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Review

Smart home energy management systems: Research challenges and survey

Ali Raza [a], Li Jingzhao [a,*], Yazeed Ghadi [b], Muhammad Adnan [c], Mansoor Ali [d]

[a] School of Electrical and Information Engineering, Anhui University of Science and Technology (AUST), China
[b] Department of Software Engineering, Al Ain University, United Arab Emirates
[c] Department of Electrical Engineering, National University of Computer and Emerging Sciences (FAST), Chiniot-Faisalabad Campus, Pakistan
[d] Postdoctoral Research Fellow, Electrical Engineering Department, Ecole de Technologie Superieure, ETS, Montreal, Canada

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ABSTRACT

Electricity is establishing ground as a means of energy, and its proportion will continue to rise in the next generations. Home energy usage is expected to increase by more than 40% in the next 20 years. Therefore, to compensate for demand requirements, proper planning and strategies are needed to improve home energy management systems (HEMs). One of the crucial aspects of HEMS are proper load forecasting and scheduling of energy utilization. Energy management systems depend heavily on precise forecasting and scheduling. Considering this scenario, this article was divided into two parts. Firstly, this article gives a thorough analysis of forecasting models in HEMs with the primary goal of determining whichever model is most appropriate in a given situation. Moreover, for optimal utilization of scheduling strategies in HEMs, the current literature has discussed a number of scheduling optimization approaches. Therefore, secondly in this article, these approaches will be examined thoroughly to develop effective operating scheduling and to make wise judgments regarding

Abbreviations: ABCOA, Artificial Bee Colony Optimization Algorithm; AC, Air Conditioner; ACF, Autocorrelation Functionality; AI, Artificial Intelligence; ANFIS, Adaptive neural fuzzy inference system; ANN, Artificial Neural Network; AQPSO, Adaptive Quantum-behaved Particle Swarm Optimization Algorithm; AR, Autoregressive; ARIMA, Autoregressive Integrated Moving-Average; ARMA, Autoregressive Moving-Average; ARMAX, Autoregressive Moving Average with a Variable; BDCloud, Big Data and Cloud Computing; BFO, Bacterial Foraging Optimization; BigComp, Big Data and Smart Computing; BPSO, Binary Particle Swarm Optimization; CNN, Convolutional Neural Networks; CSM, Clustered Sequence Management; DE, Differential Evolution; DER, Distributive energy resources; DG, Distributive Generation; DI, Discomfort Index; DL, Deep Learning; DMOBCC, Discrete Multi-Objective Bacterial Colony Chemotaxis Algorithm; DRL, Decentralized Deep Reinforcement Learning; EDA, Estimation of Distribution Algorithm; EP, Evolutionary Programming; ES, Evolutionary Strategies; ESS, Energy Storage System; FARMAX, Fuzzy autoregressive moving average with an exogenous variable; FC, Fuzzy Cluster Analysis; Fed Avg, Federated averaged; FHT, Fast Hartley Transform; FL, Fuzzy Logic; FQI, Fitted Q-iteration; FR, Fuzzy Reasoning; FRL, Federated Reinforcement Learning; FWA, Fireworks algorithm; G2V, Grid-to-Vehicle; GA, Genetic Algorithm; GD, Gradient Descent; GRG, Generalized Reducing Gradient; HEDE, Harmony EDE; HEM, Home Energy Management; HEMC, Home Energy Management Controller; HEMS, Home Energy Management System; HGPO, Hybrid GA-PSO; HMI, Human-machine interaction; HPEMC, Heuristic-based Energy Management Controller; IA, Interruptible; IoE, Internet of Energy; IoT, Internet of Things; IRLS, Iterative Reweighted Least Squares; ISGT, Innovative Smart Grid Technologies; LES, Least Squares Estimation; LF, Load Forecasting; LMS, Least Mean Square; LP, Linear Programming; LSA, Lighting Search Algorithm; LSSVM, Least-squares Support Vector Machine; LSTM, Long Short-term Memory; LWR, Locally Weighted Regression; MA, Moving Average; MAPE, Mean Absolute Percentage Errors; MAS, Multi-Agent System; MCMC, Markov Chain Monte Carlo; MDPs, Markov Decision Processes; Meta-RL, Meta-Reinforcement Learning; MILP, Mixed-integer linear programming; MINL, Mixed integer nonlinear; MINLP, Mixed-Integer Non-Linear Programming; MIP, Mixed-Integer Programming; MMR, Mid-Market Price; MMSE, Minimal Mean Square Error; MOMINLP, Multi-Objective Mixed Integer Non-linear Programming; MRAN, Minimum Resource Allotting Network; NIA, Non-interruptible; NILM, Non-intrusive load monitoring; NLP, Nonlinear Programming; NSGA-II, Non-Dominated Sorting Genetic Algorithm-II; OHEMS, Optimal Household Energy Administration System; PSA, Power Shiftable; P2P, Peer-to-peer; PACF, Partial Autocorrelation Function; PAR, Peak-to-Average Ratio; PBO, Polar Bear Optimization; PCA, Privacy-Perseverance Principal Component Analysis; PCC, Point of Common Coupling; POMDP, Partly Observable Markov Decision Process; PSO, Particle Swarm Optimization; PV, Photovoltaic; QP, Quadratic Programming; RB, Radial Bases; RBF, Radial Basis Function; RL, Reinforcement Learning; RMSE, Root Mean Square Error; RTES, Real-time Electricity Scheduling; RTP, Real Time Pricing; SAPSO, Stimulated Annealing Particle Swarm Optimization; SARSA, State-Action-Reward-State-Action; SG, Smart Grid; SLT, Statistical Learning Theory; Social Com, Social Computing and Networking; SOn, Semester On; SPRMAN, Security Protocol Review Method Analyzer; SQP, Sequential Quadratic Programming; SRWNN, Self-Recurrent Wavelet Neural Network; SSC, Semi-Supervised Clustering; SSNN, Smart Superficial Neural Network; SSVRCCS, Seasonal SVR with Chaotic Cuckoo Search; STLF, Short-term Load Forecasting; SVM, Support Vector Machine; SVR, Support Vector Regression; ToU, Time of Use; V2G, Vehicle-to-Grid; V2H, Vehicle-to-Home; V2X, Vehicle-to-Something.

* Corresponding author.
E-mail addresses: 2020190014@aust.edu.cn (A. Raza), jzhli@aust.edu.cn (L. Jingzhao), yazeed.ghadi@aau.ac.ae (Y. Ghadi), m.adnan@nu.edu.pk (M. Adnan), mansoor.ali.1@etsmtl.net (M. Ali).

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usage of these techniques in HEMs. Finally, this paper also presents the future technical advancements and research gaps in load forecasting and scheduling and how they affect HEMs activities in the near future.

1. Introduction

Electricity is probably the most widely adaptable energy source in present-day economies around the globe, it is inextricably related to both social and financial advancements. The rise in electrical power has surpassed that of all other fuels, resulting in steadily rising proportions in the entire fuel mix [1]. As increasing, particularly rural, portions of the global population in emerging nations begin climbing the energy ladder and connecting to electricity grids, this pattern is anticipated to persist during the coming periods. The majority of the main source of power utilized by humanity, involving which is utilized for producing power, pertains from fossil fuels [2]. Fossil fuels must be switched out as they severely harm the atmosphere, ecosystems, and people's well-being as their availability will be mostly reduced through the current century. Burning fossil fuels is the main cause of how much Green House Gas (GHG) emissions from human activity, particularly CO2, are released into the earth's atmosphere. As a consequence, the projected generation of electricity is inextricably connected to GHG emissions and climate

Fig. 1. Information flow presented in this paper.

change caused by humans [3]. The foundations of the evaluation of projected environmental damage brought on by human activity are estimates regarding how the worldwide energy infrastructure will evolve across the coming millennium. As both global warming and environmental degradation are acknowledged as serious issues, power infrastructure architects, administrators, energy legislation makers, authorities, and creators globally are concentrating on employing and minimal pollution sources of energy for the generation of electricity. As a result, the growth of carbon-free methods for power generation should pay special attention to how significantly electricity contributes to the worldwide emissions of green house gases [4]. Nowadays globe's energy needs are met by Renewable Energy Sources (RES). Biomass, waterpower, geothermal energy, wind, solar power, and nautical energy are all included in RES. The green renewable power source is primary, pure, and limitless source of electrical energy. Authorities all across the globe are promoting saving energy, providing incentives for individuals who consume less power, and putting clean energy sources into practice [5]. Other options include reducing energy and utility prices through the establishment of productive renewable energy systems, alerting customers to their consumption of energy, using appliances that save energy, swapping out conventional devices for smart ones, and utilizing modern power communication technologies [6]. There are various benefits of using clean energy and power-efficient technology, reduction in global warming, better sustainability in the power industry, improved supply safety. Generating little residual waste, having little influence on the ecosystem, and sustained for the near future in light of socioeconomic and ecological concerns [7]. The electrical infrastructure becomes more complicated and variable because of green power supplies. Power professionals consider minimizing and monitoring energy utilization to reduce costs and promote sustainability. Accurate and real-time information on the usage of energy is needed to manage utilization and efficiency [8]. Due to the inability of existing grids to supply this requirement, consumers are not actively involved. As a result, the existing grid are transforming towards smart grids (SGs) [9]. The complete information flow presented in this paper is shown in Fig. 1.

A power network called the SG enables two-way communication between the utility and consumers. To effectively offer a sustainable, affordable, reliable supply of power, it incorporates the behaviors of all individuals who are related, including suppliers, customers as well as those who capitalize on both [10]. Household units in China use forty percent of the total power produced as per United Nations Statistics Division. SG vision thus demands consumer's involvement in system functioning, power market, and administration of energy. Smart grid infrastructure and equipment must be sensitive to scenarios involving household power usage. Home Energy Management System (HEMS) technologies are those that are capable of responding to changed situations on their own, without human involvement [11]. The HEMS model of SG is shown in Fig. 2.

HEMS is an intelligent energy management system that enables homeowners to track the production, storage, and utilization of energy as shown in Fig. 3 [12]. A personal smart device for real-time control and surveillance of various functioning methods of intelligent home devices via communication and sensing methods employed in homes [13]. The framework of HEMS is a feedback control system in which the difference error between output and the input signal is controlled through feedback from sensing devices by analyzing the user interface panel to give instructions to intelligent appliances [14]. HEMS provides various functionalities such as: Keeping a tab on how electrical components operate and conveying essential information regarding the real-time energy consumption of every household appliance [15]; Controlling different household devices either manually or wirelessly; Administration towards power production, preservation, and utilization; An alarm will be sent if any anomalies are identified; Keep record related to energy and real-time pricing in order to reduce power consumption [16].

HEMS is essential nowadays due to their ability of computerization and suggestions in HEMS operation, which reduce power wastage, and results in efficiency improvement. HEMS are demand-response implements that shift and reduce demand to better a consumer's home's generation and use of energy profile [17]. HEMS is crucial for real-time monitoring and implementation of renewable energy sources, permitting a greater application of green energy while raising the advantages of capital investments [18]. HEMS provide residents with a greater degree of autonomy regarding the amount of power consumed in the home by making it simple to allow them to manage it in keeping with their choices, plans, and living [19]. Homes will be ready to cope with the evolving power market, due to the HEMS's capacity to respond to shifting power patterns, innovations, and legalities. For the purpose to conserve power, reducing the consumption of electricity, and producing environmentally friendly houses, smart homes are developed, constructed, intended, and operated uniquely from conventional homes. The adoption of smart HEMS has become increasingly appealing for power companies and clients because of dealing with energy scarcity and rising demand for load. HEMS is vital these days as smart cities, smart homes, and modern civilizations all depend on it [20]. The rising growth of smart electricity systems leads to a greater demand for load forecasting (LF) because accurate, resilient, and effective smart electricity systems are dependent upon accurate forecasts of generation, consumption, and preservation. Forecasting enables power strategists to recognize how certain factors affect energy usage and helps them make recommendations. Hence, HEMS makes crucial techniques and tactics for making an informed decision, enhancing household effectiveness

Fig. 2. Smart grid model.

Fig. 3. HEMS model.

and possible use of energy [21]. HEMS use LF approaches to assist them make choices about energy management and preparing enhancements that can assist them to deliver effective and dependable energy operations [22]. LF of residential energy consumers will become even more crucial in the design and management of the smart grid [23].

Load forecasting is a method employed to foresee the amount of electricity necessary in order to constantly equilibrium the availability and load conditions. The most crucial data for organizing and supplying energy is obtained from load predictions. Additionally, it is crucial for the administration of the energy system [24]. The main purpose of forecasting load is to predict the future load on a system for a specified time period. LF may be categorized into three primary categories: Long-term LF is employed to forecast load up to 50 years in advance for expanding planning [25]; Medium-term LF often estimates load on a weekly, monthly, and annual basis, for optimal planning of operations [26]; In order to conduct daily operations and reduce costs, short-term LF is utilized for real-time load forecast on a per-hour basis for a maximum of one week. There are several advantages to short-term load forecasting (STLF) at the residential level for managing decentralized energy production, local demand, and integration into the grid [27]. In HEMS, the role of load forecasting is typically utilized for balancing both the demand and supply of electrical power. A time-series forecasting technique is used to anticipate future electricity requirements by considering historic load variations using electrical consumption as an objective. The data from smart meters and sensors are used in the forecasting process [28]. Power sector administrators have to predict the futuristic requirement of energy with the lowest possible rate of error if they want to supply load shedding free, continuous power to the consumer. Energy providers may save several millions of money using load forecast that has a lower rate of inaccuracy [29]. The forecast of energy use is one of the major pillars of smart power management. Given that the use of energy changes with different appliances, better energy, and peak demand predictions are essential for effective scheduling, upgrades to distribution infrastructure, and energy production. In order to conserve resources, it is crucial to have reliable energy demand predictions [30]. LF enables HEMS to schedule power appliances to operate at renewables during peak demand times at low cost to maintain the stability of the power grid [31]. LF helps to determine the optimum time to charge the energy storage system during low demand and peak generation time and utilize that energy during peak demand and high consumption rate [32]. LF is effective in calculating the cost of energy and planning budgets according to their consumption [33]. For HEMS, one of the key elements is load forecasting, which is utilized for energy balance control and planning to improve convenience while paying low electricity bills [34]. One highly important consideration is prediction precision: Because the majority of choices in the field of energy must be determined by projections of future demand, decision-makers in this area require reliable forecasts.

A household desire for premium and reliable power is on the rise as the IT era emerges into reality. Bidirectional exchange of information, modern metering structures, battery backups, and home area networks will transform the nature of utilization of electricity and conserve energy at usage premises via the entry of the intelligent grid era alongside the development of sophisticated connectivity and data infrastructures that connects different types of equipment and resources collectively [35]. As a result, with the consumers' authorization, the HEMS could have a crucial part in the most effective collaboration and scheduling of different intelligent devices and the development of clean energy sources [36]. In order to save money on energy and reduce the power Peak-to-Average Ratio (PAR), individuals have the ability to schedule their residential energy consumption due to the emergence of the smart electricity system [37].

Scheduling in HEMS is the ability to manage residential device operations to help user to accomplish desired objectives and priorities under the constraints of time and resources available to reduce energy consumption, electricity payment, peak load demand, and maximize user comfort [38]. Effective scheduling practices involve switching at any time both schedulable electrical devices like cooling systems, heating systems, washers, laundry dryers, and electric vehicles as well as non-schedulable electrical items including screens, lighting, presses, kitchen appliances, and portable devices [39]. In order to design the most effective appliance scheduling, a variety of schedule control techniques have been utilized. scheduling energy use while considering several strategies [40]. Prior to scheduling, Distributive Generation (DG), Real Time Pricing (RTP), and Demand response (DR) output power must be delivered to the energy management control. RTP uses the predicted statistics. To provide fully autonomous management of home appliances, every device has smart plugs, and a scheduling system controller will connect to every terminal via wireless communication networking [41]. HEMS used to schedule home devices by shifting or curtailing loads by taking advantage of the DR program to run appliances at the time of low rates of electricity ensuring users' comfort [42]. HEMS schedules heavy-load appliances to consume power from clean energy resources when there is peak demand or rates are high for using grid power, this result in reducing the grid's burden and ensuring its stability [43]. With the help of gadgets that measure energy usage patterns at the appliance levels and continually track how much electricity is used by different home electronics. Hence, HEMS gives a variety of consumption schedules in an effort to save power plus annoyance expenses [44]. To ensure for all electrical equipment functions properly for the duration of their lifespans, routine maintenance is performed upon them. Finding a schedule for a servicing interruption of electrical units over a certain length of period is the aim of the maintenance schedule by HEMS [45]. HEMS allows a schedule of power storage devices to store energy at peak generating times from the grid or renewable sources and consume at a high time of use rate [46]. HEMS helps in scheduling appliances according to seasonal conditions temperature, wind, snow or rain, and sunlight or clouds to provide user comfort [47]. HEMS automatically performs the scheduling of appliances to balance demand and supply [48]. The reduction of power expenses and simpler device scheduling are the main goals for home users [49]. The extent to which the consumer desires to utilize an appliance at the needed time instant and for the appropriate time duration, resulting in the desired convenience, is known as customer pleasure in a home. Hence, HEMS utilizes load forecasting and scheduling which plays an important role in smart energy management systems [50].

With various emphases, many publications have examined recent research on load forecasting systems for HEMS. Rolling-Ant Lion Optimizer-Grey Modeling (1, 1)) was presented in [51]. To assess its efficiency and viability, two instances of yearly electricity usage in China and Shanghai city were chosen. The result proved significantly improved annual power load forecasting accuracy. A novel energy load forecasting approach utilizing Deep Neural Networks presented in this study [52], namely LSTM-based Sequence to Sequence (S2S) architecture performing well in one-hour resolution data. In [53], the suggested model predictive controller had 96–98% optimal efficiency with excellent long-time LF. Support Vector Machine (SVM)-based load predictive EMS used in [54], 0.004866 seconds of training and produces 100% accuracy. A Markov chain-based sampling approach in [55], was suggested as a way to provide forecasting using little computer work and less need for past data. An educational building's hourly real-world data was incorporated in [56], and reviewed using a Self-Recurrent Wavelet Neural Network (SRWNN), which reduced load forecasting inaccuracy from 8.7% to 3.7%. In [57], Deep Neural Networks resulted in efficient and resilient forecasts. For instance, Mean Absolute Percentage Errors (MAPE) and Relative Root Mean Square Error (RRMSE) decrease up to 17% and 22% in comparison to shallow neural network and 9% and 29% compared to Double-Seasonal Holt-Winters (DSHW), respectively. In [58], A straightforward approach was suggested and evaluated using three distinct designs, including Multilayer perceptron, Support vector regression, and Multiple linear regression. The proposed load forecast method has high accuracy and low computational cost. The Suggested hybrid dynamic fuzzy time series model in [59], accurately predicted the average monthly electrical consumption for all sectors with a mean error of less than 3% and a good decrease in forecast errors. In [60], the firefly algorithm was presented. The Mean Absolute Percentage Errors (MAPE) of the combined model decreased to 0.7138%, 1.0281%, 4.8394%, 0.9239%, 9.6316%, and 7.3367%, accordingly, when contrasted with each of the six distinct models by taking load data from two provinces of Australia. In [61], Modern online approaches and complicated tree-based combination techniques with a MAPE of 2.55 percent of 1 hour for 6 months were more accurate using online support vector regression than before. The study showed the effectiveness of Convolutional Neural Networks (CNN) in [62], According to experimental findings, CNN surpassed SVR despite delivering outcomes that were on par with those of ANN and deep learning techniques. This study in [63], proposed a brand-new non-intrusive load monitoring (NILM) technique that includes appliance use patterns to boost the accuracy of prediction and proactive load detection. A model founded on recurrent neural networks and long short-term memory (LSTM) in [64], evaluated on a collection of genuine household intelligent meter datasets, and its efficacy thoroughly contrasted to several comparisons load forecasting. In this investigation [65], a fresh SVR forecasting model suggested, sample information from four conventional commercial towers' taken. The result showed SVR model offers a higher degree of prediction accuracy and stability in LSTF. A seasonal SVR with chaotic cuckoo search (SSVRCCS) model [66], in order to get more precise predicting results numerical findings verified by employing the information sets from USA and Australia. Ridgelet and Elman neural networks provide the foundation for the proposed two-step forecast algorithm in [67]. To increase the precision and capabilities of the prediction engine, all of its settings are selected using a cutting-edge smart method. In [68] research presented a novel Deep Neural Network architecture for STLF useful in different time series forecasting roles, and versatile. Deep learning's potential was utilized in the investigation [69]. It showed that incorporating characteristics obtained through unsupervised deep learning as input in cooling demand forecasts may boost the effectiveness of building energy forecasting. Paper [70], provided an IoT-based deep learning system that can autonomously determine attributes of data collected and provide a precise prediction for the upcoming load level when weather conditions matter. In [71], on the basis of the particle swarm optimization regression vector machine technique, the STLF model was created. Then an adaptive pricing system was created to direct user behavior regarding power usage and modify grid demand. Utilize Seq2Seq learning in [72], to forecast photovoltaic (PV) production and a load of household appliances. In accordance with the outcomes of the forecasts, we next optimize HEMS offline using Q-learning. For the reason of designing power-management platforms, researchers in [73], offer a unique multi-behavior including bottleneck features long short-term memory (LSTM) framework that incorporates the predicted behavior of long-term, short-term, and weekly feature modeling. In [74] Regression employed linear, seasonal linear, and quadratic models were used to produce straight forward prediction model that was determined to be the best suitable for Korean seasons. The non-schedulable LF method in [75], depends on (LSTM) paradigm in combination with a semi-supervised clustering (SSC) strategy, taking into account the most significant factors that might have an impact on the electrical power use of the non-schedulable appliances. In [76], the LF residual CNN with layered LSTM framework has been proposed: the first phase of data purification and remaining CNN with LSTM network. The major objective of architecture in [77], was to provide insights into energy usage and power reliability while introducing an artificial intelligence level to energy use across a testing open-pit mine. The accuracy of the suggested dynamic combined power load forecasting technique in [78], reaches 99%. The combined system might predict unusual usage of electricity in advance and offer trustworthy support for planning manufacturing processes. Specifically, for employing multi-state gadgets in [79], the study suggested deep generative using a non-intrusive load monitoring strategy's ability to employ short-term device loading estimates instead of only past attributes is a significant benefit. This work in [80] uses the innovative STLF-Net two-stream deep learning (DL) model to overcome the issues with STLF by anticipating the last hour's head demand prediction This research [81] provided an understandable artificial intelligence (XAI)-based comprehensible deep learning method to the multi-step home load projection issue. In [82], Predicting household electrical consumption using the fuzzy cluster analysis (FC), least-squares support vector machine (LSSVM), and a fireworks algorithm (FWA). The hybrid approach presented in the current study exhibits excellent precision, and the approach is reliable and flexible. The time series clustering system proposed in this research [83], includes a multi-step time series sequence to sequence (Seq2Seq) load forecasting technique for homes. The suggested approach in [84], integrates picking features, deep learning algorithms, and multi-time scaling resemblance assessment to develop a high-accuracy and consistent load prediction algorithm for individual home residential consumers. In this paper [85], an effective hybrid AI-based system is suggested for precise power consumption and generation predictions that consist of three steps for energy data handling for better prediction and result in reduced MAPE error.

For consumers in automated houses, a variety of resources for decision-making are being stated to maximize efficiency and incorporate household appliance scheduling with power suppliers. In [86], A mathematical model for home devices' deferrable jobs is divided into interruptible and non-interruptible, as well as power-adjustable and power-nonadjustable, chores. based on Mixed Integer Non-Linear (MINL) was developed to minimize cost and improve the experience of users. In this research [87], a multi-objective automated Non-dominated Sorting Genetic Algorithm-II (NSGA-II)-based improved automated power scheduling was developed. It is aided by a NILM approach. In [88], an artificial neural network (ANN) developed a hybrid lighting search algorithm implemented to forecast the best ON/OFF condition for household devices. Appliances operated on-time more effectively as a result, saving money. In order to reduce client energy and durability expenses. In [89], an optimization strategy was suggested that takes into account the value of lost load of gadgets, power rates, and operational constraints of devices. In [90], to reduce consumer energy expenses, an enhanced artificial bee colony algorithm schedules the activity of household devices in accordance with energy pricing, clean output, and individual needs. In [91], As a consequence of predicted inaccuracies in power pricing and system loads, a chance-constrained optimization-based approach that has an elevated degree of precision is developed for scheduling load in a volatile environment. A home energy management controller in [92], utilized mixed integer nonlinear optimization. Home appliances can perform deferrable, curtailable, and critical functions. In order to lower the customer's power cost while taking the user's comfort level into consideration, devices are managed in reaction to fluctuating pricing indicators. A distributed optimization approach for scheduling is suggested in [93]. The system for storing energy and energy trade among homes are planned in the global HEMS, while the programmable household devices (such as the air conditioner and washing machine) be scheduled in the local HEMS. In [94] research offered a system for scheduling domestic devices during certain scheduling times that reduced computing complexities, reducing total cost while compromising the functioning of non-schedulable equipment. For cost and peak reduction for home power units in [95], suggested wind-driven optimization using the min-max regret-based knapsack algorithm in order to maintain their choices while efficiently controlling the main home energy loads. In order to address the unpredictability of Solar generation for load scheduling in intelligent houses linked to residential solar energy systems, a robust technique was proposed in [96]. In this study [97], a DSM framework for scheduling domestic devices using techniques (binary particle swarm optimization, genetic algorithm, and cuckoo search) was provided. The approach simulated in a scenario of time of use pricing. A mixed-integer linear programming (MILP) in [98], used to design the scheduling issue with the goal of minimizing community peak demand while adhering to restrictions that take into account the initial timings and permitted latencies for various appliances. For domestic clients, provided a power scheduling plan in [99], for establishing the appropriate balance between costs and discomfort. Integer and continuous variables are used in the formulation of the optimization issue known as power scheduling. In [100], Using a revolutionary grassroots method, algorithms quantify customer energy usage behavior to predict home demand, giving an accurate assessment of the real quantity of controllable resources to schedule appliances. This study in [101] offered a multi-objective DR optimization model that was created as a multi-objective nonlinear programming challenge constrained by a series of regulations. The framework was resolved via a Non-Dominated Sorted Genetic Algorithm (NSGA-II) to determine the scheduling of household appliances for the future to reduce cost and inconvenience as well. An enhanced genetic algorithm (GA) in [102], with great computational effectiveness and strong resiliencies presented by combining the multi-constrained integer programming approach and the genetic algorithm. In [103], To manage a smart house, real-time electricity scheduling presented. The suggested management platform seeks to reduce the cost money by carefully planning the scheduling of smart equipment and enhancing the use of green power. A stochastic Mixed-Integer Linear Programming (MILP) methodology applied in [104], to explain the self-scheduling issue, allowing for the best estimation of the state of household devices over the duration of the day and a quick convergence to optimal solution. Dragon fly algorithm was suggested in [105], as a solution to the real-world issue of smart houses. Shift able devices may be planned in accordance with the immediate price signal from the utility, which allowed them to serve a vital part in demand-side load control. This study in [106], introduced a self-scheduling approach to the HEMS applying MILP, and it recommends a unique formulation of a linear discomfort index (DI) that takes consumer preferences into consideration when determining how to operate household devices on a regular schedule. This paper [107] suggested a novel scheduling scheme for the real-time HEMS based on the Internet of Energy (IoE). The scheme is a multi-agent method that considers two chief purposes including user satisfaction and energy consumption cost. The main objective of this work in [108] to integrate a HEMS via a smart thermostat. (DR) of the air conditioning system optimized with the help of the demand response (DR) and photovoltaic (PV) self-consumption provided by MILP. A two-phase design offered in [109], to minimize the computational burden, in the initial phase assessing the hourly device scheduling while using a looser collection of constraints, and the subsequent phase considering a smaller set of equipment in an intra-hourly time frame. Utilizing the ideal load sharing energy administration method in [110], offers an equilibrium action at the output level. The success of the centralized management of energy approach in a grid-connected islanded system is validated by simulations of the HEMS method utilizing smart superficial neural network (SSNN) and numerical calculations. This article [111] suggested an affordable HEMS scheme for the micro grid architecture. The C++ framework integrates instantaneous scheduling of home devices to demonstrate the effectiveness of the proposed cost and energy reduction measures. In [112], A probabilistic optimization technique used as a result of the unpredictability of supply, demand, and power prices. The patterns of appliance operation times, battery backup, and plugin EV charging cycles, as well as power buying and selling times for the periods that followed in the selection timeline, are determined by the solution to the issue. The HEMS that was suggested in this research [113], can provide optimized load scheduling for the usage of equipment in a specific home. In [114], community loads scheduling plan that is dynamically grouped. Using particle swarm optimization (PSO) with user-defined limitations, a comparatively flatter power demand was achieved. An innovative scheduling technique in [115], for the HEMS was proposed in this study and depends on the mixed-integer programming (MIP) paradigm. the algorithm combines and takes into account total cost reduction, peak load shifting, and inhabitants' contentment with their level of thermal convenience. In order to effectively schedule appliances at home to reduce energy use, we developed an effective HEMS regulator in [116], employing a variety of heuristic optimization approaches, including Genetic Algorithms (GA), Binary Particle Swarm Optimization (BPSO), and Wind Driven Optimization (WDO). This research in [117], suggested multi-agent deep reinforcement learning optimization for immediate form multi-home energy administration including EV charging schedules. In order to communicate with each other and come at the optimal conclusion. The HEMS that was suggested in this study [118] can accomplish optimized scheduling of loads for the usage of devices in a specific residence. The approach, which relies on the genetic algorithm, offers suggestions to the client to help them better manage their home's energy requirements. Using a Meta-Reinforcement Learning (Meta-RL) framework, this research in [119], developed a portable scheduling technique for HEMS with various workloads, that can reduce data reliance and extensive learning time for other information-driven methods. A programmable heuristic-based energy management controller (HPEMC) recommended in [120], to operate an apartment complex in a way that minimizes electricity costs, lowers carbon emissions, boosts UC, and lowers PAR. In this work, a PAR and a system for energy control are used to resolve the request-responsive device schedule issue.

For the purpose of developing effective operating plans and making wise judgments on consumption and production, current research has provided a number of methodologies, including mathematical optimization, model predictive control, and heuristic control. owing to the wide range of modeling characteristics, including appliance models, timing variables, and targets, it might be hard to assess the efficacy of the methodologies in the available research.

The current study offers a review of the HEMS literary works with an emphasis on load forecasting and scheduling and their impact on HEMS functioning and results. The structure of the work that is being given makes it possible for the reader to comprehend and contrast key factors such as load forecasting, scheduling, and outcomes in well-known and recent works of literature despite going far enough inside each of them.

2. Optimization technique in load forecasting

In this section, a number of forecasting techniques are examined to determine the best equipment prediction regarding energy usage.

2.1. Multiple regression

A statistical method called regression modeling examines the connection between a dependent variable called y and any number of independent factors $x_1, x_2, \ldots x_k$ [121]. The regression technique seeks to find a model that most effectively captures the connection among these factors in order for the outcomes of the independent variables may be used to forecast the results of the dependent variables [122]. The amount of load is determined using a multiple linear regression approach with respect to an informative variable like the climate and other variables that affect the amount of electricity used [123]. The system developed via this technique has the following form:

$$y = b_0 + b_1x_1 + b_2x_2 + \ldots + b_kx_k + \varepsilon. \quad (1)$$

Where y is the load, x_i is he affecting factors, b_i is regression parameters with respect to x_i, and ε is an error term. After parameters are calculated, this model can be used for prediction [124]. Assuming that all the independent variables have been correctly identified and therefore the standard error will be small. Researchers employed this technique to meet their needs, with the objective to test the efficacy of the MR methodology adaptations for STLF in a real-world network. comparing the 24-hour load prediction with different methods. Regression model evaluation of season fluctuation [125]. To forecast the need for Irish energy, created a climate-load method utilizing regression; afterward, researchers updated it to create an adjustable regression approach to forecast morning-ahead load. Researchers created a regression-based approach to forecast energy use in relation to past meteorological information, radiation from the sun, local populace, and client category as shown in Fig. 4 [126]. The multi-linear regression models for short-term load forecasting are relatively easy to develop and update regularly with widely available commercial computational software used in these investigations [127,128].

Multiple regression analysis facilitates the investigation of connections among different devices in the HEMS. Through the simultaneous consideration of many distinct factors, including user behavior, ambient circumstances, and the kind and efficiency of appliances, this thorough study supports the creation of prediction models that may direct efficient energy management tactics at the device level.

Multiple regression offers an equilibrium between interpretability and predictive accuracy, it is a useful and easily obtainable method for load forecasting. However, it is important to carefully evaluate assumptions and data validity.

2.2. Exponential smoothing

A statistical technique for predicting time series is exponentially smoothed. It is a common method of estimating demand and it's easy to use but effective. This load prediction approach relies upon time series & solely considers usage histories with the goal to find trends previously which could be beneficial and comparable to the current load trends [129]. As a subject age, this method utilizes weights that decrease exponentially. In predicting, greater weight is often allocated to recent data compared to earlier information [130]. To create the flattened data and derive estimations, an exponential smoothing technique is applied. Certain series of information show cyclic or yearly trends that a polynomial framework cannot adequately capture. The examination of various such information may be done using a variety of methods [131]. Certain series of information show cyclic or yearly trends that a polynomial framework cannot adequately capture. The examination of various such information may be done using a variety of methods [132]. The Day-Ahead prediction approach discussed in this study was developed by Holt and Winters and is often referred to as the Winters' technique for this instance, the linear trajectory framework is given a seasonal modification. There are two different kinds of modifications employed, the multiplicative approach and the model based on additives [133]. This study employs a multiplicative theory, and the projected outcomes are computed using the calculation procedure shown below:

$$\tilde{y}_{T+h} = (a_t + h.b_T).S_{t-p+h} \tag{2}$$

$\tilde{y}_{T+h}$ - the forecasted value;
a_t - the level of the time series;
h - the time horizon;
b_T - the trend of the time series;
S_{t-p+h} - the seasonal adjustment;

Given its low performance when compared with other fitting methods exponential smoothing is a probabilistic method for forecasting which is rarely employed for load projections. Nevertheless, it may be more practical to use an easy process to feed the demand projected compared to a complex one which is likely to provide shortcomings whether a time sequence is fixed and usage is comparable to previous levels with no any significant period variation [134]. A combination of models that combines energy spectra and adaptive autoregressive modeling with exponentially smoothed models has been outlined. The best pattern elimination strategy for short-term LF is soothing. Relative to a typical prediction method, this methodology helps to reduce demand estimation inaccuracy by 12% [135]. Two different structure combinations are offered, that are employed to anticipate short-term power consumption while employing seasonally exponentially smoothed variables as their foundation models. Results demonstrate that each of the suggested pairings is capable of beating competing standards, despite the possibility that collective generation may have an impact on predicting accuracy as shown in Fig. 5 [136].

Exponential smoothing integrates at device-level based on assigning exponentially decreasing weights to previous data, spotlighting recent data while progressively reducing the impact of earlier records to predict device-level energy usage pattern depending on past usage trends.

Exponential smoothing is a useful and efficient technique for short-term load forecasting, that can adapt to shifting patterns, but it requires careful parameter tweaking.

2.3. Iterative reweighted least-squares

Transforming an irregular optimization issue into a series of regression-based challenges is the fundamental concept underlying iterative reweighted least square (IRLS). The procedure begins by estimating the framework's variables initially, updating these repeatedly unless convergence is achieved [137]. The values of the weights are changed according to the remainders from the prior step at every stage, identified the framework's sequence and variables using an IRLS technique [138]. In order to establish the best beginning point, the approach

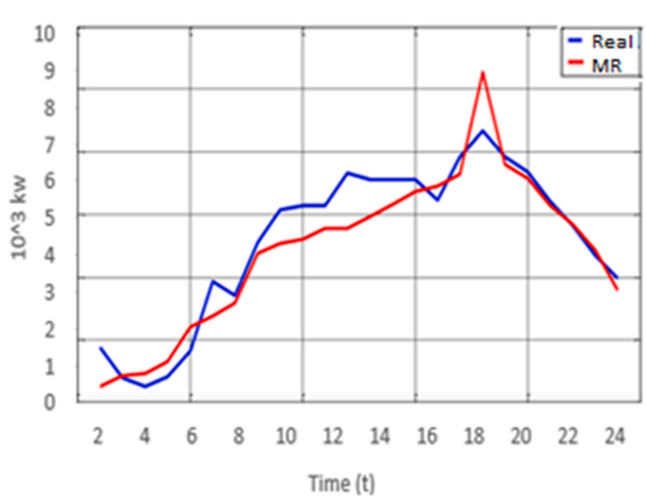

Fig. 4. load forecasting using Multiple regression [126].

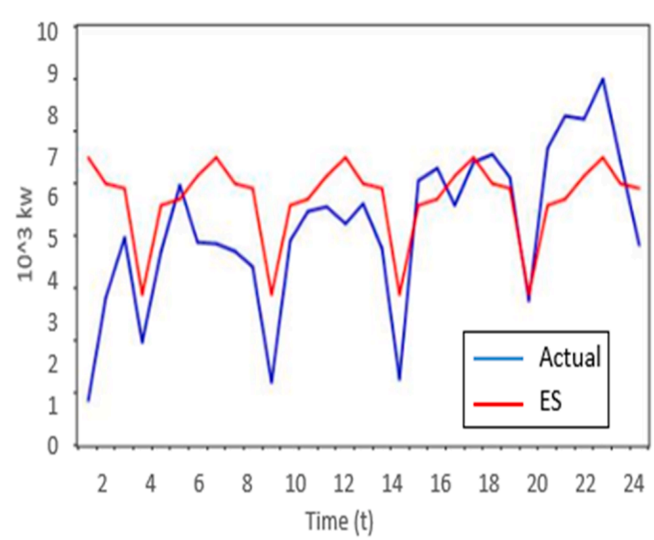

Fig. 5. Load forecasting via exponential smoothing [136].

employs a controller that manages just one factor at once. To find a less-than-ideal model of the load dynamics, the partial self-correlation function and autocorrelation coefficient for the resultant distinct previous load data is used [139]. In order to choose the ideal model to use and then estimated its parameters, a three-way decision variable is created using the weighting operate tuning parameters and the weighted sum of the squared residuals [140]. Take into account the linear measurement equation-based prediction of parameters issues, identified the framework's sequence and variables using an iteratively reweighted least-squares technique. In order to establish the best beginning point, the approach employs a controller that manages just one factor at once. To find a less-than-ideal model of the load dynamics, the partial self-correlation function and autocorrelation coefficient for the resultant distinct previous load data is used [141]. In order to choose the ideal model to use and then estimated its parameters, a three-way decision variable is created using the weighting operate tuning parameters, and the weighted sum of the squared residuals. Take into account the linear measurement equation-based estimation of parameters:

$$Y = X\beta + e \tag{3}$$

β is a p x 1 vector of the undetermined variables, e is a n x 1 vector of random deviations, and Y is a n x 1 vector of observes. X is a n x p matrix of known parameters (depending on prior loading information). The iteration approach may be used to find the unidentified vector. IRLS techniques such as Newton or Beaton-Turkey might be utilized [142]. It is described how to anticipate the per-hour heating demand utilizing an informed-by-data algorithm. The time of the day, day of each week, and day of each year are used as predictors in the technique, which relies on the Generalized Additive Model. It was mentioned how adopting the autoregressive model for the model's residuals may improve prediction accuracy. It additionally looked into how the amount of learning samples affected the algorithm's performance in Fig. 6 [143]. Suggested a collaborative strategy for evaluating the variables of a seasonal multiplicative autoregressive model using least-squares and the IRLS technique. In Scotia Energy company, the procedure was used to forecast load [144].

In order to better understand the interactions between different devices and their energy usage inside the HEMS, factors like appliance efficiency, user behavior, and ambient conditions are taken into consideration when using IRLS to regression models

IRLS is a strong method for load forecasting, particularly for non-linear correlations, but it can be highly computational and needs precise variable tweaking.

2.4. Autoregressive

An autoregressive (AR) model predicts future actions by employing information about previous behavior. This form of evaluation is employed whenever there's a relationship between time series quantities and the foregoing and following numbers [145]. Just past information is used in autoregressive modeling to forecast future behavior. Thus, an autoregressive model of order p can be written as

$$y_t = c + \varphi_1 y_{t-1} + \varphi_2 y_{t-2} + \ldots + \varphi_p y_{t-p} + \varepsilon_t \tag{4}$$

white noise (t) is. Similar to multiple regression, except that the factors that predict are based on the lag of y_t. This is known as the AR(p) model, or the autoregressive model of order p. The least mean square (LMS) technique may be used to live tweak the unidentified factor [146]. Amazingly adaptable at addressing a variety of various time series trends are autoregressive models. When load is considered as a linear aggregation of prior loads, an AR model may be employed to represent the load profile [147]. Presented two periodic autoregressive frameworks including a self-regressive approach to hourly load projections, each with an optimal cutoff stratified algorithm. Developed a technique for optimal criterion satisfying in an autoregressive system [148]. This approach eliminates subjectivity and increases the precision of predictions by determining the minimum number of variables needed to describe the chance factor [149]. Regarding hourly load prediction, two regular autoregressive (PAR) models were created [150]. A minimal range of variables is needed by the method to convey unpredictable elements and increase prediction precision. In hourly-based LF, periodic autoregressive is provided [151]. Using a foundation of past electrical load information, suggest a wavelet multiscale decomposition-based autoregressive technique for predicting of 1-h forward load. This method takes into consideration the asymmetry of the time-dependent. dataset by applying a multiple-resolution compression of a signal applying the redundancy haratus wavelets transformation. If the electrical statistics are updated often, then is an extra computational benefit because it is not necessary to calculate again the wavelet transformation of the complete signal in Fig. 7 [152].

Autoregressive method involves the modeling of present energy usage of a device as a linear combination of its historical energy consumption, considering a prior number of previous time steps. This enables the system to record fluctuations and trends in device-level energy usage in HEMS.

Autoregressive models identify temporal patterns in load forecasting, especially in short-term scenarios, though they may have downsides with non-linear pattern.

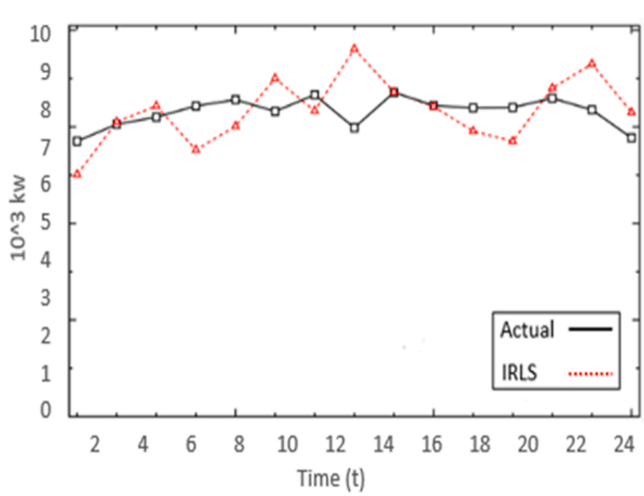

Fig. 6. load forecasting via iterative reweighted least-squares [143].

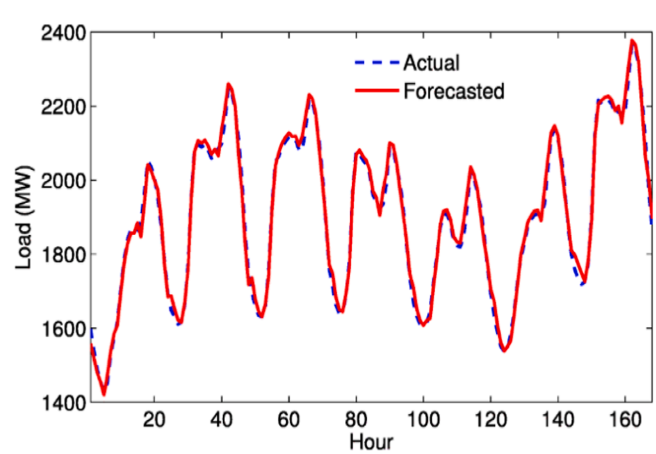

Fig. 7. load forecasting via Autoregressive [152].

2.5. Moving average

When analyzing information from time series, the moving average (MA) approach is employed to smooth off short-term swings and spot long-term patterns. It's a straight forward approach that entails computing the mean of a particular number of continuous measurements throughout time [153]. The present state of the time sequence Y (t) is calculated using a moving average models approach as a linear blend of each of the most recent and prior values corresponding to the white noise sequence. In mathematics, it is represented as

$$Y(t) = a(t) - \phi_1 a(t-1) - \phi_2 a(t-2) - \ldots - \phi_q a(t-q). \quad (5)$$

The backshift operator on white noise modifies:

$$Y(t) = \phi(B) * a(t) \quad (6)$$

$$\phi(B) = 1 - \phi_1 B - \phi_2 B^2 - \ldots - \phi_q B^q \quad (7)$$

Utilizing a weighted moving average for forecasting potential demand is an especially useful version of the MA approach [154]. The simple moving average provides an upcoming one-period-ahead prediction by taking the median of the previous k data. It suggested that each of the k observations has a comparable value [155]. The projections for anticipated demand are expressed in feet. Y_t becomes accessible whenever a fresh real-world demand phase is detected, which allows the measurement of the prediction inaccuracy, which is $Y_t - F_t$

In essence, the approach uses prediction inaccuracy to modify the estimate for the prior demanding phase [156]. It subsequently creates the following prediction horizon.

$$F_{t+1} = F_t + \alpha(Y_t - F_t) \quad (8)$$

whereα is a constant between 0 and 1.

Every fresh prediction consists only of the previous prediction including a correction considering the mistake resulting from the previous estimate. A modification factor that's close to 1 will represent an important modification value, rendering the prediction more susceptible to changes in past demand depending on the inaccuracy from the preceding period [157]. The upcoming projection, which depends on previous needs, will become more flexible when the number is near 1. The estimate will contain relatively minimal change whenever the level is near 0, keeping it less susceptible to previous fluctuations in need [158]. In this instance, the estimates for the foreseeable future will be significantly flattened and won't take into account any previous fluctuations in demand. These predictions will always lag any trends or modifications to historical demand [159]. The use of moving averages (MA) for predicting load is examined in this research illustrate in Fig. 8. The actual research at Malaysia's University Teknologi PETRONAS (UTP). load prediction used in the investigation were Semester On (SOn) and Semester Off (SOf). Later, the amount of usage load for both SOn and SOf was predicted using MA [160].

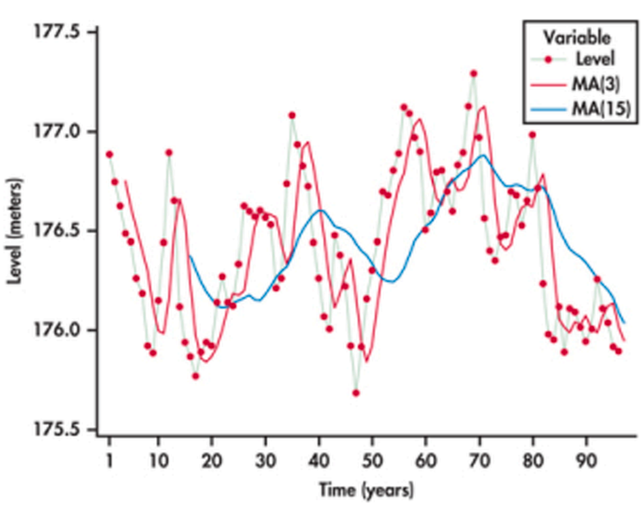

Fig. 8. load forecasting via moving average [160].

MA approach smooths out variations and reveals fundamental patterns of use by estimating the mean energy usage over a given window of time. Taking into account past data within this movable time range helps the system understand the short-term fluctuations in energy usage at the device level in HEMS.

MA is a simple and helpful method of load forecasting, particularly for smoothing data and spotting short-term patterns. However, its drawbacks should be taken into account for more precise forecasts in dynamic circumstances.

2.6. Autoregressive moving average

In order to accurately reflect the simultaneous synchronization and the moving average aspects of a time sequence, the Autoregressive Moving-Average (ARMA) method integrates the Autoregressive (AR) and Moving-Average (MA) models. The ARMA model is frequently employed in predicting time sequence analysis [161]. The time sequence' present level y(t), is linearly represented by the ARMA framework as a function of its values at earlier times [y(t-1), y(t-2),] and in units of earlier values of white noise [a(t), a(t-1),]. The design for the ARMA of degree (p, q) is expressed as:

$$y(t) = \varphi 1 y(t-1) + \ldots + \varphi p y(t-p) + a(t) - \varphi 1 a(t-1) - \ldots - \varphi q(t-q). \quad (9)$$

The variables involved are determined either via the use of a highest possible-likelihood method or via a recursive methodology [162]. Introduced a novel duration-temperature load estimation approach. According to that technique, the initial time sequences of monthly highest demands are divided into predictable and random load elements, the stochastic component of which is calculated using an ARMA model [163]. Updated the settings in their adaptable ARMA framework using a WRLS approach. Employed a flexible ARMA framework for load estimation, modifying its parameters based on the current errors in predictions [164]. The adaptive method surpassed traditional ARMA algorithms when deviation training factors were derived via minimal mean-square errors [165]. An adjustable ARMA algorithm is generated to anticipate the electrical system's short-term demand. The Box-Jenkins transmission function technique is currently rated as one of the more effective techniques for anticipating short-term loads. The precision of the Box-Jenkins method remains restricted since it does not take into account the predicting inaccuracies that can be updated. By using the minimal mean square error theory, the tailored technique first calculates the margin of error training parameters, followed by improving the predictions based upon both the one-step-ahead error predictions and their coefficients. The technique can handle every odd operating circumstance thanks to its capacity to change [166]. The sequential of simulating Greece's energy demands is discussed throughout the paper. Depersonalization of the given real load information is performed as shown in Fig. 9, and then an offline ARMA model is fitted to the data. The sequential phase and estimation of the parameters of ARMA models with distortion is carried out with the presumption of the information at hand may be described by an ARMA framework. The obtained findings demonstrate that the suggested approach is effective [167]. An ARIMA model is created to predict the short-term electricity load in New South Wales, Australia, and to correct remaining inaccuracies utilizing the weighted average technique. Reliability is improved over one ARIMA framework by this combination approach [168].

ARMA offers a thorough insight of device-level energy consumption behavior by integrating past observations and the influence of recent fluctuations, enabling the HEMS to make deft forecasts and wise judgements instantly.

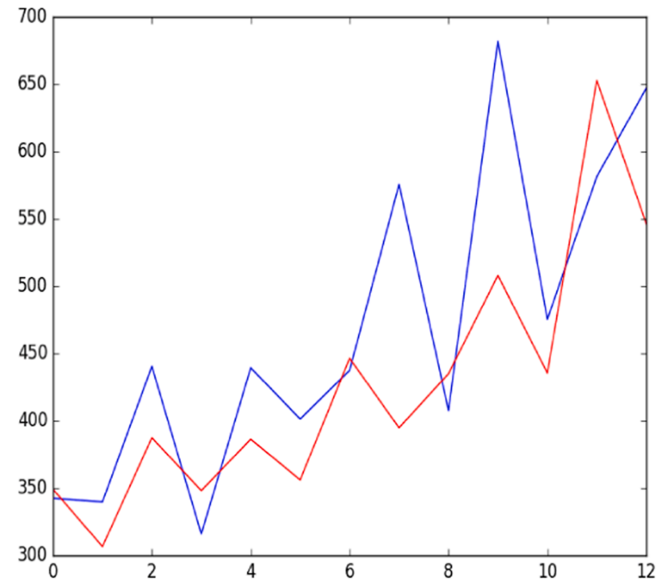

Fig. 9. load prediction via ARMA [167].

ARMA models offer a balanced method for short-to medium-term planning that works well for addressing temporal relationships in load forecasting. However, they have drawbacks due to their sensitivity to parameter selections and non-linear trends.

2.7. Autoregressive integrated moving average

A well-liked time series technique for predicting and studying data from time series is called Autoregressive Integrated Moving-Average (ARIMA). Both static and dynamic series of data can be handled by this generalization of the ARIMA model [169]. The ARIMA framework includes three parts: moving average (MA), integration (I), and auto regression (AR). The MA component symbolizes the dependency of the present level on previous mistakes, whereas the AR part simulates the reliance on a present amount in the period sequence on prior results. By comparing variances among successive findings, the I factor is employed to maintain time sequence stable [170]. In addition, the ARIMA method provides advantages compared with artificial neural networks, the latest version of algorithms for forecasting, including a more straightforward methodology as well as an increasingly established technique [171]. By integrating AR (p) and MA (q), it is demonstrated in the research that the theoretical representation of ARIMA (p, d, q) is accurate. The variations from the actual information readings with past readings is substituted using the observed values, whereas Integral (I) indicates the division of raw readings that enables time series to get stable. The irregular time series are converted to the stable state using the limited contrast of the information points by ARIMA (p, d, and q) [172]. Description of ARIMA (p, d, q) in the discipline of mathematics

$$\varphi(L)(1-L)^d yt = \theta(L)\varepsilon t \quad (10)$$

$$(1-\sum_{i=0}^{p}\varphi iLi)(1-L)^d yt = (1+\sum_{j=1}^{q}\theta jLj)\varepsilon t \quad (11)$$

$$y(t) = \phi_0 + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \ldots + \phi_p y_{t-p} + \varepsilon t - \theta_1\varepsilon_{t-1} - \theta_2\varepsilon_{t-1} - \ldots - \theta_p\varepsilon_{t-p} \quad (12)$$

where $y(t)$ and t stand for the real amount and the variation in it at the time point t, accordingly; i and j are simulation variables; and p, d, and q are positive numbers, indicating the sequence corresponding to the autoregressive, incorporated, and moving average components of the framework, accordingly Using the information's autocorrelation functionality (ACF) and partial autocorrelation function (PACF), p and q are typically determined [173]. The PACF plotting assists with figuring out whether the ACF plot is capable of categorizing irregular time series according to the maximal sequence of AR (p). Employed the pattern part to predict the rise in overall load, the climate characteristics to predict the climate-sensitive load part, and the ARIMA model to construct the faux-weather cyclic element of the week highest load as shown in Fig. 10 [174]. Utilized past data along with a season ARIMA simulation to foresee the burden using seasonal fluctuations [175]. Constructed a real-time load prediction ARIMA system with the effect of the weather as a factor explaining it [176].

By taking into account past energy consumption patterns at the device-level energy usage, ARIMA integrates autoregressive (AR), differencing (I), and moving-average (MA) components to capture complicated temporal dynamics. The HEMS can produce precise forecasts and well-informed judgements thanks to this technique.

ARIMA models are a flexible and effective tool for load forecasting with periodic variations and trends in short- to medium-term instances, but careful parameter tweaking is essential.

2.8. Genetic algorithm

The workings of inheritance and genetics served as the inspiration for genetic algorithms, often known as genetic algorithms (GAs). They are frequently employed to resolve optimization issues that need comparing a large number of potential solutions in order to choose the optimum one. an autoregressive moving average with a variable framework for demand-side projections is identified using genetic algorithm approaches. The approach provides an opportunity to move to the global extreme of a complicated fault field by emulating a naturally evolving mechanism. It is a method related to global exploration which replicates the progression of development in nature and works as a probabilistic optimization method [177]. The GA is competent in asynchronously converging to the ideal global result and thus boost the estimation precision of the prediction because it assesses numerous exploratory indicates at once and doesn't demand that the query space be distinct. There is an overview of the broad structure of the genetic algorithm procedure. The D-dimensional vector data P, whereby the fitness parameter f(p) has been allocated, indicates actual value parameters that are decided by the algorithm for genetics [178]. A selected spectrum for every degree is used to create the baseline collection of k parental vector Pi, i = 1, k. Right after that, every parental vector establishes a child by fusing (crossover) members of the present

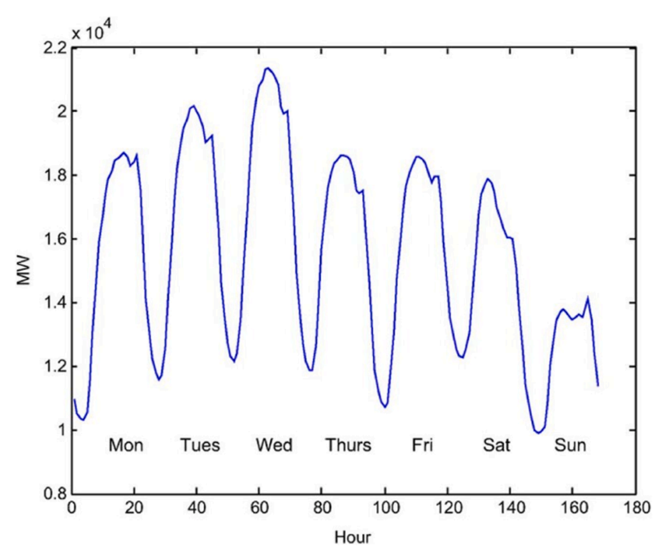

Fig. 10. ARIMA prediction [174].

population. As a result, 2000 additional people are acquired. To choose the new parents for the subsequent generations, k people are randomly picked from among them, having a larger likelihood of going to those with the greatest performance values. until is not enhanced this procedure recurs. defined the overall demand profile according to the ARMAX format shown below.

$$A(q) * y(t) = B(q) * u(t) + C(q) * e(t) \tag{13}$$

While q-1 is the back shift function, A(q), B(q), and C(q) represent the coefficients for the autoregressive (AR), exogenous (X), and moving average (MA) portions, accordingly, y(t) is a load at period t, u(t) is the external thermal intake at time t, e(t) is white noise at time t, and u(t) is a temperature input [179]. Select the approach in [180] which correspond to your needs as the uncertain prototype(s) that ought to ultimately pass inspection for future estimation of load. A fuzzy autoregressive moving average with an exogenous variable approach in [181] was given for predicting demand for power. Heuristic analysis and adaptive programming are used in conjunction to address the method, which is presented as a sequential optimization issue. Utilized an algorithm in [182], based on genetics that utilized enforced mutation, a newly designed expertise-augmented mutant-like activator. In [183], the ideal neural network design and linking parameters were developed using a GA to solve a single day power demand prediction issue. In [184] Many GA-based demand forecasting strategies in the STELF domain are currently described, although intriguing findings have emerged.

To resemble the processes of natural selection, these solutions go through selection, crossover, and mutation rounds. Fitness functions assess each solution's performance according to standards such as energy efficiency. Genetic algorithms develop via multiple generations and determine the best device-level tactics, which helps smart homes use energy efficiently.

When working with complicated models, genetic algorithms provide a potent optimization method for load forecasting; nevertheless, one should take into account the computing costs associated with them.

2.9. Support vector machine

A guided machine learning approach called Support Vector Machine (SVM) is employed for both regression and classification analyses. A categorization and regression evaluation technique centered around statistical learning theory (SLT), that examines information and finds trends. It integrates generalization regulate handle a method to deal with the scalability problem [185]. In [186], demonstrated that using time series projections instead of heat and other climatic data can increase the accuracy of halfway demand forecasts. In [187] Researchers called the technique C-ascending support vector machines, which changed the detrimental value of traditional support vector machines by penalizing hypersensitive mistakes with greater severity compared to distal oblivious faults. According to an experiment, the team conducted, C-ascending support vector machines using raw data that has been genuinely organized regularly to predict conventional support vector machines. In [188], suggested an SVM-based method to rank particular components in accordance with how they affect loading predictions by reducing the number of characteristics that reduce system capacity. In [189], researchers further enhanced the SVM by employing an empirical learning approach to assess the relationships across both input and output variables. Utilizing the idea of regionally ranked regression, this approach was developed by altering the probability function of the conventional SVM. The discipline of system observation, improvement, and standard assurance benefits from the suggested approach. introduced a novel short-term load forecasting approach in [190] using scaled SVM in conjunction with the fuzzy C-mean clustered technique. They grouped each of the input samples based on their level of resemblance. demonstrated that an SVM-based model in [191], offers more declaring mathematics for predicting load on electricity compared to an artificial neural network. The framework eliminates the drawbacks of general artificial neural networks (ANN), such as their poor generalization, the tendency to become stuck in incomplete minimums, and the inability to do global optimization. In [192], offered an SVM-based short-term load forecasting method using the Adaptive Quantum-behaved Particle Swarm Optimization Algorithm (AQPSO). The QPSO was modified to include a variety-guided framework and the AQPSO technique is used for automatically identifying the unbound variables for the SVM model. The mathematical framework has been shown as able to increase precision, boost global convergent capacity, and shorten the duration of operation. a revised form of support vector regression (SVR) was introduced in [193], to address the prediction of load challenge. Authors created the framework by using locally weighted regression (LWR) to alter the risk factor of the SVR technique yet preserve the regularization term's fundamental structure. centered upon the Stimulated Annealing Particle Swarm as shown in Fig. 11 in [194], Optimization (SAPSO) method, which blends the benefits of Particle Swarm Optimization with the Swarm Optimization method. For selecting the SVM model's variables, a novel technique is used. Mathematical experimentation has demonstrated that the algorithm could enhance precision, increase converging capacity, and decrease operating time.

There are several ways to increase SVM model's capacity for global optimization and precision. Here are a few crucial methods: Feature engineering (consider transforming attributes that symbolize the fundamental connection); Hyperparameter tuning (through techniques like grid search or randomized search to determine which one best matches the data); Cross-validation (to evaluate the model's effectiveness using several dataset subsets); Data preprocessing (take handle outliers, missing data, and scale or normalize features); Ensemble approaches (Combining many SVM models for improved prediction performance is by bagging or boosting); Kernel selection (kernel parameters to determine which combination produces the best outcomes for the particular issue); kernel parameters to determine which combination produces the greatest outcomes for the particular issue; Incremental learning (adjust over time to fresh data without having to completely retrain the model); Model stacking (integrate SVM's features with those of other forecasting techniques to provide a forecast that is accurate and reliable overall.); Regularization techniques (Use strategies including dropout or incorporate a penalty term in the price equation to avoid overfitting). One may improve SVM model's accuracy of predictions and capacity for global optimization by carefully weighing these tactics.

SVM can build models to forecast energy consumption at the device level based on use trends and historical data. It may also be used to spot anomalous energy usage patterns in devices and assist in the diagnosis of

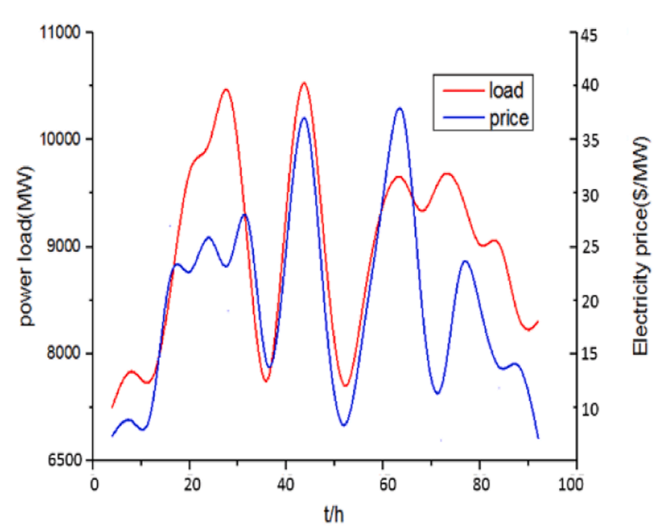

Fig. 11. load forecasting via Support vector machine [194].

faults.

Divide up the energy usage of devices into several groups so that various kinds of devices may have customized management plans. It is appropriate for capturing intricate interactions inside the HEMS, guaranteeing efficient device-level energy management, due to its flexibility to different kernel functions.

SVMs are a reliable method for load forecasting, but careful parameter adjustment is necessary, particularly when working with intricate and non-linear interactions.

2.10. Adaptive demand

A kind of prediction of demand known as adaptive demand forecasting modifies the projected demand in response to alterations in the root factors that influence need. The method of adaptation modifies the prediction to better represent the present condition while taking into consideration the shifting environment. In order to maintain up with the shifting load circumstances, the mathematical assumptions for prediction are readily modified. In the energy control network, flexible load projection is a piece of software that may be utilized remotely. Using the Kalman filtering principle, a regression approach is employed. In order to calculate the subsequent state vector, the Kalman filtering method typically employs the present forecast inaccuracy and the most recent meteorological data collection methods. To establish the state vector, not just the latest observed demand and climate data are examined, but also the whole history collection of data. Shifting from multiple and adaptive regression evaluations is possible with this method of activity [195]. created a flexible Hammerstein framework in [196] that includes a lattice architecture for coupled operations and an axial gradient design. Their strategy made advantage of a combined Hammerstein irregular operational link between demand and heat that changes with time. Their method outperformed the commonly employed RLS (Recursive Least-square) algorithm in terms of performance. In [197] improved and used the method. The capacity to predict the entire system's hour load up to five days in advance has improved. In [198] modeled the impacts of a direct load control approach while presenting an appropriate-time sequence framework. Created an integrated framework in [199] for predicting load that comprises three elements: baseline load, category load, and residue load. The Kalman filter is employed to simulate the initial load, and the model's settings are adjusted using the exponential scaled recursion the least-squares approach. showed a real-time climate-adaptable STLF solution in [200] that is effective in practice. Utilizing the WRLS (Weighted Recursive Least Squares) algorithm, execution is carried out by an ARMA approach, and its variables are computed and revised remotely. Utilizing time series evaluation in [201], circumstances. With this method, periodic structures are handled by self-correlation optimization, in alongside revising model settings, the time series' order and framework can be modified to account for changing circumstances. used a wavelet evolve-Kalman dictate approach in [202] to predict demand.

Adaptive Demand necessitates the real-time tracking of energy use trends on each device using smart meters and sensors. Whenever and the way devices are generally used is something the system learns by analyzing user behavior and preferences. Through constant learning from equipment connections, machine learning algorithms optimize adaptive techniques over time, improving the HEMS's capacity to proactively control energy usage at the device level.

Although it comes with infrastructure challenges, adaptive demand forecasting improves load forecasting accuracy by dynamically modifying estimates in real-time and providing efficiency advantages in managing home energy networks.

2.11. Expert system

As a consequence of developments in the AI sector, an entirely novel discipline has formed. Authoritative engineers developed a computational program known as expert system as shown in Fig. 12. Researchers create an information-based expert framework by extracting LF information from export in the real world. The system of specialists is provided with characteristics that blend scientific and statistical approaches [203]. All of this data is given as statistics and if-then regulations and are made up of a collection of connections. The aforementioned rule foundation is utilized every day to provide predictions due to fluctuations in system demand and variations in both organic and imposed conditions which influence how much power is consumed. Although a few of the regulations remain constant as time passes, some need to be apprised on a regular basis. With the purpose of creating multiple regulations for various methods, the rational and syntactical links involving climate demand and the prevalent everyday load forms are being extensively studied. The procedure often includes the time of year being considered, the day of the week, the temperature, and changes in the temperature at the time [204]. Developed several load expansions models in [205] using a knowledge-driven method to load prediction that incorporates present system expertise, demand development trends, and horizons period information. In [206] utilized a two-stage predicting process for the Korea Electric Power Corporation. An ANN first undergoes training to anticipate the beginning load, then following that, a system of fuzzy experts adjusts the projected load to account for seasonal fluctuations and holidays that are public. There are various hybrid approaches in [207] that forecast load by combining an expert structure with different LF algorithms. In particular, dashes integrate fuzzy logic with expert systems. In [208] processed the climate and load facts, added a fuzzy inference procedure, and used a trained system to make predictions. The job is done offline and is depending on the operator's perception and specialization developed several load expansion situations in [209] using an empirical power-forecasting technique that integrates system details already in place, load development trends, and perspective period statistics. In [210] used an integrated skilled system and NN approach with three stages for preparing a site, projections, and planning for growth. To predict load for Egypt Electric Corporation, a neural network and exporting system are combined in [211] to build an hour predictions framework.

Integrate domain-driven information about consumer tastes, energy usage, and equipment behaviors into a rule-driven framework. Develop a collection of rules that specify how devices should behave depending on variables like the time of day, user behaviors, and energy prices by encoding domain-specific information. Incorporate sensors and feedback systems to continually track data at the equipment level, giving the expert system actual time inputs.

By combining human experience, expert systems provide insightful load predictions and provide conclusions that are easy to understand. However, in situations where expert input is not continuously available, they may not be able to adapt to changing conditions.

2.12. Artificial neural network

A computer framework termed an Artificial Neural Network (ANN) is modeled after the nervous system in the brain of a human being. The framework consists of a network of interconnected "neurons" which can derive results from inputs providing the network of neurons with data as

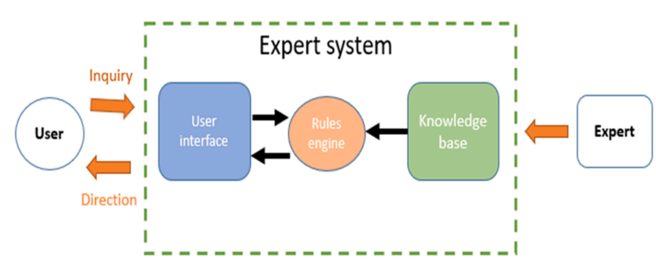

Fig. 12. Expert system model.

shown in Fig. 13 [212]. Neural networks have a capacity to reduce dependency on an operational version of prediction system, claims in [213]. Artificial neural networks can take a variety of forms, including multidimensional perceptron structures and autonomous nets. The system contains a number of secret levels. Every buried level has a large number of neurons. When inputs have been multiplied by weight ωi and combined with a limit, an inner product value known as the net value is created. In this case, the function that activates y is transmitted via the net functional NET employed in [214] to generate the device's final result, y(NET). The primary advantage in this situation is the fact that the majority of forecasting strategies found in the scientific literature lack a requirement for a load estimate. But training usually requires a long time. Employing completely interconnected feed-forward sort neural networks as the basis, we provide the approach mentioned in [215]. The weights used to link inputs, hidden units, and output components together to form the system's outputs are linear in nature. As a result, the weights of output are subject to linear problems that may be resolved. When solving the linear equations over the resultant the weights, the results weight optimization training technique initially employs traditional back propagation technique to enhance the undetectable weights during every loop via the data used for training (epoch). The ANN-based system was created and placed into use in [216] for the Pacific Gas and Electric Company's energy management unit. Special occurrences like vacations, extreme heat, freezing snaps, and additional events that disrupt a load's regular rhythm were carefully modeled. A method was suggested in [217] employing the unsupervised/supervised training idea and the past relationship between load and heat for a certain period, day type, and hour of the day.

In order to anticipate hour electrical consumption having a waiting period of 24 hours, they employed this method. In [218] conducted an actual investigation regarding estimating power usage in Singapore to contrast a statistical model to a neural network model. Based on their findings, an entirely trained NN algorithm that performs well when adapting historical data might not do as well when predicting future events. presented a recurring NN in [219] for simulating the South African utility's STLF. It represented the load as the result of an evolving system, impacted by the climate, duration, and other external factors, by utilizing the inherently irregular dynamical characteristic of NN research in [220] employed ANN to perform forecasting of short-term loads for the Ahmednagar site. Later demand may be anticipated employing this method, which was actual wage-based prediction. In order to create a specialist system in [221] developed a group of ANNs and hired them as tools in combination with an overseeing skilled method. Additionally, they looked into how well the ANN approach to short-term load forecasting carried out after the models underwent training via reverse propagation on real load knowledge.

Providing the neural network with historical information about user behavior, ambient factors, and energy use at the device level. Create a

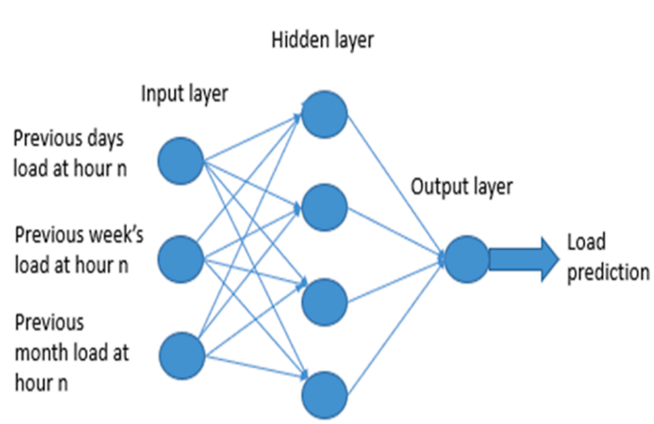

Fig. 13. Load forecasting Artificial neural network model.

neural network design that is specifically suited to capture the intricate connections in energy utilization, including layers, nodes, and activation functions. Utilizing optimization and backpropagation techniques, train the neural network to identify trends in past data and enhance prediction accuracy. Put the trained ANN to use in real-time prediction so that the HEMS may anticipate and modify device-level energy usage according to the circumstances at hand.

When working with non-linear structures, artificial neural networks are an invaluable resource for load forecasting. However, proper model tuning and data concerns are essential.

2.13. *Fuzzy logic*

A centralized fuzzing system called fuzzy theory is capable of identifying and approximating any uncertain vibrant system, or load, within a compacted collection of arbitrary precision. Fuzzy logic is a method for evaluating variables that permits the computation of several potential facts via one parameter. Fuzzy logic takes advantage of an open, imperfect range of facts and biases to address issues, allowing a variety of exact results to be drawn [222]. Researcher discovered demonstrated fuzzy logic may effectively draw parallels from vast amounts of data.

In mathematics, it is denoted as first-order

$$V_k = \frac{L_k - L_k - 1}{T}, A_k = (V_k - V_k - 1)\Big/ T \tag{14}$$

Fuzzy logic algorithms operate in two phases, namely learning and virtual prediction. Steps of instruction employ past data from meters to simulate 2 m inputs. utilizing the initial and subsequent differences of the provided data, a fuzzy rule is constructed that relies on a two-output fuzzy-logic structure. Following the training phase, it is connected to the control system to forecast load. By fitting the highest likelihood function, the centroid defuzzifier creates an outcome sequence. For load estimation, many fuzzy techniques are employed [223]. Proposed a fuzzy set theory-based skilled system in [224], for STLF. The modifying task was handled by the specialist system. An immediate projection was made and assessed for the Taiwan electrical grid. Created a fuzzy linear program framework in [225] to describe uncertainty in the projections and input information regarding the electrical generating planning issue. Developed a non-linear optimization system in [226] for STLF using fuzzy decision-making techniques with the goal of reducing modeling faults. Simulation-based annealing and the most abrupt decline approach are used in searching for the ideal approach. Employed a hybrid approach in [227] for predicting load that combines fuzzy logic in addition to neural networks and trained systems. Fuzzy weight variables are sent into the neural network as inputs, and a fuzzy rule interpretation process corrects its result. Developed a fuzzy model in [228] to represent the electrical power scheduling challenge. Since it can capture the unpredictability of the procedure, this method works better than traditional predetermined designs, according to computer assessments. Proposed a fuzzy reasoning framework in [229] for merging data implemented in regional load prediction that forecasts either the amount and areas of upcoming electric demands. Various areas' load development is influenced by a variety of contradictory elements, such as prices, proximity to a roadway, and the range to power lines. Provided an approach of fuzzy inference in [230] for STLF in electrical systems. To minimize prediction mistakes, their strategy combines tabu search with supervised training to optimize the inferential architecture. Offered a different approach to the conventional experimentation strategy for figuring out fuzzy member roles. It uses a computerized model development in [231] process that makes recourse to clustering calculation, evaluation of deviation, and iterative least-squares.

Utilizing linguistic variables and fuzzy sets, create a rule foundation that accounts for the inherent variability in device-level energy administration. To express the extent to which variables, such as energy consumption and user tastes, are part of fuzzy sets, establish membership functions. To interpret the rules and decide how to optimize device energy, use a fuzzy inference engine. Adjust device-level settings adaptively by implementing fuzzy control techniques that take user comfort, energy expenses, and environmental circumstances into account.

By using human-like reasoning to address unpredictability, fuzzy logic provides a reliable method for load forecasting; nevertheless, careful rule development and expert input are necessary.

Various aspects, such as the particular properties of the data, the scope of the system, and the prediction task's objectives, influence the selection of the optimal load forecasting approach. Every method has benefits and drawbacks. Whenever there are distinct linear correlations between the predictor factors, regression models work well. Time series information can benefit from exponential smoothing techniques, which provide weighted averages that adjust to shifting trends.

For time series forecasting, autoregressive methods are highly effective, particularly when working with stationary data. For intricate, non-linear problems, genetic algorithms are an adaptive optimization method that works well. Artificial neural network is good at extracting intricate correlations and patterns from data. Both linear and non-linear forecasting problems can benefit from support vector machines, particularly in high-dimensional domains. Fuzzy logic works well with data that contains imperfect information and uncertainties. The ideal method will vary depending on the particulars of your data and the demands of your load forecasting assignment. Experimenting with various strategies and maybe utilizing a combination of ways can greatly enhance accuracy and resilience. When selecting the best approach for your situation, take into account variables like interpretability, processing capacity, and the volume of historical data that is accessible. Overall, ANN are often regarded as useful for load forecasting in residential energy administration systems because of their capacity to identify intricate patterns and links in previous data. (Table 1)

Table 1
Characteristics of different forecasting approaches used in HEMS.

Method	Process	Features	Applications	Pros	Cons
Multiple regression	Collect historical data to build a regression model	Interpretability using parameters and builds a model employing analytical statistics	Residential and commercial load prediction	Adaptability and flexibility	Premise Vulnerability and dependency on accurate information
Exponential Smoothing	Iteratively time series predicting methodology	Manage seasonality and apply exponentially decreasing weights to estimate future outcomes.	Demand forecasting and short-term load prediction	Minimal past data requirement and responds effectively to seasonality and trends	Sensitivity to initial factors, and limited long-term prediction.
Iterative reweighted least-squares	Incorporates iteratively altering coefficients	Responding to non-linear relations and reliable estimations via iterative refinement	Simulate complicated and dynamic associations among factors in load estimation.	Resilient to outliers	Computation challenge, vulnerability to initial conditions and weighting scheme tuning
Autoregressive	Data from a time series based on previous linear estimations	Track's dependencies across time in data	Modeling time-series data	Effective in identifying time-related trends and suitable for short-term forecasting	Susceptible to the model order selection and might not accurately portray non-linear patterns.
Moving average	Calculates the mean of the data elements within a sliding frame.	Offers a smooth trend line	Short-term load forecasting, finding trends and reducing noise in past data.	Useful for mitigating abrupt fluctuation and less computational capacity required	Lag behind abrupt changes and might miss complex trends
Autoregressive moving-average	Taking moving average of previous values	Tracks temporal connections	Model time-series data	Short to medium term load estimations	Difficulty comprehending non-linear trends
Autoregressive integrated moving-average	Integrate the moving-average, autoregressive and differencing parts to predict time series datasets	Manages irregular data and detects patterns over time	Robust, adaptable and medium-term load projection.	Ability to adapt to different time series and capture intricate temporal trends	Parameter sensitive, intractable in some cases, and requires an adequate volume of past data
Genetic algorithms	Solutions evolving over successive generations.	Heuristic optimization method exploring a wide solution space	Optimize parameters to increase precision in complicated models	Powerful in intricate and non-linear interactions and resilient against local maxima	Difficulty to comprehend the optimization process and computationally intensive
Support vector machine	Determine hyper plane that optimally divides the data points to maximize the margin between various classes.	Adequate in high -dimension space, and appropriate for both classification and regression tasks	Widely used in classification tasks	Robust against overfitting	Limited suitability for multi-class problems
Adaptive demand	Continuously updating estimations and model based on real-time information and evolving conditions	Adaptability to real time changes in demand trends	Provide accurate prediction	Increased precision and adaptability to shifting conditions	Dependable on communication infrastructure and real-time data
Expert systems	Integrating human knowledge into a rule-based framework	Flexibility to different forecasting situations.	Optimize forecast utilizing expert analysis and take benefit of domain-specific expertise	Employing human knowledge and comprehensible decisions	Reliance on specialized expertise, and possible difficulties in fully encapsulating a dynamic system
Artificial neural network	Training a structure of linked nodes to understand complex connection and linkages	Non-linear modelling, flexibility with numerous data types, and ability to identify complex patterns	Employing load forecasting to simulate intricate, nonlinear connections in energy usage	Manage intricate patterns, flexible in handling numerous data types, and excellent accuracy	Overfit with insufficient data and Black-box nature
Fuzzy logic	Incorporates rules and linguistic factors to simulate uncertainties and imprecise information	Linguistic expressions and human-like approach to decision-making	Indicate the variability and unpredictability in patterns of energy usage	Imitate human reasoning in ambiguous situations.	Rule development requires expert assistance and is sensitive to rule allocation.

3. Optimization technique in load scheduling

The optimum scheduling for HEMS is determined in this part by examining a variety of scheduling methodologies.

3.1. Linear programming

Developing an optimization problem with linear constraints and an objective function to minimize or maximize is known as linear programming [232,233]. The amount of restraints and the amount of parameters determine the cost of computation of a linear programming task [234]. There aren't any local minimum multiples in that particular sort of programming challenge [235]. LP is frequently the easiest to solve; another quality of this kind is clarity. The choice factor should have one goal and be non-negative [236]. In [237] The cost of desire to spend, which was set for every customer and identified to a value that every member in the Licensed Electrical Contractor (LEC) was ready to spend in addition to the cost of energy of the grid in order to add to a drop in the minimal pollutants resulting from the grid, was assessed in order to determine how to maximize the social advantages achieved by a LEC using peer-to-peer dealing. It additionally communicates the user's tendency to purchase local PV power. The criteria originate from Vienna, an Austrian city. The length of the research lasted a year. The optimization technique made use of linear programming as its framework. In [238] centered upon figuring out the percentage of customers who supply DR to those customers. These metrics were determined by considering note of the past behavior rate of the customer's behavior in response to an actual time call for a power reduction; the DR, the last-day Rate (LDR), and the cut-rate are terms used in the computation of the Time Rate (TR). The significance of the TR is that, based on this number, an end-user is chosen to take part in the DR to lower energy consumption corresponding to the demand; the research's innovation lies in this selection of the customer's result shown in Fig. 14. The research had one day as its timeframe. In [239] aimed to reduce operational expenses by addressing the optimization of a big Electrical Conductivity (EC). There was actual time and day-ahead optimization done. The adaptability of function that the transmission system operators would be offered was decided by the day-ahead paradigm. The development of a parallelizable LP. This model considers the transfer of energy both inside the EC and throughout the EC and the power grid.

Establish a specific purpose that embodies the HEMS's objectives, such as balancing the use of devices. Determine the decision factors that, based on user choices, indicate the energy usage of each device. To guarantee practical and workable solutions, create limitations based on variables such as energy availability, device specs, and user preferences.

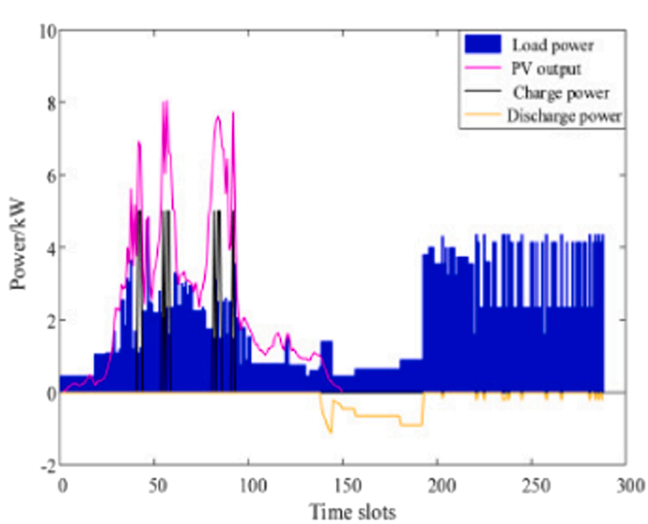

Fig. 14. load scheduling via Linear programming [238].

To identify the best solutions that fulfil all constraints and the specified objectives, use LP solvers. For effective device-level energy management, incorporate dynamic optimization by regularly updating the LP model based on real-time data. This will enable the HEMS to adjust to changing conditions and user behavior.

linear programming is an effective technique for load scheduling and distributing resources optimization, it is important to take into account its premises and its drawbacks when attempting to capture non-linear connections.

3.2. Mixed integer linear programming

Mixed Integer Linear Programming (MILP) expand linear programming by permitting certain variables to take discrete, integer values, in order to include decision variables that are not continuous. The outcome factors in MILP are regular, numbers, and scalar, while the goal product and restrictions are both linear [240]. This technique can help decision-makers comprehend energy systems and develop environmentally friendly paths to achieving energy goals [241]. The outcome factors in MILP are regular, numbers, and scalar, while the goal product and restrictions are both linear. The branch-and-bound technique is the approach that is utilized most often to solve issues involving MILP [242]. It is not vital to employ a nonlinear framework which is harder to figure out since integer parameters permit modelling estimates of nonlinear behavior. Furthermore, integer parameters render optimization issues nonconvex, which makes them much more challenging to resolve [243]. The device schedule optimization issue in [244] presented into a MILP challenge, which is computationally feasible. The utilization-scheduling method in a residential system has been examined by the researchers. The decrease of EC charged by the consumer is the investigation's primary target. regarded as six gadgets each for six homes. The findings indicate that the price decrease has increased by 3–16%.

The MILP approach for scheduling devices in intelligent houses was rolled out in [245]. The research is centered on reducing the expense of power. The suggested comprehensive HEMS design takes distributed power production and the power storage facility into account. To decrease costs overall, controlling loads for both thermostat and une-thermostatic systems were modeled utilizing MILP.

It is demonstrated [246] that a multiple-layer design founded on MILP optimization technique can be used as a Clustered Sequence Management (CSM) multi-objective optimizing approach at the power utilization level. It also explains how to classify devices using an ordered technique's load record and its levels of independence for consumer prioritization. In accordance with the American Society of Heating, Refrigerating, and Air-Conditioning Engineers (ASH-RAE) norm, the results demonstrate that the design is typically capable of decreasing expenses by nearly 13 percent and PAR proportions by nearly 45%, eliminating consumer's unease, and accomplishing the ideal amount of time for employing non-interruptible postponement loads. Utilizing MILP in [247] as shown in Fig. 15, an effective power management approach, lowers the price of energy and PAR by planning electronic devices and electric vehicles charging and discharging activities. For particular day-ahead electricity forecasting for efficient energy utilization alongside the potential for buyers to generate power themselves using a micro grid created up of solar and wind energy, an Improved Differential Evolutionary Artificial Neural Networks (EDE-ANN) structure is established. To verify the viability of the suggested cost-effective technique, which relies on the created MILP system.

Create a desired function that maximizes effectiveness in device-level energy management by taking into account both discrete and continuous decision factors. Determine constant factors for continuous decisions (e.g., energy use levels) and integer parameters for discrete actions (e.g., equipment on/off modes). Set limits according to user preferences, energy availability, and device specs. To discover the best solutions that balance discrete and continuous variables, incorporate MILP solvers that can handle mixed-integer optimization issues. For

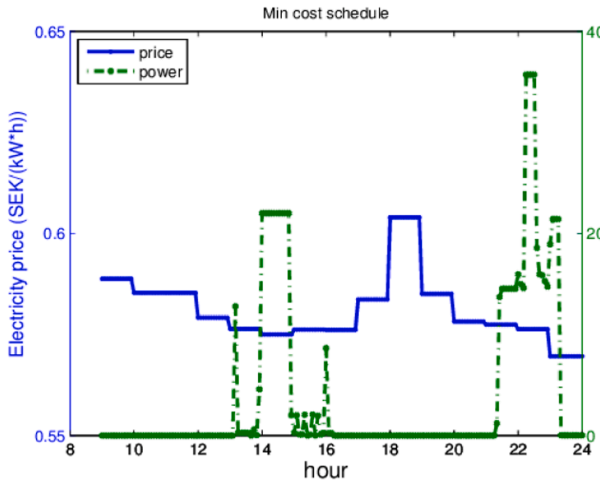

Fig. 15. load scheduling by Mixed integrated linear programming [247].

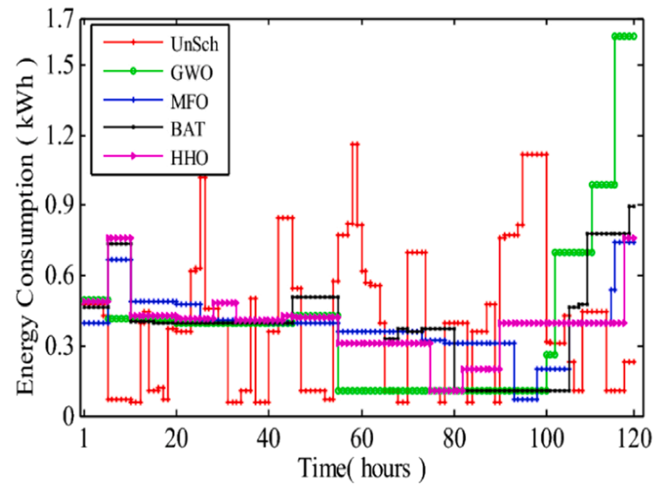

Fig. 16. Load scheduling by Non-linear programming [255].

efficient device-level energy management, design a dynamic MILP framework that changes in actual time based on changing circumstances.

With its ability to handle discrete choice variables MILP improves load scheduling skills and provides best practices in situations involving both discrete and continuous judgements.

3.3. Nonlinear programming

A system having non-linear interactions can be optimized by non-linear programming (NLP), which makes it possible to reflect real-world situations more accurately [248]. Distinctive feature of nonlinear systems is that they may be exceedingly challenging to solve and that the only conceivable approach in cases when nonlinear constraints are present is the local optimal point. The generalized reducing gradient (GRG) and quadratic programming (QP) approaches are employed to solve nonlinear issues [249]. The repeated nature of NLP's computational techniques is common. Another distinctive feature of nonlinear systems is that they may be exceedingly challenging to solve and that the only conceivable approach in cases when nonlinear constraints are present is the local optimal point [250,251]. Utilized NLP in [252] to decide how to operate devices at various intervals. The decrease of EC and customer weariness are the goal objectives taken into account in this strategy. With ToU, and RTP, several cost and incentive-based programs are utilized. In order to account for the unpredictability associated with EVs, battery backup structures, and modest-scaled RESs, a stochastic-based HEMS model is presented. The outcome demonstrates that the suggested approach significantly lessens customer and EC stress. To predict the demand and dispersed production accounts, investigators [253] introduced a short-term memory neural network. It applies a variety of workable demand-side management strategies and dispersed energy resources in the most effective way possible using a flexible technique. The nonlinearly constrained optimization strategy was addressed utilizing the sequential quadratic programming (SQP) method. Each working day was intended to last 15 minutes. [254] proposed a non-linear foreseeable energy conservation technique for a house with a Solar rooftop and a battery-powered by lithium-ion ESS as shown in Fig. 16. The important compromise between storage aging for lithium-ion batteries and managing energy effectiveness is additionally investigated and analyzed, as well as the difference in prescriptions for building regulation, advanced charging estimator methods, and non-stationary PV/battery systems. The concept of saving energy as a model forecast presented considering perfect long-term projections, the computational results show that the intended regulated arrangement provides a target value between 96% and 98%. Additionally, with minimal financial losses and a suitable cost composition, the incidence of failure for battery energy may be reduced by 25%. [255] proposed an NLP probabilistic framework of a HEMS, which takes into consideration supply concerns for EVs and green resources. By including an exhaustion response measure, the algorithm maintains residential satisfaction while optimizing the client's cost in several DR aspects. The energy consumption might be greatly reduced by the recommended HEMS to 42 percent. The recommended probabilistic approach was found up to 31% less expensive for customers to implement versus the conventional strategy. The most significant differences between determinism and probabilistic HEMS were demonstrated using TOU, CPP services. The elevated TOU and CPP prices and the techniques for punishing I/C plants have a significant influence on the timeline.

Create a goal function that takes nonlinear correlations between the variables into account. Determine the decision factors that correspond to the power use of every gadget and the types of trends in its use of energy. Establish restrictions that take into account consumer preferences, specification at the device level, and other nonlinearly related elements. Use NLP solvers that can handle nonlinear optimization issues to identify the best strategies that fulfil all constraints and the specified objectives. Create a dynamic NLP model that can adjust to changing circumstances in real time, enabling the HEMS to optimize device-level power management in accordance with altering environmental factors and user's behavior.

In situations with complicated dynamic systems, non-linear programming provides a more accurate optimization method by accounting for non-linear interactions, which improves load scheduling precision.

3.4. Mixed integer non-linear programming

Optimization is extended by Mixed-Integer Non-Linear Programming (MINLP) to manage either discrete and non-linear continuous decision variables. Additionally, nonlinear problems and a few numerical innovators might be included [256]. For scheduling devices in a variety of situations, including regular, economical, and intelligent with varied user convenience, MINLP is employed in [257]. The issue may generally be classified into the category of multi-objective mixed integer non-linear programming problem (MOMINLP) depending on the previous limitation and goals, can be expressed as follows:

$$\mathrm{minF(x)} = (\mathrm{f1(x), f2(x), \ldots, fn(x)})^T \tag{15}$$

$$g_i(x) \leq 0, \mathrm{i} = 1, 2, \ldots, \mathrm{I}$$

$$h_j(x) = 0, \mathrm{j} = 1, 2, \ldots, \mathrm{J}$$

While n is the number of target factors, $g_i(x) <= 0$ and $h_j(x) = 0$are inequalities limits and equality limits with the degree of I and J independently, and x is the optimization factor vector encompassing the beginning time, operating state, and operational capacity for Non-Interruptible (NIA), Interruptible (IA) and Power Shiftable (PSA) correspondingly [258–260]. The MINLP approach is taken into account in [261] for the optimization of power centers. The suggested strategy aims to lower the overall expense of a power center. The main goal is to plan day-ahead devices using an RTP system at a resource hub. Varying loads and periods of energy use are taken into account. The method demonstrates that there is a reduction in the total price of an energy center and the overall price of grid-purchased power. The investigators of [262] employed MINLP to schedule 10 home appliances to reduce electrical conductivity. The ToU mechanism is utilized in the suggested layout with the option of providing consumers with incentives in busy times. The findings indicate in Fig. 17 a greater than twenty-five percent reduction in electric conductivity. [263] discussed the differences among savings in costs and energy usage minimization techniques. Through a progressive energy sector that uses Energy Storage System (ESS) and responds to consumer demand, the researchers created a successful strategy for restricting money revenue losses in the context of electricity volatility. The nonlinear optimization problem paradigm that is being employed shows that the DR nodes are known by now. It additionally possible to determine where the nodes should be placed for the DR scheme to produce a MINLP. To gauge the advantages of the suggested strategy, the proposed technique is evaluated using the 33-bus distribution infrastructure.

Create a goal function that takes into account both discrete and continuous factors and reflects objectives such as cost minimization or efficiency maximization in device-level energy management. Determine continuous variables for nonlinear interactions (e.g., energy use levels with nonlinear dependencies) and integer variables for discrete decisions (e.g., device on/off states). In addition to discrete limitations, establish constraints that capture nonlinear interactions, such as patterns of energy use or environmental dependence. To discover the best answers, use specialized MINLP solvers that can handle both discrete and nonlinear optimization problems. For efficient and flexible device-level energy management inside the HEMS, implement a dynamic MINLP model that adapts in real-time to changes in user behaviors, device specifications, and ambient factors.

Through the consideration of both discrete choices and non-linear relationships, MINLP improves load scheduling accuracy and provides a potent method for optimizing a broad range of scheduling scenarios.

3.5. Particle swarm optimization

In Particle Swarm Optimization (PSO), a population of solutions (particles) is iteratively adjusted depending on their efficacy both individually and collectively, emulating social behavior as shown in Fig. 18 [264]. PSO examines the bounds of its goal parameter by altering the routes of discrete entities referred to as objects. Each particulate follows a path that can be described as a time-based location vectors. Since it was introduced, it has undergone a lot of upgrades. Researchers used teamed up-evolutionary PSO with probabilistic particle repulsion to solve the appliances scheduling. PSO is a population-level optimization technique that uses heuristics to find answers by letting potential outcomes roam freely in the solution domain without interacting with one another [265]. The movement of the particles is typically in the direction of the top functioning unit and the highest position they have ever been in individual best. We employed a co-evolutionary variant of PSO [266] to solve the issue. The technique of division and conquest used by co-evolutionary PSO involves breaking the vector to be optimized into numerous element vectors and having a swarm optimize every part. We further enhanced the co-evolutionary PSO's effectiveness by including stochastic resistance between the elements [267]. In our method, the particles depart from the individual and globally optimal locations on certain repetitions, subject to a risk that depends on the number of repetitions. We employed the binary form of PSO [268] to optimize such schedules since certain of the considerations, such as switching on and off the water heating system and the swimming pool pump, are bipolar in nature. [269] discusses and analyses an optimal household energy administration system (OHEMS), that additionally encourages the integration of RES and ESS as well as integrates homeowners into DSM activities. By organizing residence and ESS devices in accordance with changing energy prices the recommended OHEMS reduces the electrical power cost. Through the use of several knapsack challenges, a limited optimization challenge is numerically established. It is subsequently resolved via heuristic optimization methods like Binary Particle Swarm Optimization (BPSO), GA, Bacterial Foraging Optimization (BFO), Wind Driven Optimization (WDO), and Hybrid GA-PSO (HGPO) algorithms. The suggested method's and heuristic methods' efficiency is evaluated using MATLAB models. Experiments revealed that the ESS and RES deployment reduces the electrical bill. A smart and mega-layer power administration framework alongside a human-machine interaction (HMI) as the user interface level, the control level, and a load level made up of multiple power appliances is put forward in [270,271]. The structure uses an innovative method that combines harmonically search methods and the particle swarm algorithmic structure. Eq. serves as an example.

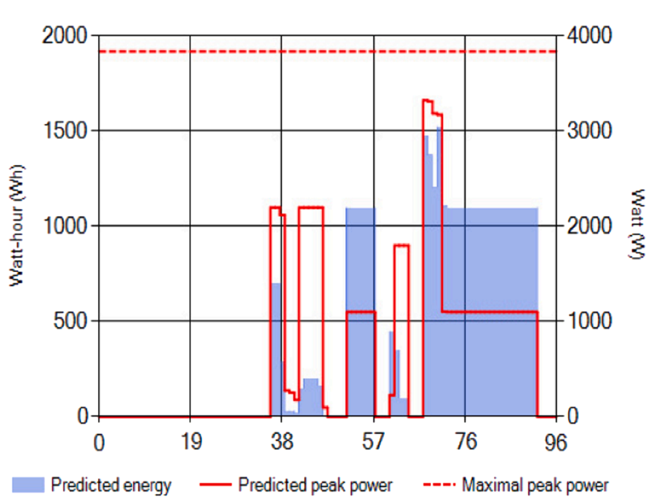

Fig. 17. load scheduling by Mixed integrated non-linear programming [262].

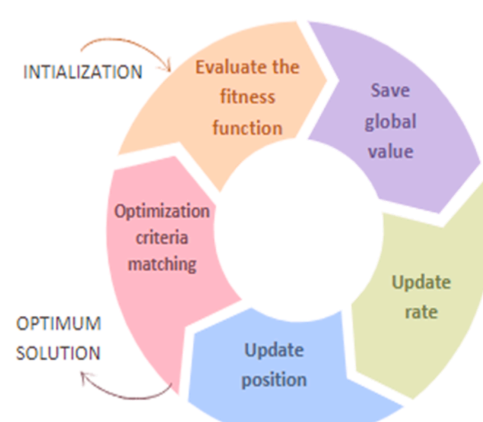

Fig. 18. Particle swarm optimization model.

$$mC - \sum_{a-1}^{n} e_{a,t} \sum_{t-1}^{L} .R(t) \quad (16)$$

Whereas n is the count of loads that comprise the SHEMS; a n is the sequence quantity of demands in the SHEMS; C is the total expense for electricity usage; R(t) is the cost of energy at t periods; $e_{a,t}$ is the amount of energy for the ath demand at t periods; because L is the total optimization timeframe. The NLP paradigm is used to provide the solution for SHEMS's optimum management model. In comparison to the traditional NLP approach, artificial intelligence algorithms are used often to handle these issues due to their fundamental principle, versatility, and quick solution velocity. The hybrid technique is combined with the harmonic searching and the particle swarm optimization technique to resolve the problem. The results of the experiment showed a successful modification of power cost and demand graph.

Model gadgets as particles in a multivariate space, where the location and velocity of every particle indicate device-level characteristics like energy usage. Create an objective function that reflects the aims of HEMS, such as maximizing efficiency or lowering energy costs, and that the particles are trying to optimize by moving collectively. Particles can iteratively change their locations and velocities by defining particle interactions and updating criteria to emulate the social behavior of a swarm. During each cycle, allow particles to react to variations in device specs, ambient circumstances, and user behavior to achieve real-time adaptability. In order to provide an ideal configuration for device-level energy administration within the HEMS, extract the best solution from the particle's final locations.

Particle Swarm Optimization is a reliable method for load scheduling that efficiently optimizes allocation of resources; nevertheless, in dynamic circumstances, precise parameter adjustment is essential to get optimal outcomes.

3.6. Genetic algorithm

In order to replicate natural selection, Genetic Algorithms (GA) evolve a population of possible solutions through selection, crossover, and mutation. GAs operates on sequential patterns similar to biological ones that develop gradually in accordance with the rule of surviving through an impulsive interchange of organized data [272]. It may be employed to identify the best or nearly best solutions to issues that might otherwise require an eternity to resolve [273]. GAs operates on sequential patterns similar to biological ones that develop gradually in accordance with the rule of surviving through an impulsive interchange of organized data as shown in Fig. 19 [274]. Additionally, it is employed in ML and scientific research to address optimization issues. Genetic algorithms frequently use evolving choice, mutation, and replacement mechanisms to supplement or substitute groups with the goal to improve the general best result [275]. Employing the Accelerating Genetic Algorithm, the researchers of [276] modelled a multifaceted scheduler in a grid structure. in a position capable of handling issues with a huge query area, this electrical grid work planning issues with a huge query area, this electrical grid work planning, it needed to enhance and rate up the calculation and resolution process for GA optimization. Similar search issues may be performed live as a result of the rapid convergence. It was accomplished by narrowing the first search field to ensure the original randomized pool only contained feasible options. To generate the chromosomes of the initial group, heuristic techniques were included to do this trimming, and when the process begins, a Minimum-Minimum, Maximum-Minimum, and a Lowest First in First out chromosome are formed. The researchers in [277] used GA in a demand-side administration plan with the goal of reducing the climax-to-average load pattern proportion with the objective to enhance the requirement to ensure the utilization of spinning reservations, hence improving the intelligent grid's performance. The analysis of household, business, and factories loads revealed that GA may be utilized to reduce these demands so the spinning reserves is employed, which lowers total electricity costs. With the goal to implement proactive response to demand involvement, the researchers in [278] used GA to device management. The study was run using the Nigerian power sector, and the optimized procedure was designed to get a set of planned per hour utilization values for every appliance with the lowest possible total electrical expense. In other words, load will be adjusted according to price, more loads being assigned to hours of a day when prices for electricity are lowest. The electricity expense in a hrs.-based tariff profiling was lower, according to the findings. The investigators of [279] coupled GA with particle swarm optimization to build a mixed approach for regulating energy in intelligent grids. The combination is necessary to allow the load planner to maximize the benefits of both load planning approaches and improve efficiency. Both price of energy and usage were lowered, according to the findings. Performance is one of the main issues when applying GA and additional optimization methods to identify issues. Because of this, it might not be the optimal option to employ in real-time applications. the investigators in [280] also showed that a unit commitment problem may be handled utilizing fuzzy reasoning, thereby raised convergence speed.

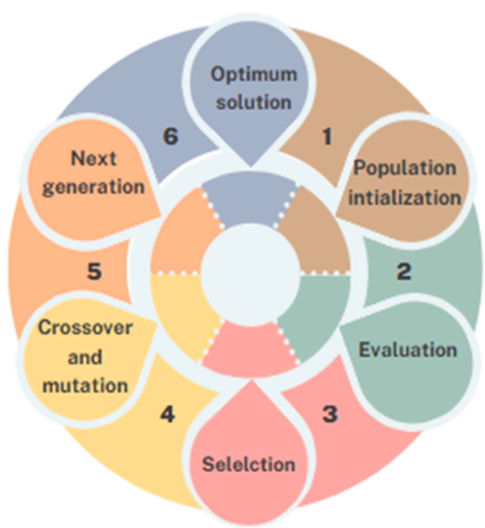

Fig. 19. genetic algorithm model.

Illustrate device settings as chromosomes, with each gene denoting a device-level parameter (such as the timetable for energy usage). Create a starting population of chromosomes, or possible solutions, that represent various HEMS device setups. Establish a fitness function that assesses each solution's performance according to standards including affordability, user ease, and energy efficiency. Utilize genetic operators like as crossover and mutation to combine and modify the genetic makeup of preexisting solutions to produce new ones. Let the population to iteratively develop over several generations, breeding and choosing solutions with greater fitness, until an optimum or nearly optimal solution for managing energy at the device level emerges.

Although their computing requirements and sensitivity to factors should be taken into consideration, genetic algorithms provide a potent optimization method for load scheduling, especially in complicated settings.

3.7. Simulated annealing

Through a method that mimics the annealing process in metallurgy, simulated annealing steadily reduces the likelihood of adopting less-than-ideal solutions through iterative solution space exploration as shown in Fig. 20 [281]. In a vast searched space, it is a metaheuristic method that matches better efficiency for an optimization issue. It is usually employed in discrete searching areas, such as the traveling salesman issue [282,283]. Simulated rinsed might be preferable to

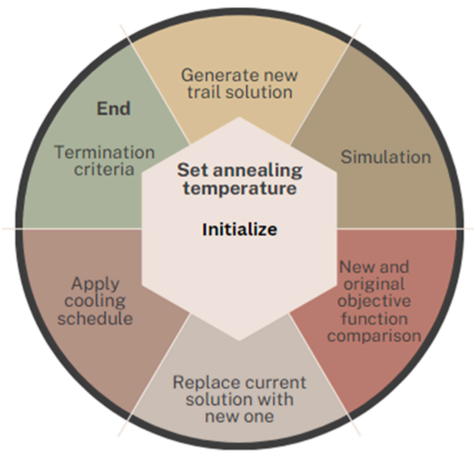

Fig. 20. Simulated annealing algorithm.

accurate methods like descent of the segmentation in situations when it is crucial to obtain a projected overall balance instead of a specific localized ideal level for a specified length of duration [284]. In [285] presented a system for managing home energy to schedule fluctuating loads with a grid source of solar energy. The suggested method uses the straightforward, effective technique of simulated annealing, that is employed to find the general optimal. For the purpose to achieve low electricity expenses, this research aims to identify the ideal times of day to utilize appliances in the house. Then, an analogy is drawn among the optimization goal function and practical annealing. The results show the amount of both energy and cash the intended household management strategy will conserve at the conclusion of each month, demonstrating the efficiency of the procedure. SA was additionally utilized in [286] to schedule appliance usage optimally with the aim to minimize both the price of energy production and monthly bill payments. In [287], two neighborhood HEMS connections are being created, and a simulated annealing restoration procedure is employed in conjunction with them. Hill climbing along with additional tactics for certain queries, such as tabu search, are studied in many variations. Yet, initial evaluations showed that SA was clearly superior to any of the other techniques. The suggested SA approach delivers an arbitrary motion on every iteration after starting at a selected initial phase. As a combined region, the decision of moving is determined in two stages: first, the atomic reposition, and then, the specific motion inside the neighborhood. Decreasing the total amount of iterations to ensure every parameter receives an identical run time allowed for extra computations in an increasingly complicated neighborhood. By combining the Improved Differential Evolution (EDE) and Harmonic Synthesis algorithms, [288] creates an original HEMS while lowering the total amount of trials to ensure every configuration have an identical run duration. The most recent best-known results have been enhanced with the simulation-annealing approach for virtually all circumstances, according to a credible examination of older data. To maximize energy use, homologous recombination employing HSA and EDE operators is also done. Rough MATLAB models are used to determine the effectiveness of the new approaches developed (Harmony EDE (HEDE)). A tasking-home complex with a variety of intelligent gadgets is where the simulations are conducted. The results of the simulation show how effective the proposed technique is in lowering costs and PAR.

To direct the optimization process, create an objective function that reflects HEMS aims, such as maximizing efficiency or minimizing energy costs. As the working solution for the optimization process, begin with a basic setting of the device's characteristics. Put in place a temperature schedule that regulates the likelihood of admitting subpar solutions, enabling the system to first investigate a larger solution area. Define a process that produces neighboring solutions (gadget setting perturbations) and assesses the fitness of those solutions in relation to the goal function. Explore the solution space iteratively, approving or disapproving new options in accordance with the simulated annealing probability, and progressively lower the temperature in order to converge on an ideal configuration for the HEMS's device-level energy control.

Simulated annealing is a flexible and resilient optimization technique for load scheduling that takes parameter configurations and computing needs into account. It is ideal for managing complicated circumstances.

3.8. Colony optimization

A group of optimization techniques known as "optimization of the colony" are based on genuine insect colony behavior [289]. Ants may actually use the pheromones to find the quickest route through their nests to food available in the real world [290]. Substances called pheromone are released by insects' bodies and fall to the ground, where they leave a path that every ant may follow to find nutrition [291]. Given the potency of those pheromones during subsequent trips to the nutrient origin, additional ants in the group will employ these advantageous routes as shown in Fig. 21. ACO makes use of this phenomena and utilizes it to tackle actual optimization issues [292]. A HEMS built on the Artificial Bee Colony Optimization Algorithm (ABCOA) is described in [293]. A clever bee swarming foraging optimization system makes up the bee colony technique. Worker bees, observer bees, and scouted bees are the three groups of bees that make up a colony. It is thought that a single artificial honeybee is employed for every food source. In this instance, a colony's entirety of sources of food and worker bees is equal. Worker bees return to this location to eat and perform. The bee whose diet was removed becomes a scout and starts looking for a new source of nourishment. Bees dance, and viewers choose food sources based on the dancing. The issue of optimization may be resolved by XYZ's supply of food, and nectar suggests a superior resolution. The method plans the usage of residential devices in accordance with the cost of power. In order to keep power expenses to a least, projected outdoor Celsius, power production, and consumer demands are gathered and utilized. Experiments verify the technique's efficiency and can save power expenses by 47.76%. The Discrete Multi Objective Bacterial Colony Chemotaxis Algorithm (DMOBCC) is a novel HEMS idea that was presented in [294]. BCO relies on a process-based paradigm which roughly represents a number of typical behaviors of E. coli microbes across their lifespan, includes chemotaxis, cooperation, removal, replicating, and motility. A newly developed chemotaxis technology and communications platform are built to streamline microbial optimization during the whole optimization period. However, subsequent operations like rejection, replicating, and relocation are not implemented until the specified

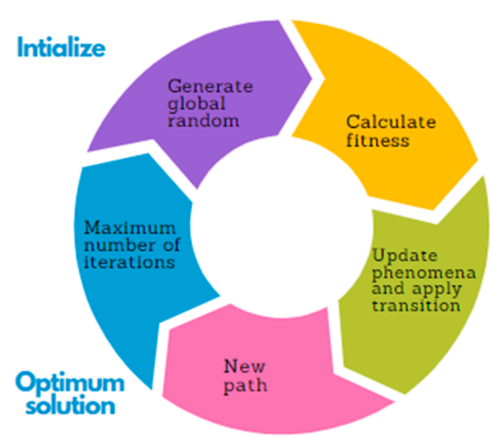

Fig. 21. Colony optimization model.

requirements are met. A group of microbes is first initialized using DMOBCC. Chemistry charges and standards are then continually evaluated in a solution the environment, and the best solution is discovered via iterations. The aim functionality minimizes energy costs for customers while ensuring the highest degree of pleasure. The framework uses the optimization features of duration intervals technique to create an ideal method. Investigations were conducted to demonstrate the optimization approach for the period, and the effectiveness of the solution that was provided was confirmed by simulation findings.

Draw a graph depicting device-level setups, with nodes standing for states (such as energy consumption schedules) and edges for state transitions. Pheromones may be used to indicate the attractiveness of various configurations, and they can be updated in response to the system's preferences and the fitness of solutions. Play as ants moving over the graph, each ant building a solution by selecting configurations dependent on pheromone levels in a probabilistic manner. Analyze the viability of the ant-constructed solutions taking into account aspects such as savings, energy conservation, and user convenience. By simulating the pheromones' transpiration over time, pheromone dispersion enables the system to adjust to changing circumstances and converge towards optimal device-level energy management in the HEMS.

Ant Colony Optimization is a reliable approach to load scheduling, especially in complex and dynamic circumstances. However, for best results, details of execution and parameter adjustment must be taken into account.

3.9. Evolutionary algorithms

The concept of "evolutionary computation" (EC) applies to a heuristic-based technique that mimics a number of the fundamental concepts of biological development on a computer, including procreation, mutation, replication, and choosing as shown in Fig. 22. Three key phases comprise the design of an EC system. A collection of alternatives is picked in the initialization stage, which is the first phase, often at arbitrary. The evolution iterations, which have two functional stages each, including a fitness assessment and choosing and community reproduction and variability, constitute the following step. The standards for choosing to enable the choice of the ones who executed most effectively in request to establish an additional population via procreation and variance methods. The health assessment involves assessing the goal functions acquired for every one of the ones of the initialization the population. When the assessment of the optimizer algorithm on a user satisfies the completion criterion, this fresh populace is re-evaluated, and an additional iteration is achieved. Genetic algorithms (GA), evolutionary programming (EP), evolutionary strategies (ES), DNA programming (GP), training classifier algorithms (LCS), differential evolution (DE), and estimation of distribution algorithm (EDA) are all members of a group of techniques known as evolutionary learning algorithms. [295]

Evolutionary approaches have the advantages of not requiring slope

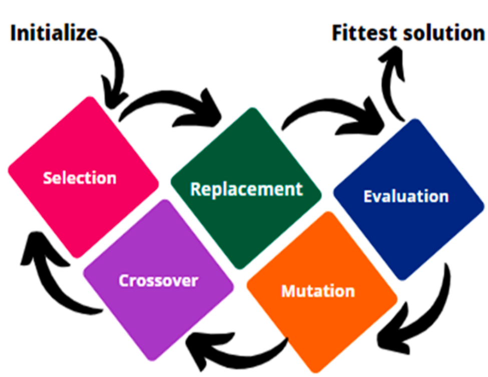

Fig. 22. Evolutionary algorithms.

generation, being able to be executed in simultaneously and being very investigative. This makes it possible to employ computational evolution for optimized performance and hunt in fields in which the framework is not effectively defined beforehand (for instance, improving an undefined function that outlines a consumer's usefulness for consuming electricity or forecasting projected electricity the marketplace cost), in contrast with conventional search strategies. However, evolutionary strategies have intrinsic weaknesses in terms of integration, comprehension, can produce unanticipated results, and there is no assurance that the most effective methods will be found [296]. Due to its benefits, EC procedures have been applied in a number of domains [297,298]. A differentiating (EA) for the multiple-purpose administration of lithium-ion batteries capacity in a data center for DR [299], a bi-level (EA) for assessing the retailer's ideal energy prices in the context of DR tactics, and a population-level evolution technique are other evolutionary methods that have been utilized in the DR context. Additionally, other iterations of the GA are being applied in the context of multiple goals, principally using the Non-Dominated Classifying Genetic Method II (NSGA II) [300]. The NSGA-II is an approach based on evolution that effectively manages a wide range of limitations despite utilizing an exclusive approach to find Pareto-optimal approaches to multiple objectives [301]. It has experienced extensive use in DR for the multi-objective allocation of demand [302–306].

Create a starting population of diversified solutions that correspond to various HEMS device-level setups. Establish a fitness function to assess each solution's performance according to factors including cost-effectiveness, user comfort, and energy efficiency. Utilize genetic operators like crossover, mutation, and selection to combine and modify the genetic makeup of preexisting solutions to produce new ones. Let the population to iteratively evolve over several generations, choosing and spreading options that are more fit, until the HEMS finds an ideal or nearly ideal solution for device-level energy management.

In complicated contexts, evolutionary algorithms provide a potent optimization method for load scheduling that takes parameter settings and computing needs into account.

3.10. Fuzzy logic control

Fuzzy Logic models uncertainties and imprecise facts using linguistic variables and rules, enabling flexible decision-making Additionally, it covers all midway alternatives between YES and NO. Given that fuzzy logic is a sort of artificially intelligent program, it may be viewed as an element of AI [307]. Fuzzy reasoning is a rule-driven paradigm that relies on someone's personal expertise, forming it feasible to apply it explicitly only as a component of AI software while the course of action is underway. By reducing usage and cost of energy, FLC is employed in HEMS to regulate household electrical devices. The four processes of fuzzification, defuzzification, rule basis, and inference algorithm were used to create FLC. In addition to being easy to use and handling both linear and non-linear systems founded on language principles, FLC doesn't need a mathematical framework. [308–310]. For the day-ahead scheduling of cooling systems, the FLC was created in order to obtain the best heat scheduling in respect to projections for outside temperatures and power costs [311]. In an intelligent house setting, DR is administered via intelligent HEMS. The outcome of the experiment demonstrated FLC's capacity for reducing power consumption and timing the use of the cooling systems. An earlier effort also used FLC for home automation to schedule devices [312] To increase customer satisfaction and reduce energy usage in homes, the researchers projected costs and modelled consumer comfort using fuzzy approaches. Additionally, a fuzzy reasoning inference system-based excellent quality simulation of power use for each domestic building is described [313]. In this study, a photovoltaic (PV) system is connected with HEMS to lower electrical and energy costs related to the power usage patterns of household items. The data provided to the fuzzy framework is the kind of device and its current usage, and the result is the likelihood that each unit will begin operating within the next minute. By taking into account high-power-consumption devices, the designed FLC can only regulate certain varieties of domestic devices. In order to schedule equipment operations and create a prototype which can satisfy user demands for immediate demand management, [314] suggested a SHEM multi- agent system (MAS) using a method. It was additionally developed and verified to employ a new fuzzy energy factor in the FLC method for immediate demand regulation. The suggested method was given the moniker AG0-FLC. "AG0" signifies the regulatory strategy used by a cognitive entity. A smart meter system has a feature that allows the remaining load curve's shape to be altered. The results of the AG's with FLC were investigated using a PC-based the LABVIEW program for automation of homes with FLC. A fuzzier, better engine, and fuzzified are every component of FLC.

Create a rule foundation that uses fuzzy sets and language variables. To show the extent to which variables (such energy use or user preferences) are included in fuzzy sets, develop membership functions. To evaluate the criteria and decide on equipment scheduling and power optimization, use a fuzzy inference engine. Alter device-level settings adaptively by implementing fuzzy control techniques that take user convenience, power expenses, and external factors into account.

Fuzzy Logic allows for flexibility by allowing for inaccurate inputs and changing user settings, which makes it appropriate for situations involving changing and unpredictable home energy management inside the HEMS as shown in Fig. 23.

Although careful rule development and expert input are crucial, fuzzy logic provides a robust solution to load scheduling by combining human-like reasoning to address uncertainty.

3.11. Artificial neural networks

The process of training an Artificial Neural Network (ANN) a network of linked nodes to recognize intricate patterns and correlations in past data. The components that make up an ANN's fundamental building block are linked together by unidirectional connections, every link's intensity being specified by a numerical weight. The neural networks, and in specifically the ANNs, mimic how humans think through a set of methods. ANNs are programs that, although not exact replicas of organic nerve infrastructure, have been influenced by them. Since the beginning of AI, ANNs have been created as connectionist theories, that are huge chains of basic processors that are heavily coupled and operate simultaneously [315]. While ANNs might be classified as both machine learning and AI methods that are influenced by nature, we feature them in this study as an independent group because they are frequently used in DR contexts.

The components that make up an ANN's fundamental building block are linked together by unidirectional connections, every link's intensity being specified by a numerical weight. Nodes may be input, output, or hidden, which alter data as it is being sent between inputs to outputs. Each unit generates the linear combination of its inputs, which are subsequently sent to the transfer function which determines its output. In order to forecast the energy produced by solar panels and residential consumption during a particular time frame. In [316], designed and simulates an artificially intelligent HEMS with an automatic learning prediction method utilizing the network of neurons. The suggested technique was tested using a trio of buildings that each had 3.3 p of PV capacity. With this approach, the personal consumption of solar energy may be increased by up to 8% while the use of energy can be decreased by up to 25%. The online learning method uses a Model of Radial Bases (RB) and combines cutting-edge resource utilization methods with increasing requirements. The capability of the entire system is enhanced using a virtual learning method founded on the Minimum Resource Allotting Network (MRAN) concept. A data handling technique called ANN, which replicates human cognitive processes and models nonlinear networks, is being used as an adaptive regulator to manage household items [317]. To quickly solve monitoring and forecasting issues, ANN-based methods may be utilized in place of simulators. To provide very comfortable heat conditions in residential structures, an ANN-based enhanced temperature management system was additionally created [318]. The ANN regulation approach can, according to the findings, enhance the thermal environment in residential structures. In [319], ANN and an evolutionary framework were employed to plan weekly devices with optimal energy use in the housing market, thereby lowering the peak demand and enhancing the utilization of green energies. By getting precise energy-related decisions, an autonomous algorithm-based ANN was implemented in [320] to lower the overall electricity price and operating lag for the need for energy. By regulating residential power use, the ANN approach may successfully handle the power usage. In a study [321], the ideal number of neurons for every hidden layer and learning rate were chosen for the PSO-based ANN to

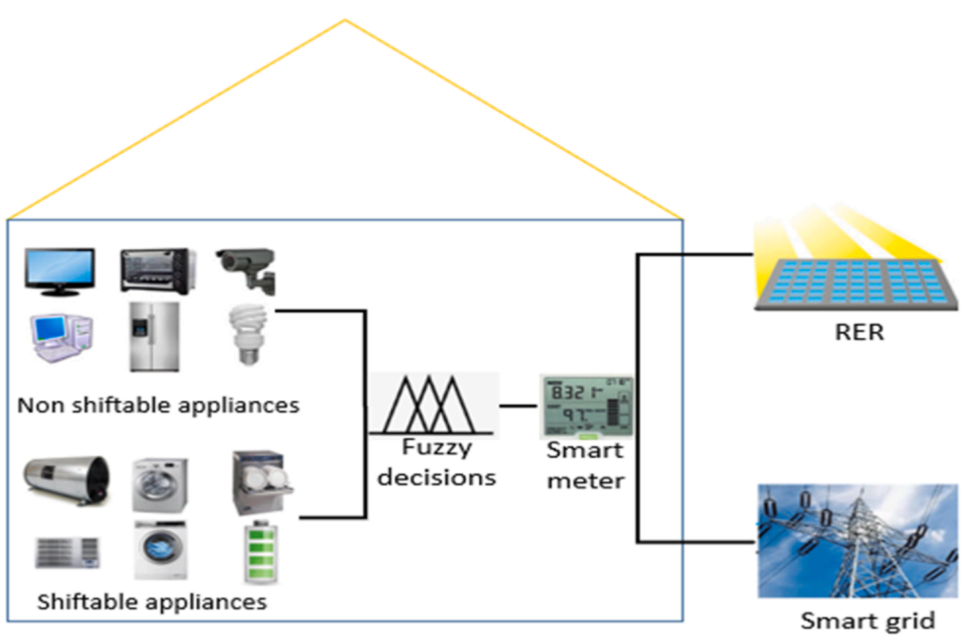

Fig. 23. Fuzzy logic model.

enhance its performance.

Feed the neural network with previous data on user behavior, environmental factors, and energy usage at the equipment level as input parameters. Give details about the neural network's design that are specific to the extent of energy consumption at the device level, such as the number of layers, nodes, and activation functions. Utilizing optimization and reverse propagation techniques, instruct the neural network so that it can recognize patterns in past data and increase its forecast accuracy. Put trained ANN to use in immediate forecasting so that the HEMS may anticipate and modify device-level energy usage according to the circumstances at hand. Incorporate methods for adaptive learning so the artificial neural network (ANN) may continually modify its model in response to fresh input, enhancing its efficacy and precision in energy management in smart home environments as shown in Fig. 24.

While careful model tuning along with data concerns are essential, artificial neural networks are a strong tool for load scheduling, particularly when working with non-linear patterns.

3.12. Adaptive neural fuzzy inference system

Fuzzy logic and neural networks are used in the adaptable Neural Fuzzy Inference System (ANFIS) to describe complicated, non-linear connections in an adaptable manner. Initial ANFIS methodology proposed a mixed training paradigm. While result variables are discovered using the Least Squares Estimation (LES) approach, underlying factors are determined using Gradient Descent (GD) as shown in Fig. 25 [322].

The optimization decision mechanism utilized during learning is critically important as it allows ANFIS to accomplish superior results.

The ANFIS, an AI regulator utilized in HEMS, is a smart system which plans and manages residential load in order to save energy. Several layers are included in the ANFIS framework, and no numeric model is necessary [323]. In [324], an ANFIS-based regulator for an intelligent home was put into place. The controller itself takes into consideration a fuzzy component and a smart search database. The input comes from outside sensors, output feedback, and fuzzy subsystems. The suggested regulator decides on the best energy schedule based on variable pricing while reducing energy use. However, the controller ignores additional factors like user desires and DR techniques. Also provided in [325] is a smart prediction method based on ANFIS for HEMS. This method is employed to strengthen the connections across the devices which send the reconfiguration schedules to the ANFIS. The effectiveness of the suggested ANFIS is superior to that of the traditional ANFIS, according to the results. [326] addressed about how to anticipate the effects of an integrated green power generating plan using the AFNIS approach. A combustion engine and an effective condensing oven make up the hybrid technology. Four ANFIS models were built, trained, assessed, and utilized to forecast the operating temperature of the framework using data from outdoor testing sets. Owing to the estimate process, all recognized ANFIS frameworks possess Root Mean Square Error (RMSE) values lower than 0.42 C, Variance value lower than 1.23, and Coefficient of Determination (R2) values above 0.996. This demonstrates that the ANFIS/TRNSYS models are capable of predicting a system's operating temperature correctly in a range of scenarios. The successful management of ESS, scheduling devices, and incorporated green energy is presented in [327] using a smart multi-agent Adaptive Neuro-fuzzy inference method embedded in HEMS. Regularly occurring wind speed, temperature, sunlight, and power prices are gathered and evaluated in the suggested MANFIS framework as inputs to validate the conclusions. The management of power generation, preservation, and

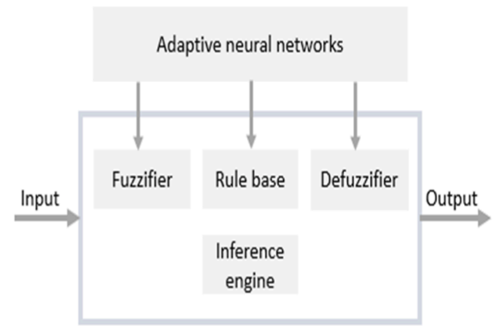

Fig. 25. ANFIS model.

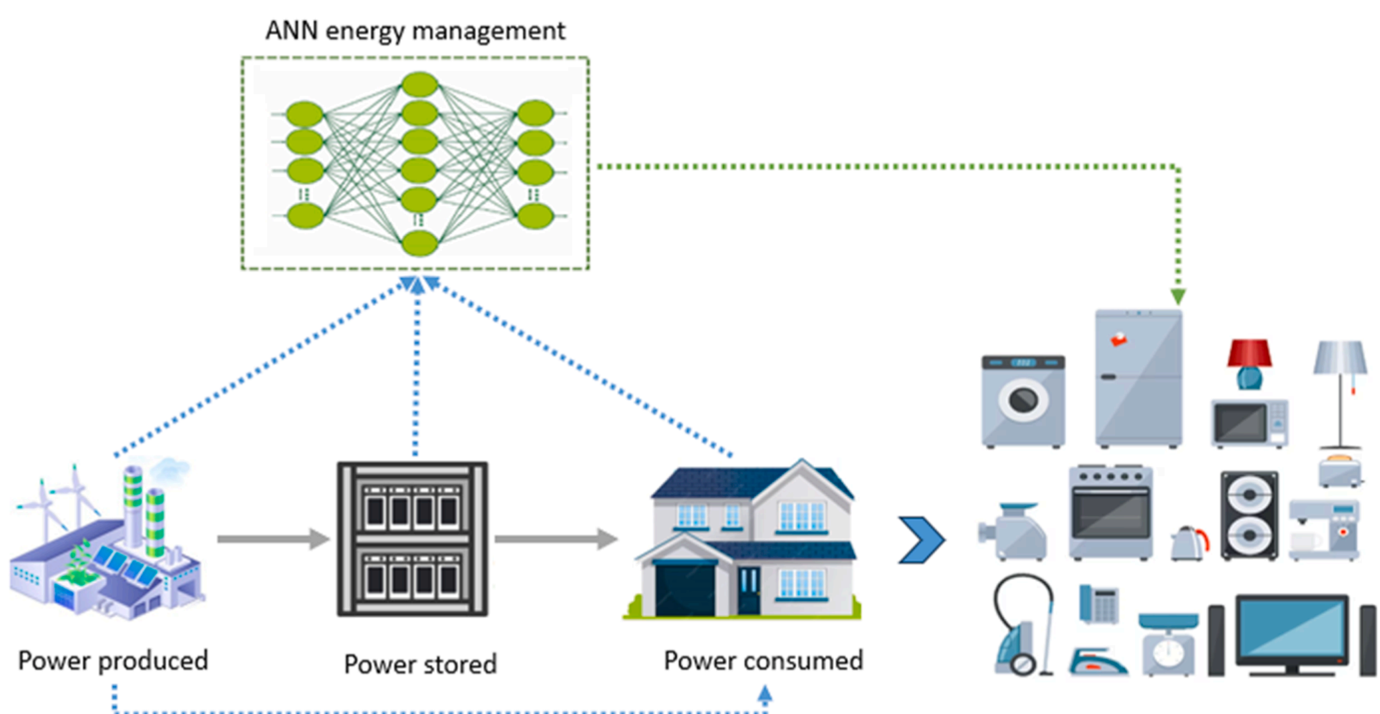

Fig. 24. Artificial neural network model.

planning is determined by three ANFIS regulator outputs.

Feed the ANFIS model with past information on user conduct, ambient circumstances, and energy usage at the device level. Develop a hybrid system that can acquire knowledge and infer complicated associations from trends in energy consumption by combining neural networks with fuzzy logic. To improve predicted accuracy, train the ANFIS

model with a hybrid learning approach that combines the advantages of neural networks with fuzzy logic. Employ the ANFIS model to make predictions in real time, enabling the HEMS to adjust quickly to shifting circumstances and user behavior. Utilize ANFIS's flexibility to continually improve energy-management tactics at the device level, enhancing agility and effectiveness in the context of smart homes.

ANFIS is an effective load scheduling method that provides flexibility and precision when simulating non-linear connections; nonetheless, it is important to carefully assess the quality of the data and model parameters.

The optimal load scheduling method is not an all-encompassing solution since a technique's efficacy varies depending on a number of parameters, such as the objectives of optimization, the degree of complexity of the scheduling challenge, and the unique features of the HEMS. Every method has advantages and disadvantages. When tackling linear optimization issues with clearly specified objectives and constraints, linear programming is an effective method. MILP is helpful in situations when some variables must have discrete values. Because of their versatility, genetic algorithms are effective for solving complicated, non-linear optimization issues. Although ANNs may effectively capture complicated connections in data, their training may necessitate a large volume of data. PSO is effective in allocating resources optimally and exploring solution domains. The ideal method will vary depending on the particulars and demands of your load scheduling issue. It is usually a good idea to try out a variety of strategies, maybe utilizing hybrid approaches or combining numerous tactics, in order to determine which way works best for your specific situation. The intricacy of the scheduling issue, computing capabilities, and the particular limitations of the system should all be taken into account. Overall, ANN are often regarded as useful for load scheduling in home energy administration systems because of their capacity to simulate complicated connections and resources allocation.(Table 2)

Table 2
Characteristics of different scheduling approaches used in HEMS.

Method	Process	Features	Applications	Pros	Cons
Linear programming	Developing a linear constraint optimization problem with a minimize or maximize objective function	Mathematical optimization that deals with linear relations	Optimize resource allocation	Effective for complicated problems	Constraints on keeping non-linear relations
Mixed integer linear programming	Considering both discrete and continuous decision factors	Appropriate for complicated scheduling issues involving discrete decision-making	Discrete decision-making, like the on/off modes of devices or the discrete amounts of resources	Manages continuous and discrete factors	Scaling problems and needs precise formulation
Nonlinear programming	Optimized a non-linear connection network	Manages non-linear demands and limitations	Simulate non-linear relationships, such as price functions or device activity.	Capacity to identify non-linearities	likely involving intricate algorithms.
Mixed-integer non-Linear programming	Manage continuous and discrete non-linear decision factors	Permits to handle discrete and non-linear factors	Demand non-linear interactions in addition to discrete decision-making	Offers the most effective responses in a variety of scheduling scenarios	scalability issues and demands accurate modelling.
Particle swarm optimization	Influenced by the bird's social behavior	Optimization employing population and effective solution space exploration	Search problems and optimizing resource allocation	Effective for space exploration and flexibility in response to changing load scheduling conditions.	Less beneficial for discrete or combinatorial problems
Genetic algorithm	Evolution-inspired processes	Exploring various solution spaces	Efficiently allocate resources and satisfy energy needs.	Flexibility to accommodate various schedule situations	Gradual convergence and needs precise parameter adjustment
Simulated annealing	Influenced by metallurgical annealing.	Probabilistic optimization	Allocating resources and effectively satisfying energy demand	Adaptability to a variety of limitations and resilience towards becoming trapped in local optima	Sensitive to temperature schedules and cautious parameter adjustment can be necessary
Colony optimization	Use pheromone trails to iteratively identify the best solutions by utilizing ants' foraging behavior	Flexibility to dynamic circumstances and decentralized optimization in load scheduling	Adjustment to constantly evolving conditions	Appropriate for complex non-linear optimization challenges.	Slow convergence and vulnerability to variations in parameters
Evolutionary algorithms	Include gradually evolving a population of natural selection-inspired outcomes	Consider a variety of solution spaces	Efficiently allocate resources and satisfy energy needs.	Effective for a variety of scheduling scenarios and flexible for complicated, non-linear issues	Intensity of computation and possibility of delayed convergence
Artificial neural network	Inspired by the human brain	Deep learning competencies for recognizing complicated patterns	Using load scheduling to simulate complicated connections and resources allocation	Incredibly good at managing unstructured data	Lacks interpretability
Fuzzy logic control	Models' uncertainties and vague information using linguistic factors and principles.	Modeling complex load scheduling scenarios	Represent the ambiguity and unpredictability in patterns of energy use.	Ability to adjust to the arbitrary human mind, ability to represent intricate, non-linear interactions	The requirement for expert participation during rule creation, rule selection and accessibility difficulties
Adaptive neural fuzzy inference system	Hybrid approach combines fuzzy logic and neural networks for modeling	flexibility in handling different kinds of data and dynamic load scheduling situations	Adjust to shifting patterns of energy use	Adaptable learning and able to identify intricate load scheduling trends	Requires a large amount of data to train and model's interpretation may be difficult

4. Future technical advancements in load forecasting & load scheduling in HEMS

This section examines several optimization approaches to establish the best load prediction and scheduling for HEMS.

4.1. Block chain

A blockchain is a distributed, open, decentralized digital ledger that records activities across several computers. Purpose is to prevent record tampering without affecting all following blocks and network agreement [328]. Block chain was developed with the goal of enabling digital currency trading outside a middleman. Hence, cryptographic evidence rather than faith is used to support monetary transactions among two sides. If a large number of centers are trustworthy, changing the proof-of-work agreement method that currently records activities on the block chain would prove computationally unfeasible [329]. For a block to be published on the block chain, miners must successfully complete challenging validation processes. A nonce is a number that satisfies this requirement. For defining each of the data in a block, an individual hash value is generated [330]. A whole new hash can be produced by just one modification in the block. The hash value also contains a hash of the preceding block, linking all blocks together to form a cryptographic hash tree that is recorded in every block. When nodes come to an agreement on earlier released blocks, the current condition of the structure is revised. Bitcoin, a cryptocurrency assistance, is a particularly well-known application of block chain [331]. Information stored on the block chain can also be better protected by public and private keys. Clients can communicate utilizing decryption and encryption methods through the usage of public and private keys. Although confidential keys allow an individual to be hardly ever recognized, open keys guarantee that users are reachable on the block chain [332]. By maintaining open keys nameless, confidentiality can continue to be protected. When an end-user accepts information to be stored in block chain technology, the individual's confidential keys are employed as an electronic signature. The data is subsequently verified before being posted to the block chain using the user's private key. Additionally, data may be encrypted and transferred secretly with the recipient's open key. The recipient can then use a confidential key to decode the information [333]. Block chains that are confidential, may enhance confidentiality further by limiting membership to just authorized clients [334]. In order to maintain a trustworthy circumstance, complicated and computation-costly agreement techniques, such as proof-of-work, are needed since open block chains permit accessibility without requiring users to prove their reliability [335]. Relative to the simple procedures normally utilized in a relied on, personal block chain, like proof-of-authority, they're high in energy and sluggish [336]. An intelligent contract is an automatic digital key that's permanently and openly inserted in the block chain. They are ensured to run instantly if specific block chain circumstances are met [337]. They are open commitments which are accessible to everyone so they are visible accords that are assured to be carried out automatically. Block chain and intelligent contracts study has evolved into numerous additional uses since their initial concentration on unreliable markets for finance, most notably in electrical energy [338]. HEMS communicate wirelessly that might be breached and picked up, giving burglars extra methods to breach residents' security [339]. Residents have to send load projections and maybe cost offers to the distribution system operator for the function of electricity management in trans active distribution networks having a significant number of HEMSs [340,341]. The consumer's behaviors and behavior may be inferred from the energy usage statistics, which is highly confidential [342]. A homeowner's real estate may be lost as a result of the breach of privacy and possible theft of user's data, increasing their vulnerability to cyberattacks. A field of attack for malevolent attackers to determine if a HEMS customer is at residence or not is provided by the supplied load prediction [343]. Additionally, a prolonged intercept will raise the likelihood of a successful forecasting, leaving HEMS clients open to a cunning thief. Hence, to protect the privacy of customer data, we suggest implementing intelligent contracts within an encrypted block chain. Block chains are tampered evident-resistant distributed databases [344]. The block chain stores transactional information in blocks, which are collections of records that keep on expanding. Each record additionally contains an expiry date and a hash associated with the block that came before it. A block chain-based smart agreement is a piece of script that is continuously run if certain events take place in the block chain [345]. The block chain will be utilized to facilitate safe transmission of data across homeowners and the Demand side operators. Yet, since one might utilize estimated information to more accurately forecast forthcoming user behavior, it may be more essential to preserve projected information than actual data. In the framework of the Internet of Things (IoT) in the home, experts in [346] look into block chain's potential application in intelligent houses. To the finest of our knowledge, no research has been done on security procedures for day-ahead or hour-ahead anticipated load data in a HEMS architecture. The writers of [347] performed an important effort to recommend the use of block chain in the optimization of power frameworks. They addressed a day-ahead optimal scheduling of loads strategy for power distribution networks as a way to reduce expenses for energy in infrastructure with distributed power resources. Here, a block chain is employed to ensure appropriate payment while coordinating scheduling in a micro grid.

Use a blockchain to track relationships, transactions, and usage of energy at the equipment level in a decentralized, impenetrable ledger. Use smart contracts to optimize energy use, enable peer-to-peer energy transfers, and execute and enforce device-level deals. By encrypting information from devices on the blockchain, you may improve privacy and security of data while guaranteeing safe and open access for authorized parties. Utilize blockchain agreement techniques to verify and confirm activities at the device level, improving the accuracy of data pertaining to energy. Allow for a decentralized and visible strategy for energy management. This will maximize energy savings in a trustless environment by enabling safe and independent device interaction inside the HEMS as shown in Fig. 26.

Despite current obstacles, blockchain technology promotes efficiency and trust by bringing reliability and safety to load forecasting and scheduling in residential energy administration.

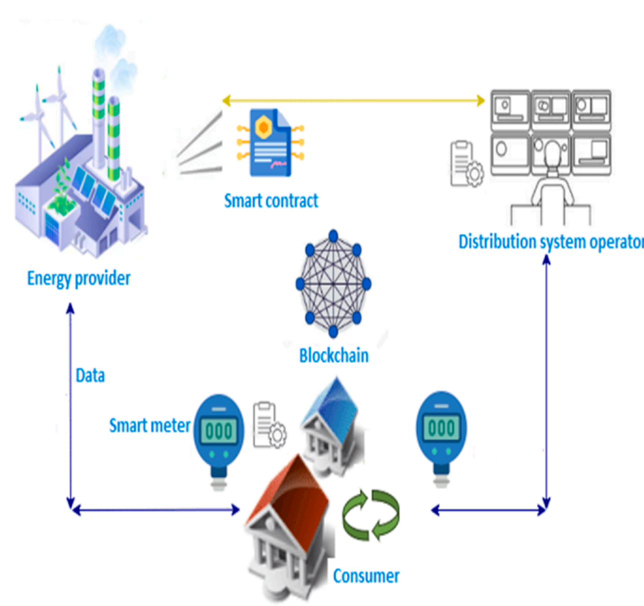

Fig. 26. Blockchain model.

4.2. Federated learning

Federated learning (FL) entails securing privacy, generating insights without disclosing raw data, and training machine learning models across decentralized devices [348]. A growing machine learning initiative called FL seeks to address the issue of information islands while protecting the confidentiality of information [349]. It describes several users working together using a number of centralized databases in decentralized machine learning environments as shown in Fig. 27 [350]. Google proposed it for the initial time in 2016 in order to anticipate client input across a great number of devices while retaining information locally. The overall description of FL's initial procedure is discussed [351]. The federated averaged (FedAvg), that serves as the basis of FL in numerous additional investigations, is a type of federated learning technique. Every gadget initially acquires a general global method, which will be used to conduct subsequent localized learning. In addition, numerous localized upgrades using localized data that are specific to each will enhance the downloaded generic approach, which will subsequently be sent to the internet for storage in an encrypted state [352]. Furthermore, a refreshed universal version will then be sent to the receiver using the mean version of local forms developed in the cloud system. The aforementioned steps are then repeated unless the tool performs as expected has passed [353]. With the advent of these advances, the conflict among data exchange and security for distributed units will be resolved. FL is suitable for activity when information is delicate to security since it has an attribute that the information is not disclosed to third centralized database [354]. To include cross-organizational activity within the federal structure, FL might be expanded. Develop an integrated version that is dynamically constructed for several individuals, information sources, and characteristic levels. This makes it possible for everyone to realize the advantages of shared and localized collaboration while upholding the confidentiality of information [355]. The globe has transitioned into an era of portable technology these days. Since every piece of equipment only produces a little amount of information, the overall amount of gadgets may not be contrasted. Clearly, FL is better suited for enhancing models in this situation [356]. Due to the diversity of gadget assets, FL is focused on imbalanced information as opposed to distributed focus systems, which focuses mainly on weighed data sharing. In FL, every user has total autonomy, and the server does not control the learning procedure, and the center does not distribute data [357]. FL thus represents a system that uses decentralized cooperation to integrate machine learning models with information fusion. FL is a decentralized solution that allows dispersed customers or organizations to independently trained a cooperative approach yet preserve localized data. Without disclosing any raw data, this strategy can help business organizations exchange cooperative models [358–360]. The rapidly expanding Internet of Things (IoT) movement has given customers the chance to enhance the interaction of clients with HEMS. applications of HEMS frequently need plenty of different data for training to build a strong system [361]. Customers intend to cooperatively educate their acquired information in effort to accomplish higher efficiency in such apps because one user wouldn't have adequate information to teach such a system, raising concerns about personal information security [362]. Current methods for cooperative learning require aggregating information algorithm upgrades on the web in order to carry out load prediction, which can lead to the disclosure of confidential data. These methods also need a large amount of communication capacity and additional cloud computing costs [363]. In [364] to address the aforementioned issues in a home, we introduce Pri Resi, a load-predicting solution with privacy protection, robust interaction, and no use of cloud services. Initially, we present a decentralized federated learning architecture that enables homeowners to directly analyze all collected information on the border by propagating modifications to the model across the intelligent home agents in each dwelling. In order to obtain communication-efficient and excellent forecasting outcomes, we additionally provide a gradient choice load-predicting method to lower the quantity of pooled gradients and the rate of gradients broadcast. Tests using real-world datasets indicate our system can predict loads with a precision of 97% with protecting residents' confidentiality. We think that other applications for smart homes can make extensive use of the de-centralized federated learning architecture that we have suggested. In order to control the electrical use of numerous intelligent homes in [365] equipped with residential appliances, PV systems, and battery storage, this paper suggests a unique federated reinforcement learning (FRL) technique. The establishment of a decentralized deep reinforcement learning (DRL) framework made up of regional HEMS and a generic server makes the suggested FRL method new. DRL operators for HEMS build and transmit their regional algorithms to the GS using utilization statistics. Once the generic technique for regional HEMS is updated, the GS compiles the regional versions into one, updates it, and communicates it to the DRL representatives. The DRL units then repeatedly recreate their specific versions by replacing the prior localized model with the corresponding global version. In [366] the best use of dispersed information and hasten the convergent procedure, we offer a recurring neural network-based demand-side estimator in this study. It is trained via federated training on clustering users. In [367] Many stores in the retail sector monitor and hold the intelligent meter data, and they are not prepared for sharing it. In order to accomplish this, a decentralized learning-based technique of identifying the traits of power consumers is suggested. This approach can protect merchants' confidentiality. To derive characteristics from information gathered from smart meters, privacy-perseverance principal component analysis is particularly used. Given this, a federated artificial neural network is trained using three weighted average algorithms to connect data from smart meters with customer socio-demographic variables.

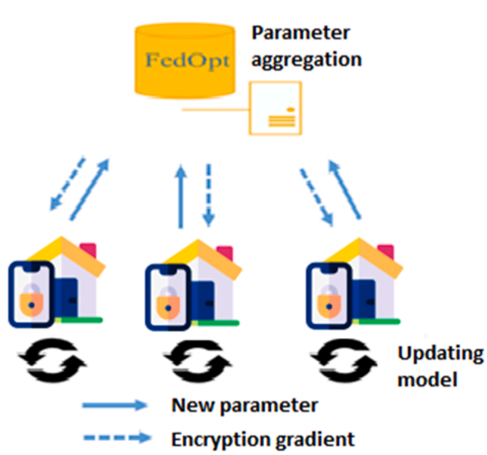

Fig. 27. Federated learning model.

Despite transferring raw data, devices use their data to locally train machine learning algorithms that identify trends in their unique energy use. With the use of federated learning, model updates from various devices may be combined to create a global model that incorporates knowledge from the whole HEMS. Maintaining raw data on the devices and only exchanging encrypted model updates with other devices throughout the federated learning process guarantees user confidentiality. To assist the HEMS, adjust to a range of user preferences and behaviors, enable decentralized optimization of device-level energy management tactics. Put into practice a dynamic federated learning strategy to enable the model to constantly improve over time based on device data collected in real-time, hence facilitating efficient and customized energy management.

Federated Learning encourages cooperation while protecting the privacy of personal data by offering a privacy-conscious method for predicting load and scheduling in residential energy administration.

4.3. Reinforcement-learning

Nearly all methods of learning revolve around the concept of acquiring knowledge through interactions. Reinforcement Learning (RL), among the many intriguing computer methods to gain knowledge through interactions, constitutes one of these techniques [368]. A focused-on-objectives agent has to acquire new skills while navigating an unpredictable atmosphere, and RL expressly takes this into account [369]. The two distinctive features of RL are delayed rewards and trial-and-error style of exploration. With the use of the idea of Markov Decision Processes (MDPs), the RL issue is defined. In MDPs, the agent gets an illustration of the surroundings state at every single sequential, discrete time step t (St 2 S), decides a course of action (At 2 A s) in accordance with the condition, and then discovers its way to the situation of the following time step St 1 during which it gets a monetary reward (Rt 2 R r) – as a result for its action [370]. Two elements known as the agent and surroundings take part in an ordinary RL challenge [371]. The environment where an agent engages, serves as both a learning and decision-making tool. In response, the atmosphere changes its condition and offers awards according on the agent's behaviors. Through conducting a sequence of acts as it responds to changing surroundings, RL aims to acquire a method of control to maximize its future predicted reward [372]. As a non-linear approximation is employed to encode the resultant function, traditional RL algorithms become unsteady [373]. Deep RL is being suggested as a highly effective method for overcoming the enchantment of dimensionality, making RL appropriate for solving complex issues, and making continuous states possible. [374] The Deep RL approach addresses the issues with correlations among sample and unpredictable goals by using simultaneously an experience playback of previous action state pairings and a periodic upgrade for the target network to assess rules. By using the expense and convenience of the consumers as a reward operation, Q-learning is additionally often utilized at the HEMS level to improve the scheduling of devices. While [375] resolve this restriction, O′Neill et al. [376] incorporate predetermined uselessness functions for the consumers' discontent on employment scheduling. In this case, a state is made up of a pricing series of a merchant or, a trajectory that shows how frequently an individual uses particular devices over a period of time, and occasionally the order of importance of the thing being examined. The HEMS's activity is to switch the relevant equipment at times t, and the incentive is calculated depending on the clients' happiness. In [377,378] Fitted Q-iteration (FQI) at the consumer layer (HEMS) enables the HEMS to choose the best regulation order for heat devices for any given phase of the 11 days considering day-ahead price alerts, according to [379, 380]. The HEMS's goal is to reduce the price of power use on a regular schedule. Using a collection of past information, the FQI method predicts the state-action value equation offline and matches it utilizing in two ways linear regression or ANNs. Making the best day-ahead loading description, that is then offered on the marketplace, is another example of how FQI is used at the HEMS. The researchers suggest a HEMS approach combining RL and Fuzzy Reasoning (FR) to improve the user's experience and choices while sacrificing energy use [381]. The suggested approach took into account consumer input by incorporating it to its command reasoning via fuzzy concepts such as incentive operations. Additionally, Q-learning is employed for making the most effective choices possible when scheduling the running of intelligent devices by moving controlled devices from peak times to non-peak times. The method suggested in [382] employs one participant, fewer state-action pairings, and fuzzier reasoning as incentive units in order to speed up learning. For scheduling devices, a technique that utilizes the MDP's tree-like structure and the State-Action-Reward-State-Action (SARSA) technique is presented in relation to Q-learning methods in [383]. SARSA is a kind of value-based RL which concentrates on rule learning and evaluates the worth of a rule at a certain point of time by implementing that specific strategy. According to the experiments, SARSA and Q-learning are able to produce comparable scheduling for a limited number of devices throughout a 24-hour period. Even if Q-learning is only sub-optimal, the schedule is still reached in substantially quicker repetitions employing the version of SARSA. A two-level deep RL-based power monitoring system is suggested by the authors in [384,385]. The technique uses a first-level schedule for the adjustable appliances in households and an actor-critic methodology. The combined washing machine (WM) and air conditioner (AC) loads, that are computed at the initial layer combined with the set load of the uncontrolled devices, are covered by the saving energy scheme and EVs planned at the subsequent phase. A DQN-based HEMS that took into account simultaneously the scheduling of EV charging and the schedule of gadgets is provided in [3885]. Using a deep RL approach that utilizes trusted zone regulation optimization, [386] proposed dealing using discrete and continuous operations to simultaneously optimize the timings of all types of equipment. The method took three different types of appliances deferrable, relatable, and crucial appliances into account in the simulation framework and straightaway learned via raw observational evidence of the device statuses, real-time energy pricing, and the outside temperature. Multi-agent reinforcement learning was just proposed enabling the ideal scheduling of different domestic devices to maximize the consumption of energy [387]. We provide a viable EMS method in [388] that can take advantage of short-horizon estimates of system uncertainty and relies on secure reinforcement learning. The capacity of the resilient EMS method to use short-horizon predictions allows it to beat existing modern algorithms in regard to resilience and cost-effectiveness, as demonstrated by testing findings using actual datasets.

Describe the energy management environment in terms of the RL framework, whereby utilization trends are states and gadgets are agents. Create an incentive program that promotes energy-saving behavior while taking into account the effects on the environment, user convenience, and price. Establish a discrete or ongoing action space that reflects potential device-level operations, including power optimization or scheduling adjustments. Select between training agents to make judgements that maximize cumulative rewards over time using policy gradient approaches. Give RL agents the ability to react instantly to modifications in user behavior, the surrounding environment, and energy costs in order to maximize the HEMS's device-level energy administration as shown in Fig. 28.

Although careful assessment of training data and exploratory methodologies is necessary, reinforcement learning offers a dynamic approach to load forecasting and scheduling in residential energy management, giving flexibility and optimization characteristics.

4.4. Metaverse

The phrase "metaverse" is made up of the words "meta" and "universe," and it was first used in 1992 [389]. Metaverse is currently a cutting-edge form of communications. metaverse refers to the subsequent version of the worldwide web, where clients may interact using software programs and each other via avatar in a virtual environment

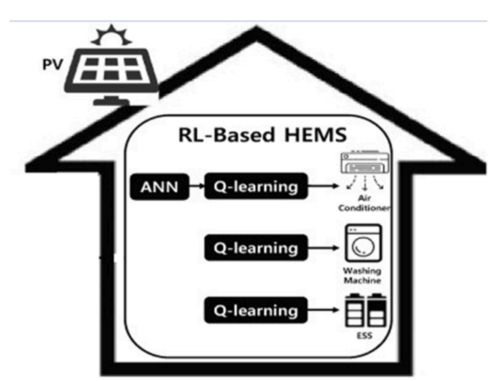

Fig. 28. Reinforcement learning model.

[390,391]. Participants in Metaverse receive a thoroughly deep interaction with interactive and collaborative tasks. Virtual world, scaling, quick synchronization, decentralization, monetary rewards, connectivity, and privacy are a few of the essential requirements for a successful metaverse. The metaverse framework often has many levels, comprising technology (6 G), user experience (wearable gadgets), decentralization (block chain), and geographic computing [392,393]. The meta universe is a synthetic globe made up of user-controlled virtual characters, electronic items, virtual worlds, and various other digitally produced components where people can interact, work together, and socialize using virtual identities on any intelligent device. It is believed that humans are the center of the virtual world [394]. The world of people is made up of human users, their internal psychologies, and their social relationships. Individuals can communicate with and regulate their personal avatars via human computer interface and extended reality technologies for entertainment, employment, socialize, and connect with other virtual beings in the virtual world [395]. In order to facilitate multi-sensory information understanding, delivery, interpreting, and storing in addition to controlling objects, the real world provides the metaverse in backing systems (such as sensing, control, exchanges, processing, and keeping infrastructures). This enables productive relationships with each of the electronic as well as people realms. In accordance with ISO/IEC23005 and IEEE 2888 standards [396,397], the digital realm is made up of a number of interrelated dispersed virtual realities, and every sub-metaverse may provide consumers portrayed as avatars of reality with a variety of virtual items and amenities and virtual spaces, Using interaction, artificial intelligence, digital twin, and block chain-based techniques, the meta universe system [398] creates, updates, and maintains a virtual environment using enormous amounts of information obtained from the real one as inputs. Clients located in physical spaces can deeply regulate their avatars in the meta-verse via their senses and physiques for various group and social events [399]. IoT-enabled detecting facilities plays a significant role in the physical world's digitalization and transformation through ubiquitous devices such as sensors and actuators, and the resulting IoT data is conveyed and handled through exchange and processing facilities [400]. To facilitate massive virtual world creation and numerous virtual world offerings, a virtual system in the digital realm processes and manages the created electronic data of the real and virtual human's realms [401]. By leveraging linked electronic gadgets enabling digitization the IoT framework connects the physical and digital worlds, allowing data circulate effortlessly across them. Particularly, metaverse demonstrates distinctive characteristics through several angles: Consumers may get both mentally and emotionally attached to the computer-generated realms because it is realistic enough [402]. The boundaries of the reality are imposed by the limitation of space and the immutability of time. The term "hyper spatiotemporally" relates to the breaking of the boundaries between space and time, since the meta world is a digital time and space continuity that exists side by side with the actual one [403]. The metaverse sustains a tight financial framework and an enduring worth structure having a high degree of autonomy, according to the viability. On one side, it ought to be public and on other side constructed with a decentralized design. The metaverse' s interoperability implies that individuals may navigate between virtual worlds without their immersion being interrupted [404] and the digital components for reconstructing virtual environments are transferable between different systems [405]. The word "scalability" describes the capability of the metaverse to continue operating effectively regardless of the number of simultaneous users and avatars, the degree of scenario intricacy, and the kind, breadth, and variety of user interactions [406]. The dispersion of the virtual world is comprised of diverse physical objects, varied physical environments, mixed varieties of data, heterogeneous forms of communication, and diverse psychology in humans. Additionally, it relates to the inadequate compatibility of metaverse technologies. The research in [407] suggested a method for implementing metaverse-driven virtual control of energy. This makes it easier to understand and proactively manage the needs of energy systems. The study of markets utilizing the metaverse is now receiving more attention. Electricity may be shown in a power trading framework as a digital currency that can be portrayed using token to speed up trades. Tokens like these may be divided into two categories: fungible and non-fungible tokens. In particular, power is convertible and may be traded for any quantity according to the consumer's preference. Power with a verified source and a distinctive identity, yet, is not transferable and is regarded as NFT [408,409]. In this project, a 3D virtual environment is used as an interface for an automated residence to give an improved interaction. A residence host also serves as an operating system for household appliances. A monitoring interface is offered as a means of communicating data across the physical and virtual universes that operates according to a standardization procedure. An individual may operate and track household gadgets using an intuitive interface which operates both simply and practically everywhere and at any moment via the World Wide Web with the aid of a 3D virtual space. A metaverse load forecasting system in [410] utilizing an evolutionary algorithm-BP neural network structure is suggested in this research. A method for creating scene-based models for categorization is developed taking into account the peculiarities of the information being analyzed. The analyses conducted demonstrate that the prediction model developed in this research performs much better than the BP neural network approach and can successfully estimate energy demand.

To produce replicas of real-world devices for the HEMS, design gadgets in the Metaverse. By providing intuitive and realistic control, Augmented Reality (AR) and Virtual Reality (VR) interfaces enable consumers to engage with virtual equipment. Make advantage of the Metaverse to show both past and present energy statistics, giving users a fun and educational experience. By enabling users to exchange and improve device-level energy management techniques inside the virtual setting, you may facilitate cooperative decision-making. Integrate real-world IoT devices with their virtual counterparts in the Metaverse to provide a comprehensive and interactive solution for household energy administration. Create a comprehensive and active strategy to home energy management by seamlessly integrating the actual IoT devices with the virtual representations of gadgets in the Metaverse as shown in Fig. 29.

Although real-world integration challenges and security concerns require consideration, the metaverse presents a fresh method for load forecasting and scheduling and offers a virtual environment for testing and optimization.

4.5. Digital twin technology

A digital twin is a digital replica of a real-world item, an individual, or procedure, placed within a virtualized replica of its surroundings.

Fig. 29. Metaverse model.

Digital twins used to model real-world events and their results, which will ultimately assist it make smarter choices [411]. During the course of its lifespan, the relationship remains dynamic and bidirectional. DT is a computerized modelling method that incorporates several fields of study, numerous physical factors, numerous levels, and numerous possibilities [412]. It is suitable with a variety of modern methods, including big data analysis, AI-powered cloud services, and the widely used intelligent sensors and 5 G connectivity [413]. A virtual representation in the digital realm is created using a vast amount of information sources. The correspondence connection among the digital body and the actual thing follows, so a "replica" of the unit is created [414]. In actuality, DT is the process of making electronic imitations of a structure. This "cloning" is frequently termed "digital twin". It is developed on the data framework and is a digital, active modelling of solid entities. In an ideal world, DT may be used to gather all data calculated by a real item [415]. On the basis of DT, superior simulators for physical objects may be created for modelling a variety of physically entity occurrences [416]. Its architecture based on; An actually existent entity's behavior, regulations, and real-world statistics, comprising hardware information, employee data, and data pertaining to the environment, are together referred to as its "physical layer" [417]. The bodily layer realizes the connection among the bodily structure and DT, and the model layer is a reflection of that level. data layer comprises different information of its physical level and the model level, which is the foundation to accomplish the integration of the physical layer and the model layer [418]. The data layer receives the different data from the physical layer and the model layer, and stores it in the respective databases, model libraries, regulations libraries, and understanding bases. The layer of application might validate the twin approach, carry out realistic modelling and optimization modelling on tangible item, and realize electronic administration of the whole item life chain via the facts gathered by the data layer. We are unable to test certain occurrences through the energy system due to the reliability of the electrical supply and the limitations imposed by real-world operation circumstances [419]. Electrical software for system modeling, a stable state evaluation, sophisticated systems, physical platforms utilizing the realistic-time digital trainer, and intermittent and stable state evaluation have all been created to model actual electrical facilities [420]. The modeling system can effectively handle dominant incidents, such as energy flow estimation, short-circuit protection assessment, devices regulating approach, and optimized functioning scheduling [421]. The main strategy is to employ the existing physical approach, followed by low-dimensional conversion and additional techniques to insert the information gathered into the current framework in order to determine the pertinent signals. Considering the significance of HEMS in the energy system, an ES must take into account their function in the network as both energy vendors and end users, especially with regard to versatility solutions provided by demand-side management activities. Intelligent meters and Internet of Things (IoT) gadgets are present in the HEMS for these motives in addition to improved observation and comprehension of the power network. In [422], the researchers use a DT architecture to track a number of metrics, decrease the use of electricity via an extensive match, and show that a 40% energy savings is possible. This is an illustration of a variety of services that may be provided using DT design. The researchers of [423] employ a DT technique to track residential performance in addition to the production of green energy with the goal to enhance the general efficiency of the smart city through optimum scheduling. By using a soft-ware-in-the-loop technique, the investigators of [424] proposed an approach for nearly immediate administration DR in SES that is capable to optimally utilize the opportunities that is offered by IoT. They demonstrated the advantages that DR methods at the home level may bring to the grids. [425] concentrated on predicting demand, a crucial component of a DT control structure. They specifically suggested an intelligent house architecture that utilizes cutting-edge computing that makes use of the web for handling information and more analysis. Both IoT gadgets and humans gather their input information. In [426], writers examine a DT that utilizes machine learning in conjunction with Energy PLUS simulation in order to examine the possibility of facilities to respond to need and offer flexible solutions to the system. Using the CAFCLA framework (Context-Aware Framework for Collaborative Learning Activities), the researchers of [427] examine the value of cutting-edge computing for intelligent structures and provide a method. In [428], the writers use an example in Rome, Italy, to demonstrate how to use a DT strategy that utilizes BIM and GIS. Owing to the usage of AI, the suggested DT model is helpful for efficient oversight and control both during the development stage and during the running stage. The researchers come to the conclusion that the proposed method may control loads in the most effective manner, resulting in an increase in RES for personal use and a decrease in overall power use. The use of BIM in DTs deserves special attention since it has been increasing and naturally evolving over the past few years, using the lessons discovered in factories [429]. In this study [430], a power management tool is introduced that may provide energy resources throughout an area with optimum supervision, arranging, projections, and coordinating offerings, permitting the best selections given customized targets.

Create virtual replicas of each gadget in the HEMS by building digital twins that closely resemble their real-world counterparts. Enables constant tracking of device-level energy metrics by enabling real-time synchronization between physical gadgets and their digital twins. Utilize statistics in the context of a digital twin to examine past and current energy data, spot trends, and enhance device-level functions. Make use of the digital twin for energy consumption trends forecasting, predictive modelling, and insight-driven device-level strategy adaptation. By using the digital twins of these devices to enable remote control and optimization, you can improve the flexibility and effectiveness of residential energy monitoring.

With virtual simulations, digital twin technology provides a dynamic and effective approach to optimize energy usage for residential energy management. It is a potent instrument for load forecasting and scheduling.

4.6. *Artificial intelligence*

Artificial intelligence (AI) is a program that, given a random universe, will function at least as well as a person. (AI)-based smart approaches that address challenging real-world issues in a variety of industries are growing increasingly commonplace these days. Because of its representational logic, adaptability, and explanatory abilities, systems powered by AI are being created and utilized around the globe in an extensive spectrum of sectors [431]. Artificial intelligence (AI) has had a simulated expansion in popularity during the last 20 years. AI is an investigation of how humans can program systems to perform tasks that individuals now perform more effectively [432]. AI-based systems have swiftly transformed from a research hypothesis into established and extremely commercial goods, emerging apparently from nothing. AI offers effective and adaptable ways to find answers to a range of issues that are frequently intractable via others, conventional and conservative approaches [433]. Today, its use is expanding into numerous areas of our daily lives, and its uses have been shown to be crucial for decision-making and guidance. The primary goals are to create an idea of smart data handling and create machines capable of exhibit specific behaviors that are close to those of human smartness [433]. Deep learning techniques build based on the brain's neural network structure, which constitutes an advancement above conventional ANN technologies. A solution to the gradient issue related to neural network training is now resolved, that significantly enhances the feature collection and categorization capabilities of these systems [434]. This was accomplished through boosting the quantity of concealed layers in networks and putting forth effective learning techniques. Various modelling architectures and free of charge software platforms are being created for deep learning methods depending on the issues and requirements. The deep learning algorithm uses a significant quantity of computation, a big volume of learning information, and multiple variables [435]. Knowledge graphs are commonly utilized in semantic searching and autonomous query responding, which is another essential area of artificial intelligence research [436]. Each node indicates an entity, and every edge indicates the link among entities in the knowledge graph, which organizes information in the manner of networks in order to describe the relationships among objects in reality [437]. The basic objective of knowledge graph study is to provide understanding based on unorganized data and to conduct out organized interpreting, information logic, and automatically building knowledge bases [438]. Data extraction, information fusion, and information computing make up the three components of the knowledge graph [439]. An expert system is a type of computing program that uses knowledge from certain disciplines to tackle particular issues [440]. To tackle complicated issues using logic and judgement like specialists, it may replicate the cognitive processes employed by human specialists [441]. A basic expert system is made up mostly of a tool for inference, a repository of information, and a collection of information [442]. The electrical infrastructure has a variety of issues that call for the expertise of planners, developers, managers in associated occupations. Some depend on professional expertise, while others combine judgment founded on knowledge of outcomes from mathematical analytic techniques [443]. The most developed AI technique currently employed in electrical networks is expert systems. The primary use cases are now malfunction rehabilitation, energy system forecasting management direction, and energy network tracking and problem diagnostics [444]. An agent is a dynamically operating unit that has excellent self-control capabilities. It is a computing program that is freely linked and uses a standard technique to connect to outside entities. This is how a scattered smart technology operates. It refers to a thing which is capable of working independently and is able to communicate with protocols and semantic compatibility. It belongs to the field of dispersed AI innovation. It is projected to have a promising future in the next wave of deploying regulatory system because of the benefits of flexibility and accessibility [445]. The goal of this article [446] is to demonstrate the bounds of XAI for use in energy sector. The usual difficulties that arise when employing XAI in these applications are initially discussed, after which we examine and analyses the most recent research on the subject as well as current developments in the field. We anticipate that this work will spark interesting debates and stimulate additional study on a crucial, rising issue. The goal of this research in [447] is to investigate and assess artificial intelligence algorithms for reliably forecasting individual energy profiles for handling power in a smart home. For the purpose of predicting an individual house energy use, eight statistical models of regression are assessed. According to the experimental findings, the Radial Basis Function (RBF) kernel is the artificial intelligence approach which is best suited for predicting the forthcoming electrical usage. The day-ahead power consumption forecast method shown in this paper [448] is straightforward and effective for any EMS. In contrast with other techniques, the suggested approach was created as an element of a general EMS and is not required to be linked to any specific types of detectors or previous datasets. In [449] we create a method for scheduling residential devices optimization in light of the advancements in AI technologies. Most home equipment is split into three groups based on how often they use power. In light of that, we suggest a HEMS framework that tries to accomplish both single-objective and multi-objective optimization while reducing the maximum demand and power bills of an intelligent house. The supply and demand side management approaches form the foundation of the suggested HEMS structure in [450]. The initial approach concentrates on the scheduling and management of energy transport among production, utilization, and preservation representatives, whereas the latter addresses the scheduling and regulate of versatile gadgets to obtain the best load pattern regulation. Flows of power are managed depending on the cost of grid power, predictive information. An AI-based multipurpose optimization method combines the two planned control algorithms to concurrently maximize pleasure while minimizing expenses.

Use AI to analyses and incorporate a variety of data resources, such as user behavior, device-specific energy use, and environmental variables, with ease. Use AI algorithms for forecasting to help with proactive energy management by predicting future energy demands at the gadget level. Use AI-driven dynamic optimization methods to enable devices to instantly adjust to shifting consumer tastes and external conditions. To learn from past data, optimize energy consumption plans, and adjust to changing usage trends, apply machine learning models. Incorporate artificial intelligence (AI) technologies to offer customized energy-saving suggestions, improving user involvement and ultimate HEMS performance as shown in Fig. 30.

Although it demands extreme care to data integrity and model reliability, artificial intelligence plays a critical role in enhancing load forecasting and scheduling in residential energy management. AI offers adaptability and efficiency.

4.7. Probabilistic models

Probabilistic models represented ambiguous or unpredictable processes using the concepts of probability [451]. A simulation of an actual procedure that includes ambiguous or unpredictable parameters is

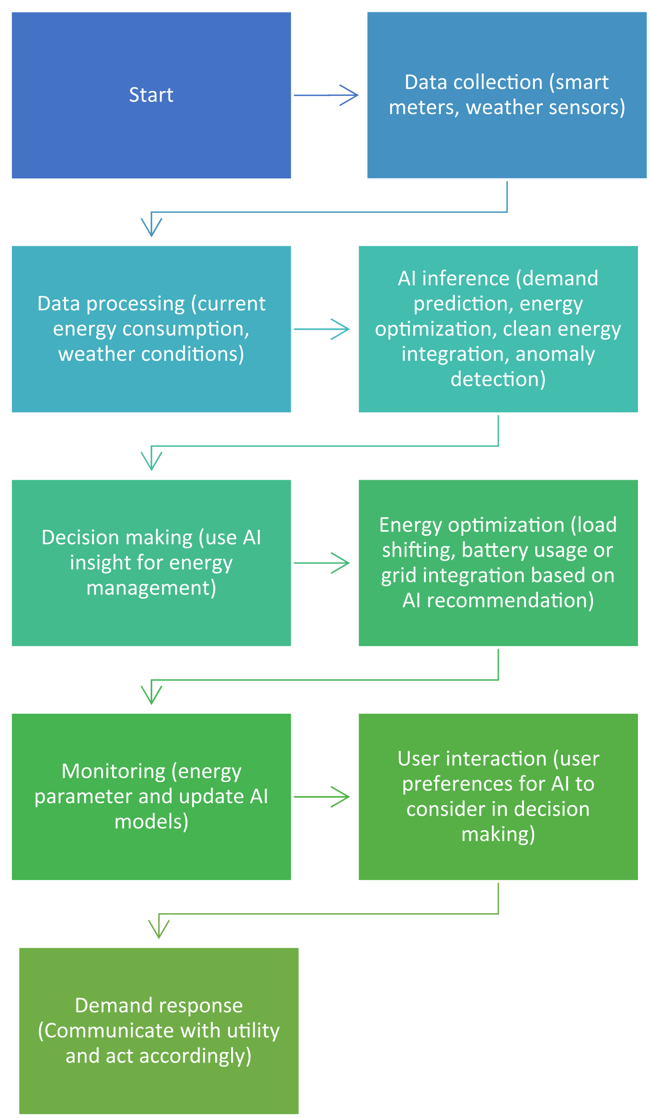

Fig. 30. AI model.

known as a probabilistic model. Estimating the likelihood of eventual results for an entity using statistics or previous information is the primary objective of probabilistic modeling [452]. Since unpredictability can be expressed in probabilistic designs, they have particular advantages for applications in a reality where facts are frequently imprecise [453]. In most flexible and developing systems, these frameworks may also frequently be changed as improved information become accessible. last decades indicate a sharp increase in interest in probabilistic models [454]. This is being become feasible in large part by continual improvements in processing power, quicker connections, and less expensive memory, which have helped solve several of the known Big Task challenges [455]. Probabilistic frameworks are founded on the idea that, even though the connection may be pretty correctly designed, additional factors need to be involved in order to compensate for variations seen in the real facts [456]. Probabilistic models that use likelihood distributions to adjust for these elements are hence known as probabilistic frameworks. Furthermore, probabilistic frameworks are crucial because they serve as the foundation for a lot of research in fields like data mining, machine learning, and AI [457]. Their design and resolution are based on the cumulative rule and products rule, which are both of the fundamental principles of probability science. Yet, their seeming ease may be deceiving, since all but the simplest of models may ultimately turn conceptually insoluble [458]. Utilizing information in [459] from a live Danish house, a numerical simulation is created to simulate an online HEMS operation. The quantile-copula group outperforms the RLS-based approaches for forecasting marginal distributions and preserving the time-dependent correlation, according to modelling findings, which demonstrate the suggested frameworks' reliability. In [460] research, an actual everyday utilization pattern for homes is produced using a clearly diversified probabilistic model. Home utilization patterns are predicted using the discrete-time Markov process concept and Cox regression. The suggested framework may incorporate social behavior heterogeneity based on specific traits and record the length of occupied conditions. In [461] provides a model predictive control technique to control DR in a HEMS, considering the variability in the current solar energy and the prognosis for the outside climate, the suggested controlling design guarantees that both the DR scenario and inside temperature regulation are fulfilled with a significant likelihood. rather than computationally restricting a sampling-based technique, unpredictability is included in the MPC concept utilizing stochastic restrictions. This research in [462] developed a stochastic load projection approach based on demand scenarios. It is suggested that one conduct an energy usage examination to determine the likelihood of every consuming event for a certain family would materialize during any given period of times. The findings of the analysis are then combined with PLF to create a load projection for a specific home. In [463], an innovative model for residential energy control proposed, utilizing a stochastic optimization technique, in the framework of a household power center founded on green power by two-point approximation approach. For the purpose of illustrating how well the suggested strategy works, figures are given. This article [464] provides an introductory overview of stochastic power demand projections, highlighting key approaches, approaches, and assessment strategies as well as frequent misconceptions. Additionally, we emphasize the requirement for more funding for investigations like replicable examples, probabilistic load prediction assessment and appraisal, and a mechanism for taking into account technological advances and energy legislation. Research in [465] suggested a probabilistic prediction approach centered around boosted probabilistic settings networks. Initially multivariate input values are used in a correlation assessment. Furthermore, a proposal for an adjustable B-SCN network design is made in order to build the forecasting design and considerably increase the reliability of modelling outcomes.

Following that, employing the Gaussian technique to create the ranges of confidence, likelihood estimation is utilized to achieve the framework's estimate of its level of uncertainties. The primary outcome of this work [466] is the use of the Polar Bear Optimization (PBO) approach to effectively resolve the issue of scheduling of DR appliances in the HEMS to minimize electricity consumption costs in addition to the peak-to-average ratio []. By conducting several investigations for a home customer using different foundation loads, uninterruptible deferrable, and interruptible deferrable devices underneath an on-demand tariff program, the usefulness of the suggested probabilistic optimization technique is demonstrated. This investigation [467] presents an efficient Fast Hartley Transform (FHT) based technique to assess stochastic dependability and computing the generation expenses for all the units in the whole system. The FHT was utilized throughout the convergence phase. the probabilistic simulation methodology presented in this research [468] enables an examination of the possible effects of any important interactions among the unidentified variables contributing to the HEMS problem. The associated possibilities of unidentified parameters are produced using a Copula-based paradigm creation approach. The likelihood of any uncertain load being present or absent on any given day is also taken into account in order to produce more precise predictions. To represent the deferrable device load novel designs are proposed in [469]. Estimation and division methods are then used to manage the architectural issue under consideration in a decentralized manner. The regionally created decentralized CoHEM method enables clients to calculate their scheduling algorithms employing just local consumer data and neighbor-to-neighbor messaging. In order to optimize an intelligent micro grid's day-ahead activities, a novel framework in [470] that uses the Monte Carlo simulation approach is presented in this work. It takes into account the demand unpredictability of EV charging facilities.

Establish a probabilistic model that takes user behavior and external variables into consideration, along with other irregularities in device-level characteristics. Give parameters like energy use probability distributions so the HEMS can simulate the possibility of various outcomes. Utilize stochastic optimization techniques to optimize device-level scheduling while taking changing probabilities into account. Incorporate risk assessment tools to determine how uncertainty could affect energy management choices. Give the HEMS the ability to adaptively modify device-level tactics in response to uncertain situations by allowing them to be based on probabilistic forecasts as shown in Fig. 31. This would improve overall resilience and effectiveness.

By incorporating uncertainties into account and strengthening system resilience, probabilistic models provide a useful method for load forecasting and scheduling in home energy management. This allows for more informed decision-making.

4.8. Peer to peer energy trading

The rise in dispersed power sources in these days has altered the electricity supply chains. Energy production and consumption are both evolving drastically at the same time, and typical energy customers are evolving into prosumers [471]. Prosumer-generated power is unpredictable and sporadic since it is greatly impacted by the amount of radiation and the weather, both of that are continually fluctuating [472]. Here are various choices available to prosumers that have a power excess. The power may be transmitted to the electrical grid, saved in a battery for future utilization, or the additional power may be traded to different power users [473]. Peer-to-peer (P2P) trade in electricity is a sort of cooperative economy that may be implemented inside the exact same electrical grid and refers to the exchange of power amongst electricity prosumers. As P2P energy trading enables power prosumers to trade their surplus electricity to customers who require energy, it can result in monetary gains. The purchasing points and the power lines depict the power and monetary transaction that takes place across prosumers and consumers. Energy can be sold by a prosumer to a consumer. On an administrative level that serves as a power exchange manager, the full negotiating phase is conducted. The trade arrows pointing in a single direction signify that customer may only get power from the administrator for power exchange. The arrows indicating

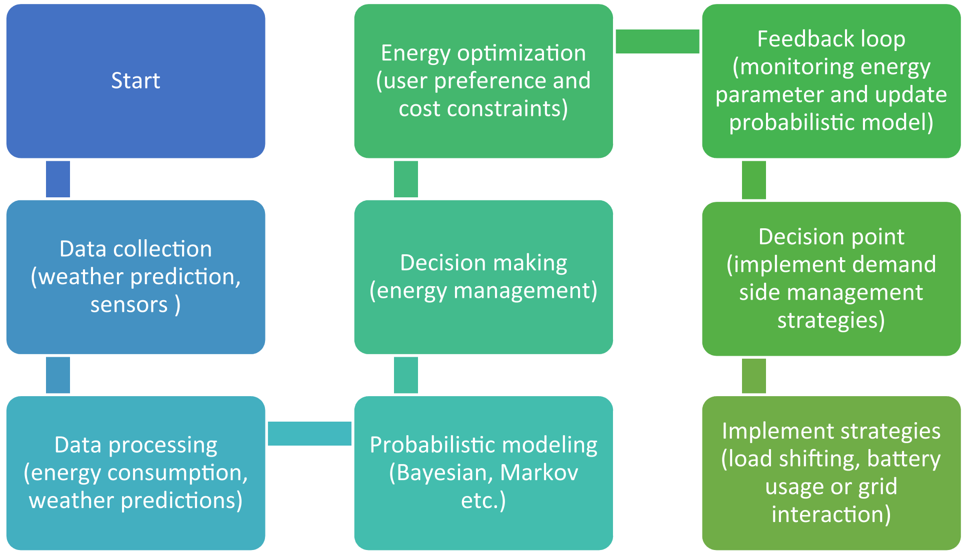

Fig. 31. Probabilistic model.

bilateral selling signify that power can be purchased and sold by prosumers to the organizer for power share [474]. If users of the network cooperate by sharing some its facilities, the design of a dispersed network can be referred to as P2P connections as shown in Fig. 32. Despite the assistance of intermediate firms, other peers may directly utilize such common assets, delivering the functionality and materials made available by the community [475]. There are two tiers in a P2P network. The virtual layer essentially gives participants a secure channel over which they may choose the terms of their electrical commerce [476]. In an online environment where data of all types is transferred, purchases and sales are made, a suitable marketplace system is used to pair the purchase and sale requests, and then payments are completed upon efficient request verification, it ensures that everyone uses the system equally [477]. A fast and safe database serves as the brain of the peer-to-peer power network. To participate in power trade, all market players must be enabled to interact with each other through the information network. Organize the players on an appropriate trading site. accessing the marketplace equally for every player [478]. To maintain network safety and dependability, supervise trade and impose constraints on member actions. A P2P network's data structure aids the market's functioning, which includes market reservation, transaction guidelines, and a precisely specified auction style [479]. By pairing selling and buying requests at close to actual time detail, the market operation's primary goal is to give players access to an efficient power dealing procedure. Tariff structures are created as integral aspects of trading and are utilized to successfully regulate the demand and supply of power. P2P rates vary fundamentally from those employed in conventional energy marketplaces [480]. Through the use of a specific auction method during P2P trades, a prosumer's EMS guarantees the availability of power. To that end, a trans-active meter provides an EMS accessibility to the prosumer's actual time buyer and seller data [481]. Utilizing this data, the EMS creates the prosumer's production and use profiles and chooses a bid approach to engage in trade on for them [482]. At contrary, the physical layer is simply a physical network that renders it possible for power to be transferred between vendors to purchasers after the monetary agreements among both sides have been

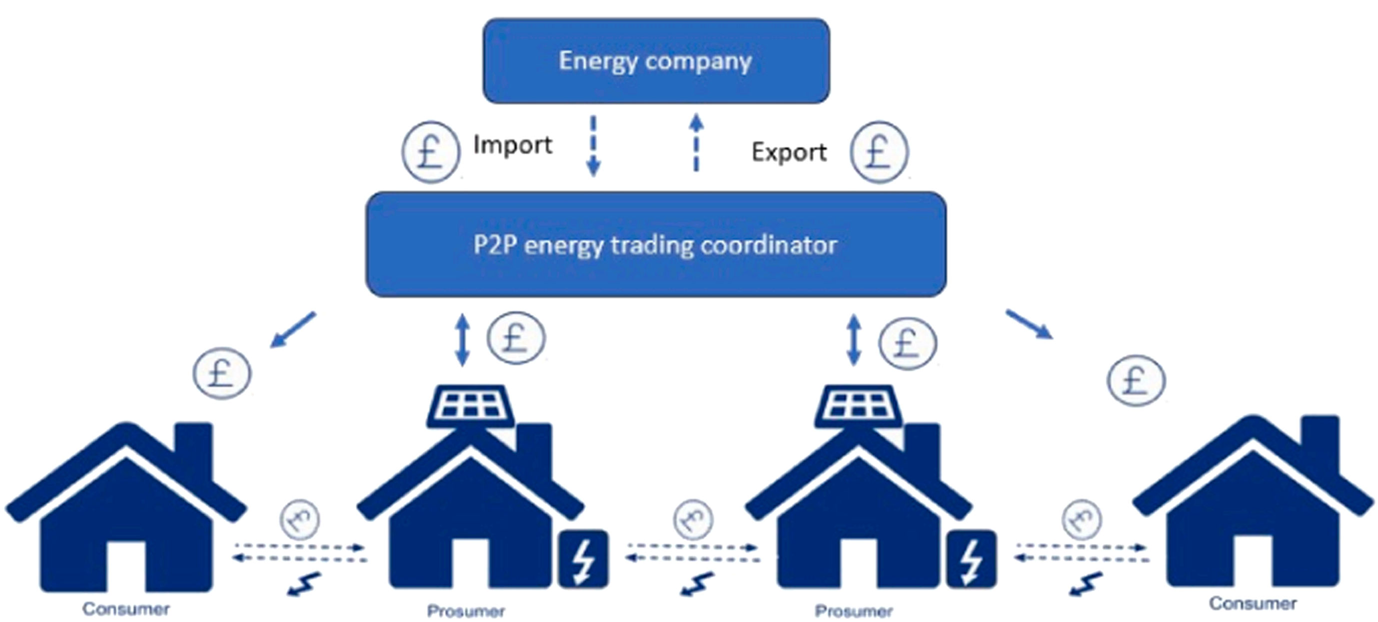

Fig. 32. P2P energy trading model.

made through the virtual layer system [483]. The grid-dependent and island-based micro grid networks enable peer-to-peer trading. It is crucial to identify the locations at which the main electrical grid connects in order to balance the need for electricity and production in a grids-connected systems. In order to engage in peer-to-peer trade, every prosumer has must possess the necessary meter technology. Every prosumer specifically has to have a trans active meter [484] as well as to a conventional power meter. The identification of consumers and the sharing of data inside the network are two key components for interaction in peer-to-peer trade. There are several P2P connectivity designs, comprising hybrid form, unorganized, and organized systems, in research [485]. The selection of an interactive infrastructure must satisfy the IEEE 1547.3–2007's efficiency recommendations for the incorporation of DER, which involve delay, productivity, dependability, and privacy. A substantial amount of market players must be present inside the network for P2P trading of electricity, and a portion of those players must be able to generate power [486]. The goal of P2P energy trading ought to be explicitly stated since it influences the creation of rates and the market structure. The next phase market regulations and energy legislation will undoubtedly play a major role in determining how well P2P trading works. Federal laws determine the types of market designs that are permitted, the distribution of charges and taxes, and the integration of the P2P market in the current power market and distribution infrastructures [487]. The goal of P2P energy trade in a distribution system featuring incorporated STLF was established in this study [488]. Applying the Mid-market price (MMR) strategy for P2P trading utilizing probabilistic incorporated STLF, the best approach for the intended purpose is suggested. This research [489] concentrates on the method to achieve as an enormous save utilizing multi-agent deep reinforcement learning to identify the most effective strategy with efficient power transactions and DSM methods. In this sense, a partly observable Markov decision process (POMDP) is used to define the energy market and DSM issue facing domestic families. To organize demand response techniques and balance out possible production consumption disruptions in the hour-ahead daily setting, a peer-to-peer electricity trading network between residential structures is suggested in paper [490]. Initially the daily domestic power management systems are developed while taking into account the features of adaptive household devices and battery backup. With regard to domestic consumers' hazard choices, the pain and potential monetary harm associated with conducting demand responses are measured. A double-auction process is used to foster cooperative demand response programs in the event of disruptions, and a P2P energy trade marketplace is created.

To create an open and safe ledger for tracking energy flows between devices, apply blockchain technology. To ensure effective and trustworthy operations, use smart contracts to regulate and uphold energy trading deals between devices. Give devices the freedom to independently determine energy costs in response to customer tastes, supply, and demand to create a vibrant and competitive marketplace. In order to precisely measure and validate energy transfers and guarantee honest and open transactions, integrate smart metering technologies. Encourage peer-to-peer energy trading among users to advance ecology and energy conservation inside the HEMS.

Peer-to-peer energy trading creates a decentralized and effective energy market, which changes load forecasting and scheduling; nevertheless, infrastructural and regulatory issues must be carefully considered

4.9. Energy harvesting

The process of transforming ambient energy sources into useful electric power for home energy systems is known as energy harvesting Untapped forms of energy are all around us; they can be utilized to power sensors as well as additional technology [491]. These resources include electromagnetic waves, both synthetic and natural illumination, waste heat, heat slopes, air movement, tremors, noise, as well as our own physical motions. It is more essential than before to produce power independent of mains electricity or storage due to the explosive rise of wireless sensors and emerging uses like portable electronics as well as related to IoT [492]. A lot of research has been conducted done on capturing energy systems, many of which are based on well-known concepts such the electrodynamic, solar power, and thermoelectric effects. However, more advanced, frequently miniaturized systems having the capacity to produce electricity more effectively and using more types of resources have emerged in the past few years.

Many of them make use of innovative concepts, and others take advantage of advancements in MEMS and nanotechnology. Others even integrate them alongside sensor materials to provide genuinely self-sustaining devices [493,494]. Solar power harvesting isn't a novel idea. Photovoltaic (PV) innovation is always used in solar energy gathering activities nowadays. Photovoltaic cells are employed in a variety of industries, including aircraft and conveyance. Solar panels are an economical means to generate energy when location does not pose a problem. Actually, this is already happening and an amount of the energy that is delivered via the power system is now being supplied by PV panels. But converting PV panels onto free surfaces offers an individual set of difficulties and needs a lot more study. N-type and P-type silicon are the main components of photovoltaic (PV) cells. positively charged particles go towards the P-type semiconductors and negatively charged electrons migrate towards the N-type semiconductor as a result of sunlight [495,496]. Many piezo substances are also pyroelectric. The capacity of certain elements to transform thermal energy into electric power when either heated or cooled is known as pyro electricity. The magnitude of variations in temperature is precisely correlated to the pyroelectric current [497]. Pyroelectric energy production differs from thermoelectric energy gathering in that it requires no heat gauges and may be accomplished by merely subjecting a substance to environmental changes. Varying temperatures between thermocouples are essential for thermoelectric generation of energy. Heat harvesters that use air as a transfer carrier are made up of air-circulating lines that are buried beneath the ground. According to the environmental temperature variance, the air can collect or releases warmth from the surface [497]. Convection may make air flow feasible, without the requirement for a rotating motor. These devices could be able to turn on the turbine and generate power by using the air movement [498]. A system of liquid conduits inserted into the home construction can be used to gather and carry heat as an additional energy-harvesting technique [499]. This technique is frequently used to melt snow and ice off the pavement surface and to lower summertime roadway surface temperatures caused by hot pavement. The heated fluid from these mechanisms is used in another use to heat buildings. There are numerous attempts to utilize piezoelectric devices for capturing energy in a range of sectors [500]. floors for foot traffic contained piezoelectric materials. Energy harvesting from diverse environmental energy sources, including either water and wind exerted stresses [502] and the tremors of buildings [501], is another new application area for piezoelectric materials. Studies have looked into using piezoelectric technology to harness the power produced by human motion [503]. Piezoelectric substances are also used to power transmitters and sensors that sense signals by creating energy from oscillations [504,505]. In RF energy (radio frequency) gathering, electromagnetic waves, including Wi-Fi or cell phone frequencies, is captured and transformed into electrical power that is useful. This study in [506] discusses ways to control energy for energy harvesting, which has been determined to be the dependable resource of power in WSNs. The power administration strategies are created to use gathered power effectively. The assessment categorizes the power management strategies into groups that reflect different use needs. In [507] for household energy administration equipped with energy harvesting, namely solar arrays, and preservation capacity, this research proposes a battery-aware probabilistic management paradigm. The load behavior, the environment, climate prediction, utility, and client tastes are all considered as part of a single Markov process of choice in the model and management reasoning. In this study [508], we create a beneficial hybrid approach for predicting energy generation and use, helping to increase the harvesting of energy by giving the involved green energy experts useful predictions statistics. In this section we incorporate an echo state network with a convolutional neural network for reliable prediction of clean energy output and utilization. Outlined a future for energy-harvesting techniques in [509] for Internet of Things (IoT) gadgets which can advance investigations into the 5 G era. We suggest that the primary element of IoT devices will involve various energy harvesting and control approach at the circuit, equipment, and network levels. In-depth current reviews of the research regarding all of the aforementioned techniques for capturing energy are provided in this publication [510]. It provides details regarding every harvesting tech's financial aspect, model creation, deployment initiatives, and harvesting concept. It is concluded that a number of these energy harvesting techniques have advanced enough to produce self-sustaining roadway electricity.

Install sensors that can harvest energy from the environment, such as thermal, kinetic, or solar energy, in your gadgets. When ambient supply is minimal, store gathered energy using energy storage devices like batteries or capacitors for future use. Use sophisticated power management systems to effectively control and distribute the energy that has been gathered to power the gadget. Give gadgets the capacity to adjust how they operate in response to the amount of energy that can be captured, therefore maximizing energy use instantly. Reduce the HEMS's need on external power sources by integrating energy harvesting with effective device-level energy management to create a self-sustaining ecosystem.

By supplying renewable energy sources, energy harvesting enhances sustainability to household energy management. However, initial expenses and irregularity should be taken into account. Energy harvesting also helps with load forecasting and scheduling.

4.10. Electric vehicle (V2G & G2V)

Among many appealing options for assisting clean power resources and operating automobiles without consuming oil or gasoline is the utilization of battery packs. Regarding their usage in static and dynamic uses, yet, the price of fuel cells remains a significant hurdle [511]. Cells may often be made cheaper by reducing material prices, improving process efficiency, and raising the rate of manufacturing [512]. The term "Vehicle-to-grid (V2G) and Grid-to-Vehicle(G2V)" refers to yet another, more efficient alternative. While the battery remains within it, the V2G technology allows for the usage of the battery pack to support grid services, G2V to fill batteries of vehicles [513]. Given the availability of plug into facilities, EVs are developing a number of new uses, including vehicle-to-grid (V2G) and vehicle-to-home (V2H), which have the ability to help regulate the electrical system voltage, frequency, and in a variety of additional purposes. In order to lower consumers' power purchase prices, EVs are used to reduce peak load demand during the peak tariff phase [514,515]. In order to use EV, HEMS developed a charging management approach, however EV is mostly employed as storage device. However, a daylong loss in EV battery life might possibly interfere with consumers' ability to drive whenever they choose [516]. The capacity to provide a steady power supply during an unanticipated interruption is one of the most exciting potentialities of EV in V2H mode. In principle, EVs are able to link to the grid (V2G) or to a house (V2H). In both situations, EV improves grid resilience by supplying uninterrupted electricity despite blackouts [517]. In contrast to V2H, V2G has a complicated network and suffers from higher losses because of their remote locations. As a result, EV for V2H applications offers more potential over V2G in regards to control approach and installation difficulties [518]. Furthermore, it is always risky to install V2G in an actual electrical grid due to current utilities company laws and regulations and the net-metering price for exporting surplus electricity to the grids [519]. As an ordinary domestic user, EV deployments are as G2V, V2H, and V2G modes of operation. Using an electronics-based simultaneous AC/DC adapter, the EV battery is connected to the grid and the home demand terminal. The converter regulates the path of the power flowing from the electrical grid to the batteries and from the batteries to the house loads [520]. The key operating techniques that have been taken into account to lower running expenses for a consumer owning one or two EVs are G2V, V2G, and V2H. The comparative economic benefits of V2H and V2G at high priced period and charging solely (G2V) are also contrasted in J SCI IND RES. EV owners can trade the power they fill their vehicles with at the power peak of workplaces, because costs for electricity are significantly lower. This allows for demand transfer throughout the whole electrical system. Additionally, the signal degradation factor for energy is considerably larger in downtown districts that are not near an energy facility. In order to meet the electrical needs in smart communities at a shorter geographical distance, numerous EVs may be found in downtown districts, enabling a quick and reliable power supply. As a result, the vital V2G infrastructure necessary for intelligent cities has an enormous opportunity to develop into vehicle-to-something (V2X) innovation, allowing the utilization of an EV's power anyplace in a smart city by using different gadgets at residence that demand power, i.e., vehicle-to-home (V2H).

The amount of EV assistance differs based on how many EVs are offered to each individual client. We made the assumption that the power prices between each of the modes of V2G and V2H are equal in order to illustrate our optimization strategy. The decision was deliberate in order to show the viability of each operational [521]. The total charging burden of (EVs) with (V2G) capability is estimated utilizing strategies for data mining within this paper employing a data-driven approach. The collective charging load is subtracted from the total V2G output of the EVs that are placed beyond the meter to get the resultant charging demand. The expense of continually surveillance, gathering, and preserving extensive EV data is eliminated by the suggested approach. By conducting numerical evaluations with actual data on the charging habits of EV users, the applicability and efficacy of the suggested technique are confirmed [522]. The main goal of this research [523] is to explore how charging and discharging affect load fluctuations and spikes. In order to forecast how different scenarios of auto usage may affect charging conduct, this research constructs a load estimating framework and an EV charging concept. presents a Markov Chain Monte Carlo (MCMC) based recharging method that effectively addresses the forecasting of EV behavior and addresses the problems associated with high electrical consumption throughout peak periods. This study [524] proposed an EMS approach for MG with an electric vehicle parking lot (EVM), (PV) arrays, and changing loads linked to the network while taking into account the Point of Common Coupling (PCC). A dynamic computing approach is used by the EVM-EMS to optimize the (G2V) or (V2G) rates of EVs. It does this by using forecasts of future solar power production and projected demand. This algorithm takes into account user preferences while lowering demand's reliance on the power grid and enhancing MG effectiveness. This research [525] presents a smart deciding method powered by artificial neural networks (ANNs) that uses information collected by a machine-to-machine advanced metering infrastructure for EV charging scheduling and load control. The ANN was implemented to determine when (G2V) or might (V2G) using information regarding household electrical utilization and EV demands for energy.

To optimize electric car charging depending on price of energy, grid demand, and customer preferences, create a dynamic charging plan within the HEMS. Allow the EV and HEMS to communicate in both directions so that the system can react to grid circumstances and support demand response initiatives. In order to maximize the usage of clean energy sources for charging the car, integrate EV charging with the generation of green energy. Use load balancing techniques to effectively divide energy use, preventing peaks in demand and lessening the burden on the electrical system. To provide individualized supervision of EV charging schedules and guarantee a smooth integration with entire home energy management, take customer preferences into account while designing the HEMS as shown in Fig. 33.

Even though they present infrastructural and grid governance issues, electric cars play a critical role in load forecasting and scheduling by bringing dynamic energy demands, helping to create a more sustainable balanced HEMS.

4.11. Data science

The heating and cooling units in structures have been a major contributor to the steady growth in power usage in the past decade. The amount and worth of power used every day in structures is influenced by anticipated power loads, transit, preservation, and usage habits [526]. The enormous quantity of data associated with this procedure is now able to reliably monitored, gathered, and stored thanks to innovation. Additionally, this system has the ability to meaningfully analyses and utilize such information [527]. It should come as no surprise that using data science approaches to improve power effectiveness is presently generating a lot of focus. In order to extract information, identify trends, and provide insightful conclusions and forecasting from massive amounts of data, data specialists construct methods and techniques [528]. It includes every stage of the information evaluation handle, from data preparation and harvesting through data examination, outline, and summary [529]. Data science, therefore combines technological techniques with scientific approaches [530]. Despite the reality that these methods are the ones used most often in energy effectiveness and administration. The goal of categorizing a group of items is to determine the category for each one based on its characteristics [531]. Decision trees are frequently used to carry out and display such categorization. Numerous approaches may be used to create decision trees [532]. To quantitatively assess the connection among parameters is the primary goal of regression studies. To do this, you must determine if the factors are autonomous. Finding out the nature of their relationship's reliance becomes crucial since they aren't [533]. To explain whether the proportions of reliant parameters fluctuate as the scores of independent factors stay constant, regression modelling is frequently employed in estimation. Organizing things into subgroups depending on how similar they are known as clustering [534]. Because the categories to which items can be allocated are unknown, it is unsupervised. There are several types of clustering analysis based on the standard employed to quantify resemblance. Under the context of implications laws of kind, A implies B, associations are helpful tool for illustrating the meaning of fresh details collected from raw data and thoroughly represented for deciding [535]. These guidelines show how qualities with a high dependability frequently overlap in a record set. Sequential identification approaches include methods for locating statistically significant trends in facts, where the trends' frequencies are split in an ordered fashion [536]. Finding anomalies involves locating objects, occurrences, or experiences that diverge from predicted trends or in contrast to the typical behavior of other information objects [537]. For one to analyze information and subsequently use a framework to anticipate or keep track of the period term's future trends, time series analysis is done on details that are collected over a period [538]. Methods from data science are often applied to assist and enhance fundamental areas of energy administration and productivity. Power need, also known as electricity demand, is the quantity of power needed at a specific moment period [539]. HEMS pays special attention to loads, which are the amounts of hot and cold resources that have to be provided or taken away from the structure in order to maintain the pleasure of its inhabitants. loads can be categorized as either internal or external. The quantity of interconnected elements that must be considered makes it exceedingly difficult to identify typical configurations of home loads [540]. Therefore, it is crucial to create processes that can predict the highest demand for a particular day and estimate the consumption of energy either short or medium term [541]. Still, various data science methods are being used in recent years to create prediction models using historical information. Due to their capacity to recognize historical trends and extend them to novel scenarios, such frameworks are incredibly useful [542]. User behavior is a crucial element that affects the use of energy and significantly affects power load. Data science methods have been utilized in a number of studies to demonstrate how different buildings have different energy demands depending on the behaviors of the residents [543]. Therefore, a more economical control of electrical demand depending on customer behavior might lead to significant benefits. Data produced by HEMS is significant [544]. These statistics include details about the condition of the devices, power, humidity, climate, and other variables. They may thus be examined and used to obtain regulations that enable structure administration [545]. The research of issues pertaining to energy effectiveness and environmentally friendly growth have been stimulated by new rules. irrespective, if the structure is being built from scratch or is undergoing refurbishment, each have become a top concern for home architects and homeowners [546]. Analyzing the relationships among power loads, actual utilization, and various construction elements, Data science approaches are a useful tool for gaining knowledge of significant relationships and trends among those components whenever their state must be evaluated and possible faults discovered [547]. Data science may also be used to check the HEMS systems' operating state and spot any problems. It is feasible to identify system faults and their effects on other devices by constantly tracking the structure. From a managerial standpoint, it is much more intriguing to foresee such errors by outlining the circumstances that typically result in them [548]. In order to find out and comprehend the ways in which consumers consume power mostly

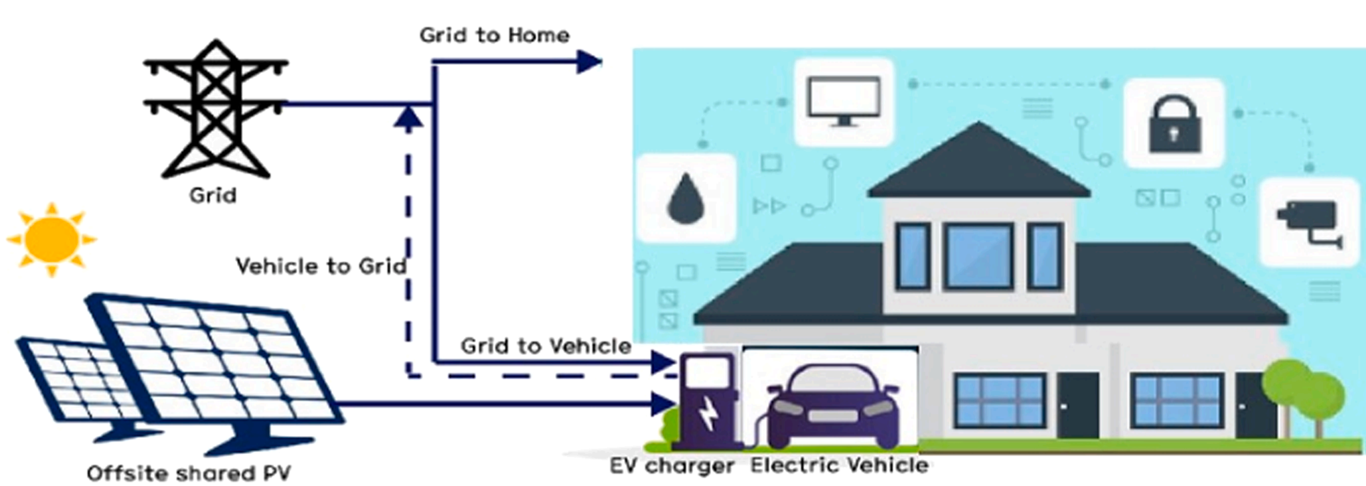

Fig. 33. EV model.

companies have turned to data science for fiscal evaluation regarding electricity usage. Despite making some businesses stronger competitors than some, internal growth and usage of data science methodologies to obtain these insights [549]. Identifying power fraud. On rare occasions, malfunctions in the measuring equipment result in incorrect billing for operations and utilization of power. Such errors may be the result of careless handling or unintended error. Numerous methods are being effectively used to identify these aberrations [550].

In order to implement data science at the HEMS device level, analytics must be used to make well-informed decisions: To create a complete dataset, collect device-level data on user behavior, energy consumption trends, and ambient factors. To acquire pertinent information and generate useful variables that support precise energy management models, apply data science approaches. Utilize machine learning techniques to develop forecasting prediction models for energy usage, allowing for active device-level optimization. Use data science techniques to find anomalies, such as anomalous device performance or patterns of energy consumption. To adjust to evolving user behavior and maintain ongoing improvement in the HEMS's device-level energy management, apply iterative data analysis and model refining as shown in Fig. 34.

Although careful consideration of data quality and processing needs is necessary, data science plays a significant role in enhancing load forecasting and scheduling in residential energy management, giving better precision and effectiveness.

4.12. Smart appliances

Smart appliances are a framework with data and interaction that enables automated or online regulation, depending on individual preferences or outside impulses through a power grid or independent supplier [551]. A home area network may be used by an intelligent device to communicate with utilities, link with other customer-based equipment, or link to third-party systems [552]. Household devices that are connected to an intelligent system's generation or distribution might be categorized as intelligent gadgets. Intelligent Thermostats regulate an HVAC in the platform's environment [553]. Self-learn technologies of usage habits and easy-to-use interfaces are among the new capabilities. Smart lights enable consumers to alter their light requirements via scheduling periods and eliminate over-illumination, which lowers energy demand for brightness [554]. Smart lighting systems have the ability to be operated online and can enable demand-side management programs in reaction to data collected from suppliers of energy [555]. Intelligent plugs are gadgets that are placed next to an electrical outlet and an item that uses power. Owing to the integrated intelligence, these gadgets possess the ability to transform non-smart gadgets to those that are smart [556]. Gadgets called smart hubs combine a number of intelligent linked gadgets in an intelligent house setting. The fundamental goal for intelligent hub is to unite all of these gadgets' functionality and connect to each other in a coordinated manner through a home system [557]. The capacity to connect intelligent water heaters to other HVAC regulators makes the entire system intelligent. They are able to interpret facts, perceive, take action, and interacts [558]. They have to execute A/D and D/A transitions for the purpose to detect and respond. Periodically, these gadgets carry out sense and transmit (wirelessly or wirelessly) detected information to the center [559]. Additionally, information detected may be transferred straight to the server if standards permit it. Upon sending the detected information, smart devices ought to, wherever feasible, carry out some rudimentary statistical analysis [560]. Actuating may additionally be managed from a distance. Residence devices can be categorized into three groups under the DSM: non-adaptable, adaptable, and dual-functional equipment. Devices like lights, TVs, computers, and hair dryers that are connected to base load are considered non-flexible and are not subject to network management [561]. The framework may autonomously run the flexible gadgets, which are connected to routine demands or proactive duties (heating and cooling). Devices of dual-purpose, such as washing machines and dishwashing machine can function in both flexible and rigid ways at different periods [562]. For instance, there are occasions, when a customer is unaware of when scheduling the dishwashing machine, will run for as long as it is inside a set window of schedule. Transient loads are often presented by such devices Intelligent plugs that can assess electrical usage and regulate functioning in real-time are included with smart home devices both adaptable and of bidirectional origin [563].

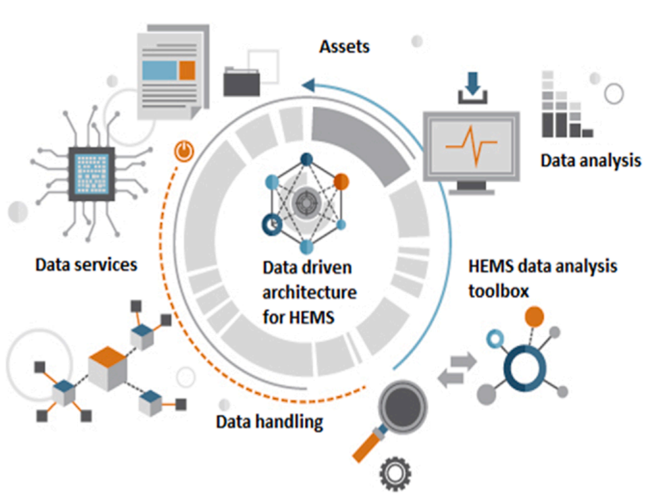

Fig. 34. Data science model.

Developing smart and energy-efficient gadgets is a necessary step to integrating smart appliances at the device level of a HEMS: To facilitate interaction and exchange of information with the HEMS, interconnect equipment to the IoT. Install sensors in devices to track consumption trends and program energy-saving functions according to consumer requests and current circumstances. Utilize machine learning techniques to gain knowledge from past data, enhancing the HEMS's smart device scheduling and behavior. Give your appliances the ability to react to signals from the grid or HEMS so they may take part in demand response programs and use less energy during peak hours. Give homeowners an intuitive interface via which they can interact with and manage smart appliances, giving them the ability to adjust settings and track energy use in real time as shown in Fig. 35.

Smart appliances optimize energy use and adjust to real-time demand, which improves load forecasting and scheduling and makes HEMS more effective.

4.13. Security protocols

A security protocol refers to a protocol for communication that uses encryption methods to enable interacting instances to attain a confidentiality objective [564]. A communication protocol refers to an agreed-upon series of acts carried out by a number of interacting instances with the objective attain a certain simultaneously acceptable target [565,566]. The IoT and essential devices are both present in the complicated design of smart home systems. Cyberattacks are a problem for this essential equipment and networks [567]. The HEMS thus needed a lot of study to safeguard prevent monetary damage, security gaps, electrical privacy, and human casualties caused by these assaults. To make sure that information and interactions inside the framework are secure, private and the subsequent security procedure needs to be followed [568]. The user or HEMS device must demonstrate their legitimacy to the system's server or customer during authentication. A secure key is often required for server authentication. The use of cards, optical scans, speech recognition, and biometrics are other methods of authentication [569]. A server uses authorization to ascertain if the user

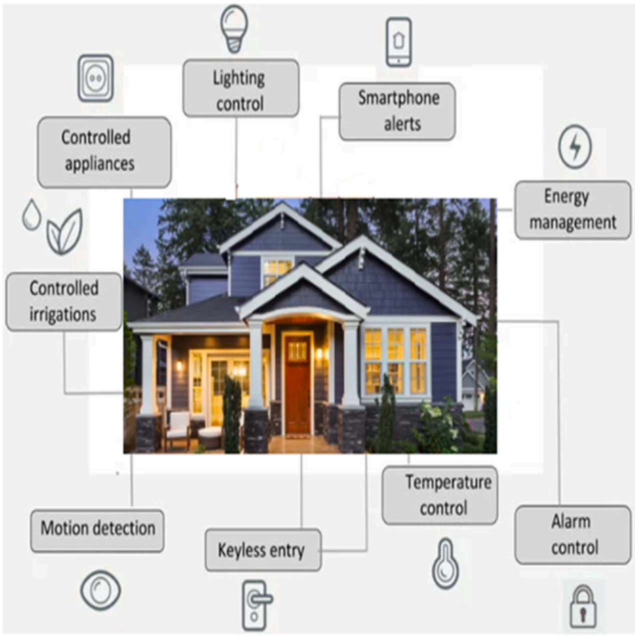

Fig. 35. Smart appliances in HEMS.

or HEMS devices is permitted to utilize an attribute or get accessibility. Authentication and authorization are typically combined so that a server can identify the user who is making the access request [570]. The process of converting data to an anonymous code which conceals what it actually means is known as encryption [571]. To prevent information from being accessed, altered, or deteriorating, encryption is employed in HEMS device interaction. It operates by scrambling data into an encrypted form which is able to be decrypted with a specific electronic secret [572]. A firewall is a network protection tool used to defend HEMS against outside threats. It examines both the inbound and outbound information flow of HEMS and allows or rejects transmitted information according to a set of privacy protocols [573]. A routine software upgrade for HEMS devices is a collection of modifications made to a program to modify, correct, or enhance it. Typically, adjustments to software are made to address bugs, secure vulnerabilities, add fresh functions, or enhance functionality and efficiency. The capacity to safely preserve and regulate data collected by hems equipment as well as how and to which extent protected details regarding hems devices is exchanged with permitted entities is typically referred to as data privacy [574]. In order to safeguard HEMS gadgets' crucial records and data, physical security is crucial. As the concepts of work and cooperation change, emerging danger situations appear. The three basic parts of the physical security system are: restriction of access, ongoing active observation, and assessment [575].

Employing security protocols at the HEMS device level entails defending against online threats: To guarantee that only authorized devices can connect and interact with the HEMS, establish strong authentication procedures. To safeguard the transfer of data among gadgets and the HEMS and stop unwanted access to private data, use robust encryption techniques. Establish secure Application Programming Interfaces (APIs) to facilitate communication while maintaining data confidentiality and integrity between devices and the HEMS. Upgrade and safeguard device software often to fix bugs and guard against potential attacks. Install surveillance systems to keep an eye out for unusual activity and to report any possible vulnerabilities in the HEMS's device-level network as shown on Fig. 36.

In spite of possible difficulties with installation and maintenance, safety precautions are essential for preserving the privacy and authenticity of information in load forecasting and scheduling, guaranteeing a safe and dependable HEMS.

Fig. 36. security protocol model.

4.14. Internet of thing

The Internet of Things (IoT) is the connectivity of actuators and sensors for the purposes of communicating with one another via interfaces utilizing an integrated structure, for supplying common functions for the specified devices, applying information analysis, and expressing knowledge inside a cloud system [576]. IoT utilize the idea of a "smart environment" that employs ICT technology to make management, security, learning, transit, amenities, and various other fields more informed, collaborative, and effective [577]. The phrase "Internet of Things" (IoT) refers to a future where not just individuals; but also items, would be constantly linked to and capable to communicate with one another via the Internet. Numerous innovative uses, including those for, energy-efficient living, and surveillance of the climate, are anticipated to be made possible by the IoT. [578] asserts that the IoT has an opportunity to upend the financial sector as we currently know it by lowering reliance on centralized institutions and encouraging an increasingly cooperative sector with lower prices and robotic procedures [579]. Much operational tangible equipment's that includes sensors, actuators, regulate units, cloud servers, specific IoT regulations, networking levels, developers, consumers, and a business layer are all included in an IoT framework, which can be tangible, online, or a combination of them [580]. Smart meters and devices that have access to the World Wide Web and have some levels of smartness are anticipated to significantly improve control of energy and effectiveness. A totally linked and sensitized atmosphere will serve as the end consequence [581]. In fact, when we transition to smartphones and other gadgets, a massive amount of data and communication signals will be produced. As a result, settings and algorithms will be improved, increasing their precision and opening up novel and intriguing opportunities [582]. Additionally, it will result in exceptionally precise tracking of power flow, through contextual understanding and actual data rather than past information trends. This will help to minimize mistakes and prevent overpowers since delivery of power can be readily anticipated and rectified in virtual instant. Statistics on residential power consumption in real-time gathered using smart meters [583]. Utility collects this information and utilize it for predictive models that project energy consumption over specified time frames may be developed, enabling utilities to schedule their load accordingly. Demand response programs can be combined with IoT to help suppliers control peak demands by giving consumers initiatives [584]. IoT monitors power usage in real-time to spot abnormalities in usage trends, enabling homeowners to make the necessary adjustments to cut down on wasteful utilization of power. Consumers may manage their power use remotely thanks to IoT. Homeowners may be enabled to plan their electrical consumption to occur at periods of low demand, lowering their expenditures on electricity and assisting utilities in managing peak demand. IoT-driven approaches can provide enhanced load estimation and scheduling of HEMS, reducing wasted electricity, lowering customer electric expenditure, and enhancing the general dependability of the power system [585].

In order to deploy IoT at the individual device level of a HEMS, an intelligent and interconnected network must be built: Integration of sensors: Integrate sensors into items to get up-to-date information on energy usage, external variables, and gadget health. Use common IoT protocol stacks, such CoAP or MQTT, to facilitate safe and easy data sharing between devices and the HEMS. To facilitate centralized data collection, evaluation, and administration for effective control and surveillance, and to link equipment to a cloud platform. Give consumers the ability to monitor and manage their residential energy systems from any location by enabling remotely control of devices via the Internet of Things as shown in Fig. 37. Utilize IoT data for sophisticated analysis to improve overall energy efficiency in the context of smart homes, optimize device activities, and provide insights into trends in energy consumption.

Despite careful evaluation of privacy and compatibility is required, IoT technologies play a critical role in improving load forecasting and scheduling, delivering real-time data for optimal resource allocation and enhanced energy management.

4.15. Cloud computing

Cloud computing is a method of allowing everywhere, practical, immediately structure connections to a shared group of programmable IT assets which may be swiftly provided and issued via little managerial or supplier communication. Among the latest recent developments for delivering resources as needed through the web is cloud computing [586]. It provides an alternate method for using the current assets while utilizing the least amount of actual hard discs. It lowers the financial costs associated with buying, caring for, and upgrading as assets are exchanged over the web [587]. The cloud computing concept [588] was inspired through the idea of grid computing, which aims to enhance the adaptability and dependability of structures while lowering the expense of processing by pooling resources for computation [589]. Cloud computing is a method of allowing everywhere, practical, immediately structure connections to a shared group of programmable IT assets which may be swiftly provided and issued via little managerial or supplier communication [590]. As a result, cloud technology may be viewed as a distributed framework that offers servers over an online network. In this sense, an offering is thought of as a work that is fully computerized and may be provided to consumers via a standardized and uniform process [591]. Furthermore, cloud facilities are opaque to ultimate consumers, that are not required to understand their fundamental design or understand its precise location [592]. Regular and accessible upgrades and enhancements made possible by cloud computing are easily accessible to consumers. With the help of cloud computing, it is possible to continuously store and analyze over million intelligent meter information points while offering service to great number of customers [593]. The computational ability and data preservation capacity of the cloud may ideally provide a high level of secure preservation of big volume of information as well as a broad range of offerings for many customers [594]. Customers are catered to in the context of cloud-based offerings through IT services accessible online. These features are separated on servers of the suppliers, so the consumer is not made aware of how they are operated [595]. Based to quantity of intelligent meters and clients linked to the infrastructure, as well as the necessary computer resources for the administration implementation, cloud technology's computational capacity and information retention limits may be scaled [596]. An affordable solution across a lot of people may also be guaranteed with these cloud-based solutions. Regarding the installation of cloud-based power supervision services, these primary tasks are necessary: -gathering, storing, and presenting real-time information from intelligent meters [597]; guaranteeing that freshly created smart meters can be integrated into the framework; -calculating utilization and expenses across various time intervals;-the physical remote administration of electrical equipment; -near real-time power oversight and administration of energy consuming equipment; -easy and quick installation of smart meters, consumers, and integrated features; secure and dependable realization of the aforementioned services[598]. An ECCREM design with three tiers is given in [599] order to reduce latencies and increase computing efficiency. A two-phase energy administration technique for successive scheduling is presented keeping the design in mind, taking system dependability and use of resources needs into view. This research analyses [600], the wirelessly produced electricity surveillance systems that are now in use and also discusses our suggested GSM-based cloud computing-based intelligent power tracking solution.

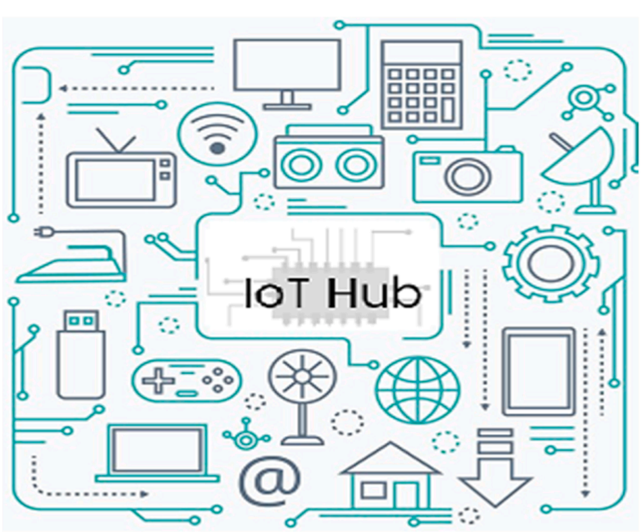

Fig. 37. IoT in HEMS.

Utilizing cloud services for improved connection and data analytics is a key component of utilizing cloud computing at the gadget level of a HEMS: By processing data locally on gadgets, edge computing features may minimize delay and improve decisions in real time. Device-level data may be sent to the cloud for centralized analysis and preservation, providing thorough insights and the ability to track past trends. To handle different data loads and make sure the HEMS can adjust to shifting device configurations, make use of flexible cloud services. Optimize energy management techniques using real-time and historical data by using machine learning models for predictive analytics in the cloud. Utilize cloud technology to provide remote device administration, giving consumers safe and effective access to manage and control their residence's electric systems from any connected device as shown in Fig. 38.

Although connection and security issues must be taken into account, cloud computing's flexibility and immediate time features help residential energy management systems estimate and schedule loads more effectively.(Table 3)

5. Mathematical modeling

5.1. Probabilistic and fault analysis of HEMS load forecasting and scheduling model

The suggested probabilistic modeling of a HEMS tries to determine the best forecasting and scheduling strategies by taking into account events in numerous linked energy sources and equipment. This allows us to swiftly solve the scheduling and prediction issues. In this case, as

Fig. 38. Cloud computing model.

illustrated in Fig. 39, the predict supply, i.e., $P^p(t)$, may be modified according to the predicted demand $D^p(t)$ by minimizing the frustrated or hindered demands H(t). A closed-loop control system is modeled for this purpose, as demonstrated in Fig. 39.

The closed-loop framework incorporates projected demand $D^p(t)$ and responds $P^p(t)$ to analyze these two

foreseen variables. A regulated load flow through supply and demand is necessary to offer an optimal load flow among various sources of energy. $P^P(t)$ must be synchronized with $D^p(t)$ for such a reason.

$$P^p(t) = D^p(t) + b_o \tag{17}$$

while b_o is the artificial backup and is essentially a supply derived from HEMS. In this scenario, the impact of $P^P(t)$ and $D^P(t)$ is evaluated by continually adjusting the returning demand $R(t)$ utilizing HEMS and modifying b_o. As an outcome, $P^p(t)$ and $D^p(t)$ acquire synchronized stability.

To test the aforementioned scenario and account for possible outcomes, it is considered as a delay time frame, i.e., average delay or latency (A_l). A_l can represent as,

$$A_l = \lambda_{i1} \tag{18}$$

In (18), the model only matches a single period. A more generalized form of Eq. (18) can be written as

$$A_l = \frac{1}{n}\sum_{i_1=1}^{n_1}\lambda_{i1} \tag{19}$$

Hence, a closed-loop delay is denoted by i_1. n_1 represents the impact of this interruption on a synced connection. likewise, in order to handle response to demands in real-time, it is assumed that the actual demand $D^a(t)$ in an energy system is synchronized with $D^p(t)$, as well as the inclusion of randomness or variability $V_D(t)$

$$D^a(t) = D^p(t) + V_D(t) \tag{20}$$

By adding the A_t model from (19) into (20)

$$D^a(t) = D^P(t) * \left(\frac{1}{n}\sum_{i_1=1}^{n_1}\lambda_{i1}\right) + V_D(t) \tag{21}$$

To constantly monitor using a probabilistic closed -loop framework, which is illustrated in Figs. 39, (21), may be represented in a generalized form as

$$D^a(t) = \sum_{i=1}^{n}\left\{ D_i^p(t) * \left(\frac{1}{n}\sum_{i_1=1}^{n_1}\lambda_{i1}\right) + V_{D_i}(t)\right\} \tag{22}$$

where $V_D(t)$ denotes the random variation among $D^a(t)$ and $D^p(t)$, and it may be determined using an auto-correlation probabilistic method, i.e.

$$V_D(t) = E\{D^a(t) * D^p(t)\} \tag{23}$$

when, $D^a(t) \to D^p(t)$, the random deviation(t)→0, which achieves asynchronous stability as

$$P^P(t) = D^P(t) \tag{24}$$

likewise, when considering generating response trends in real-time, the actual supply $P^a(t)$ is expected to be synchronized with the prior supplies $P(t-1)$ and $P^p(t)$, with the inclusion of some randomness $V_p(t)$.

$$P^a(t) = P(t-1) + p^P(t) + V_P(t) \tag{25}$$

Hence $P(t-1)$ is a controlling variable that, in instantaneous time, resets a closed-loop feedback network to the prior time frame to ensure load flow matching among need and response characteristics. As illustrated in, $P(t-1)$ is managed by a HEMS to offer an ideal $P^a(t)$ by incorporating latency in (25), it becomes

$$P^a(t) = \left\{P(t-1) * \left(\frac{1}{n}\sum_{i_1=1}^{n_1}\lambda_{i1}\right) + P^P(t) * \left(\frac{1}{n}\sum_{i_1=1}^{n_1}\lambda_{i1}\right) + V_P(t)\right\} \tag{26}$$

(26) can be represent in a generalized way as a closed loop feedback system

$$P^a(t) = \sum_{i=1}^{n}\left\{P(t-1) * \left(\frac{1}{n}\sum_{i_1=1}^{n_1}\lambda_{i1}\right) + P^P(t) * \left(\frac{1}{n}\sum_{i_1=1}^{n_1}\lambda_{i1}\right) + V(t)\right\} \tag{27}$$

where $V_P(t)$ indicates the random divergence across $P^a(t)$ and $P^p(t)$, and it may be calculated using a self-correlating probabilistic approach, i.e.

$$V_P(t) = E\{P^a(t) * P^P(t)\} \tag{28}$$

As well, whenever $P^a(t) = P^p(t)$, the random variation $V_P(t) = 0$, that ensures reliability in HEMS by attaining a balanced power between $P^a(t)$ and $P^p(t)$.

$$P^a(t) = P^p(t) \tag{29}$$

To completely minimize an $V_P(t)$, i.e., $V_P(t)$ approaches to zero, the control factor $P(t-1)$ must be optimally set to equalize power across $P^p(t)$ and $D^p(t)$.

The power deficit is expressed in the form of hindered demand H(t), which may be written as

$$H(t) = C^a(t) - P^a(t) \tag{30}$$

where $C^a(t)$ represents the convey demand, which must always be met at specific times in order to ensure optimal load management. balancing need and responsiveness.

The $H(t)$occurs, when

$$C^a(t) > P^a(t) \tag{31}$$

By adding an A_l in (30)

Table 3
Characteristics of different futuristic optimization approaches used in HEMS.

Method	Process	Features	Applications	Pros	Cons
Block chain	Decentralized ledger to keep track and validate energy-related transactions, guaranteeing privacy and security	Security, disclosure, and decentralization	Dependable and transparent load estimating and scheduling	Improves data security and cultivates stakeholder confidence	Energy industry regulatory concerns and elevated computing requirements
Federated learning	Allows training of a global model without transferring raw data	Maintaining privacy and working together across edge devices	Enabling cooperative load estimating, planning, and optimization	Effective cooperation and flexibility across a range of device contexts	Difficulties managing device data heterogeneity
Reinforcement learning	Incorporates an agent learning decision-making experience via trial and error	Delayed rewards, sequential decision-making, and trial-and-error	Adaptive energy usage and device regulation	Adjust to evolving circumstances and perform effectively in dynamic settings	Difficult to design and train appropriate reward functions
Metaverse	Incorporates virtual and real-world experiences	Improving energy management in a digital environment and using virtual representation	Virtual worlds experiences	Perpetual investigation, cooperation, and creativity	Restricted integration of real-world data, security concerns with digital models
Digital twin technology	Creating a digital duplicate of a real object, process, or system	Permits optimization, evaluation, and validation without affecting the real product	Giving a realistic and dynamic depiction of the home energy system	Insights in real time and the capacity to experiment with various scheduling techniques in a virtual setting.	Dependence on precise modelling and possible difficulties incorporating real-world data
Artificial intelligence	Making judgements and learning from data	flexibility in evolving circumstances and real time decisions abilities	maximize resource utilization, adjust to user actions	flexibility in changing circumstances	Possibility of bias prediction and dependence on continual model updates
Probabilistic model	Using statistical techniques to take uncertainties into account	Risk evaluation, uncertainties estimation, and likelihood distributions	Maximize utilization of available resources and improve the adaptability of HEMS	Offer information about uncertainty and make informed decisions	Reliance on precise assumptions about probability distributions
Peer to peer energy trading	Permits direct interaction between energy suppliers and buyers	Real-time rates, decentralized interactions,	Assist in creating a decentralized energy structure	Ability to trade surplus energy directly	Difficulties with legislation and reliance on technological infrastructure
Energy harvesting	Includes accumulating and transforming ambient forms of energy	Lessening dependency on outside energy sources	Used in HEMS to supply power to gadgets	Lower environmental effect and the possibility of achieving energy independence	Irregular energy supply, reliance on certain environmental factors, and initial installation expenses
Electric vehicle	Charging and discharging	Intelligent and bidirectional charging	Balance home energy consumption	Decreased carbon emissions and grid stability	Balancing unstable green energy resources offers difficulties
Data science	Acquiring crucial knowledge and insights from data	Multidisciplinary, focused on data, anticipatory, and descriptive	Optimize resource allocation and forecast trends of energy use	Making smarter decisions via data-driven insights	Data quality, difficulties managing noisy and volatile information
Smart appliances	Use connection and sensors to regulate their function	Energy tracking, IoT connection, and flexible operation	Schedule and forecast loads by modifying appliances operation	Enhanced energy savings and better resource distribution	Interoperability issues, and dependence on communication network
Security protocols	Putting access restrictions, authorization, and encryption into practice	User authorization, reliable communication methods, and encryption	Protect private information and provide secure interaction inside HEMS	Increases the HEMS overall security	Execution intricacy, and requirement for regular updates to tackle new security vulnerabilities
IoT	Linking gadgets to the internet	Equipment communicates with one another and centralized networks	Employed in scheduling and forecasting loads to allow for real-time tracking	Enhanced automation and energy administration	Standardized communication methods, security issues
Cloud computing	Remote servers for storing, processing, and assessing data	Access to data remotely and expandable computer power	Used in cloud-based data mining, storage, and joint optimization load estimation and planning	Accessible powerful backup and recovery options	Internet access, privacy issues, and possible threats to data security

$$H(t) = \{(C^a(t) - P^a(t)) * (\frac{1}{n}\sum_{i_1=1}^{n_1}\lambda_{i1} \quad)\} \tag{32}$$

(32) is generalized by converting it.

$$H(t) = \sum_{i=1}^{n}\{(C^a(t) - P^a(t)) * (\frac{1}{n}\sum_{i_1=1}^{n_1}\lambda_{i1} \quad)\} \tag{33}$$

$H(t)$ will maintain a feedback channel and send it back to the infrastructure as backlogged demand/returning demand R(t). It will nevertheless be linked via a closed loop interruption, i.e., λ_{c1}. As a result, as shown in (30), the formula for the backlogged demand R(t) will be expressed in the form of $H(t)$, coupled with the multiplier for a certain closed-loop equivalent lag.

$$R(t) = C^a(t) - P^a(t) \tag{34}$$

$$R(t) = \sum_{c1=1}^{n_1}(\frac{1}{\lambda_{c_1}}) * ((C^a(t) - P^a(t)) \tag{35}$$

(35) is now written as

$$R(t) = \sum_{c1=1}^{n_1}(\frac{1}{\lambda_{c_1}}) * \{\sum_{i=1}^{n}(\frac{(C^a(t) - P^a(t)}{n}) * (\frac{1}{n}\sum_{i_1=1}^{n_1}\lambda_{i_1} \quad)\} \tag{36}$$

The reserve or backup $b(t)$ may be written as

$$b(t) = P^a(t) - C^a(t) \tag{37}$$

while into the reserving phase

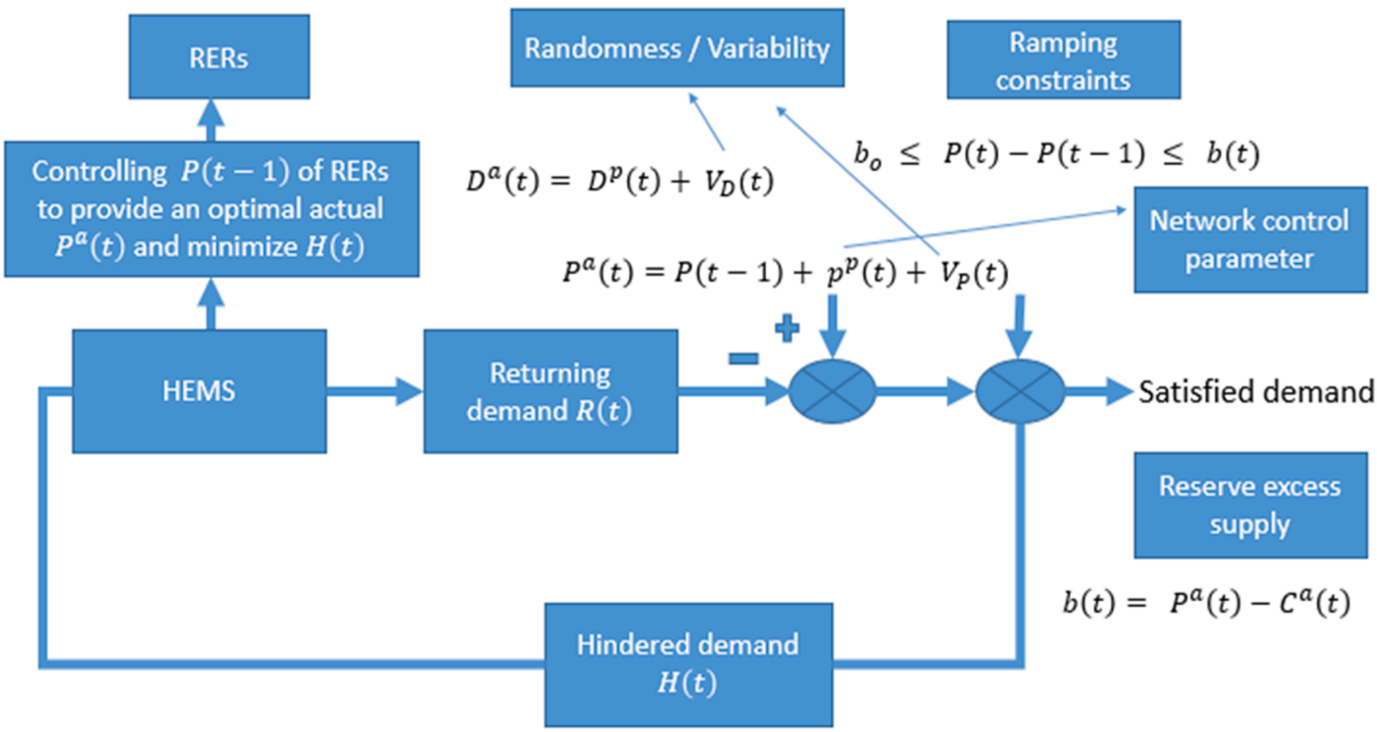

Fig. 39. Load forecasting and scheduling model of HEMS with fault analysis.

$$P^a(t) < C^a(t) \tag{38}$$

By adding delay

$$b(t) = \{P^a(t) - C^a(t)\} * (\frac{1}{n}\sum_{i_1=1}^{n_1}\lambda_{i1}) \tag{39}$$

(39) generalized into

$$b(t) = \sum_{i=1}^{n}\{\{P^a(t) - C^a(t)\} * (\frac{1}{n}\sum_{i_1=1}^{n_1}\lambda_{i1})\} \tag{40}$$

If there are reserve b(t) needs, the rules for criterion ought to be provided

$$b_o < b(t) \tag{41}$$

The $P^a(t)$ needs to be increased using a HEMS. This will reduce $H(t)$ and bring b_o and $b(t)$ as near to one another as practicable. This action can be accomplished via the stepping-up constraints approach; alternatively, if

$$b_o > b(t) \tag{42}$$

Following that, we have to reduce $P^a(t)$ so that b_o and $b(t)$ are as near to one other as feasible.

This may accomplish via the scaling down limitations method. While ramping limitations are present

$$b_o \leq P(t) - P(t-1) \leq b(t) \tag{43}$$

From (15), $P(t) - P(t-1)$ may be written as

$$b_o \leq P^p(t) + V_p(t) \leq b(t) \tag{44}$$

The major challenge in this instance is maintaining the backlogged/returning demand, i.e., R(t), steady in all cases. This may be accomplished by minimizing $V_p(t)$ using a HEMS. For that, we must manage the setting b_o in order to properly synchronize it to $b(t)$, obeying the gradual up and down requirements from (41) and (42).

As a result of minimizing $V_P(t)$, (44) may be written as

$$b_o \leq P^p(t) \leq b(t) \tag{45}$$

The synchronization of $P_p(t)$and $D_p(t)$ may be done using (17), i.e.,

$$b_o \leq D^p(t) \leq b(t) \tag{46}$$

It is clear from (46), as the load flow equilibrium across demand and response is accomplished. In this case, HEMS will not just offer optimal load flow equalization among different equipment and energy sources, however it will additionally serve as an energy reserve that adjusts for RER instability.

We will compare our proposed HEMS probabilistic and fault analysis model with HEMS case study and realistic model to verify the effectiveness of our presented framework in real time.

In a testbed home of the Smart Campus Green & Smart Building Park, Benguerir, Morocco the technology created in this study has been put into place as part of a pilot project. This project's scope comprises critical loads, flexible loads, a 3.75 kWp grid-connected solar energy system, and 6.4 kWh of stored energy battery packs. Two complementary control approaches form the foundation of the put forward HEMS structure: supply-side management, which schedules and controls power dispatch between generation, consumption, and storing agents, and demand-side management, which schedules and controls flexible appliances for the best possible load profile modulation. The price of grid power, forecasting data (including solar power and climate), and consumer tastes are the main factors that influence how energy flows are managed. An AI-based multi-objective optimization method combines the two created control algorithms to concurrently minimize costs and maximize comfort factor. Fig. 40 provides a modular operational strategy of the system. As can be seen, a "Monitoring Module" collects and stores the data collected by the different sensors and meters in a database. The database is a component of the "Data Management Module," which also has a sub-module dedicated to forecasting. A "Human–Machine Interface" (HMI) is used to visualize the data, providing complete insight into the system's past, present, and future states. By indicating their preferred level of comfort, the user may also communicate with the system through the HMI module. These together with the

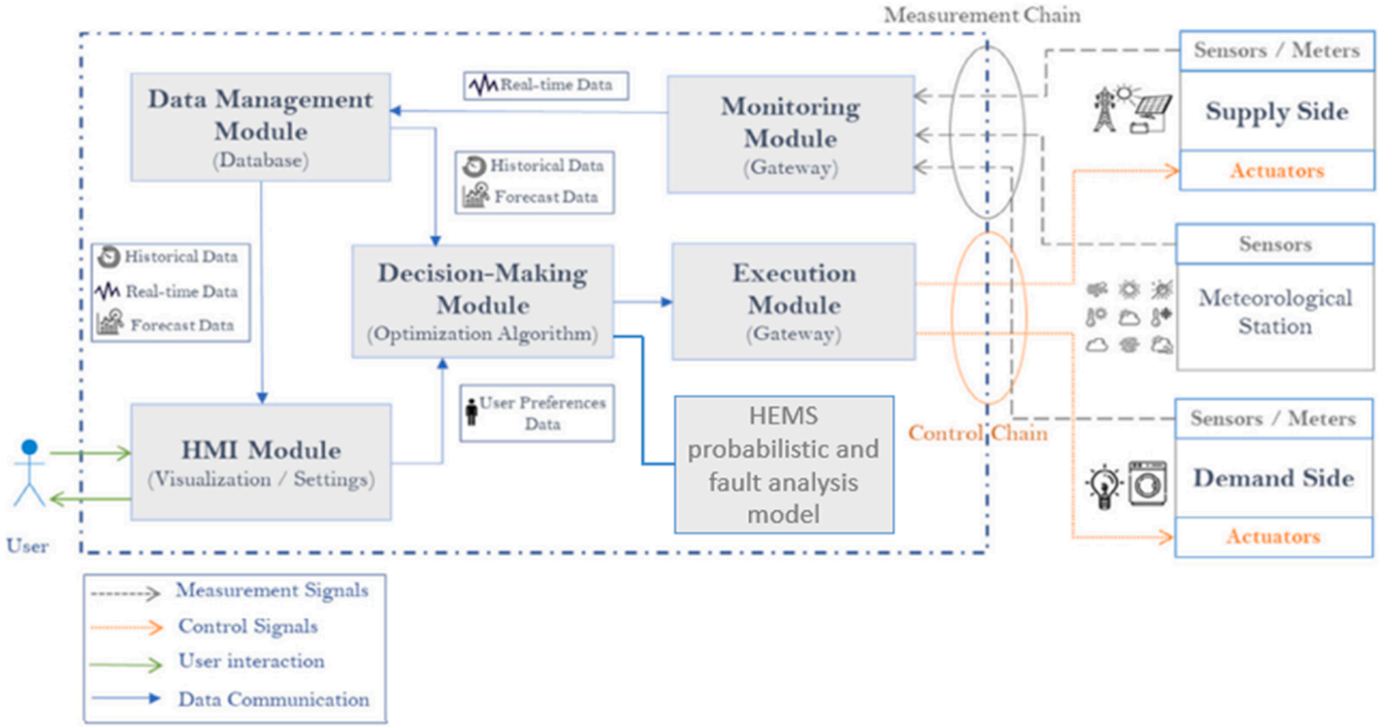

Fig. 40. A modular functional architecture of the case study HEMS.

measured and forecasted data make up the dynamic portion of the optimization issue that the "Decision-Making Module" is supposed to solve. An "Execution Module" is in charge of giving actuators instructions in a set of setting points to control them in accordance with the outputs of the optimization algorithm after deciding how the system should operate. It is noteworthy that the system functions in a closed loop based on this description, which involves a control chain and a measuring chain. The general physical architecture of the will be provided in the next section integrated HEMS. Next, the decision-making module will be the center of attention, with control techniques being designed for overseeing the supply and demand sides [601]. If we integrate our proposed generic HEMS probabilistic and fault analysis model with decision making module as shown in Fig. 40, the demand and generation can be balanced satisfying the supply and demand side management. Based on forecasts for PV generation, user preferences, and power prices, the optimization goals are to save expenses and maximize user comfort.

Our presented model is operational in all kind of real time scenarios and case studies as; it balanced all kind of demand and generation program uncooperating reserve to balance the generation and demand. In order to fully use the renewable energy sources and take into account the sustainability of the batteries, a practical HEMS model featuring plug-in electric cars, battery packs, and sustainable energy is first constructed in this study [602]. Next, an enhanced genetic algorithm (GA) with the dual objectives of minimizing electricity purchase and maximizing renewable energy utilization is suggested. This is achieved by combining the genetic algorithm (GA) with the multi-constrained integer programming approach. The system uses a declining-horizon formulation to optimize, at sample instant, the HEMS operation by combining the potent formulation abilities of a model predictive control mathematical programming challenge with those of a MILP-based mathematical programming problem. The structure is intended for a house in Portugal's Algarve. The system's results are contrasted with other experimental findings from a commercial PV battery control system. It has been confirmed across all simulations that the MILP-based model predictive control yields improved outcomes with statistical significance. In [603,604], the actual consumption and generation patterns of a normal Portuguese home with a small-scale solar system installed at home are working. The real-time digital system simulates these profiles. simulator that makes use of actual hardware. Within the case studies, for a whole day, three distinct situations are simulated. taking into account the demand response initiatives and a 2 kW solar power plant. Various situations for pricing are taken into account, as well as how well home energy management works system is assessed in every situation. An estimation is made of the HEMS socially acceptable flexibility potential.

The techno-economic potential of homes in a three-community cluster sample region calculated using approaches such as cluster analysis, energy-economic optimization, and a digital household poll that is socially accepted. About one-third of the participants, according to the results, accept the established system [605]. In [606] employed readily scaled, user-friendly impact indicators that may be readily available to homes and operate as natural incentives for energy conservation on the social, economic, and environmental fronts. The measures show observable benefits to homeowners that are achievable under Germany's market-based energy pricing structure and Algeria's government-subsidized pricing structure. The suggested technique uses voltage control (VC) technology to lower domestic appliances' power usage and minimize appliance moving. The survey's findings are utilized to create typical load profiles for the workday and the weekend [607]. The decision-making tool (IRRHEM) for smart home electrical energy management is proposed in this study [608]. The use of natural resources, the disclosure of the IRRHEM solution, and the residents in cases of resource mismanagement or wasteful behavior, as well as the collection of related actions at the same moment. Furthermore, according to the suggested guidelines for intelligent thinking, residents' actions. All operations are developed and carried out using OWL (Ontology Web Language). Semantic Web Rule Language, or SWRL.

6. Comparison of our and present and futuristic optimization techniques and literature of smart HEMS

Table 4

7. HEMS challenges

Despite the fact that energy administration in HEMS is successfully established and broadly accepted, resolving current issues is essential for the evolution of the worldwide market [617]. Identifying current issues paves the door for potential future energy management options. A huge degree of development is gone undertaken to enable the SG properly interact with houses and continuously advantageous for society, yet its aggregation causes various obstacles and impediments [618]. The growing reciprocal trade among electric grids and intelligent homes presents several technological issues for contemporary grids, notably power-quality regulation [619]. Research regarding the reliability of power often attests to the permissible conduct of power sources, which includes voltage limitations and oscillations evaluation [620]. In recent years, intelligent electrical grids have incorporated multiple generating supplies from various technologies that mostly rely on power electronics devices, which makes it more challenging to regulate the standard of electricity [621]. All energy administration system must take into account quality of power limitations to ensure equilibrium among contemporary supply and demands. Inverter devices featuring high rates of switching that could exceed as much as 2–9 KHz are the primary single-phase supplies used in interconnected micro power schemes in intelligent houses [622]. The suitable restrictions for power production in intelligent residences must thus be reevaluated in light of the necessity for more study. In contrast to older models, advanced household equipment's have higher harmonic frequencies and lower intrinsic currents [623]. With the proliferation of such modern electronic

Table 4
Summary of comparison of existing review of load forecasting, load scheduling and futuristic optimization techniques in HEMS and our work. Note: PY: published year; MR: multiple regression; ES: exponential smoothing; IRLS: Iterative Reweighted Least-Squares; AR: auto regression; MA: moving average; ARMA: autoregressive moving average; ARIMA: autoregressive integrated moving average; GA: genetic algorithm; SVM: support vector machine; AD: adaptive demand; EP: expert system; FL: fuzzy logic; ANN: artificial neural networks;.

PY	Duration	MR	ES	IRLS	AR	MA	ARMA	ARIMA	GA	SVM	AD	ES	FL	ANN
2015	2012–2015	√	×	×	×	×	×	√	×	×	×	×	×	×
2016	2013–2016	×	×	×	×	√	×	×	×	×	×	×	×	×
2017	2014–2017	×	×	×	×	√	×	√	×	×	×	×	×	×
2018	2015–2018	×	×	×	×	×	×	√	√	×	×	×	×	×
2019	2014–2018	√	×	×	×	√	×	×	√	×	×	×	×	×
2020	2015–2020	√	×	×	×	×	×	√	×	×	×	×	×	√
2021	2015–2021	√	×	√	√	×	×	√	√	×	×	√	√	×
2022	2013–2022	√	×	√	×	×	×	√	√	×	√	×	√	×
Our work	Up to 2023	√	√	√	√	√	√	√	√	√	√	√	√	√

LP	MILP	NLP	MILP	PSO	GA	CO	EA	AFNIS	B	FL	RL	M	DDT	AI	PM	P2P
×	×	×	×	×	×	×	×	×	×	×	×	×	×	×	×	×
×	×	×	×	×	×	×	×	×	×	×	×	×	×	×	√	×
×	√	√	×	×	√	√	×	×	×	×	×	×	×	×	√	×
×	×	×	×	×	×	×	×	×	×	×	×	×	×	×	×	×
×	×	×	×	×	√	√	×	×	√	√	×	×	×	×	×	×
×	×	×	×	×	×	×	√	×	×	×	×	×	×	×	√	×
×	×	×	×	×	×	×	×	×	×	×	×	×	×	×	√	×
×	×	×	√	√	×	×	√	√	×	×	√	√	×	×	×	×
√	√	√	√	√	√	√	√	√	√	√	√	√	√	√	√	√

EH	EV	DS	SA	SP	IoT	CC	Review	REF
×	√	×	×	×	×	×	This work offered a comparative review of the HEMS literature, emphasizing modelling methodologies and how they affect HEMS results and activities.	[609]
×	√	√	×	×	×	×	A concise synopsis of the smart HEMS's functional components and structure is provided, along with load scheduling strategies.	[610]
×	×	√	√	×	×	√	The characteristics of energy use in the residential sector are examined in this article. Research was conducted on energy conservation, household use of energy, and the effects of energy administration systems on the home load profile	[611]
×	×	√	×	×	×	×	This study offered a thorough analysis of both past and present HEMS research, taking into account different DR programs, intelligent technologies, and load scheduling devices.	[612]
×	×	×	×	×	×	×	This review article provides an in-depth analysis of several optimization strategies and how they are applied to save electricity costs, balance load, minimize power consumption, and maximize user comfort.	[613]
×	×	×	×	×	×	×	This work provides a thorough analysis of the HEMS literature, citing key ideas, setups, and supporting technologies.	[614]
×	×	×	√	√	×	×	This review article essentially discussed HEMS for various scenarios and circumstances based on various climate conditions, various appliances, various controllers with algorithms, various homeowners, and various lifestyles.	[615]
√	√	×	×	√	×	×	The purpose of this study is to provide an extensive, methodical assessment of the literature on technical and computational scheduling optimization strategies in HEMS.	[616]
√	√	√	√	√	√	√	Briefly discussed methodology, process, features, pros, and cons of load forecasting, scheduling and futuristic optimization techniques in HEMS and implement each topology at device level of smart home which result in smooth operation, saving energy and cost. Moreover, HEMS load prediction and scheduling framework is offered with a probabilistic and fault evaluation that upholds load flow balance between need and supply for continuous operations. Presented probabilistic model compared with Smart Campus Green & Smart Building Park, Benguerir, Morocco case study, verifying the validity of our framework in real time scenario. The Future work and HEMS challenges are also highlighted.	Our work

LP: linear programming; MILP: mixed integrated linear programming; NLP: non-linear programming; MINLP: mixed integrated non-linear programming; PSO: particle swarm optimization; GA: genetic algorithm SA: simulated annealing; CO: colony optimization; EA: Evolutionary algorithm; ANFIS: Adaptive neural fuzzy inference system; B: blockchain; FL: federated learning; RL: reinforcement learning; M: metaverse; DTT: digital twin technology; AI: artificial intelligence; PM: probabilistic models; P2P ET: Peer 2 Peer Energy trading

EH: energy Harvesting; EV: EV (V2G & G2V); DS: data science; SA: smart appliances; SP: security protocols; IoT: internet of things; CC: cloud computing; REF: reference gadgets, many harmonics will rise sharply to dangerous levels, particularly fifth-harmonic voltage. With large levels of household production, particularly if intelligent homes can operate islanded, considerable uncommon functioning conditions for future grids may be feasible [624]. Low-voltage systems may experience issues with damping stabilization as a result of the ongoing decline in resistive demands and rise in capacitive stress from electronic gadgets and low-frequency resonances issues due to the load's constant shift in nature [625]. Provided an earlier study on the topic of intelligent houses that examined several difficulties a like: A house that has an accumulation of electronic components implanted in a system without utilizing a methodical and integrated approach is referred to be inadvertent [626]. Lacking mutual consent, interoperability is difficult in terms of both rules of syntax and interpretation. However, a smart residence must still have a variety of devices and programs that can easily connect with one another. A key difficulty is developing systems that meet expected dependability requirements, especially when they are connected to informal collection in automated residences [627]. Dependability, connectivity, interconnection, expansion, cost-effectiveness, protection, significant data visualization, cloud-based storage, and low-power and adaptable nodes for sensing are a few examples of issues for the smart home that mentioned [628]. Monitoring performance: The widespread usage of web-based devices has made it challenging for cellphone carriers to effectively control their flaws, productivity, and security [629]. Investigation of vast amounts of data: These data originate from interconnected machines with different processing power levels where the information is preserved, analyzed, and gathered. For huge data, intelligent and efficient database systems are crucial [630]. Cloud assistance: For smart devices, cloud storage may be the most convenient way to store and analyze enormous volumes of information. The shared hosting capacity is made available on demand thanks to cloud computing. Intelligent gadget design encompasses a wide range of concepts, including portability, dimensions, wireless connection, minimal power consumption, small battery life [631], and affordability. Smart gadgets ought to be equipped to fulfil all of those needs as they grow more widespread. This research demonstrates that substantial changes must be made to the current electricity grid in order to attain stability. To capitalize on the economic advantages of RES, energy administration must establish a marketplace for renewable power and ultimately develop technological expertise [632].

8. Conclusion

In intelligent configurations, energy administration has become a service that tries to use energy responsibly and effectively. Benefits of energy administration are flexible and may be used in any intelligent setting. By forecasting and strategically arranging the usage of home appliances, HEMSs reduce the total electrical generation and usage of homes. Hence, study into and marketing of HEMSs might help energy companies, the community, and homeowners. This article presented an overview of HEMS, necessity of load forecasting and scheduling in smart environment for smooth operation of overall power structure. The methodology, process, features, pros, cons, and conclusion of each prescribed load forecasting, scheduling and futuristic optimization techniques are briefly analyzed to predict and manage resources and loads and to choose best approach according to situation. Moreover, each optimization technique is applied at device level at HEMS. This article discusses upcoming developments in load forecasting and scheduling technology and the way it may impact HEMS operations in the coming years. The HEMS load prediction and scheduling framework is offered with a probabilistic and fault evaluation that upholds load flow balance between need and supply. Our presented probabilistic model compared with Smart Campus Green & Smart Building Park, Benguerir, Morocco case study, verifying the validity of our framework and validates that illustrated probabilistic model is readily to implement in all kind of real time scenarios to meet the balance between the demand and supply. The study given here gives a comprehensive assessment of the load prediction and scheduling literature with a focus on optimization techniques. Future work and HEMS challenges are also highlighted. While energy administration is a current hot topic, it continues to confronts several obstacles that prevent future development and advancement. As a result, this paper suggested a number of prospective avenues and perspectives that might lead future investigations to broaden our understanding of HEMS.

Future work

Future paths and prospects for improving HEMS in futuristic smart settings are highlighted. Future research and reviews will focus on concerns such as the necessity to integrate the IoT with present HEMS technology and the ecological impacts of increasing green energy use. To maximize the advantages of incorporating ESSs into electrical networks, creating universal mechanisms that are adaptable with changing load needs may be an appropriate future approach. To reduce excessive set up and upkeep expenditures as well as unexpected devastating outages, automated ESS sizing procedures may be suggested in the future. one EV cannot provide the power requirements of an intelligent surroundings. synchronized regulation is crucial when several EVs are linked to the electrical grid. Therefore, creating robust strategies that coordinate the management of EVs will be a possible future focus. In addition, a further option for EV control to use is the development of specialized, safe, and confidentiality regulating technologies. As a result, it will increase consumer knowledge and persuade consumers that EVs are not exposed to dangers to their confidentiality or safety. Another intriguing option is to create consumer-friendly DR tactics, as consumer appeal is crucial to the success of DR campaigns. Additionally, it is essential to raise knowledge of and promote the advantages of DR in order to draw greater attendees, particularly homeowners. User happiness is essential to DR programs effectiveness. However, a few research has examined this issue. Therefore, it is advised that the focus for future research be developing scalable and adaptable DR optimization methods that also ensure user satisfaction. Researchers discovered expected HEMS restrictions that can be researched and fixed, like: The scheduling techniques and client choices are not in synchronization. The absence of virtually generated, actual systems that went through testing using actual models or prototypes. At times, executions lack the required smart indicators. Failing to properly take account of customers' wants, which makes them feel compelled to use less energy to provide comfort. The SG, RES, and HESS are not coordinated

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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