from 2000–2014 is used as test samples. The performance of this model is examined using the squared correlation coefficient (r2) and Mean Square Error (MSE) using statistical error tests. The SVM model has been proven by giving the building energy consumption output equal to statistical data. The operation of IREMS, which effectively performs switchover between local storage and the grid to energize the loads, is validated using an SVM classifier and a laboratory model setup (Arun and Selvan, 2017). The energy savings by the IREMS are calculated using a load profile for a residential premise, which turned out to be significant.

6.2. Decision trees

Classification and regression are the most common applications using machine learning. Decision trees are used to achieve these tasks, but decision trees are most commonly used for classification and are often referred to as decision tree classifiers (Hu et al., 2009; Bertsimas et al., 2017; Alsagheer et al., 2017). The term tree indicates the structure of the classifier. The dataset is indicated at the top level, called the root node, nodes in the decision tree classifier indicate the attributes of the data, and branches connecting the nodes are the decisions taken by the classifier. The leaf node denotes the final result of the classifier. The architecture of decision trees is shown in Fig. 10. Steps to be followed to design a decision tree are:

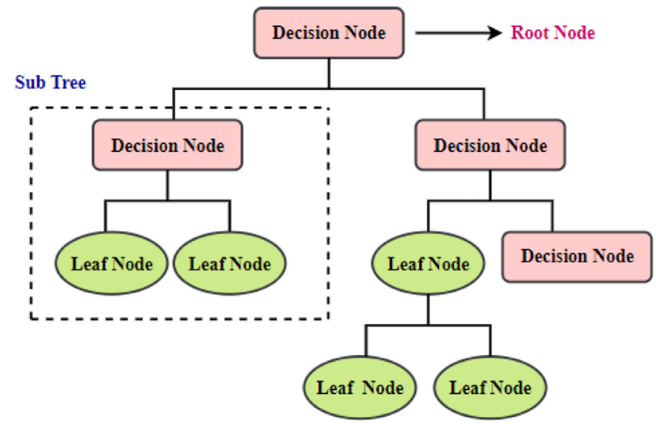

Fig. 10. Structure of Decision tree.

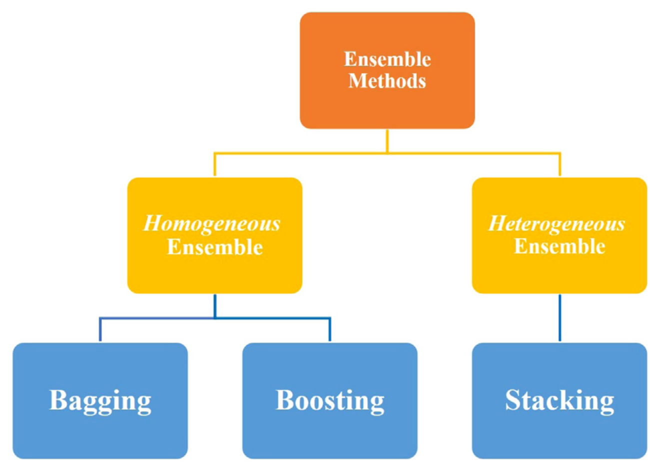

Fig. 11. Classification of ensemble methods.

- Step 1: The first level of the decision tree consists of the root node, which consists entire dataset, says S.
- Step 2: Aiming the available attributes, the best is selected using Attribute Selection Measure (ASM).
- Step 3: Data is further divided into subsets, making sure that the selected attribute has the best value
- Step 4: A node is created in the decision tree with the best value of the attribute.
- Step 5: Various decision trees are recursively designed using the subsets of the dataset created in step 3.
- Step 6: Process is repeated until it reaches the final node, where the lead node is encountered.

6.3. Ensemble methods

Multiple models (commonly referred to as "weak learners") are trained to tackle the problem and integrated to get better results underneath the ensemble learning paradigm of machine learning. The basic claim is that by combining weak models, more precise and reliable models are designed.

Advanced ensemble techniques are classified into two categories. They are homogeneous and heterogeneous ensemble methods. Fig. 11 shows the classification of ensemble methods and their brief explanation is given below:

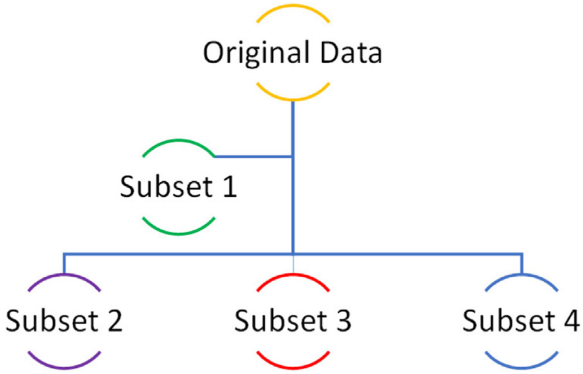

Fig. 12. Bagging technique overview.

1. Homogeneous ensemble:
Models of a homogeneous ensemble all use the same base learning method. Bagging and Boosting are the two popular techniques that generate a great diversity by assigning weights or sampling to training examples. However, they typically only use one type of base classifier to create the ensemble.

    - Bagging:
    The Bagging technique for integrating the outputs of various models (for example, all decision trees) to create a more generalized result. If we build all models on the same data set and then integrate them for a given input, there is a strong probability that these models will generate the same output. Bootstrapping is one such strategy. The subsets (bags) of data are used in the Bagging (or Bootstrap Aggregating) technique to obtain a good idea of the distribution (complete set). The size of the bagging subsets may be smaller than the original set, as shown in Fig. 12. Bagging's primary drawback is that it enhances model accuracy at the expense of interpretability. The inability to identify which features are to be selected while sampling is another drawback of Bootstrap Aggregation.
    - Boosting:
    A set of algorithms known as "Boosting" transforms weak learners into strong learners. Boosting technique is used for enhancing the model predictions of any learning algorithm. The basic idea of this technique is by sequentially training the weak learners, each learner is trying to improve its antecedent and converting them into strong learners.
    Comparing bagging and boosting as shown in Fig. 13, it can be seen that weak learners in bagging are trained parallel using randomization, whereas the learners in boosting are trained sequentially with each learner aiming to minimize the errors of the learners former to them. For classification and regression problems, both bagging and boosting techniques can be used. Boosting has the drawback of being sensitive to outliers because every classifier is required to correct the mistakes made by the previous. As a result, the technique is overly reliant on outliers.

2. Heterogeneous ensemble :
Decision trees, SVM and ANN comes under the heterogeneous ensemble, which consists of models having different base learning algorithms. Similar to boosting, a prominent heterogeneous ensemble technique is stacking.

    - Stacking:
    Stacking is a technique that builds a new model by combining predictions from multiple models (for example: K-Nearest Neighbours (KNN), decision tree, or SVM). On the test set, this model is utilized to make predictions. In contrast, blending is similar to stacking, except it only makes predictions using a holdout (validation) set from the train set. To look at it another way, unlike stacking, the predictions are based solely on the holdout set. The holdout set and predictions are combined to create a model that is then tested on the test set.
    From Fig. 14, the distinct samples are not taken for training data to train classifiers. Instead of, training is done for each classifier individually using the entire set of data. Each classifier in this process functions independently, allowing for the use of classifiers with various techniques and hypotheses. As an example, training the current model using a decision tree, a random forest, and a linear regression classifier and then merging their predictions using SVM.
    The advantage of stacking is that it can combine the positive aspects of several effective models to perform classification or regression tasks and produce predictions that perform better than any individual. However, when dealing with large datasets, the computational time will be higher because each classifier will need to work independently on the large dataset.

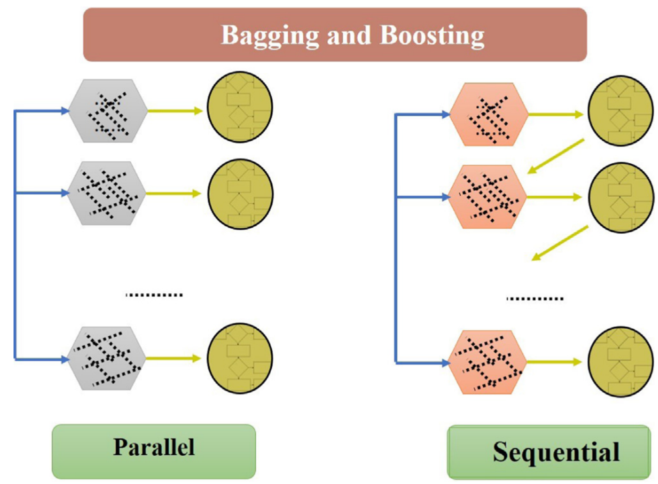

Fig. 13. Comparison of boosting and bagging technique.

In these Ensemble methods, individual models are combined in this technique to improve the model's stability and predictive capability. As illustrated in Fig. 15, it permits better predictive performance and combines many ML models into a single predictive model. This method is based on learning several simple models and combining their output to produce a final decision (Lutins, 2017). It provides composite production with absolute accuracy that exceeds that of individual models. These methods gain accuracy and robustness by combining data from numerous modelling approaches (Li et al., 2009). The limitation of this approach is assigning equal weights to different models even though some models perform better than others.

Max Voting, Averaging, and Weight averaging are the three basic/simple ensemble techniques, and the max voting approach is frequently used (Veni and Rani, 2014; Singh, 2018). To develop predictions for each data point, this method utilizes multiple models. The predictions of each model are counted as a 'vote.' The final prediction is based on the majority of the models' predictions. In averaging, many predictions are made for each data point, similar to the max voting technique. The average of all the model predictions are applied to this technique to make the final prediction. In regression problems, averaging can be used to make predictions and estimate probabilities in classification problems. The Weight of each node is also considered an averaging technique.

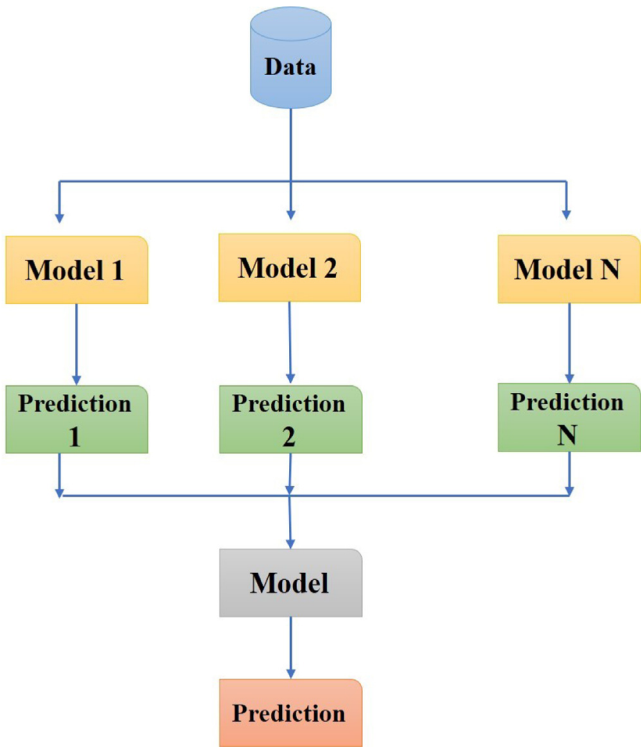

Fig. 14. Stacking technique overview.

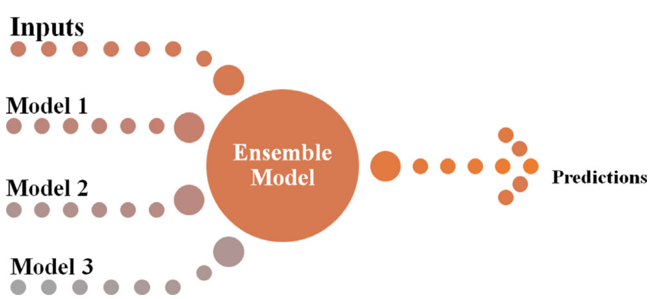

Fig. 15. Working of ensemble methods.

7. Deep learning (DL)

DL is a subset of ML inspired by the functionality of neurons that led to the concept of ANN. It is implemented with the help of deep neural networks with multiple hidden layers, as shown in Fig. 16. DL collects the data of all the Artificial neurons and adjusts the data pattern (Vargas et al., 2017). DL needs enormous data in terms of data interpretation compared to ML. ML will divide the problem into different parts for the problem-solving approach and solve them individually with suitable algorithms, whereas DL is end to end solving approach (Shrestha and Mahmood, 2019). Based on what it has learned, ML uses algorithms to parse data, learn from data and make informed decisions (Zhang et al., 2018; Alzubaidi et al., 2021). Decisions in DL are taken by the training obtained in the layers present in the structure of DL. The weights of each node determine the accuracy of the algorithm.

7.1. HEMS with ANN

The ANN-based HEMC presented in Ahmed et al. (2016) used a Feed-Forward neural network type and the Levenberg–Marquardt algorithm to train the ANN. Four domestic loads, namely EWH, AC, REF, and WM, were simulated considering physical and operating characteristics. Collecting the demand response data, HEMC is applied to achieve cost and power optimization. The suggested ANN controller switches the EWH, AC, REF, and WM, allowing the loads to remain within the demand limit value. The HEMS presented in Ashenov et al. (2021) is based on Q-learning and ANN. The system schedules appliance consumption based on its type to reduce overall electricity bills and discomfort while minimizing overloading. A Load Management Algorithm (LMA) that functions based on Artificial Neural Network forecast models is developed on HEMS (Mahapatra and Nayyar, 2019). The proposed LMA-based HEMS helps increase non-conventional DGS usage in the household load sector. Using NN and NARX prediction models, it is demonstrated that the suggested HEMS performs energy integration. A multi-objective optimization method has been designed by combining the two specified strategies in order to decrease cost and maximize the comfort level simultaneously (Rochd et al., 2021). Electricity costs, prediction data, and customer preferences have all been considered while controlling power flow. The simulation findings show that energy management can lead to significant cost reductions. The growing impact of these savings has a significant effect on PV system profitability. Yuce et al. (2016) proposes an intelligent scheduling system based on ANN and GA. The proposed scheduling methodology aims to reduce grid energy usage based on weekly generated appliance schedules.

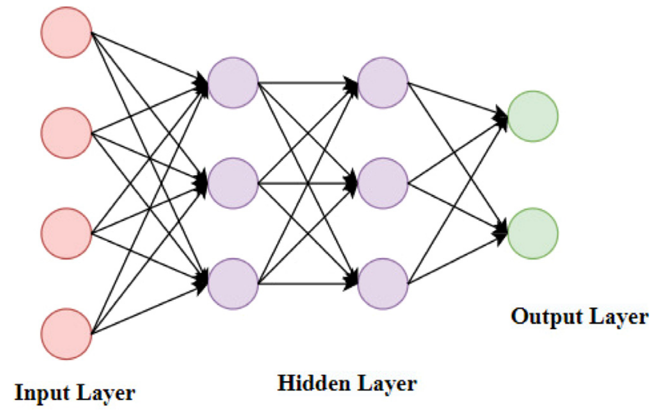

Fig. 16. Deep learning neural network.

A Poly Function Approximation (PFA) algorithm with Machine Learning is proposed (Keerthisinghe et al., 2018) to minimize the electricity cost. It focused only on scheduling to reduce the grid energy usage without considering other constraints. Gaussian Process Regression (GPR) with ML is used to calculate the system parameters, and it is an efficient tool between the user and utility (Ahmed et al., 2020). To forecast the energy consumption, a comparison of three ML algorithms, SVM, K-NN, and ANN (Shapi et al., 2021). SVM is proven to be better than KNN and ANN. A smart home consists of both thermal & electrical controlled loads. Still, when DER are integrated, the system complexity increases because DER's power varies daily, monthly or seasonally. Due to this, the user cannot predict how to manage the load. A short-term power prediction is made using ML algorithms based on current power use for one week. Foremost power consumption data has been separated into train and test data sets. Eight ML models are done and compared based on the data set. Data training calculates Root Mean Squared Error (RMSR) and Mean Absolute Error (MAE). The eight models of MAE and RMSR are compared (Din and Marnerides, 2017), and the results show that among all RBF models is the most suitable machine learning algorithm, but the computation time is more. In Krishna Prakash and Prasanna Vadana (2017), a residential energy management system (REMS) had proposed efficiently switching loads to renewable sources based on its charging–discharging and on-grid

Table 2
Comparison of ML algorithms.

Ref.	Optimization technique	Aim	Achievement	Drawbacks
Shapi et al. (2021)	SVM, KNN, ANN	To forecast energy consumption	SVM is more efficient compared to other two techniques	More time taken to run algorithm
Krishna Prakash and Prasanna Vadana (2017)	ANN,SVM	Automatic switchover of Appliances	SVM is more efficient compared to ANN	Comparison is not shown graphically
Ahmed et al. (2020)	Gaussian Process Regression (GPR) with Machine learning (ML)	To calculate system Parameters	Compared to PSO and GA, the results show ML is effective tool for designing EMM	Users' satisfaction and PAR is ignored
Gariba and Pipaliya (2016)	Naïve Bayes Classifier	To mitigate more energy consumption	Using this technique, the total cost of electricity is minimized	This algorithm shows poor performance in real systems
Keerthisinghe et al. (2018)	Poly Function Approximation (PFA) algorithm with Machine Learning (ANN)	Cost minimization	Compared to MLIP the proposed techniques show best results in dynamic programming	Estimating day ahead energy demand
Xu et al. (2020)	Reinforcement Learning (RL)	Controlling appliances	Using proposed method control and decision making and future challenges in electrical power system	No other comparison is done with other methods
Mnih et al. (2015)	Deep Reinforcement Learning (DRL)	To improve energy sharing	The proposed method optimizes energy transactions across buildings in order to achieve a net zero energy balance	No RES is preferred
Rajasekaran et al. (2017)	ACO and Machine Learning	To reduce energy consumption	ML is used for analyzing energy patterns and further reduce the energy consumption	Without integration of PV and EV
Liu et al. (2020b)	Double Deep Q-Learning (DDQL)	Scheduling Appliances	This method is more efficient compared to PSO	Without integration of PV and EV

Table 3
Comparison of overall techniques.

Technique	Advantages	Disadvantages
Conventional	These techniques are useful since they will lower overall energy consumption and have a long-term impact on the sustainability of the facility. Using less energy will result in long-term financial savings, decreased greenhouse gas emissions, and environmental sustainability.	Over a longer span of time, they have little impact on the total quantity of energy utilized in the building.In this regard, DSM programs are riskier since expected energy price reductions would result in lower financial savings and a longer payback period.
Meta-heuristic	Acquiring the solution accurately and quickly. It is simple to acclimate to the user's various preferences.	Generally time-consuming for resolving complex optimization matters and analytical methods suffer from slow convergence.
Math-heuristic	Solves large scale linear problems accurately,give a proper solution that is especially helpful for difficult issues and has unique properties like self-protection and self-organization	computational complexity is high, sluggish convergence, and difficulties in selecting the best control parameters can all lead to inaccurate results.
Artificial intelligence	ML solves the problem by dividing it into sub-parts, solves these sub-parts individually and takes less time for training data. Whereas DL can work on large amount of data, depends on larger machines and takes less execution time for testing data.	ML works on smaller data sets and are dependent on lower machines. For testing data, the execution time will be more.As DL takes more time for execution it works on large amount on data.

availability to reduce power consumption through the grid. Using ANN, SVM, and Machine learning algorithms, automatic switches over had performed to suggest optimized human-like decisions. A comparison of ANN and SVM proves that the accuracy is higher in SVM, but user comfort is neglected with the reduction in PAR. Rajasekaran et al. (2017) proposes an experimental approach of using NILM technology by establishing the sub-metering system for each load to estimate its future development using bin packing algorithms. The ML Algorithm controls the feedback systems to create an energy-efficient smart home and smart grids, and the limits are similar to Krishna Prakash and Prasanna Vadana (2017). HEM optimization strategy (Liu et al., 2020b) is proposed for scheduling appliances using Double Deep Q Learning (DDQL) and Deep Q Learning (DQL). To ensure discrete decision-making, price prediction is required for the Optimal Load Management method, which can be developed utilizing an RTP algorithm and human activity prediction. Gariba and Pipaliya (2016) presents a method for reducing energy usage by combining the Naive Bayes classifier and Hidden Markov Model to model human behaviour.

In achieving efficient home-based DR, Xu et al. (2020) proposes an RL-based home energy management, but how the power consumption is decreased is not shown. RL is applicable for controlling and supporting appliances in a dynamic environment (Thrun and Littman, 2000; Glavic et al., 2017). Better results are shown in Mnih et al. (2015) using Deep reinforcement learning (DRL) with both DL and RL. DL helps in learning features from a vast amount of data and making RL suitable for solving many problems. A fully automatic EMS based on RL is proposed (Nguyen et al., 2017) to make the best decisions for customers. Regarding cost dissatisfaction to control electric drives, deep reinforcement learning was used in HEMS (Vázquez-Canteli et al., 2019). In HEMS, DRL was applied by integrating ML with simulation and battery energy storage. For storage scheduling in microgrids (François-Lavet et al., 2016) with a different types of controllers, Deep Q-learning was proposed but focused mainly on scheduling by neglecting PAR. Multi-agent DRL was proposed to improve energy sharing in Prasad and Dusparic (2019). Two reinforcement learning algorithms (Mocanu et al., 2018) were applied for optimal control problems in the building but not concentrated on short-term and long-term stability. Table 2 shows different ML algorithms comparison and the comparison of ML with Meta-Heuristic Algorithms (see Table 3).

8. Conclusion

This article discussed the evolution of optimization techniques from math heuristic to Meta heuristic and AI-based optimization. Although math heuristic techniques can solve large and complex problems, their inability to include the non-linearity constraints and problems like the rise of high dimensionality has made them vulnerable to modern problems. Meta-heuristic methods, also called nature-inspired algorithms, serve as a better alternative to the math heuristic approaches. Still, the premature convergence and high optimization time for significant variable problems lead to incompatibility for many real-life scenarios. The smart optimization techniques based on AI are the future of optimization, as it is capable of parallel processing, pattern recognition and better decision making. Further, this study can be extended to implementing Deep Reinforcement Learning in HEMS.

CRediT authorship contribution statement

Mounica Nutakki: Writing – original draft, Conceptualization, Methodology. **Srihari Mandava:** Supervising, Reviewing at each stage and editing.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Dr. Srihari Mandava reports a relationship with VIT University that includes: employment.

Data availability

No data was used for the research described in the article.

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