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Review article

Optimal load forecasting and scheduling strategies for smart homes peer-to-peer energy networks: A comprehensive survey with critical simulation analysis

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P2P trading platform
P2P pricing mechanism
P2P approaches

ABSTRACT

The home energy management (HEM) sector is going through an enormous change that includes important elements like incorporating green power, enhancing efficiency through forecasting and scheduling optimization techniques, employing smart grid infrastructure, and regulating the dynamics of optimal energy trading. As a result, ecosystem players need to clarify their roles, develop effective regulatory structures, and experiment with new business models. Peer-to-Peer (P2P) energy trading seems to be one of the viable options in these conditions, where consumers can sell/buy electricity to/from other users prior to totally depending on the utility. P2P energy trading enables the exchange of energy between consumers and prosumers, thus provide a more robust platform for energy trading. This strategy decentralizes the energy market more than it did previously, opening up new possibilities for improving energy trade between customers and utility. Considering above scenarios, this research provides an extensive insight of P2P energy trading structure, procedure, market design, trading platform, pricing mechanism, P2P approaches, forecasting techniques, scheduling topologies and possible futuristic techniques, while examining their characteristics, pros and cons with the primary goal of determining whichever approach is most appropriate in a given situation for P2P HEMs. Moreover, an optimal and robust P2P HEMs load scheduling framework simulation model is also proposed to analyze the P2P HEMs network critically, thus paving futuristic technical research directions for the scientific researchers. With this cooperation, a new age of technological advancements ushering in a more intelligent, more interconnected, and reactive urban environment are brought to life. In this sense, the path to smart living entails reinventing the urban environment as well as how people interact with and perceive their dwellings in the larger framework of a smart city. Finally, this research work also provides a comprehensive overview of technical challenges in P2P HEMs in terms of load forecasting and scheduling strategies, their possible solutions, and future prospects.

ABBREVIATIONS	
AD	Adaptive Demand
ADMM	Alternate direction approach to multipliers
AHC	Automatic Healing Capability
AI	Artificial Intelligence
ANFIS	Adaptive neural fuzzy inference system
ANN	Artificial Neural Network
APM	Adjustable penalty mechanism
AR	Autoregressive
ARIMA	Autoregressive Integrated Moving-Average
ARMA	Autoregressive Moving-Average
ARMAX	Autoregressive moving average with a variable

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ABBREVIATIONS	
BS	Bill Sharing
CC	Cloud computing
CDA	Continual double auction
CEMS	Communal energy management system
CEMU	Central Energy Management Unit
CES	Community energy storage
CO	Colony optimization
CVaR	Conditional value-at-risk
DA	Double Auction
DAM	Day-ahead market

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ABBREVIATIONS	
DER	Distributed energy resources
DG	Distributed Generation
P2P	Developed a novel deep learning based STLF framework
DR	Demand response
DRAs	Demand response aggregators
DRO	Distributional robust optimizations
DS	Data science
DSM	Demand side management
DSO	Distribution system operator
DTT	Digital twin technology
DV2G	Directed Acyclic Graph-based V2G protocol
EA	Evolutionary algorithms
EBT	Ethereum Blockchain Technology
Trade	Energy Cost Optimization via Trade"
EI	Energy internet
EMS	Energy Management System
ES	Exponential smoothing
ESC	Ethereum smart contract
ESs	Energy subscribers
ET	Energy Trading
ETS	Electricity trading and sharing platform
ETTs	Energy trading transactions
EV	Electric vehicles
FL	Federated learning
GA	Genetic algorithm
HEMS	Home Energy Management Systems
HVAC	Heated, ventilated, and air-conditioned
IoT	Internet of Things
IPFS	Inter Planetary File System
IRLS	Iterative Reweighted Least-Squares
KKT	Karush-Kuhn-Tucker
KP	Knapsack Problem
LF	Load forecasting
LMPs	Locational marginal prices
LP	Linear Programming
MA	Moving Average
MARL	Multi-agent reinforcement learning
MBED	Multi-bilateral economic dispatch
MCEN	Multi-carrier energy network
MDP	Markov option Process
MG	Micro Grid
MILP	Mixed-Integer Linear Programming
MINLP	Mixed-Integer Non-Linear Programming
MMR	Mid-market rate
MOGO	Multi-Objective Grasshopper Optimization
MR	Multiple Regression
NG	Nano Grid
NLP	Nonlinear Programming
NSP	Network service pricing
OBL	Oppositional based learning
OCOA	Oppositional coyote optimization algorithm
P2P	Peer-to-Peer
PAR	Peak-to-average ratio
PDs	Probability distributions
P2P	Peer to peer
PSO	Particle swarm optimization
PTDF	Power transfer distribution factor
PV	Photovoltaic
RF	Random Forest
RL	Reinforcement learning
RTMs	Real-time markets
SA	Simulated annealing
SCADA	Supervisory control and data acquisition
SCPM	Smart contract participation matrix
SDR	Supply and Demand Ratio
SG	Smart Grid
SO	System operator
STEP	Smart electricity Exchange Platform
STLF	Short-term load forecasting
ET	Energy Trading
SVM	Support Vector Machine
TEM	Transactive Energy Market
V2G	Vehicle to Grid
V2H	Vehicle to Home
VPPs	Virtual power plants

1. Introduction

Electricity is a prime form of energy. The regular functioning of the economy and community massively depends on electricity. Energy needs are increasing due to rapid urbanization, globalization, and industrialization [1]. Based on a poll taken, by the competitive authority in 2019 as shown in Fig. 1, worldwide growth is the main factor in the increased wide energy utilization, and that's about double the rate of the mean rate of expansion through last decade [2]. The need of electric power is growing enormously, and the number of power source modes is running out quite rapidly. Hence, it's important to manage power means correctly to maximize their utility, and reduce production expenses and environmental risks. Hence, power agencies aim to rely less on fossil energy because of the depletion of carbon reserves, fluctuating rates, and greenhouse gas emissions [3]. As a result, consumers have to reduce their power utilization by altering their usage behavior. The deployment of energy management systems and energy-efficient gadgets leads to control of power consumption which benefits cost deduction and carbon emission [4].

Influenced by worries about global warming and ecological preservation, authorities around the world are encouraging individuals to employ less power through the inclusion of clean energy resources and the practice of paying benefits to those who accomplish the green energy. In the framework of smart cities, green power is essential since it helps achieve objectives of sustainability, lessens ecological impact, and promotes power flexibility [5]. As a result, the energy industry is moving towards being more sustainable, reliable, and integrated as shown in Fig. 2. The complexity, irregularities, and uncertainty of electrical systems are becoming more of a concern as renewable energy sources become more widely used [6]. Energy professionals take into account minimizing and tracking energy use to reduce costs and promote sustainability. Correct and real-time data on energy utilization is required for controlling energy use and its effectiveness. Due to the inability of existing grids to supply this requirement. This initiated the development of a modular grid known as a Smart Grid (SG) as shown in Fig. 3 [7].

SG is an autonomous technology that can rapidly solve accessible issues in a system, decreases the workforce, and aims to provide eco-friendly, dependable, safe, and high-quality power to all users. The idea of a "smart grid" integrates the entire electricity generating and transportation network into single framework, enabling the infrastructure to an entirely more intelligent and cleaner [8]. Given the perfection of executing several distinctive features like analyzing the habits of both providers and customers, the idea of a Smart Grid has become a reality [9]. The energy system can be constructed by employing distributed autonomous computers to make the electrical system a self-healing

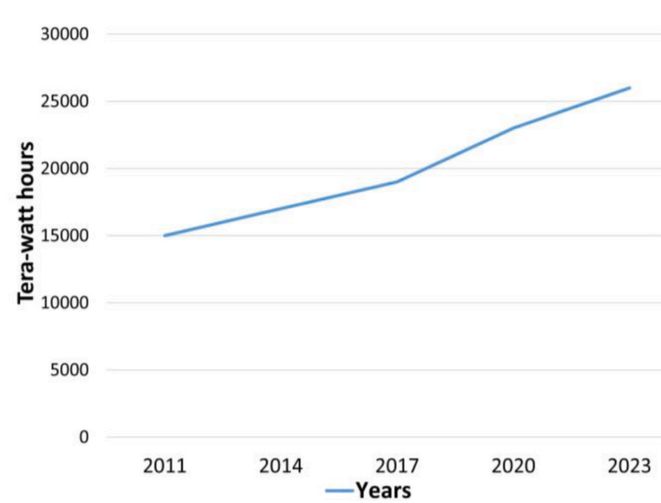

Fig. 1. World power consumption.

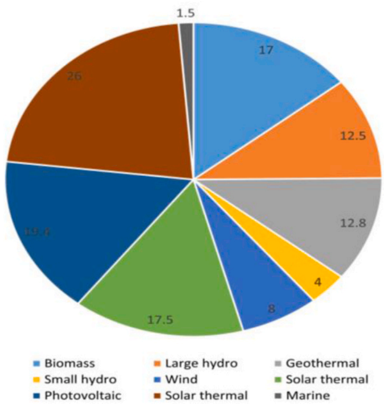

Fig. 2. Global clean energy scenario by 2030.

Fig. 3. Smart grid model.

infrastructure, grid-level computing, evaluation tracking of all transmission devices, addressing the whole electrical system as an extensive flexible electrical infrastructure, and Supervisory Control and Data Acquisition (SCADA) systems, intelligent [10].

The smart grid is addressing nearly all of the inquiries relating to the issues with the current grid. Smart Grid may monitor the entire system, regardless of the provider and consumer ends. The quantity of power used by a customer in his house may be precisely determined, and the provider can keep track of how much electricity is used by specific customers [11]. In this aspect, the smart metering idea is having a revolutionary impact. Smart Grid offers security elements that may shield its infrastructure from all types of potential harm [12]. The Smart Grid's ability to identify faults and fix itself is becoming an essential component of modern society. The Intelligent grid is digital in contrast to the traditional grid, which is electromechanical. The distinction between solely and bilateral communication systems is obvious for both systems. The traditional grid was created using a hierarchical architecture [13]. However, the Smart Grid technology is entirely network-based. The old grid offers relatively few options for customers. The smart grid, however, prioritized client preferences. As a result, the Smart Grid system offers users a wide range of options. Since the intelligent grid is becoming increasingly sophisticated, it is crucial to comprehend its characteristics in order to guarantee that it is used to its full potential [14].

The attributes of a smart grid system are as follows: The Smart Meter is the finest device in the domain of electricity production and use for data collection because of its distinctive characteristic in Smart Grid technologies [15]. Utilizing cutting-edge meters and communication networks, intelligent meters enable clients to track their energy usage in real-time. The Distributed Generation (DG) component of the Smart Grid is crucial. Distributed generation is the process of producing electricity using multiple resources for energy [16]. In addition to having a relatively reliable supply of energy through the grid, massive generation from the power plant has various effects including an ecological effect on transmission and distribution. Integration of green power is another crucial component of the Smart Grid. Increasing the grid's REI (Renewable Energy Integration) capacity enables the nationwide system to securely satisfy users' increased demand [17]. The dual-direction network of communications allows it to be simpler for vendors and clients to employ the Smart Grid technologies. In the smart grid, communication is similar to telephone calls, with customers being informed about the cost and consumption of the power along with its production, and suppliers are informed of the precisely billed consumption of the power [18]. Automatic Healing Capability (AHC) is an ability that all smart grid technologies must have. This function allows the framework to automatically identify abnormal circumstances like over current, spike voltage, and fault current, relay the data to the centralized management room and automatically repair or resolve any disruptions that may have arisen. The online systems and infrastructure of the smart grid can be attacked to take advantage of weaknesses in the system. Because of this, a system's cyber security has to be sufficient in effectiveness to ensure seamless operation [19]. Implementing smart grids contributes to substantially lowering carbon emissions since it allows for incorporating clean energy sources, optimal energy production, and reliable energy delivery [20]. Given that the Smart Grid assures the safety, tidiness, and automation of the power production and delivery network within the same structure, there have to be certain regulations that are enhancing the efficiency of the entire system. Different nations are developing various types of strategies to make the electrical grid intelligent. Urban environments are become more intelligent and networked in the recent period brought about by the rapid growth of technology. The rise of Smart Cities signifies a fundamental change in the way we plan, oversee, and live-in metropolitan areas [21]. The incorporation of cutting-edge technology into several facets of municipal infrastructure, government, and services is at the core of this transition. A key element of smart cities is the smart grid, which offers an intelligent and networked electric power system that promotes increased adaptability, long-term viability and performance. Smart Homes have developed as essential elements as a logical progression of this urban growth, supporting the overarching goal of a smoothly integrated and productive urban ecology [22]. Households use 33 percent of the total power generated. Hence, to realize the SG goal, end users must be involved in the system's functioning, the marketplace's power, and managing energy [23]. Consequently, adaptive grid networks and appliance technology are needed for home power consumption scenarios. The devices that can react to changing circumstances autonomously with no human assistance are known as Home Energy Management Systems (HEMS) as shown in Fig. 4 [24].

HEMS is an advanced technology that enables residents to track, regulate, and optimize their usage of energy. HEMS makes use of data collected from several equipment's and sensors to deliver statistics and autonomous controls, increasing energy effectiveness, decreasing expenses, and reducing the ecological impact [25]. The term "smart home" refers to a significantly technologically sophisticated digital home that is autonomous, multipurpose, flexible, pleasant, self-adjusting, active, or effective [26]. The most effective structure for effectively administrating, observing, and managing power production, preservation, and use in automated residences is known to be smart HEMS. A home system called HEMS allows for ongoing tracking and oversight of the operating parameters of domestic intelligent devices in order to improve their energy effectiveness [27].

For the control and oversight of all intelligent home items, HEMS needs to be more adaptable. HEMS section functions are demonstrated

Fig. 4. HEMS model.

as shown in Fig. 5; Supervision: continuous tracking of energy use with smart meters [28]. It can assist consumers in identifying the price of energy, customer preferences, and trends in their use of electricity, and it can help them find methods to consume less energy; Cataloging: Security procedure to grant individuals permission to view informative and useful info; Regulation: direct control of SG and users' smart devices to monitor consumption habits; Administration: increase energy savings by managing sources of energy and intelligent devices in response to changes in the instantaneous fashion price of power; Alert: monitoring for any anomalies and issuing alerts if any are found [29,30].

When using control via feedback, the system output signal is observed, compared to the input, and the resulting feedback is used to manage the differential error [31]. SHEMS may be modified to meet this idea since the HEMS methodology used as the system's regulator turns input energy indicators from the SG into generated signals that can be observed on the main screen of the display and controlled by intelligent appliances [32]. The information that comes from the sensing and measuring instruments is what drives the transition from source to outcome [33]. The following components are included in the HEMS framework as shown in Fig. 6; Input: by the use of clean energy sources, the conventional grid must be transformed into an SG that is more effective, reliable, and ecologically benign; Controller: The basis of HEMS is the controller, which makes judgments on measurements, sensory data, and consumer preferences; Smart devices: Employing IoT technology, devices with intellect and networks that provide remote management and tracking; Sensors: Changes in physical quantities are detected, converted to electrical impulses, and sent to the controller to provide precise energy-use data collection for intelligent device user tracking, planning, and regulating activities. Infrastructure: a system for coordinating interaction among system parts. It displays the link between the smart meter, the controller, intelligent devices, and the intelligent SG; Dashboard: a display that shows statistics obtained from SG or data on real-time utilization, user preferences, and costs associated with energy [34].

Fig. 5. HEMS features.

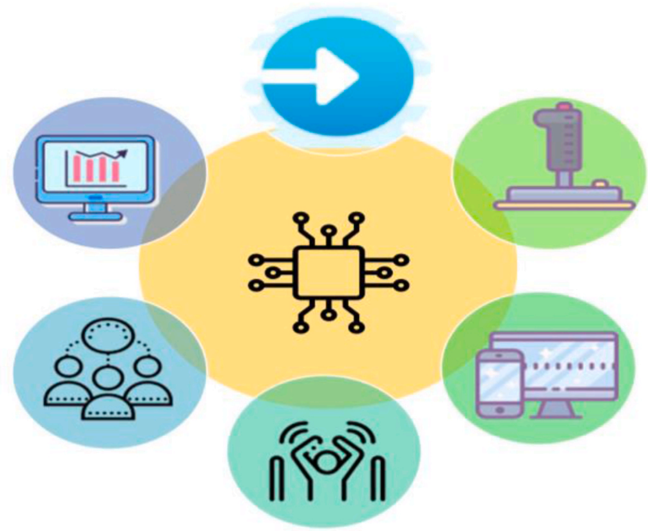

Fig. 6. HEMS component.

The fundamental objective of this method is to maintain client satisfaction while reducing power and financial costs. IoT makes it possible to sense, track, and manage the utilization of energy depending on the HEMS's ideal utilization scheduling patterns [35]. The information gathered by sensors is analyzed using cutting-edge techniques to determine customer inclinations and to track system efficiency, energy consumption, and usage patterns [36]. By maximizing power use, lowering electricity costs, and remotely turning on and off intelligent appliances. Most of the moment, people do not take the effort to schedule and estimate their gadget's usage. In order to optimize and lower energy costs during peak hours, the HEMS shifts demand in accordance with energy costs and human convenience [37]. The introduction of modern household appliances like backup storage, solar power generation, and heated, ventilated, and air-conditioned (HVAC) allow for versatility to implement the DR program. HEMS is, therefore, necessary for the functional and efficient functioning of electrical equipment under the DR program started by utilities [38]. DR was developed to regulate electrical usage. Whenever there is a surplus or a deficit of power, demand response (DR) alters the usual level of demand by raising and lowering the load [39]. To handle demand during peak hours, a DR program was established. The incorporation of Home Energy Management Systems (HEMS) into Smart Cities is a noteworthy advancement in the creation of a more technologically sophisticated, environmentally friendly, and effective urban life. A vital part of the larger smart infrastructure initiative, home energy management systems (HEMs) link each home to the city's energy grid and support the idea of a more intelligent, networked urban environment [40]. Power directors can use forecasting to identify how specific elements influences energy use and to assist them in formulating suggestions for improvement. Hence. HEMS develops essential strategies and approaches for making well-informed choices, improving home efficiency, and maximizing potential energy consumption. HEMS employ LF techniques to help them decide on energy management strategies and prepare upgrades that can help them offer reliable and efficient energy services [41]. Precise estimation of load is crucial for the electrical grid's smooth functioning, the best resource allocation, and the accomplishment of smart city projects.

A technique used to predict the quantity of power required to maintain a continual balance between energy supplies and demand circumstances is load forecasting as shown in Fig. 7. The most important information for planning and providing electricity is gleaned from load forecasts. It is also essential for the management of the energy system [42]. Predicting the expected load on an entity for a certain slot is the basic goal of load estimation. The purpose of load forecasting in HEMS is generally to balance the availability and need of power [43]. With energy consumption as the target, a time-series forecasting approach is used to predict future power needs by taking into account historical load changes. Four major categories may be used to classify LF: For expanding planning, long-term LF is used to anticipate load up to 50 years in the future; For the best operational planning, medium-term LF often predicts load on a weekly, monthly, and annual basis; Short-term LF is used for real-time load forecasting on a per-hour basis over a maximum duration of a single week with the goal to carry out daily activities and cut expenses [44]. Very short-term LF: The time bracket for this form of prediction is spanning minutes to hours (0–3 h) [45]. For controlling local demand, decentralized energy generation, and grid integration at the home level, short-term LF has a number of benefits. The forecasting mechanism makes use of data from sensors and smart meters [46]. If power sector managers wish to provide consumers with load-shedding-free, uninterrupted electricity, they must estimate the future energy need with the least feasible rate of inaccuracy. Energy suppliers may save millions of dollars by implementing more accurate load forecasts [47]. One of the main cornerstones of intelligent energy administration is a projection of energy consumption. Accurate energy and peak demand projections are crucial for efficient scheduling, modifications to distribution networks, and energy generation since energy usage varies with various equipment [48]. Having accurate power estimates is essential for resource conservation. To ensure the reliability of the electric grid, LF enables HEMS to plan electrical appliances to run on renewable energy sources during periods of high demand at a reasonable cost. Using LF, it is possible to identify when it is best to use the energy stored in the battery system during periods of increased demand and limited production. When establishing budgets based on utilization, LF is successful at assessing the price of power [49]. One of the essential components of HEMS is load projection, which is used for energy equilibrium, monitoring, and management to increase comfort while maintaining affordable power costs. Prediction accuracy is one crucial factor to take into account: Decision-makers need accurate estimates since the bulk of decisions in the power sector must be based on estimations of potential demand [50]. The accelerating rise in energy consumption in modern times exposes it as an important resource. The issue of the energy shortage in households is being addressed through the development of fresh strategies and procedures [51]. Demand side management (DSM) integration with SG is the solution to this issue. Peak-to-average ratio (PAR), often known as the consumer's capacity for scheduling their load profile efficiently to save electricity costs is made possible by DSM [52]. The establishment of renewable energies and highly efficient coordination and scheduling of various smart devices might therefore benefit greatly from the HEMS. People can schedule their household energy usage thanks to the development of the smart electrical grid in order to lower their energy costs and PAR [53].

In HEMS, scheduling is a means to control how household devices operate to enable users to complete their preferred duties and goals within the intervals and limitations of resources necessary to minimize utilization of energy, power costs, peak load demand, and increase user convenience [54]. Efficient scheduling procedures call for switching at any given moment between non-schedulable electrical equipment like displays, illumination, presses, kitchen appliances, and small gadgets as well as schedulable electric items like air conditioners, heaters, washing machines, and clothes dryers as shown in Fig. 8 [55]. Optimization of a group of equipment combined energy usage in a home over the course of a monitoring interval. Based on the degree to which their duties may be

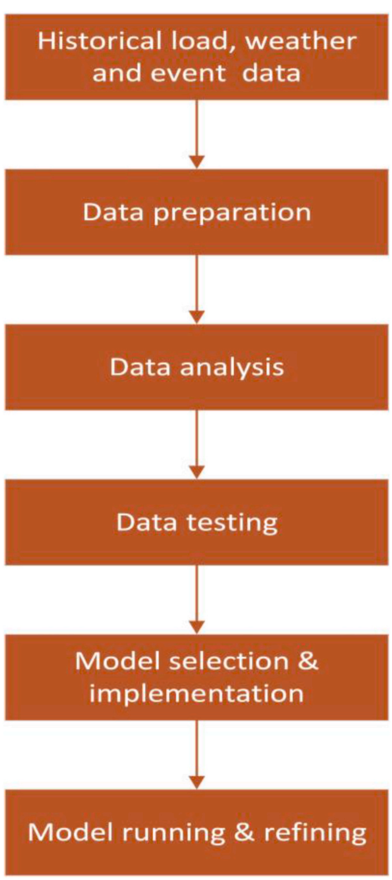

Fig. 7. Load forecasting model.

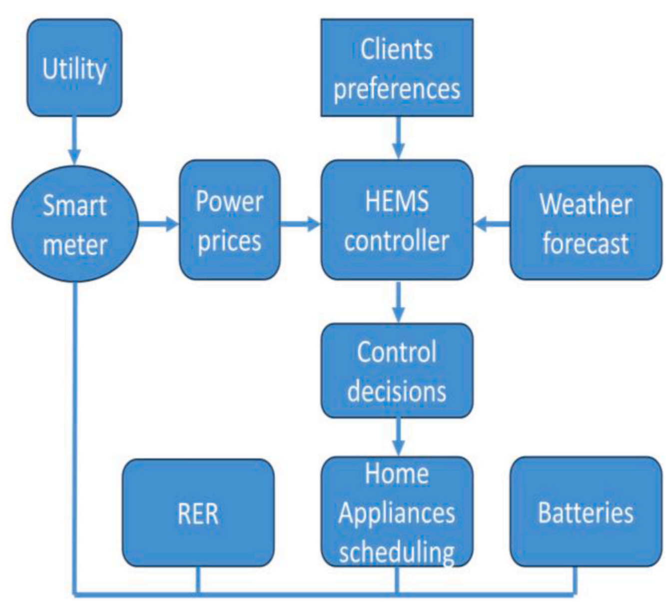

Fig. 8. HEMS scheduling model.

terminated after they are triggered, these appliances are divided into deferrable and non-deferrable categories [56]. The home has an intelligent scheduling device integrated with its smart meter that regulates how much energy is used by its devices [57]. The term "smart scheduler" refers to the smart gadget that keeps track of residential energy usage habits while making certain that the total demand stays within the predetermined range. Additionally, it makes assured that the equipment is placed at the times when energy expenses will be the lowest. It does this by automatically creating the best functioning schedules for the client's devices despite the consumer's input [58]. The scheduler can transmit and receive signals between and within the client's devices thanks to its bidirectional communication capabilities. The scheduler features extra "pause" and "resume" instructions alongside the "down" and "active" controls that allow it to regulate the deferrable loads [59]. The scheduler determines the appliance's matching likelihood for every hour according to the past period utilization trends for the equipment throughout the scheduling span, let us assume a month. This computation takes into account the day of the weeks' time, the climate, the degree of device permeability, and the number of occupants of the home [60]. This computational data is calculated and kept for every month of the year. The intelligent scheduler can determine with accuracy how likely a family is to utilize a particular device or group of equipment by tracking the information over a specified period. The scheduler constructs hourly summaries of each home appliance using these assumptions [61]. The most probable time slot probability for each gadget is utilized to create schedules autonomously. To make room for versatility in the schedules, a certain tolerance factor is included. Depending on the order of priority set by the scheduler, devices are allocated with varying levels of tolerance. Utilizing the DR program to operate devices during times of low power prices, HEMS utilized scheduling devices at home by switching or restricting loads to ensure consumers' pleasure [62]. Whenever there is a spike in demand or the cost of utilizing grid electricity is high, HEMS schedules heavy-load devices to use power via clean energy sources, decreasing the strain on the electrical grid and guaranteeing its resilience [63]. The purpose of the repair plan created by HEMS is to establish a timetable for the suspension of power unit service over a specific period. HEMS enables a schedule for electricity storage units that preserve energy from either the power grid or green energy at prime production hours and utilize at an elevated time-of-use rate. To ensure user convenience, HEMS assists in scheduling devices based on seasonal circumstances such as climate. HEMS to maintain an equilibrium between demand and supply carry out appliance scheduling continuously. The primary objectives for households are a reduction of electricity costs and the facilitation of equipment scheduling [64]. In the larger scheme of smart cities, load scheduling refers to the optimization and control of energy usage patterns in order to improve effectiveness, lower peak demand, and guarantee the power grid's dependable functioning. This procedure becomes even more important as cities expand and the need for power rises [65].

In the power pipeline, comprising MG, the expansion of distributed energy resources (DER) has significantly altered the way energy is generated, supplied, and utilized. A more transparent and distributed electric system is made possible by the enormous rise in prosumers—individuals who generate and utilize energy simultaneously [66]. Additionally, in order for consumers to use net metering programs to add power to the grid, prosumer energy managers are now also in charge of leasing transmission infrastructure. There are now 90 nations in the globe with laws requiring net metering. A rise in the production of clean energy is crucial for the move to a system that uses less carbon [67]. For this reason, it is critical that consumers of home energy find new avenues for reimbursement. With the rapid rise in the number of DERs, this problem might have a significant effect on the power market. Household green energy usage is rising, necessitating novel marketplace strategies for rate setting, decentralizing, and flexibly governing the energy network [68]. It is vital to establish regional energy markets so that produced green energy may be exchanged locally between producers and consumers without the need for mediators. By 2023, it is anticipated that the value of the worldwide intelligent house market will be $55.45 billion, and there will be 15.5 % more homes using innovative home technology than there were in 2017 [69]. Smart houses are viewed as nano grids from the standpoint of the intelligent grid. Nano grid might include plug-in electric cars as well green energy sources, and battery storage. A Micro Grid (MG) is made up of a collection of interlinked nano grids that allows for Peer-to-Peer (P2P) energy exchange between homes [70] as shown in Fig. 9.

Peer-to-Peer (P2P) trading in energy applies to the interchange of energy between energy consumers and is a kind of participatory capitalism it might be conducted under identical electrical infrastructure as shown in Fig. 10. P2P energy trading can produce financial rewards since it allows energy consumers to transfer their excess energy to consumers who need it. The power lines and purchase points represent energy and financial transactions between purchasers and buyers [71]. A prosumer may sell power to a customer. The entire bargaining process takes place on a level of administration that acts as an administrator of power exchanges. A single-direction trade indicator demonstrates that the manager is the only source of authority clients have to swap power with. The arrows designating bidirectional trading denote that prosumer may buy and sell electricity to the organizer in exchange for an energy exchange [72]. The structure of a distributed network could be alluded to as P2P connections if members collaborate by sharing part of its resources. Other peers may directly use such shared resources, providing the features and resources made accessible by the entire community, in spite of the aid of intermediary corporations. In a P2P connection, there exist two layers. Participants effectively have an encrypted way to negotiate the conditions that govern their energy trade through the virtual layer [73]. It makes sure that all parties use the platform fairly in an online setting in which information of all kinds circulates, transactions of all kinds are initiated, an appropriate marketplace structure is employed to link with transaction inquiries, and subsequently, reimbursements are processed upon effective request confirmation [74].

The central processing unit of the peer-to-peer energy infrastructure is a quick and secure repository. All market participants must be able to communicate with one another via the information network in order to engage in power trade. Set up the participants on a suitable trading platform. Allowing each participant equitable opportunity in the market. Control commerce and place restrictions on member conduct to uphold the security and reliability of the system [75]. The statistical framework of a P2P system, which incorporates market booking, transaction rules, and a clearly defined auction method, aids the marketplace's operation. The trading operation's main objective is to provide participants with access to a profitable transaction process by matching purchasing and selling bids at near to real-time detail. Tariff patterns are designed as essential elements of trade and are effectively used to control the demand and supply of energy [76]. P2P tariffs are quite distinct from those used in traditional energy markets. Peer-to-peer (P2P) trading has grown in popularity as a substitute for prosumers who are interested in participating in the energy marketplace. P2P enables prosumers to exchange surplus energy output with their peers and boost their gains and customer gains [77]. P2P energy exchange also increases end-users' adaptability, provides more chances for them to utilize renewable energy, and aids in moving to a renewable energy future. Furthermore, the other participants in the power market stand to gain from lower energy peak demand, fewer repair and operating expenses, and increased energy system dependability [78]. In smart city contexts, peer-to-peer (P2P) energy trading refers to decentralized direct exchanges of power among independent producers and end users. This creative strategy makes use of cutting-edge technology like smart metres, blockchain, and internet connections to let companies and homeowners purchase and trade extra green power [79].

Regarding P2P energy trade, LF is essential because it enables players to make wise choices about the generation, utilization, and selling of energy as shown in Fig. 11. Members in a P2P trading network could

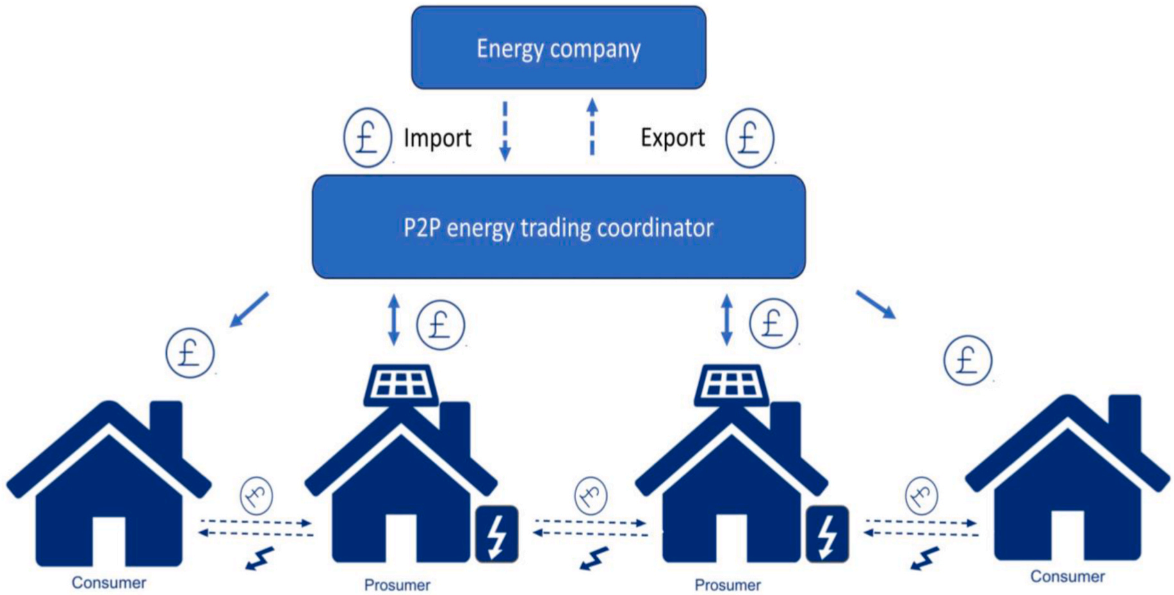

Fig. 9. P2P energy trading model.

Fig. 10. P2P energy trading working model.

Fig. 11. Load forecasting in P2P energy trading.

enhance their trading tactics and efficiently regulate their energy assets by precisely forecasting the future need for energy [80]. Using load prediction to enhance P2P trading is demonstrated herein. Gathering pertinent data is the initial stage in the LF process. Extensive details regarding utilization trends, like consumption profiles, are acquired via those engaging in the P2P trading mechanism [81]. Energy requirements are heavily impacted by the climate. The impact of weather characteristics on energy usage trends may be captured by including meteorological information inside the LF method. In order to take into account continuous variations in demand for power in P2P trading, load estimation should be done in actual time [82]. Predictions are refreshed according to the most recent knowledge thanks to constant data tracking, allowing prosumers and consumers to act quickly in a P2P environment. The peer-to-peer commerce technique's anticipated energy consumption is shown through load projections [83]. LF tools analyze the gathered data and produce precise load projections using LF approaches. These projections may be used by players to improve their energy speculation tactics, such as figuring out how much power to offer for trade, establishing reasonable pricing, and figuring out the best times to trade [84]. Demand response operations inside the P2P marketplace can be assisted by load projections. Members can more effectively balance demands and supplies by adjusting their energy use or providing extra energy for trade at times of high demand by precisely forecasting those instances. For market players, load projections serve as a means for judgment assistance [85]. Members may decide on generation, utilization, and trade depending on the anticipated energy demand, assuring they satisfy their personal energy needs while simultaneously taking benefit of trade possibilities. It is crucial to continuously assess and enhance load prediction algorithms [86]. The precision of futuristic projections can be increased by modifying prediction systems in response to responses from real statistics on energy usage and trade. LF could assist players in P2P energy trading maximize the use of clean energy, increase the entire system's productivity, and optimize their power operations. A more stable and trustworthy P2P energy exchange environment is made possible by precise load projections, which also improve processes of making decisions [87,88].

P2P energy trading's scheduling function entails optimizing the time of power output and utilization to coincide with trade possibilities and satisfy single or collective demand for energy [89]. By carefully planning their electrical loads, members may maximize the use of clean energy, reduce their dependency on the electrical grid, and improve trade results as shown in Fig. 12. The P2P trading system members examine their past consumption histories to comprehend their trends regarding power usage. High load times, resource-intensive operations, and load-shifting potential are all identified by this research [90]. Stakeholders evaluate the system's power transaction potential, taking into account their own energy offerings as well as market pricing and demand and supply fluctuations. They take into account the timing, length, and cost of possible deals. Rerouting energy use from high-demand hours to times of low demand, when energy costs may be cheaper or there could be a surplus of supplies in the trading mechanism, is known as load shifting [91]. To coincide with the best transaction windows, players change their high-energy tasks, such as using devices, recharging Electric vehicles (EV), or conducting business operations. Continuous tracking of energy prices, commerce activity, and system parameters is necessary for load scheduling. Utilizing predetermined criteria and optimization techniques, computerized systems, and intelligent gadgets connected to a P2P market can help modify power production or utilization [92]. Incorporating LF algorithms into the procedure will improve load scheduling. Having accurate predictions of future energy demand could help players in improving their scheduling choices, align their electrical loads to trade potential, and maximize energy consumption within the framework [93]. Demand and response methods, in which individuals actively change their energy utilization in accordance with grid

Fig. 12. Load scheduling in P2P energy trading.

circumstances or price indications, can be integrated into load scheduling. Members in demand response programs may optimize their energy use within the P2P trading mechanism, support grid reliability, and perhaps receive rewards [94]. P2P energy trading players may optimize their utilization and generation trends, match trade possibilities, and improve the system's general effectiveness by implementing load-scheduling algorithms. It allows members to use green energy more effectively, rely less on conventional grid sources, and build a power ecosystem that is environmentally friendly and profitable [95].

This research [96] suggested a P2P energy trading mechanism for a clustered microgrid founded on multi-objective game theory to determine acceptable sizes of decentralized generation. For two energy exchange schemes, peer-to-grid and peer-to-peer, the results of the multi-objective function are studied and contrasted. To validate the layout of the suggested design, patterns of goal parameters and participant sizes are examined. generations, incorporating devices for storing energy. The article [97] suggested a market structure that combines the advantages of these two tactics. The first step is the development of an innovative day-ahead geographical residual pricing approach that introduces a gap between the rates billed for energy imported and paid for exported in order to control the volatility related to local production consumer demand, and upward pricing. The integration of local P2P energy trading systems allows for direct consumer-to-consumer trade as well, with transaction fee penalizing the exchange of energy in accordance with probabilistically divergent geographical marginal pricing. In order to help energy consumers, make decisions, this study [98] implements a P2P energy trading strategy with an optimization framework. It does so by taking into account the hourly electricity accessible for trade via the best power scheduling of the electricity trading and sharing platform (ETS). In an entirely transactive intelligent environment, this study [99] suggested an organizational power trading strategy that simulates prosumers in the commercial, industrial, and residential industries as well as energy preservation, green energy sources, and centralized production. A hierarchical MAS with three bidding levels is created to simulate the aforementioned. In Ref. [100] researchers provide a unique adjustable penalty mechanism (APM) to encourage the defaulting consumers to complete orders. The variance fraction component and multifaceted punishment introduced by Muse lower the likelihood of high penalty rates. Case studies are done to show the viability and effectiveness of the planned APM in the P2P market. In order to anticipate the electrical, heat, and gas net loads for combined local energy systems concurrently, this research [101] suggested a multi-energy forecasting approach utilizing deep learning technology. Using real data from household-scale prosumers, the suggested multi-energy net load forecasting approach is thoroughly and exhaustively tested. In order to decrease P2P energy supply inefficiencies and congestion, this work [102] used a unique dataset that incorporates the energy usage in COVID-19 lockout to anticipate the future trends for energy demand for use. Prospective power usage figures for residential houses were predicted using three learning algorithms: Random Forest (RF), Bi-LSTM, and GRU. Utilizing the RMSE and MAE assessment criteria, the outcomes were contrasted. In order to promote technological, social, and economical advances for the reorganization of the renewable energy marketplace, this article [103] provides an in-depth guide for understanding the current microgrid's communication and control technological advances with the addition of blockchain applications. An innovative multiscale architectural scheme for P2P trading has been put forth in Ref. [104], along with inter-platform integration processes to match local operations with system-wide demands and statistical techniques to improve future planning and financial choices by considering predicted real-time activity. To improve the effectiveness of electricity trade and the precision of demand and cost predictions, a completely autonomous energy trading platform powered by ML is presented [105]. All of the financial and physical restrictions of energy distribution networks are taken into account when addressing concerns with computing utilization, communication protocols, ML job scheduling, and user-sensitive data preservation in the decentralized ML paradigm. The suggested P2P activity is made possible via d wireless connectivity. The study in Ref. [106], discusses a few business concepts that might be used in a P2P environment. We also discuss the obstacles and motivators for implementing regional or local P2P-based power services. The (P2P) energy exchange and network management of linked (MGs) are addressed in this research [107], employing a data-guided distributional resilient cooperative optimization model. First, a distributional robust optimizations (DRO) problem is used to describe the energy administration for each MGs while taking into account P2P energy trading possibilities and a variety of operational restrictions. Later, using the alternate direction approach to multipliers (ADMM), a unique decentralized pricing technique for P2P energy trade is created that is also incentive-compatible. Additionally, the Wasserstein metric (WM) is utilized to create a fuzzy set of the ambiguity probability distributions (PDs), which takes into consideration the unpredictability in load utilization and green generation The article [108] offers an arbitrage method for renewable MGs to deal with the kavolatile behavior of RESs like solar power and wind in a newly emerging market where (P2P) energy trade in transactive energy markets (TEMs) established among a day-ahead market (DAM) and real-time markets (RTMs) has taken place. For P2P trading of nano grid, a pair auction technique is suggested in this paper [109]. In the initial phase, a demand and supply association that is thought of as a two-step pricing estimator is developed in an effort to encourage the use of the regional green power and eliminate the drawbacks of conventional approaches. This connection serves as a guide for transactional correction. The concurrent game-theoretic strategy based on trade preferences is completely implemented in the following phase, and it has the potential to improve market equilibrium and therefore boost social services of the P2P marketplace.

This paper [110] proposed an optimized P2P trading approach for linked microgrids with the goal of reducing operating costs and maximizing revenues through active energy exchange while taking wind power risks into account. The suggested paradigm assures transparency and confidentiality through decentralized approaches using Nash negotiation and robust optimizations, as shown by modelling on linked microgrids, verifying its efficacy. In order to achieve up to 25 % cost reductions for residents, this research [111] presented an optimizations scheme for scheduling P2P trades, grid operations, and battery administration inside local power marketplaces. This paper [112] presented an equitable pricing framework for multi-energy networks centered around a Nash-type game, assuring trade impartiality while reducing energy costs. With the help of McCormick repose and Mixed Integer Linear Programming, the suggested technique produces effective results and illustrates possible cost reductions of 4.9 % via an instance investigation including both businesses and home prosumers. In this work [113], an ideal day-ahead scheduling method for a communal energy management system (CEMS) presented with an emphasis on user ease and financial advantages. In comparison to previous CEMS setups, the suggested system-centric CEMS uses mid-size rate trading to handle regional energy trading across various housing types, resulting in lower electric bills and higher thermal comfort content. In order to improve the system's effectiveness and confidentiality while preserving the IEEE 33-bus test system, this article [114] presented a collaborative scheduling structure for the transactive distribution network that integrates peer-to-peer energy trading, optimizes the transfer of power, and uses Nash bargaining theory to distribute interests optimally. This paper [115] showed a P2P market paradigm that optimizes trade while protecting confidentiality for interconnected energy networks. The efficacy of P2P trading in local interconnected electric and natural gas networks is improved by cooperative optimizations utilizing geographical residual pricing and equitable connection rates. The novel microgrid (MG) prosumer network described in this article [116] allowed for direct energy trade amongst MG members. P2P energy trading across MG prosumers makes use of new technologies like electric autos, battery storage, and demand side management initiatives to promote cooperation and local energy balance. The bi-level peer-to-peer (P2P) multi-energy trading architecture for linked distribution and heat exchange infrastructures is introduced in this study [117]. Consumers use an autonomous algorithm to optimize regional power scheduling and P2P trade, while network administrators use modified Nash bargaining to reduce losses and reorganize networks. In this paper [118], a system that enables prosumers to control existing DER and participate in energy trade is presented. A confidentiality and extensible market clearance technique is included in the suggested architecture, along with event-based adaptable markets, P2P trading, grid trades, and day-ahead energy planning. In short, following are the key contributions of this paper:

- This research provides an extensive insight of P2P energy trading structure, procedure, market design, trading platform, pricing mechanism, P2P approaches, scheduling topologies and possible futuristic techniques, while examining their characteristics, pros and cons with the primary goal of determining whichever approach is most appropriate in a given situation for P2P HEMs.
- An optimal and robust P2P HEMs load scheduling framework simulation model is also proposed to analyze the P2P HEMs network critically, thus paving futuristic technical research directions for the scientific researchers.
- This research work also provides a comprehensive overview of technical challenges in P2P HEMs in terms of load forecasting and scheduling strategies, their possible solutions, and future prospects.

This article as shown in Fig. 13 discusses the renewable energy integration in smart grid (SG), its infrastructure and how SG transforms into smart homes. Smart home energy management system (SHEMS) overall working which leads to smart home peer to peer energy trading networks by mean of precise load forecasting and scheduling to maintain the balance between demand and generation of homes in peers. This research discusses the overall structure of P2P energy trading which involves different layers, power, control, communication & business. For P2P energy trading, a four-layer structure is introduced in order to identify and categorize the key elements and innovations according to the purposes they fulfill. The procedure of P2P energy trading presented involves forecasting of resources to find the bid for matching peers to perform energy transaction under financial settlements. Cutting-edge market mechanisms for modern power networks with increasing DER involvement are included into P2P energy trading (see Fig. 14).

Depending on the level of centralization, market design models for P2P energy trading may be divided into three categories: decentralized, distributed, and centralized. A trading platform is required to enable peers to trade with each other and with major retail and wholesale marketplaces while abiding by the market laws. In addition, platforms may be categorized as decentralized or centralized based on the underlying underpinnings of each. The goal of P2P networks is to balance supply and demand for electricity. Numerous trading practices and regulations, such as market structure, bidding strategies, and market clearing methods, have been proposed in the literature in order to achieve this aim. The pricing mechanism section aims to provide readers with a basic understanding of the system of pricing for P2P energy trading by emphasizing market players and categorizing pricing procedures. The P2P energy trading approaches, load forecasting and scheduling techniques and futuristic optimization framework presented while discussing their process, feature, applications, pros and cons. In order to critically analyses the P2P HEMs network and create smart communities that create smart cities, an optimal and dependable simulation model for the P2P HEMs load scheduling framework is also proposed. Open research challenges, limitations and future research direction are also discussed.

Fig. 13. Information flow presented in this paper.

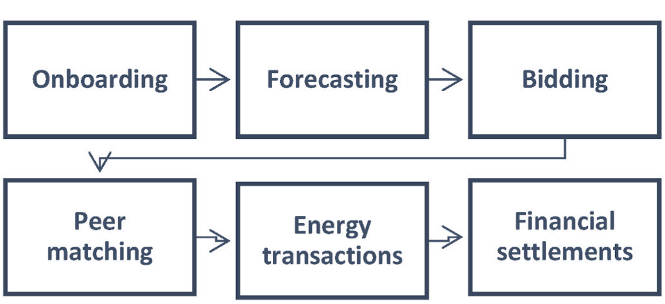

Fig. 14. Procedure of P2P energy trading.

2. Structure of P2P energy trading

2.1. First dimension

Primary P2P energy trading functions are categorized into four interconnected levels in the first dimensions. Each layer is described as follows. According to the illustration, a four-layer framework is presented for P2P energy trading to highlight and classify the essential components and advancements associated depending on the functions they serve [118].

2.1.1. Power grid layer

Feeders, transformers, intelligent meters, electronics, and other components make up the power grid layer. In this level, these elements establish connections for the distribution of power, and P2P energy trade takes place there. Despite considering connectivity limitations [119], creates a system for peer-to-peer energy trade. Here, peers that participate in power trading and induce excess voltage issues are known as prosumers. Losses are also caused by a rise in nodal voltage and overload. Concentrate on how to mitigate network energy loss issues. The optimal DC MG power delivery with the least amount of distortion is in Ref. [120]. It shows efficient energy trade as well as network energy dissipation. Some crucial criteria are the requirement of system stability and its inflexibility, with the former proving increasingly difficult.

2.1.2. Control layer

The control layer primarily comprises of the power distribution mechanism's management tasks. In this layer, several control techniques are established for maintaining the reliability and dependability of the energy provision and controlling the flow of energy comprise voltage supervision, frequency command, and active power regulation [119] focuses on a control strategy that permits energy exchange among peers in the network. To get steady frequencies and the voltage, nevertheless, unexpected variations of consumption or production might result in an imbalance in the power equilibrium. In both grids linked or islanded state, an AC microgrid uses a distributed hierarchical control. This control approach achieves appropriate energy transfer and frequency/voltage recovery. It guarantees that voltage and frequency are restored to their baseline levels [120].

2.1.3. ICT layer

Networking tools, protocols, software, and exchange of data make up the ICT layer. Sensors, cables and wireless networks, gateways, switches, servers, and other pc kinds are all considered communications devices'/ IP (Transmission Control Protocol/Internet Protocol), PPP (Point-to-Point Protocol), X2.5, and other protocols are examples. Uses for communication might range from file sharing to data exchange [121]. The terms "senders," "receivers," and "subject matter of every message transmitted across connected equipment" all relate to the data stream. This layer provides a data interchange protocol for usage in applications [122]. If more peers join in peer-to-peer trading, communication problems must be resolved for effective and quick execution. A computational examination of a networked and decentralized algorithm is provided to support this. Attention must be paid to bandwidth constraints and communication latency caused by web traffic in order to ensure effective and dependable functioning. In Ref. [123], the social motive for participating in shared consumption is reviewed and observed. It is a synchronized activity of acquiring and exchanging items that is P2P oriented.

2.1.4. Business layer

Business layers decide way energy is transferred between businesses and with other individuals. Peers, providers, distribution system operators (DSOs), and energy sector authorities are mostly involved [124]. A variety of business structures might be created at this level to execute different P2P energy trading schemes. A multi-energy management approach is suggested to investigate issues connected to prosumers' optimum energy scheduling in order to substantially decrease energy prices [125]. P2P primarily enables modest DER participants to offer their surplus electricity to others who are in need of it. Parallel to this, displays an exchange system that benefits every client economically. The author of [126] provides an examination on the viability of prosumer collaboration. The goal is to increase peer engagement in the long-term trade of energy. Although P2P energy trading enables prosumers experiencing energy scarcity to satisfy their needs, the price of energy is reduced. This is accomplished by paying less for the necessary energy.

2.2. Second dimension

In accordance with the scale of the participants in P2P energy trading, the second dimension of its design is divided into regions (composed of several Cells), premises, Microgrids, and Cells. Each single dwelling that is linked to the energy distribution network is referred to as an individual premises [127]. Microgrids are energy distribution systems that include demands and DERs and function in a regulated and synchronized manner, whether or not they are linked to the primary electrical infrastructure. A typical microgrid is made up of a number of separate buildings and DERs in a specific region that use the same MV/LV transformer. Parallel to this, Celli is a notion that has been presented in studies [128], and is a unit made up of many microgrids. It is used to specify a broader system that allows a set of DERs may be managed in accordance with a variety of goal [129]. A cell might include many microgrids and might operate both in grid-connected or isolated mode. A territory can be as big as an entire town or a region that's made up of several cells. A Microgrid, a cellular area, and commerce may all be seen as peers [130].

2.3. Third dimension

The final dimension displays the P2P energy trading mechanism' execution. It is about creating a P2P energy trading system using a pricing algorithm. Players in the local marketplace, trade officials, managers, etc. are examples of business layer constituents [131]. This layer examines how players trade energy and the way it works. To investigate issues with prosumers' best energy planning, a multi-energy management strategy is developed [132] in an effort to considerably reduce energy costs. P2P primarily enables small-scale DER participants to exchange surplus energy for scarce energy. The trading technique shown is similar in that it is profitable for every user. The writer of [133] provides a study on the viability for collaboration amongst clients. Its goal is to increase peers' sustained engagement in the energy trading market. P2P energy trading lowers the price of energy as it enables prosumers with energy scarcity to satisfy their demands. The main third-dimensional activities that occur are bidding, energy exchange, and the settlement [134].

2.3.1. Bidding

Whenever power users (producer, clients, and prosumers) form deal with one another before the energy transaction, bidding is the initial phase of peer-to-peer energy trading. Power buyers and sellers negotiate the cost and amount of energy to be exchanged throughout the bidding procedure [135]. A few bidding strategies are developing to support peer-to-peer energy trading. A smart contract is a computerized framework for operations that functions according to peer consensus. To lessen unanticipated prevention, agreements are encoded and incorporated. Blockchain stores these codes and points the contracts to them to execute the smart contract. The operation is then automated in accordance with predetermined rules [136]. A digital platform called Elecbay [137] enables peers to execute and shell out agreements as authorized. Elecbay splits money among prosumers and operators following transaction and trades energy after deducting service costs. There is a penalty if the amount of energy is inconsistent in any way.

2.3.2. Energy exchange

The second act through which energy is produced, transported, and used is energy exchange. It employs energy routing gadgets to move electricity from the source to the target for energy exchange. The ad hoc Nano Grid (NG) framework for distributed energy transfer is examined by the structure in Ref. [138]. Intelligent nodes in the NG control the flow of power. The intelligent nodes use an ad hoc wireless connection to interact with one another. The footer and header of the power packets, which are utilized for energy transfer, transport the packet along the energy network. The functional operation of the system is impacted by a substantially laden packet footer [139]. The enhanced power packet design, that routes energy packets with little footer, is the main focus. According to a power transfer strategy, a packetized router can perform three separate functions: subscriber harmonizing, transmission reservation, and power packet delivery [140].

2.3.3. Settlement

Invoices and transactions are eventually handled by settlement procedures and payment during settlement, which is the last procedure. A vendor who consented to selling an amount of power may occasionally be incapable to produce that precise quantity as specified in the contracts due to networking limits and the unpredictability of DERs [141]. The similar situational applies to a buyer. During the negotiation phase, the discrepancy among the stated and real power production or usage amount must be estimated and taxed. An autonomous P2P bargaining technique that resolves the power contract between peers is demonstrated by the author in Ref. [142]. The peers engage in bilateral negotiations to finalize a contract or loan that includes the specifics of the energy trading. These peers engage in mutual negotiations on a range of issues, including energy contracts, and they evaluate such agreements in light of a useful utility role. The plan increases system effectiveness. The auction process [143] makes use of power-based buy- and sell-orders that are presented to a social rule system. For the settlement procedure, these activities either are constantly in matching or none.

3. Procedure of P2P energy trading

3.1. Onboarding

To enable peer-to-peer energy trading, prosumers inside the distribution network divulge information about their energy production from renewable sources and dynamic demand to an authorized organization, such as an aggregator. If they have the required metering and communication systems for decentralized P2P trade, this data aids in onboarding them by facilitating net metering deployment, online bids, legal contracts, and financial reimbursements [144].

3.2. Forecasting

The characteristics of their local energy output and demand are predicted by consumers interested in advance P2P energy trading. In order to improve forecast accuracy, various techniques have been proposed. These forecasts serve as a guide for the Energy Management System (EMS), which calculates the quantity of energy needed for community consumption and P2P trading at a given time [145].

3.3. Bidding

The prosumer or the Energy Management System (EMS) on its behalf tactically sets bids or asks in the P2P market, taking into account the quantity and the target price, depending on the predetermined net import/export for P2P trading. Prosumers or EMS can bid strategically to increase their probability of winning an auction, as shown in reference. This is relevant mostly in auction-based P2P markets [146].

3.4. Peer matching

Following sections discuss optimization and game theory-based methods where bid/ask submission is not used instead trade is established taking into account net import/export, member' well-being, and system coherence. The marketplace is cleared to identify those qualified for P2P energy trading, with the goal of optimizing players' benefits inside distribution network constraints [147].

3.5. Energy transactions

Authorized players carry out P2P trades in this phase by infusing or withdrawing energy in accordance with the approved contracts [96]. Instantaneous data transfer is made possible by integrated metering and communication equipment. The grid steps in to handle variations from consumption if a prosumer can't fulfil the agreed-upon power delivery [148].

3.6. Financial settlements

The aggregator, P2P trader, or DSO verifies P2P transaction accomplishment by comparing peer meter data with market-clearing results. Penalties are imposed for departing from filed bids or requests in order to deter such behavior in future instances. P2P energy exchanges include an economic settlement that includes power charges, infusion revenue, deviated costs, network utilization, and energy transfer loss compensation [149,150].

4. Market design

P2P energy trading incorporates cutting-edge market structures for contemporary electricity networks with rising DER participation. A number of views are used to address the market designs for P2P energy trading: market classification based on the extent of centralized governance, diversification of electrical products, market reliability, interaction with third-party markets, and game theoretic approach [151]. Market models for peer-to-peer energy trading may be split into three groups based on the degree of centralization: centralized, distributed, and decentralized, as depicted in Fig. 15 and their characteristics shown in Table 1.

4.1. Centralized market

A facilitator who interacts with every peer taking an active role in P2P energy trading, appears in a centralized market [152]. The facilitator controls the energy importation and exportation of the peers or the operating state of the gadgets across the peers considering the data gathered via the peers. The liaison divides the profits of the entire peer-to-peer community in accordance with some established rules, for as by setting prices for computing individual peer's profits. The adoption of centralized market systems has been addressed in certain publications in the field, with the major emphasis being on the optimization and minimization of power expenditures. The "Energy Cost Optimization via Trade" (ECO-Trade) technique was introduced by Alametal in Ref. [153] for the optimization of electricity exchange and to prevent discriminatory pricing in a centralized market structure by integrating the P2P power transaction for intelligent houses with the DSM.

One significant benefit of centralized markets is their ability to maximize the societal well-being of the entire P2P network. In establishing supervision choices for the peers, the supervisor might decide to maximize socially beneficial areas as the goal functionality [154]. Another benefit is that decentralized marketplaces result in less unpredictability in peer energy production and utilization habits. Ahlqvistetal. in Ref. [155] covers wholesalers energy markets and compares the major benefits and drawbacks of using centralized market architectures in depth. A centralized architecture can assure the technical and financial viability of the day-ahead delivery in retail energy markets by depending on a single entity to control and making choices are performed via taking into account a variety of network-relevant factors, including the power station spot, expenses, and ramps, which are presented to the main organization as part of the bid [155].

A key drawback of centralized marketplaces is that their strain centralized organizational structures exponentially in terms of processing and interaction due to the growing number of DERs involved. Concerns about autonomy and confidentiality are among the other drawbacks [156]. When confidentiality is an issue, the data the organizer needs may reveal peer anonymity. Immediate access to peers' equipment in the midst of independence compromises peers' freedom, which may not be desired to all consumers. Finally, single-point outages at the organizers can affect centralized marketplaces. Due to the volume of data that each peer delivers to the centralized organization and its capacity to have an impact on its choices and trade results, a centralized marketplace architecture presents issues about safety and privacy [157]. Considering private data about an individual's tastes, load characteristics, and daily routines can readily be divulged during the bidding process, confidentiality might become an issue for market players. Additionally, the market fails to grow and is prone to single-point collapse because there is only one central institution managing the whole market [158].

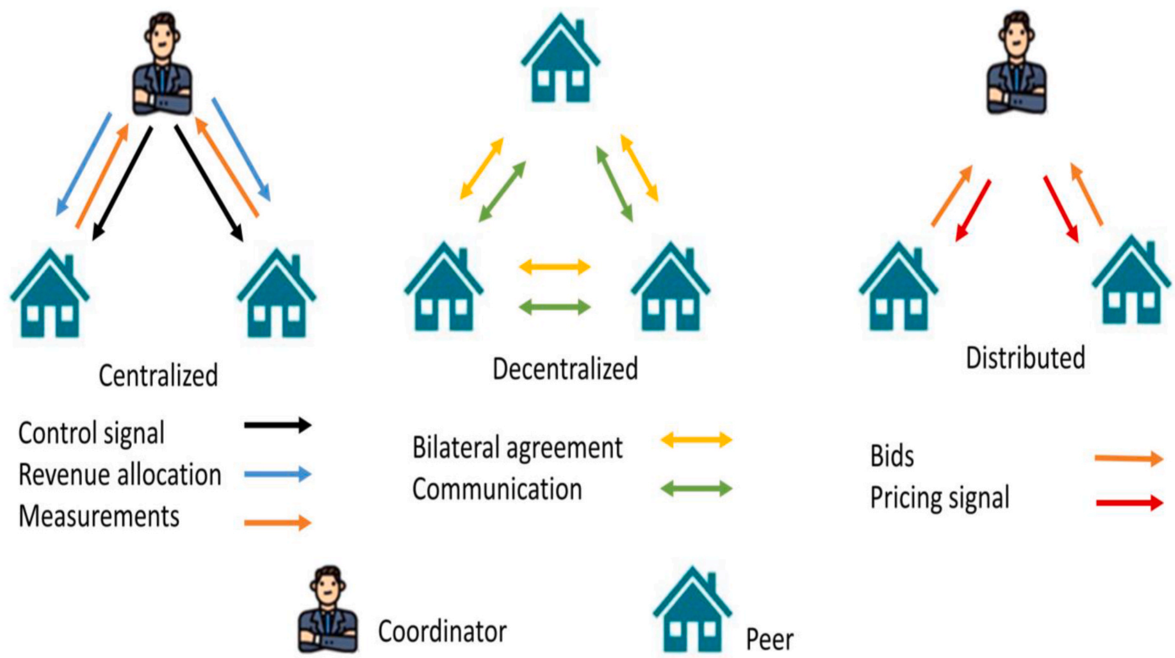

Fig. 15. P2P market design.

Table 1
Characteristics of market design approaches used in P2P energy trading.

Centralized	Decentralized	Distributed
• Delivers highly competitive coordination and overall effectiveness • Reduces supply and demand unpredictability • Assures day-ahead dispatchability. • Provides simple and clearly stated market pricing • Offers grid services and top-quality energy supply	• Offers great independence and confidentiality • High dependability • Flexibility and easy to use capabilities • Simplifies market clearing and arbitrage • Increased market clarity.	• Offers utilities and reliable electricity distribution • Encourages collaborative community and prosumer clubs • Aims to optimize pricing and benefit residents • Improves the adaptability of ICT infrastructure • Maintains a balance between centralized and decentralized solutions

4.2. Decentralized market

A decentralized market architecture eliminates a centralized organization and permits direct exchange of energy among consumers via bilateral trade, as shown in Fig. 8. Since there is no central organization to supervise and coordinate each transaction, this type of market architecture is conducted in a lesser organized way with poorer market efficiency [159]. According to the literature, decentralized market models are frequently regarded as complete P2P systems. Numerous proposals for decentralized market systems have been made in research, most of which center on maximizing social benefits and player interests. A P2P market framework founded on the multi-bilateral economic dispatch (MBED) formula was first presented by Sorinetal in Ref. [160]. This promoted proactive member behavior, enabling multilateral trade with differentiated products based on user choices, and increased welfare for society. Using game theory, Huetal.in Ref. [161] developed a decentralized energy trading system for a nonoceanic island MG. This system was able to maximize the aggregator's income while lowering every participant's electric bills.

Since there is no data is sent to a central authority and every player is entirely liable for their individual judgements and retains authority on the results of trades, this sort of marketplace offers an elevated degree of independence and confidentiality for participants. The lack of a central entity improves dependability and removes issues related to single-point failures [162]. Additionally, it provides the network with great capacity, adaptability, and simple to use capabilities, enabling users to simply enter or exit the energy trade marketplace as desired. In comparison to centralized power markets, there are few connection linkages, which is a significant feature that leads to the enhanced scalability [163].

The P2P power customer's societal impact declines and its effectiveness is reduced by the absence of a central organization to supervise and regulate all transactions effectively [164]. The lowering of welfare costs is the outcome of both sellers and buyers minimizing losses caused by non-convexities by charging a price greater than the marginal expense for their electricity. As a result of multiple hidden restrictions, such as player preferences and gadget functionality, that are challenging for the distribution system operator (DSO) to visualize and forecast, the administration of a decentralized marketplace system is recognized to be very complex [165]. Decentralized marketplace designs frequently use block purchases, that can make auctions more complicated owing to the high number of potential block kinds or permutations of supply hours, however this complexity can be reduced by using block type limits on block requests. Block contracts also offer increased versatility in intra-day sectors, enabling providers to boost their production capacity within a given period by just offering extra for the time frame in the intra-day market [166].

4.3. Distributed marketplaces

Between centralized and decentralized market designs are distributed marketplaces. In unregulated marketplaces, the liaison often exerts indirect control over participants by disseminating price signals as opposed to actively directing power import/export or the operational condition of participants' devices [167]. Distributed markets nonetheless require an administrator, allowing for greater peer behavior coordination in comparison to fully decentralized markets. Distributed markets often need fewer details from peers and do not directly regulate the gadgets of peers, providing consumers with a better level of confidentiality and independence than centralized markets. In conclusion, distributed markets combine the advantages of centralized and decentralized markets and offer a balance between the two [168].

A distributed marketplace design, like decentralized designs, can provide for an appropriate degree of player independence and confidentiality by restricting the quantity of data communicated to the central entity and by not directly regulating the functioning of equipment. This enables peers to independently maximize their own personal benefits. Improved network capacity for ICT infrastructures and simpler integration with current structures are further benefits of distributed market architectures. Distributed or hybrid market designs, according to Ref. [169], can offer a degree in network adaptability greater than that of centralized market models since the amount of market players is lowered when they are separated into groups or neighborhoods, which lowers the total communication and computing need. Connectivity restrictions can also be taken into account in distributed market architectures to prevent saturation in distribution channels. This can be accomplished, as recommended in Ref. [170], by adding a network utilization fee to incorporate network functionality into any energy exchange and provide a local pricing signal depending on network restrictions. Similar to centralized designs, a distributed energy market can assist in delivering high-quality electricity and offering a variety of grid services [171].

Due to the availability of numerous concurrent markets, the pricing techniques utilized in distributed marketplace systems may be highly complicated and may need more research to be useful for P2P energy trading. An issue connected to the considerable difficulty in combining and preserving collections of data from the many consumer groups is also included in this sort of market layout [172].

Distributed P2P energy trading market prospects will entail how to create appropriate pricing structures to support trade while concurrently delivering other activities. The price systems must take into account decision-making, peer behavior, and relevant deployment methods. In order to prevent unstable and undesirable consequences in practice, the convergence beneath the price mechanisms need extra consideration [173].

5. Trading platform

A trading platform is necessary in order to allow peers to trade with others as well as with large retail and wholesale marketplaces while adhering to the market regulations now that P2P energy trading platforms are designed. Numerous investigations and tests have been conducted in relation to trading platforms for P2P energy trade [174]. Platforms can also be classified as centralized and decentralized depending on their technology foundation as shown in Table 2.

5.1. Centralized trading

Authors haven't paid much focus on centralized or third-party trade systems. This tendency could be caused by an absence of confidence, independence, and confidentiality connected to centralized or third-party platforms that are managed by an individual or business with the intention of making a profit [175]. Because there is just one central or third-party organization, centralized trading platforms find it simpler to comply with legislation and official approval. However, because middlemen are used, these platforms could be linked to expensive trade and operation fees. A centralized trading platform dubbed "Elecbay" was introduced by Zhang et al. in Ref. [176] to facilitate grid-dependent P2P energy trading as shown in Fig. 16. The Elecbay computer system enabled users to submit requests depending on their estimates of energy usage and production, with various time slots set aside for auctioning, trading, and settling procedures. To provide a bridge between retail energy markets and communities of consumers, Zepteretal in Ref. [177] launched the Smart Electricity Exchange Platform (STEP). Instead of paying prices from wholesale markets and the grid, the STEP permitted customers as well as companies to benefit from bigger selling rates and reduced purchase prices.

Table 2
Characteristics of energy trading platforms used in P2P energy trading.

Centralized	Decentralized
• Governed by an individual or company with the goal of creating a profit • It is easier to accept regulation and government approval due to the existence of a single central or third-party entity • High transaction and service fees due to the use of intermediaries	• Energy trading through smart contracts • Low transaction and service fees • Allowing direct buyer and seller interaction without intermediary services

5.2. Decentralized trading

Researchers have paid a lot of focus on decentralized trading networks, particularly in the fields of SGs and MG networks. Beyond a doubt, the majority of the scientific literature relies on blockchain technology to provide efficient decentralized trading platforms for P2P energy trading using smart contracts [178] as shown in Fig. 17. Decentralized trading platforms may have comparatively cheap transaction and service costs for market players because they eliminate numerous levels of charges by enabling straight buyer-and-seller contact without intermediate services [179].

Decentralized trading platforms, yet, may be vulnerable to a number of administrative issues in how they acknowledge legislation and function in accordance with it. This is due to the fact that the majority of market power is transferred to consumers, while there isn't a centralized or third-party institution to guarantee that market players adhere to laws. Due to a variety of aspects that are crucial to the functioning of the energy markets, regulatory problems are exacerbated when confronted with the use of blockchain in P2P energy trading applications [180].

6. Trading algorithm

Research have been done to maximize members' earnings and encourage their participation as consumers in the regional energy market. Another goal of establishing P2P networks is to achieve electrical demand-supply balance. To this goal, numerous policies and trade procedures including market structure, bidding tactics as shown in Table .3, and market clearing processes as shown in Table .4 have been offered in the literature.

6.1. Bidding strategies

The P2P energy market is a participatory ecosystem that allows players, including producers, customers, and energy companies, to present their bids and requests in order to maximize their income. The research has established a number of bidding techniques for P2P energy trading in local energy markets [181]. Multiple studies examined various bid tactics in the power market to study the potential for setting up a P2P trading market. A number of bidding tactics are introduced in article [182], and their effects on market circumstances are examined.

Zero intelligence is the most basic kind of bidding occurs when participants offer bids and ask questions randomly. The majority of the time, no prior knowledge of the market's behavior is used in approach. Which is the widely utilized approach in the smart grid's energy market [183]. A smart bid agent is deployed to be contrasted to ZI's agent behavior in Ref. [184], which demonstrates that the total cost of power lowers when this sort of bidding is used. In zero intelligence plus When bid is conducted based on the market's historical performance, similar to how people trade stocks, in Ref. [185], a ZIP broker is suggested. Sustainability participants can adjust the margins of profit in this form of bid in accordance with the preceding orders. In game theory with

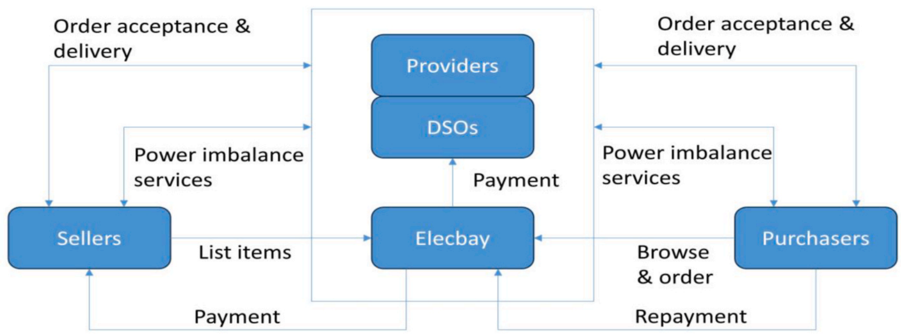

Fig. 16. Centralized Elec Bay trading platform.

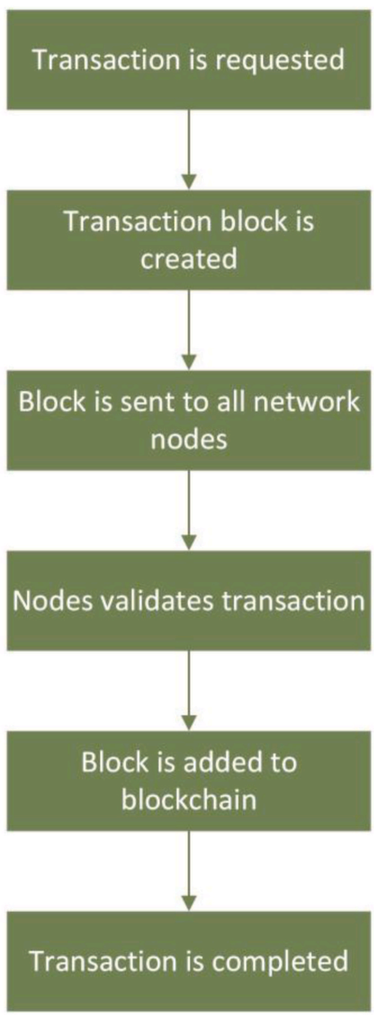

Fig. 17. Decentralized blockchain trading platform.

multiple players, both buyers and sellers are modelled. Each participant aims to dominate the game by selecting the best course of action. Additionally, offers and requests can be developed centered on a game-theoretical approach. Using this strategy, two or more market participants can place a bid depending on the price and how other participants have behaved in prior hours. The game-theoretical technique is contrasted with inversed generation and ZI methods in Ref. [186], and the findings show that it is the most effective option for providing families with locally produced energy. In Adaptive-Aggressiveness uotes are continuously modified by market participants depending on the market value during the learning process.

Table 3
Bidding strategies of energy trading algorithm used in P2P energy trading.

Zero intelligence	• Simplest bidding method • No Past market performance required
Zero intelligence plus	• Bidding is performed on past performance
Game theoretic bidding strategy	• Two or more players participate • Each player wants to win by making optimal decision
Adaptive Aggressiveness	• Quotations are automatically adjusted by market players based on the price of the market
Inversed Production Pricing	• Setting a price according to the relation of supply and demand
Intelligently bidding agents	• Makes bidding decisions based on reinforcement learning
Parallel Multidimensional willingness	• Multidimensional factors are modelled to replicate the power network volatility throughout bidding procedures
Prediction integration	• Advanced machine learning is employed to determine how the electrical market will respond to a consumer's bid using the previously collected transaction information
Cognitively bidding agents	• Cognitively bidding agents were used in many research, allowing bots to change pricing
Intelligent negotiation agent	• Agents are designed to negotiate on behalf of their users or organizations and represent those interests in order to come to a mutually advantageous conclusion
Reinforcement learning	• Emphasizes training agents to make judgements sequentially while interacting with the environment

Table 4
Marketing clearing strategies of energy trading algorithm used in P2P energy trading.

Double Auction	• Real-time trading system where participants make free-market offers and bids for power
Supply and demand ratio	• Includes methods for demand response, where users change their energy use based on current costs
Mid-market rate	• It accounts for the midway point between an exchange pair's purchase (bid) and selling (ask) rates
Pay-as-bidk-DA	• Depending on the pricing at which they make their bids, participants in the power market get paid
Greedy algorithm	• Aims to discover a globally optimum solution by making the locally optimal decision at each phase.
Distributed optimization	• requiring collaboration across several agents or nodes to discover the best solution

The paper [187] suggested a plan for the market for exchanging power that utilized blockchain. An approach is the situation whereby agents' quotes are continuously modified utilizing a learning technique based on changes in the market price, making AA work superior to ZIP in terms of adaptability and trade effectiveness. Over 98 percent on average, the A method was effective. In inversed production pricing the consumer estimates the energy output of their gadgets at 15-min periods using data gathered from past performance, establishing a price in accordance with the relationship between supply and demand. In intelligently bidding agent the agent's actions are smart, and they base their bid selections on reinforced learning [188]. In parallel multi-dimensional willingness Multidimensional factors are modelled to replicate the microgrid volatility throughout bidding procedures, such as past trade data and competitor behavior. In prediction integration Advanced machine learning is employed to determine how the electrical market will respond to a consumer's bid using the previously collected transaction information [189]. In cognitively bidding agent creating intelligent agents who bid and act nicely is still a difficulty for P2P energy trading. 'Cognitively bidding agents' were used in many research, allowing bots to change pricing after being introduced. In contrast to previous bidding systems, this one allows agents to take an active role and establish a participatory local market. A learning-based peer is employed, in accordance with [190], to assure successful bargaining, improve the quality of contracts, and lessen the likelihood of bargaining rejection. In intelligent negotiation agent Additionally, creating an "intelligent negotiation agent" is suggested in Ref. [191] to use learning skills during bid judgments' establishment of real-time resolution systems and intelligent agreements that guarantee payments only take place when power is safely transmitted to consumers is suggested [192]. In reinforcement learning By facilitating consumers' decision-making processes, Zangetal [193]. employed the RL algorithm to govern community energy storage (CES) in the local P2P energy marketplace. Trade was conducted in two phases for this study—without and with CES [194]. Consumers trade without a community battery in the actual time local marketplace in the initial stage, while those who don't succeed in trade will receive help from the energy trade in the subsequent phase, in accordance with CES. When evaluated to other trading techniques, this strategy reveals that the gains made were close to the daily transaction projection [195]. Another investigation [196] developed a learning-based bid synthesizer using the RL approach, specifically deep Q learning, to determine the best bidding strategy. According to the article's findings, the technique's effectiveness is 20 % better when utilizing this technique compared to previous ones. Additionally, finding a good trading partner in the regional energy sector takes time. Consequently, a retail power trader proposes a third-party trade approach for clients in Ref. [197] where RL technique is utilized to construct the market structure.

6.2. Market clearing strategies

Identifying the best market clearing methodology is a major focus of many research. These approaches vary depending on the community's scale, the market framework, and the players' behavior; distributed techniques, for example, are employed in massive markets. Whereas, local markets utilize auction-based procedures, while game-theoretic methods deal with participants that have opposing goals [198]. Khorasanyetal [199]. Discuss the ongoing work on potential regional marketplace for energy layouts while providing a categorization of the goal of market clearing and its techniques. Additionally, the decentralized solution for marketplace clearing, according to Khorasanyetal. [200], ensures flexibility and lowers the costs associated with accounts and connectivity. Distributed optimization techniques are also used in the article [201] for clearing markets. Yapetal.The "Linear Programming Optimization approach" is proposed by Ref. [202] as a two-stage market clearing methodology. via using a "multi-bilateral economic dispatch" (MBED) that is addressed via agreement-based optimization, decentralized flexible agreement, and creativity, Alam and colleagues [203] offer a fair and public settlement solution. Alametal employed distributed optimization techniques for market clearing and offered pareto optimization to solve the problem of unjustly distributed costs in the P2P system in Ref. [204]. They explore the impact of energy prices on total costs in a microgrid, in contrast to prior research that focus on the optimization of individual profit. The suggested model may be used to forecast agent behavior and perform cost analyses. The effectiveness of different P2P trading systems, including Double Auction (DA), Mid-Market Rate (MMR), and Supply and Demand Ratio (SDR), are examined, and an illustration of consumer choice is proposed in Ref. [205]. The authors came to the conclusion that the SDR mechanism favors purchasers of power while the DA mechanism advantages suppliers and distributors of storage. Therefore, the MMR technique is the best option for evaluating how flat the power is SDR is used in Ref. [206] to calculate the dynamic internal pricing within a microgrid. According to a technique suggested to compare the outcomes of three distinct P2P trading mechanisms—MMR, SDR, and bill Sharing (BS)—under modest PV entry, the SDR method performed better than the other two, while the performance of BS was similar to the old model. Three pricing mechanisms—MMR, BS, and SDR—were examined by Hadiyaetal [207]. in comparison to an alliance game-theory-based framework. Which were evaluated based on many measures of an Uk institution's effectiveness. Three pricing mechanisms—MMR, BS, and auction-based strategy—are provided in Ref. [208], and the findings demonstrate that the cost is lowered in these models more than BS. The game theory-based technique was discovered to be better fair and efficient than other choices if participants in the energy sector had opposing objectives, according to Ref. [209]. Yapetal. When consumers cleared the market using a motivated game strategy rather than using NEM [210], found that game concept was more practical and lucrative. Another method of market clearing is the so-called average mechanism, which uses the mean of bidding and offers to determine a market value. This strategy is scalable and utilized with double auction in Ref. [211]; all participants may participate in setting the clearing market's price.

7. Pricing mechanism

By highlighting market participants and classifying pricing processes, the following section attempts to give readers a fundamental grasp of the pricing mechanism for P2P energy trading. Energy pricing and network service pricing are the two categories into which P2P energy trading pricing schemes may be divided. A rule for calculating the worth of products or services traded is known as the pricing mechanism [212]. While network service pricing determines the cost of using network infrastructure and associated services to allow energy trading, energy pricing specifies the price of energy to match with market goals. The trading method used in P2P energy trading, which is influenced by different variables such as the generation and use of energy, may be used to estimate the price of energy [213]. According to the energy pricing methodology being utilized, the method of trade may change. For instance, in a market based on a pool, market players solely take into account the generation and use of energy, but in bilateral agreements, the trading strategy may be dependent on the other side. The methodology for categorizing pricing processes, together with ways of execution for these price mechanisms, is shown in Fig. 18 consumption, but the trading strategy in bilateral contracts may be dependent on the counterparty [214]. The classification technique for pricing techniques, including execution methods, is shown in Fig. 5.

7.1. Energy pricing

Considering that P2P energy trading takes place in an open market wherein numerous prosumers and consumers exchange power, energy pricing may be divided into synchronous and asynchronous energy-pricing systems. By defining the energy trading process and the functional features of each energy-pricing technique, this categorization offers an initial overview of energy pricing [215].

7.1.1. Synchronous pricing

In order to decide the energy price and trading quantity, synchronized energy pricing gathers proposals from market players and bases its decision on the marketplace's goal, which may be maximizing the social good or reducing production expenses [216]. This approach aims to

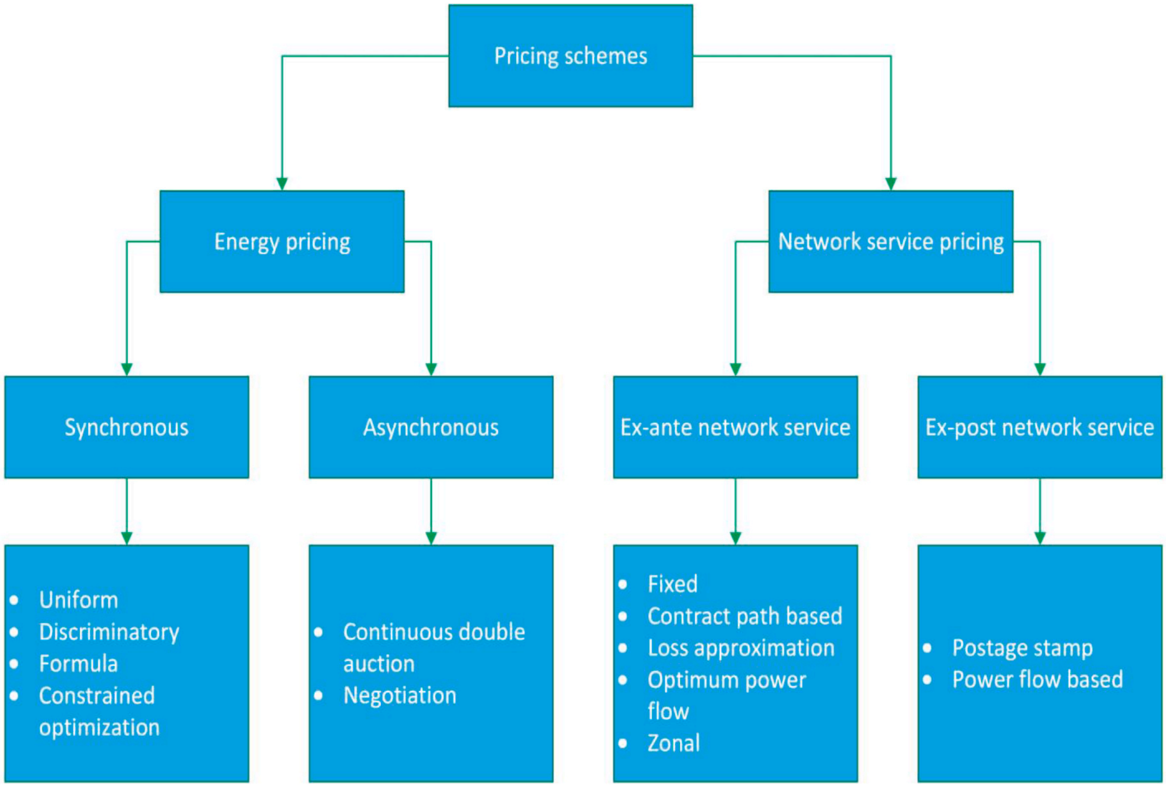

Fig. 18. Pricing scheme of P2P.

maximize the combined usefulness of every player by distributing an array of assets among players with various utility purposes. In other words, by allocating resources effectively, participant satisfaction is to be maximized. System-centric P2P energy trading is similar to the old retail power market [217]. The method of synchronized energy pricing is depicted in Fig. 21. On the basis of earlier studies, we inferred this procedure. At a specified moment, the market platform establishes an advance market for exchanging energy. Throughout the bidding time frame, prosumers and consumers each submit an official proposal that includes the offer price and trade volume. Following this time frame, the trading outcomes are decided by the market platform, and the marketplace is cleared [218]. The objective of energy pricing is to maximize market players' wellbeing. Therefore, when trading sides explicitly choose the deal's criteria, synchronous EP yields superior market effectiveness than asynchronous EP. The relative order for assets can, however, be manipulated when a party exploits its market dominance [219].

7.1.1.1. Uniform pricing. When there is consistent pricing, information from consumer and prosumer bids is used to determine the cost of energy. The cost for power is often set by an optimization process by considering an arbitrary function such as social benefit, however it can also be decided at random as long as stakeholders agree on a suitable value. The market's response to uniform pricing can aid in promoting a balance between supply and demand and reducing voltage disparities in the decentralized network [220]. Utilizing data from the process of bidding, both supply and demand curves are shown as step functions to determine the cost of power. The highest offered price at the intersection of the arcs may be thought of as the power price that will maximize marketplace excess for every buyer and seller. According to the Vickery-Clarke-Groves technique [221], the marketplace is settled using the next-highest offered price instead of the highest offer at the places where the arcs intersect.

7.1.1.2. Discriminatory pricing. With an official bid, discriminatory pricing, like uniform pricing, determines the market's results. In discriminatory pricing, each matching pair's energy price is set concurrently at the end of a trading session, therefore there is no singular energy price [222].

Argues that for players who succeed in the marketplace, it is financially better than uniform charging. The inherent sorting rule is suitable for the intent of creating discriminatory energy price. After the bidding time, the offers and requests are listed in decreasing and upward order of cost, accordingly [223]. The compatible pairs are decided upon only if the customer's bid cost surpasses the prosumer request cost. The consumer submitting the greatest bid and the prosumer requesting the lowest offer will be matched first, and the power price is established as the average of the two. The quantity of trade is calculated using the lower of the smaller bid and ask values [224].

7.1.1.3. Formula pricing. The supply and demand ratio (SDR) is calculated by dividing the total energy provided by the whole energy required. Due to the ease of obtaining bid details, SDR is utilized for setting an energy pricing. One research found that formulaic pricing depending on the SDR is superior to uniform prices when taking into account the total advantages of attendees, their desire to participate in the marketplace, and the market's fairness [225]. Formula costing generates an energy cost that follows the principles of finance. The power price may be calculated using a convex mixture of grid wholesale and retail prices. Formula pricing is linked with an aspect of learning in order to appropriately adapt to climate influences [226].

7.1.1.4. Constrained optimization. Consistent pricing depending on the merit-order parameter may be seen as an advancement in the context of utility maximization. Additional constraints like physical connections and regulations that might lower the usefulness of market actors must be given consideration when creating a system of prices for energy trading [227]. Thus, the issue of determining the price of energy may be formally described as a constrained optimization problem for achieving the optimal marketplace result. In particular, it is possible to include market operating limits in the optimization problem, such as the largest amount of power that can be bought from a provider and the physical constraints on the prosumer producers [228]. The optimization procedure can also account for the running costs of production devices like PV and battery packs as well as the constantly fluctuating grid purchase prices. Furthermore, it has been shown that energy storage held by consumers can loosen the physical constraints associated with energy pricing. As a result, it may be a more beneficial financial choice since it reduces energy prices and boosts prosumers' value [229].

7.1.2. Asynchronous pricing

Numerous bilateral agreements among prosumers and customers may be independently carried out through a transaction's time thanks to asynchronous EP. It's similar to a flea market where buyers and sellers agree on a price for the utility-satisfying energy. Additionally, this depends on a technique that produces agreement among market players in a variety of market contexts. For getting the best outcomes, decentralized decision-making techniques have been suggested [230]. A decentralized process for making choices is displayed in Fig. 21. Prosumers and consumers conduct deals by repeatedly communicating trade data, such as energy costs and trade volumes, during the opening phase of the market platform's energy exchange marketplace [231]. Depending on how a consensus is reached, the methods for exchanging data and making decisions change. Energy trading is decided between trading partners under the asynchronous EP approach, which allows for the exclusion of the financial and political impact of the centralized marketplace. Players in the market can trade energy on their own, merely taking into account the energy price and a variety of tastes, such as prestige and renewable energies [232].

7.1.2.1. Continuous double auction pricing. A renowned pricing technique used on stock markets is continual double auction (CDA). The trading procedure of the CDA method is shown in Fig. 21. Only if the price offered is more than or equal to the advertised cost does the CDA continually determine the deal for a unit quantity among a prosumer and consumer. Contrary to discriminatory pricing, prosumers and consumers are free to put forth bids and make offers as often as they wish within a trading window [233]. Due to the fact that all market players are constantly informed of bidding prices and deal outcomes via the order book, reasonable market players can contribute to the creation of trades that improve Pareto. As a result, the market tends to allocate goods in a Pareto-efficient manner [234]. The CDA is considered a pricing strategy appropriate for a decentralized market, such as peer-to-peer energy and multi-carrier energy trading, since market players may perform deals via open bidding statistics. In order to establish a CDA-based P2P energy trading strategy with no a middleman, blockchain technology has been proposed as an alternative. The SO can use transaction data from a P2P energy trading site to limit a transaction that violates the network's regulations and offer a balancing assistance for customers who are unable to acquire enough energy through the trading method [235].

7.1.2.2. Negotiation pricing. Market players can negotiate with their preferred competitor to come to a settlement. There is no assurance that these discussions will lead to successful deal closures between the contracting participants, though. The primary difference between CDA techniques and negotiation is that, while in CDA trading data is exchanged with an undetermined majority and a transaction opponent is selected depending on the swapped details, in negotiations the transaction other party is predetermined and trade facts only gets shared with that counterparty [236]. Irrespective of the extent to which market players collaborate with one another, the negotiation process ensures Nash equilibrium [237]. Additionally, it is thought that the bargaining is what leads to the market. Relative to those from, protocols perform almost as well. optimization focused on the system. Energy prices might be changed as well. Commerce, in which a customer chooses a supplier or prosumer and makes adjustments a set trading volume to maximize their return on the energy price resources [238]. Using automated trading algorithms, prosumers in order to maximize their utility use and ensure Pareto effectiveness in price-adjusted energy trading. The converging feature found in discussions in P2P energy trade may be examined using game theory [239]. It is possible to create a game-theoretic model and a contract among a prosumer and a consumer that has been demonstrating the market's stable condition. The force prosumer pricing may reach a balance level under the regarding energy as a homogenous good and assuming complete rivalry in the market product [240].

7.2. Network service pricing

Network service pricing (NSP) can be decided upon either before or after network services are actually used. The NSP may be determined by taking into account a wide range of variables, but this investigation concentrates exclusively on three elements: compensation for network consumption, system losses, and auxiliary services [241]. By examining the physical events occurring in the network, these components are put into numerical form. By outlining the order in which both pricing techniques are used throughout P2P energy trading, this categorization helps people comprehend how the pricing mechanisms for energy and network amenities interact [242].

7.2.1. Ex-ante network pricing

Before energy trading starts, Ex-Ante Network Service Pricing tries to set the NSP for dividing up network connection expenses. It has the advantage of giving market players accurate data on the NSP, improving market effectiveness and authenticity, and limiting the inappropriate use of network-related charges established by energy trading [243]. In Ref. [244] depicts the ex-ante network service pricing-based P2P energy trading structure. Market players create a trading plan that takes into consideration the NSP published by the SO before they begin trading in energy, and they subsequently trade energy based on a power pricing technique.

7.2.1.1. Fixed pricing. Fixed pricing is a simple strategy for equitably allocating the anticipated network connection cost to each marketplace player; the NSP is identified and informed before beginning energy trading. The NSP for P2P energy trading needs to be intentionally chosen, and set pricing for various time zones can be a workable approach, per Refs. [245]. Market players may choose to implement a bidding strategy that takes into account the NSP's use of consistent prices to conduct energy trading. For instance, the bid strategy suggested in Ref. [246] was developed as a linear programming problem, which represents fixed price and different market regulations. In the case of asynchronous energy trade, the NSP may be used to define the utility attributes of market players. While the price of the network's service is divided according to trade volume, fixed pricing is helpful for simulating the trading tactics of market participants [247]. However, it has issues with properly assigning network service costs since the trade volume is not linearly proportional to the power flow in the network. Therefore, market participants who incur high network operations expenses could be given access to the identical NSP as those who do not [248].

7.2.1.2. Contract path-based pricing. An electrical channel that has been predetermined between a prosumer and a client without taking power flow into account is called a contractual path. Several definitions of route distance have been proposed in past studies. In one case, by accumulating the line resistance of the linked branches, the path length among nodes wherein trading parties is situated is determined electrically [249]. The power transfer distribution factor (PTDF), which displays the minimal change in flow on the line in the network as a result of transacted power between two nodes, can be used to substitute line impedance. Use of the method provided in Ref. [250] is suggested. To determine the shortest way to both nodes, examine multiple routes and select the path with a low impedance value. Additionally, because the expense of transmission increase with geographical separation. Market participants are subject to a lower NSP whenever engaging with an investor who is either physically or electrically near them when P2P energy trading employs contract-path-based pricing [251]. This method can boost local energy trading and reduce network losses overall, but it also lowers market involvement as merchants are reluctant to do trade with electrically distant nodes [252].

7.2.1.3. Loss approximation pricing. Since the losses in network infrastructure are a complex consequence of line flows and complicated electrical laws, determining the NSP to make up for system losses is difficult. As a result, estimation of system losses rather than doing a power flow study can be utilized to establish the NSP using loss approximation [253]. There are multiple techniques for calculating network losses; for instance, loss sensitivity shows the slight alteration in system-wide losses brought on by a modification in the energy flow among two nodes. The system losses that correlate to the trade amount of both nodes where the prosumer and consumer are situated may be estimated linearly [254]. Additionally, by estimating the line flow using the trade quantity and PTDF between two nodes, it is possible to quantify system impairments using the PTDF. Additionally, the system losses may be calculated using a quadratic approximation utilizing the trade volume and transmission loss cost coefficients. Similar to the estimation made, system losses may be roughly calculated using the electrical distance [255].

7.2.1.4. Optimum power flow pricing. The most effective operating point or market outcomes in a power system network that might represent numerous physical restrictions and economic factors are determined using optimal power flow [256]. Due to the optimal power flow, locational marginal prices (LMPs) are computed to establish the costs for energy, residual loss, and congestion at various points in the network. The SO executes the optimum power flow due to the unpredictability with wholesale energy prices and the anticipated P2P market outcome under the P2P energy market presented in Ref. [257]. The SO determines the NSPs at various network nodes and alerts market players of the pricing. By taking into account the NSP they must pay and negotiating for energy trading, market players may choose their trading strategy. In the P2P energy market suggested in Ref. [258], multi-round dual auctions based on LMPs are configured; thus, prosumers and consumers situated in the same node trade energy first, and the leftover volume is transferred at the network's layer depending on unfair prices.

7.2.1.5. Zonal pricing. Fixed pricing cannot distinguish across market players, but the ideal power distribution might place a sizeable NSP on a prosumer and consumer situated in a node to be enhanced [259]. Zonal pricing can be an agreement of these two methods. A network node cluster that uses zonal pricing places an NSP in an area that it has created. For zones, the system can be set up in a variety of ways. According to the voltage level, regions are defined in the energy trading system presented. Because of this, market participants who are near the voltage level of the node can exchange energy without the NSP, but imbalanced energy can be exchanged by exceeding the voltage level of the zones with the NSP [260]. Market players are encouraged to engage in asynchronous energy trade as soon as zones are formed since the NSP is either not levied or is extremely cheap there. However, there are sizable NSPs assessed on energy exchanges conducted across zones. Zonal pricing can be utilized to determine the differential NSP, but it can also be utilized by the SO to carry out energy trade as they see appropriate. likewise, as the zone structure significantly affects trade results, lowering total trading volume can promote intra-zone energy trade [261].

7.2.2. Ex-post network pricing

The ex-post network service pricing assigns system assistance expenses such that they are in line with the real impacts of trade on the physical networks. Additionally, it is prohibited from giving market players a certain NSP prior to energy trade [262]. In Ref. [263] demonstrates how consumers and prosumers set up an approach for energy trading that takes into account an experimentally calculated NSP; this trading strategy is going to vary from the real NSP applied after the deal. Following the determination of the energy trading, the SO decides the NSP and, using the outcomes of the trading, calculates the network service cost, which is subsequently passed along to market players as reimbursement for the cost.

7.2.2.1. Postage stamp pricing. Irrespective of length or network connections, postage stamp pricing is a technique where the expense of network connectivity is distributed to market players corresponding to trade volume [264]. The NSP is determined based on the real network service expenses following energy trading, as opposed to fixed pricing. The P2P energy trading model suggested in Ref. [265] states that formula pricing is used to determine the trade outcome. approach using SDR. For assigning the overall network connectivity cost, the NSP for every market participant is computed and cost of network services based on trade volume. Auxiliary operation and regulatory are charged at settlement intervals after the bargaining procedure in a P2P energy trading system presented in Ref. [266]. A P2P energy trading paradigm is proposed in which only customers pay for network service. In this trading method, users are compelled to incur the price at the NSP established by the SO; energy is exchanged in compliance with uniform pricing. Due to the reality that trading activity is not directly proportional to the electrical flow in a network, a prosumer with a modest trading volume gets charged a tiny NSP even when the trade results in significant network operational costs [267].

7.2.2.2. Power flow-based pricing. Power flow-based pricing can determine prices by including network-related trading outcomes. As the SO has access to data on physical effects brought on by energy trade, the price of network amenities may be assigned using the price attribution rule [268]. To quantify the effect of traded power on a network, multiple techniques are employed. Employing a proportionate premise founded on Kirchhoff's current law, the energy-tracing approach may determine the impact of the transactional power to the line loss. The role of every line of trade volume can be calculated irrespective of the dealing party, so this approach can be applied to both synchronous and asynchronous energy pricing [269]. The quantity of the outflow provided by an input is calculated via the proportion of inflow from the source to the entire flow to a node. The inverted form of the sparse matrix must be calculated, hence using this approach could be challenging. The LMPs incorporate the marginal framework, minimal loss, and congested costs for every network node as a result of the computation of the optimal power flow. Based on market players' bids, the system-centric P2P energy market may concurrently determine the power price and NSP and choose the optimum market conclusion. But maintaining market openness is difficult. Recently, a method leveraging decentralized, blockchain-based LMP computations has been proposed [270] for managing data safely and openly. LMPs can also be used by the SO as a price signal to encourage the optimal market results for asynchronously conducted energy trading.

There are various pricing schemes that are presented in this section. To choose according to which scheme pricing mechanism has to be implemented depends upon the availability of the power hours and distance between peers to whom energy has to be transferred. The characteristics of P2P energy trading pricing is given in Table 5.

8. P2P energy trading approaches

8.1. Game theory

Numerous articles have proposed game theory as an effective means for tackling problems with smart power systems. Additionally, an extensive categorization has been provided for recently employed game theories [271]. Game theory is essential for making decisions studies regarding the next generation power channels. This is being intensively utilized to simulate people's rational behavior and handle energy in a wide range of statistical applications and communication techniques, and it may be successfully linked with the fields of machine learning and the IoT [272]. Game theory also makes it possible to integrate and create frameworks for price systems and reward designs. Game theory is applied in energy markets to analyze market balance outcomes for the investigation and assessment of market designs [273]. Producers and consumers in this situation have an incentive to set a rate for energy that is greater than the marginal price in order to minimize potential losses caused by non-convexities as shown in Fig. 19.

8.1.1. Non-cooperative

Non-cooperative game theory may also be utilized for complicated peer-to-peer energy trade, with no peer synchronization. When there are competing, players involved in competitive actions and it is hard to merge their tactics or make contracts amongst them, non-cooperative game theory is typically utilized [274]. Only each player's actions and compensation are used to describe the outcome. This kind of strategy is used to simulate people who have opposing viewpoints while making decisions independently. The method helps them to make appropriate and successful judgements. Additionally, this category is divided into static and dynamic non-cooperative games [275]. The static kind refers to a participant's activity when it occurs only once without being immediately aware of the other players' choices. At the same time, the dynamic framework points to a scenario in which players can repeat their previous actions. When participants are not encouraged to depart from the basic decision, Nashe Equilibrium, a prominent non-cooperative game optimal solution, causes the non-cooperative game to become stable [276]. Non-cooperative game-theoretic techniques have been put out in. Both a contribution-based energy trading system to regulate linked MGs in a competitive market setting and an inverted auction system for a single MG are examples of these. When reviewing the literature, it is apparent that Stackelberg game, a non-cooperative game theory, has been the main focus of research and development of LEMs for P2P energy trading in SG and MG platforms [277]. A non-cooperative energy trading system is developed in Ref. [278] for a centralized energy exchange among microgrids. Bhattietal [278] develop a non-cooperative, endless strategy, and multi-player game to offer a distribution level structure for energy trade.

8.1.2. Cooperative

The cooperative game theory has been demonstrated to be efficient for interacting with managing energy in P2P trades and may be used to motivate the peers to cooperate in energy trading. It enables participants to create groupings, or alliances, to maximize the advantages and make better decisions [279]. The coalition's coordinated activities are what mostly define the outcome. This idea relates to a game in which participants collaborate to maximize their gains. Its purpose is to determine the number of participants in the game of Nash Bargaining who desire to establish a coalition. Three coalition forms may be used to classify this type: coalition graph game, coalition formation game, and canonical coalition game [280]. Coalition graph game manages player connection and generates low-complexity distributed methods for network structure formation. It also examines the created network characteristics, such as reliability and effectiveness [281]. The coalition formation game analyses the network's composition, flexibility, characteristics, and coalition costs. The mechanism that evenly allocates player

Table 5
Characteristics of pricing mechanism used in P2P energy trading.

Methodology	Description	Pros	Cons
Energy pricing			
Synchronous			
• Uniform	Energy prices are determined using consumer bid data.	Discriminatory energy price	Excluding individuals' diverse interests.
• Discriminatory	Establishes market outcomes following a sealed bid	Clearing all contracts simultaneously	Disregard a person's usefulness as determined by market outcomes
• Formula	Pricing by convex mixture of grid buying and selling	System centric method	Multiple trading parties are unable to use it.
• Constrained optimization	Optimization issue to achieve the greatest market outcome	Increase market effectiveness as much as achievable.	Unavailable to specific trading parties
Asynchronous			
• Double auction	Pareto improvement	Peer centric	Excluding the diverse preferences of certain prosumers
• Negotiation	Composed of bilateral contracts	Discriminatory energy price	specific conditions to guarantee agreement
Network service pricing			
Ex-ante network service			
• Fixed	Predetermined standard pricing for distributing the cost of network services equitably	Simple pricing strategy	Limitations on cost causation-based cost allocation for network services
• Contract path based	Differential pricing based on the trade partners' contract paths	Encouraging local energy trading	Decreased market activity as a result of the hefty NSP on the trading of energy based on electrical range
• Loss approximation	Using network characteristics, estimate the cost of system losses	Calculation of system losses	The gap between the approximate result and the power flow's real value
• Optimum power flow	An efficient pricing strategy based on electricity flow analysis	Delivering the optimum price depending on the anticipated trade	Providing market transparency is limited.
• Zonal	Based on a network property, a collection of nodes' prices is uniform	Reducing excessive NSP on the strengthened node	Variations in economic performance according on zone configuration
Ex-post network service			
• Postage stamp	Splitting the cost of network services in half according on trade volume	Simple pricing strategy	Recognize the power flow produced by transaction requires a separate process.
• Power flow based	Mapping the trade outcomes into the network to set the NSP	Using the cost causation principle to determine NSP	Cross-subsidization problem

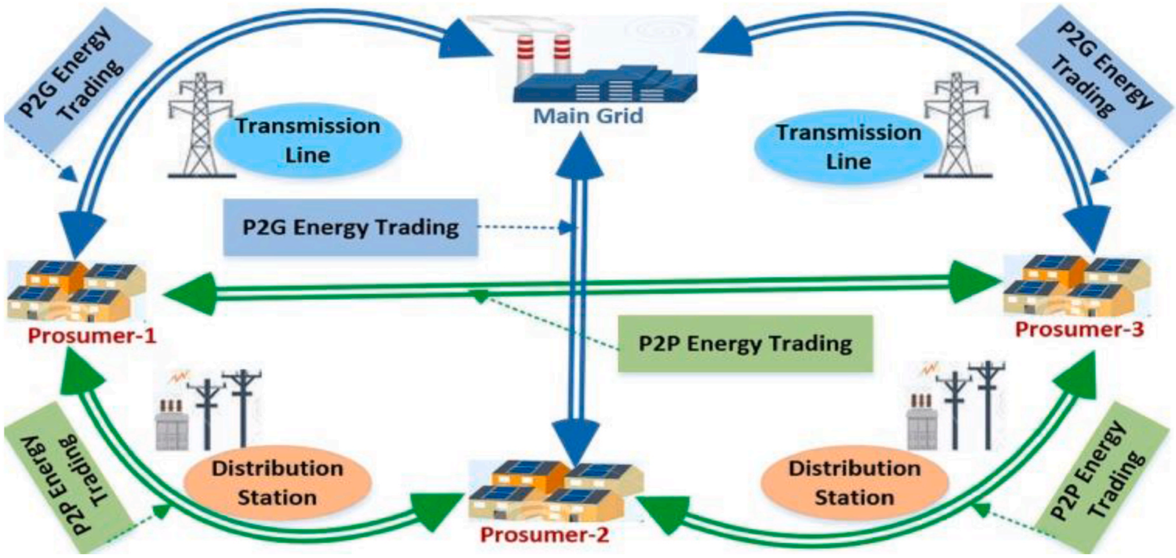

Fig. 19. P2P Game theory technique [175].

collaboration advantages is the canonical coalitions gameplay. When the entire energy surplus exceeds the whole energy deficit, the selling cost is changed using the cooperative game concept, and the purchasing price is changed when the entire energy excess is smaller than the overall energy deficit [282]. The mid-market rate (MMR) pricing model is improved, and weight factors are introduced, by the researchers of [283] employing the coalition game theory. Three pricing mechanisms—MMR, BS, and SDR—are covered and contrasted with the coalition game theory-based framework. A motivational psychological framework was presented by Tusharetal in Ref. [284] to build a P2P energy trading game employing cooperative play with the goal of boosting user involvement in the marketplace and lowering energy prices.

8.2. Blockchain

A revolutionary method called blockchain is intended to boost confidentiality and decentralize transactions. A sort of decentralized repository called blockchain technology can safely contain important data including contracts, statistics, incidents, and financial transactions as shown in Fig. 20 [285]. Important information is kept in blocks and connected by chains. Blockchain has recently been utilized in the energy sector in a variety of ways, including academic publications, test projects, and commercial models [286]. Eight major categories have been established for the initiatives: metering/billing and assurance; digital currencies, coins, and investments; decentralized energy trade; green certificates and carbon trade; grid administration; IoT, smart gadgets, automated processes, and handling assets; electrical e-mobility; and versatile campaigns and alliances [287]. Energy trading strategies and blockchain technology are emerging fields. Decentralizing energy resources, securing and expanding the blockchain network utilizing the Internet, optimizing and developing new blockchain emulate designs are the main areas of current study [288].

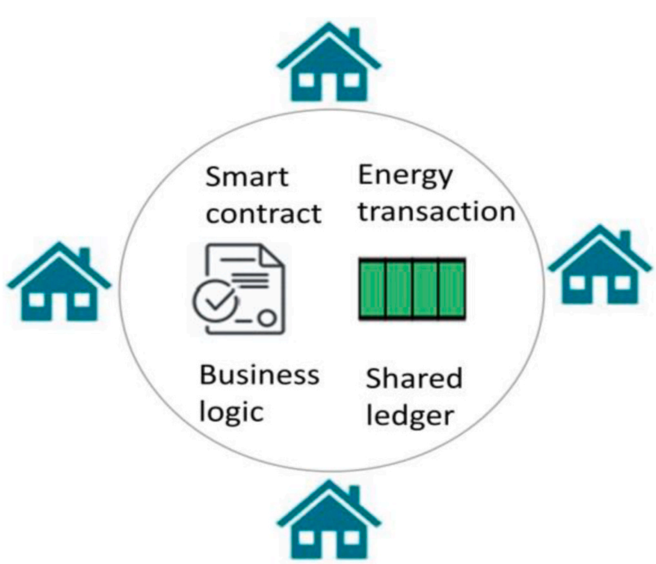

Fig. 20. Blockchain framework.

8.2.1. Smart contracts

Smart contracts are a key component of blockchain that are intended to alter the conventional method of agreement implementation in various application domains [289]. Computer programs known as smart contracts safely exist on the blockchain and autonomously carry out a contract's terms. Smart contracts, which utilize the benefits of blockchain technology, allow multiple parties to enter into a trade agreement with one another securely. Program logic, contractual owner, agreement unique identifier, account status, and confidential records are all components of smart contracts [290]. The network's miner nodes reach an accord to carry them out. Delivering a contract generation request to the blockchain system creates intelligent agreements. After the network of miners has verified the deal and reached agreement, the new smart contract is posted to the blockchain. The irreversible contract code can't be altered or updated to the blockchain [291]. This assurance states that the agreement's conditions are unchangeable. The agreement's code can still rewrite data to its own internal storage. The contract activation transaction must be sent to the network by curious nodes utilizing the agreement's distinctive identification. When an agreement activation activity arrives, the contract's code is performed [292].

8.2.2. Crypto currency

For the digital money called Bitcoin, Blockchain was first created. A publicly accessible electronic money is bitcoin. Other digital currencies, like as Ethereum [293], can be utilized for financial transactions on encrypted networks. One of these methods might be applied to P2PDET to enable digital currency transfers [294]. Task carried out by Mihaylovetal. Regional energy suppliers use this strategy to create and infuse power into the distribution system operator's (DSO's) electrical system

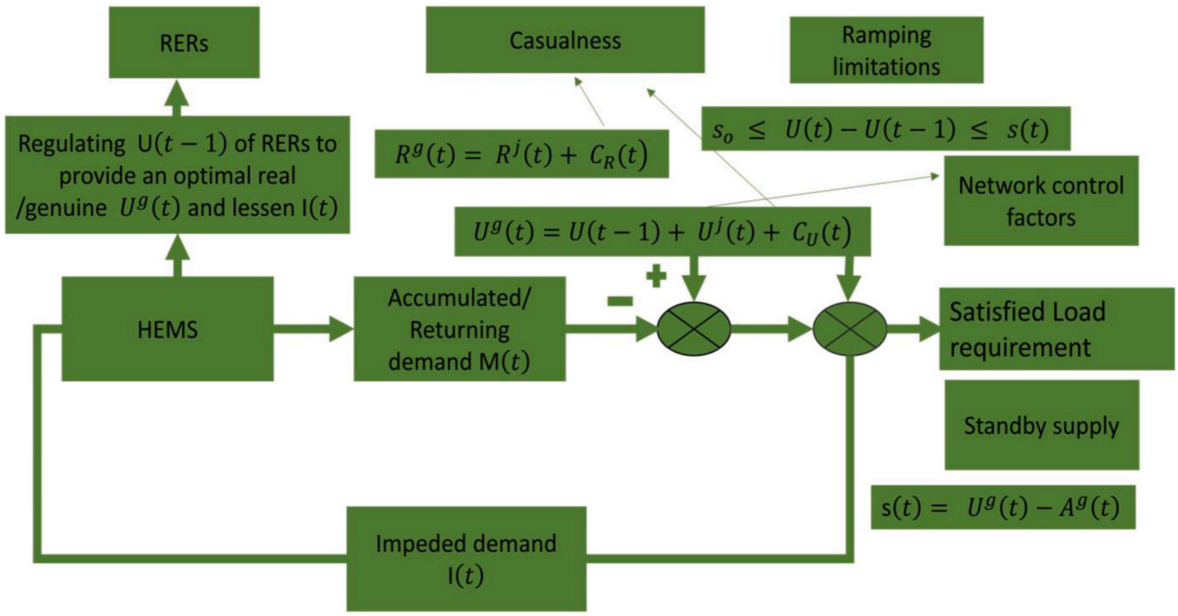

Fig. 21. Load forecasting and scheduling model of P2P HEMS with fault analysis.

$$s_o \leq U(t) - U(t-1) \leq s(t) \tag{27}$$

[295]. The DSO tracks both the electricity that producers provide into the electrical network and the customers who use in an instant. This allows the producing shop to earn money based on real consumption rather than anticipated market [296]. The system offers NRGcoin, a decentralized digital money for energy trade that is analogous to Bitcoin. On a self-sustaining exchange market, NRGcoins may then be swapped for currency-based money. NRGcoin is used by customers to pay suppliers instead of an official currency [297]. In their proposal of a blockchain system for peer-to-peer energy trade, Vangulick et al. [298] assess different concepts based on standards including market adoption, accuracy, security, confidentiality, and transparency. The suggested approach relies on an agreement on Proof of Work agreement rather than a Proof of Stake consensus, which results in an absence of transaction synchronization. When conducting energy deals with the assistance of third parties, privacy is one of the most important considerations. The goal of the study by Aitzhan and Svetinovic [299] was to simulate scenarios in order to verify the security and functionality of a P2P network for selling energy that is based on the blockchain. The created technology enables anonymized trading and pricing negotiations for energy trades. A seven-layer architectural paradigm for energy trading utilizing blockchain is suggested by Cali and Fifield [300]. The suggested layers are the following: business; management and optimization layer; information and data; connectivity; power infrastructure; electricity markets and pricing level.

8.3. Simulation

Simulation is a mathematical method for conducting experimentation on an arrangement or procedure. Simulation methods have been employed in several research to verify peer-to-peer energy trading systems [301]. Since the P2P trading energy model is still being tested in the actual world, it is important to test novel processes without incurring significant costs. Simulation is a device that is frequently utilized in these studies. likewise various models and systems may be evaluated with simulators. Simulation is used by Wu et al. [302] to verify their suggested way of pricing approaches. The unified price approach and the recognized pricing approach are the authors' two suggested user-centered pricing techniques for P2P energy trading on microgrids. A centralized marketplace body that establishes the market-clearing price on a regular schedule makes up the unified price approach [303]. The identified price approach, in contrast, places each energy exchange at various times depending on the availability of customers. A co-simulated technique that uses P2P energy platforms and energy distribution networks is proposed by Hayes and colleagues [304]. Co-simulation may be used to assess the effects of the large-scale adoption of a P2P model as well as the possible advantages and drawbacks on the energy network. As a consequence, it is argued that P2P energy trading has little impact on the system when used moderately [305]. Other academics have done simulations utilizing game theory on Elecbay, a technology already in place for P2P energy trading. The test findings demonstrate the P2P energy trade's capacity to maintain a balance between local supply and demand. In light of this, it may enable a significant increase in the utilization of clean energy sources in the power system [306].

8.4. Optimization

An essential technique to increase earnings or reduce losses is optimization. The optimization algorithms in P2P energy trading have mostly aimed to maximize user economic gains [307]. In Energy management system, it has also been utilized to maintain an equilibrium across energy supply and demand. The prosumers' energy losses were minimized as another usage. In order to attain adaptive and efficient distributed power control and management, Zhou and colleagues [308] offer a novel architecture for the interchange and integration of P2P energy over the Energy Internet. In order to minimize consumers' economic expenses, the energy exchange and integration challenge is presented as an optimization problem. In addition, they suggest combining the alternative path multiplication approach with a decentralized approach [309]. The mathematical and statistical results demonstrate the usefulness of the model and suggested method in terms of fast convergence over a period of time and a sizeable financial saving over an extended period based on real-world data sets of green power and actual time energy pricing. In the future energy system, energy administration at intelligent grids and intelligent homes will be crucial [310]. In order to handle smart electricity systems and smart houses, Steinheimer et al. [311] suggest a strategy for a framework to create and provide additional value. Via smart energy administration, autonomous service development, and utilization optimization, the paradigm enables customers to create services for managing gadgets and dispersed energy resources. This innovative method relies on home networking and algorithm to automatically optimize energy use in specific residences or large geographic areas without the help of outside parties. Establishing a social platform, such as a power community, and automating interaction and optimization both depend on P2P concepts in home networking [312]. A microgrid's effect on P2P energy transfer between smart houses has been the subject of several studies. To maximize the financial advantages of dispersed rooftop solar energy production with battery backup in a P2P power exchange setting, Nguyen and colleagues [313] offer an optimization approach. Their suggested model aims to study the viability of such renewable power by taking part in the P2P energy marketplace and looking at the financial advantages. The size of solar panels, PV permeability, P2P business profits, the existence of battery backup, and energy exchange time are only a few of the variables that are found to be sensitive to household energy savings. When a balance between regional power supply and demand is required, Long and colleagues [314] created a P2P index to evaluate the feasibility of the P2P energy transaction. By analyzing the consumers' routines for power usage, indicative demand patterns were created. The authors then used a linear programming optimization to determine the various dispersed energy supplies' ideal capacities in order to maximize the local demand-supply equilibrium [315].

8.5. Algorithm

P2P energy trade has seen extensive usage of algorithms. Algorithms are used in blockchain technology to streamline procedures. For instance, it is common practice to employ specific labels in simulations to hasten the convergent process of the modelling [316]. More specifically, algorithms that will optimize each of the P2P model's operations are constantly being developed. For the microgrids of solar power prosumers, Liu et al. [317] suggest a P2P system that utilizes price-based demand response approach. Depending on the combined photovoltaic (PV) supply and demand connection, they develop an evolving internal price structure for operations in the power distributing region. In addition, an analogous cost model is developed with regard to of monetary cost and user behavior, taking into account the adaptability of prosumers' energy consumption [318]. A decentralized iterative design process is used to create the method and execution strategy to resolve the model. As a consequence, the approach's usefulness is confirmed through a real-world example in terms of lowering costs for PV energy prosumers and enhancing PV power trade. A competitive offer technique was developed for the P2P energy exchange by Zhang and colleagues [319]. The authors specifically suggest a bidding technique that makes use of a two-phase algorithm. With this method, a balance is struck between free competition in the marketplace, member economic gain, and grid independence [320]. A trade price prediction and a risk assessment instrument are also provided as part of this procedure to aid locals in making better choices regarding the bid procedure. For the P2P energy trade network with a high number of market participants, Khorasan and colleagues [321] suggest a flexible partitioning approach as a market-clearing technique. Market participants engage in the market using the suggested technique by making their offers public. The suggested approach is based on creating a dynamic algorithm to separate an enormous amount of market participants into different groups in order to increase P2P commerce's sustainability by lowering communication and sharing of data costs [322]. Any distributed mechanism for market clearing may be utilized in conjunction with the suggested strategy. The success of the suggested strategy is illustrated by the authors using two different frameworks, the regional market and the decentralized bilateral trade marketplace. A decentralized coalition building method was created by Thakur and Breslin [323] for usage in a P2P blockchain paradigm. The suggested approach is more flexible than centralized coalition building algorithms and is applicable to microgrids.

8.6. Distributed algorithm

A distributed system connects several computers, functions, or processors, sometimes known as nodes. Distributed methods relate to the strategies employed in these systems to oversee processes and hardware. To address the packet, drop issue over unstable communication lines, a distributed approach was presented [324,325]. The run-time sum approach or an algorithm with distribution that employs the Newton Raphson method for energy trading can all be employed to solve the optimization problem.

8.7. Consensus

An algorithmic procedure for agreeing on just one data point is known as a consensus in distributed systems. The consensus problem in multi-agent systems is what the algorithm is meant to address [326]. In order to solve the problem of centralized energy oversight, distributed algorithms have been suggested [327], including a decentralized consensus-based algorithm. Scalability of centralized methods is a major challenge in the field of energy administration.

8.8. Multi market driven

For the purpose to accommodate numerous purchasers and sellers and optimize the power trade process, a multi-market-driven method is used. A multimarket-driven micro/mini-grid energy schedule with both centralized and distributed market involvement is presented by the authors in Ref. [328]. Recent research [329] have used evolving multiple-purpose market-driven optimization strategies more often. The power matching problem is addressed by broad market-driven optimization with an emphasis on consumer hourly involvement.

The most effective strategy frequently combines a number of methods, utilizing each one's advantages to handle different facets of peer-to-peer trade in energy. For instance, game theory models might optimize player tactics, and a system built on blockchain with intelligent agreements could manage the safe and fair implementation of deals. Algorithms can be used for forecasting, making decisions, and optimization, among other things. During the design stage, simulation may be used to find any problems and improve the system before it is put into use. Distributed algorithms are intended for systems in which individual components must cooperate to accomplish a shared objective. Getting consensus among dispersed nodes in a system requires consensus methods. In order to optimize trading techniques, multi-market approaches entail involvement in various markets related to energy. During the design stage, simulation may be used to find any problems and improve the system before it is put into use. In the end, the decision is based on the particular needs and limitations of the peer-to-peer energy trading situation as shown in Table .6.

9. Forecasting techniques in P2P energy trading

9.1. Multiple regression

Modelling the link between several independent factors and a dependent variable using statistics. This is a detailed instruction on using multiple regression for load forecasting in peer-to-peer energy trading: Get past data on energy output or utilization, together with the appropriate variable (climate, time of day, day of week, along with other applicable parameters) that affect load [330]. Decide whatever variable such as foreseeable energy load you wish to estimate. In the multiple

Table 6
Characteristics of different approaches used in P2P energy trading.

Method	Process	Feature	Application	Pros	Cons
Game theory	Players decide how best to utilize their resources while taking other players' plans into account	Tactical relationships and Nash equilibrium	P2P energy trading agreement and pricing techniques	Simulates strategic behavior	Behavioral presumptions
Blockchain	A connection of computing devices stores and by encryption links blocks of operations	Intelligent agreements, decentralization, and visibility	P2P energy trading with clear and safe payments	Openness, protection, and the removal of middlemen	Scaling issues
Simulation	Building a framework to simulate P2P energy trade dynamics in order to conduct evaluation	System behavior prediction, scenario evaluation	Training, optimization, decision-making, and risk assessment	Understanding system behavior and safe testing	Simple modelling might not fully represent subtleties
Algorithm	A methodical set of guidelines to carry out a certain operation or computation	Reliability and effectiveness	P2P trading of energy algorithms for optimization and decision-making	Automation and accuracy	Relies on the intricate nature of the issue and the caliber of the data that arrives
Distributed algorithm	Nodes work together to solve problems or accomplish shared objectives	Tolerance for errors and decentralization	Agreement in P2P energy trading and load balancing	tolerance for faults and flexibility	Difficulty of cooperation.
Consensus	Constant conversation and modification to achieve consensus	Failure tolerance and consensus	Reaching consensus on the legitimacy of transactions in peer-to-peer energy trading	Provides acceptance of errors and regularity.	Difficulty in reaching consensus among several individuals
Multi market driven	Different marketplaces, players react to marketplace characteristics	Flexibility and judgements based on the market	Price indications from various marketplaces are taken into account	Sensitivity to changes in the market and adaptability	Intricacy and possibility of contradicting signals

regression study, this parameter is called the dependent factor. Select uncontrolled factors that might have an effect on the dependent variable. This could consist of: climate, day of the week, time of day etc. Verify that the information is prepped and cleaned so that it can be used for regression analysis. Divide the collection of data into batches for training as well as testing [331]. The regression model is constructed using the learning set, and its efficacy is assessed using the evaluation set. To establish a relationship between the dependent and independent factors, utilize the multiple regression technique. The formula for multiple regression often takes this form: $B = x_0 + x_1A_1 + x_2A_2 \ldots\ldots x_nA_n + \varepsilon$, A_1 is dependent and A is independent variable, x_0 is intercept and x_1, $x_2 \ldots\ldots x_n$ are coefficients, ε is the error term; Utilizing the experimental data set, assess the regression model's effectiveness. Root Mean Squared Error (RMSE) is instance of standard variable. Identify factors by considering the model's efficacy and statistical importance. Incorporating or eliminating parameters may be necessary to increase the precision of the algorithm. Based on recent information, use the learned regression model to forecast upcoming energy demands [332]. Embed the load prediction algorithm in the peer-to-peer energy trading network so that users may make knowledgeable choices about the quantity of energy they use or produce. Maintain tabs on the load forecasting framework's effectiveness and make necessary updates to it. Provide members of the P2P energy trading platform with predicted load information so they can organize and maximize their energy-related operations [333].

Multiple regression is a practical and accessible technique for load forecasting that strikes a balance among accessibility and prediction accuracy. But it's crucial to assess premises and information authenticity with caution.

9.2. Exponential smoothing

A time series prediction technique for projecting potential outcomes via historical data is exponential smoothing. This is an extensive overview on predicting load in peer-to-peer energy trade employing multiple regression models. Compile past information on energy generated or utilization, which is usually done on a regular basis. Prepare and purge the data [334]. Take care of anomalies values, and make certain the time gap among each data point is constant. According to the features of the information and the degree of seasonality, choose a suitable exponential smoothing technique, such as Triple Exponential Smoothing (Holt--Winters's approach) to deal with both pattern and seasonality [335]. Separate both training and testing groups from the raw data. The testing set is used to assess the exponential smoothing model's efficacy after it has been trained on the training set. Adjust the alpha, beta, and gamma smoothness factors in accordance with the training set. The weights assigned to the algorithm's multiple elements (degree, pattern, and seasonality) are controlled by these variables. Utilizing past information, instruct the exponential smoothing algorithm on the training set. Depending on the selected smoothness factors and data collected, the algorithm iteratively changes its forecasts. Utilizing the testing set, assess the exponential smoothing algorithm's effectiveness. MAE, MSE, and RMSE are examples of common assessment criteria. To predict future energy demands, use the learned exponential smoothing algorithm [336]. On the basis of the trends, it has discovered in the past data, the model will make forecasts. Include the exponential smoothing algorithm to the network for peer-to-peer energy trading. In order to make judgements regarding energy output or utilization, players can receive anticipated load statistics. Share details regarding anticipated load with P2P energy trading members. Players can better organize and manage their energy-related tasks when there is direct interaction [337].

Although it necessitates precise parameters adjustment, exponential smoothing is a practical and effective method for predicting future loads that can adjust to changing trends.

9.3. Iterative reweighted least-squares

Iteratively changing parameters to minimize the weighted sum of squares discrepancies among projected and actual levels is the goal of the Iterative Reweighted Least-Squares (IRLS) load forecasting technique. This is a detailed instruction on using IRLS for load forecasting in peer-to-peer energy trading: Collect previous generation or demand data and pertinent variables [338]. Picking up and processed the information, taking care of anomalies and values that are missing, and making sure the time period is constant. The load estimation issue should be stated as a regression issue. Give the model's configuration attributes some starting values. Initiating the iterative optimization process requires this. Improve the parameter estimations by executing the IRLS algorithm iteratively. Usually, the steps entail: calculating the residuals, or the variation among values that are seen and those that are anticipated. utilizing a weighting function to assign residuals a weight according to their effect. utilizing the weighted residuals to update the model's settings [339]. Establish a convergence criterion that will cause the iteration to end when an appropriate number of iterations have been performed or whenever the enhancement in attribute estimations is no longer significant. Utilizing the proper measures, assess your forecasting model's efficacy on an experiment or verification database. This contributes to the precision and adaptability of the algorithm to fresh information. Embed the prediction algorithm into the peer-to-peer energy trading platform, utilizing IRLS for parameter estimation [340]. After that, participants can make decisions based on the projections. Share load forecasts with other members of the energy trading network. Members can better organize and maximize their energy-related tasks through concise and timely information [341].

While it might be highly computational and needs precise variable calibration, IRLS offers a potent method to load forecasting, particularly when working with non-linear connections.

9.4. Autoregressive

An autoregressive (AR) is a statistical modeling technique used in time series analysis. Every time there is a relationship among time series variables and the preceding and subsequent numbers, this type of assessment is used. The procedures that follow can be used to do load estimation with an autoregressive model in the framework of P2P energy trading: At periodic times, compile historical statistics on energy output or utilization [342]. Prepare and disinfect the data. Take care of anomalies and values that are lacking, and make sure the duration interval between the data values is constant. Examine the time sequence information to identify trends, cyclical nature, and correlations. For the autoregressive model, ascertain the proper time delay (p). This indicates how many previous time steps should be taken into account for forecasting the present load. Divide the information set into test and learning subsets. The autoregressive algorithm is trained on the learning set and tested on the testing set to assess its efficacy [343]. Create the autoregressive model the formula, in which the load at any given time A_t equals the linear sum of all previous loads up to the selected delay in time: $A_t = x_0 + x_1 A_{t-1} + x_2 A_{t-2} \ldots\ldots x_p A_{t-p} + \varepsilon_t$. Where $x_0, x_1, \ldots . x_p$ are algorithm parameters, and ε_t is error term at interval t. Utilizing the training data, train the autoregressive model. Utilizing least squares optimization, compute the values of the coefficients (x_0, x_1, $\ldots . x_p$). Utilizing the evaluation set, assess the autoregressive model's efficiency [344]. MAE, MSE, RMSE are examples of common assessment metrics. To predict foreseeable energy demands, employ a developed autoregressive model. Use the anticipated load as an input to estimate the following time period for every single phase in the prediction range. Include the autoregressive load forecasting algorithm to a system for peer-to-peer energy trading [345].

AR models are useful for simplifying and efficiently capturing short-term periodic trends in load forecasting; however, their efficacy may be restricted when managing more complex interactions.

9.5. Moving average

To recognize patterns and smoothing out variations, load forecasting employs moving average, which computes the average of a predetermined number of historical data points. Here is a detailed how-to: At periodic times, compile historical statistics on energy output or consumption [346]. Prepare and scrub the data. Take care of anomalies and values that are absent, and make sure the time between two data points is constant. Choose the window size that works best for the Moving Average model. The number of historical data to use in the moving average calculation is indicated by the width of the window (k) [347]. Divide the dataset into sets for testing and training. The Moving Average model is trained on the training set, and its efficacy is assessed on the testing set. Using the selected window size, compute the moving average for every increment in the practice set. The equation is as: Mov avg $_t = \frac{1}{L}\sum_{j=1}^{L} X_{t-j}$, where X_{t-j} presents the load energy at time $t - j$, L is the window size. Utilizing the data set, assess the Moving Average strategy effectiveness. MAE, MSE, and RMSE are examples of common assessment criteria. To predict foreseeable energy demands, use the moving average that has been determined. Connect the P2P energy trading platform with the Moving Average load prediction algorithm [348]. Keep an eye on the model's performance and make updates as appropriate. Retrain the model with fresh data on a regular basis to accommodate evolving patterns. Share load forecasts with other members of the energy trading network. Members can better plan and manage their energy-related tasks when there is open interaction [349].

Moving average is an easy-to-use and helpful load forecasting tool, particularly for recognizing emerging patterns and normalizing data. However, its limits should be taken into account for more precise forecasts in changing environments.

9.6. Autoregressive moving average

Involves integrating moving average (MA) and autoregressive (AR) portions to extract the time series data's cyclical and temporal characteristics. In the context underlying P2P energy trading, below is a detailed guide: At regular times, compile past data on the generation of electricity or utilization. Make sure the data has a suitable time period for relevant research and is properly-stamped [350]. Prepare and purify the data. Take care of aberrations and values that are lacking, and make sure the time gap between data points is constant. To comprehend patterns, seasonality, and trends in the time sequence data, investigate it. Examine the data visually to spot any obvious trends or abnormalities. Divide the dataset into sets for testing and training. Establish the proper ordering for the ARMA strategy MA and AR parts. To be able to do this, choose p for the AR phase and q for the MA sequence [351]. These rankings can be ascertained via statistical techniques, evaluation, or testing. Create the ARMA model formula using the selected orders as a guide: $A_t = \varphi_1 A_{t-1} + \varphi_2 A_{t-2} \ldots \varphi_p A_{t-p} + \varepsilon_t + \Theta_1 \varepsilon_{t-1} + \Theta_2 \varepsilon_{t-2} \ldots \Theta_q \varepsilon_{t-q}$; where A_t is the present load, $\varphi_1, \varphi_2 \ldots . \varphi_p$ are AR coefficients, ε_t is the error term at interval t, Θ_1, $\Theta_2 \ldots \Theta_n$ are coefficients of MA [352]. Utilizing the education and training set, retrain the ARMA model. Determine the moving average and autoregressive parameters employing techniques like the maximum probability estimations. Utilizing the evaluation set, assess the ARMA model's efficiency. MAE, MSE, and RMSE are examples of common assessment criteria. To estimate foreseeable energy demands, use the ARMA model that has been trained. Utilize the model to anticipate the load for each successive increment in the prediction window. Include the ARMA load forecasting model in the platform for peer-to-peer energy trading. Share load projections with other members in the peer-to-peer energy trading network [353].

Though they have difficulties with irregular trends and can be dependent on parameterization changes, ARMA models offer a balanced approach that is useful for addressing time-dependent factors in load projections for short-to medium-term forecasting.

9.7. Autoregressive integrated moving average

To simulate and predict time series statistics, ARIMA integrates autoregressive (AR), differencing (I), and moving average (MA) variables. This is a detailed tutorial on load forecasting with ARIMA for peer-to-peer energy trading: At periodic times, compile historical statistics on energy output or utilization. Prepare and disinfect the information. To comprehend trends, fluctuations in demand, and correlations in the time sequence information [354], investigate it. Inspect the time sequence for stationary behavior. An essential presumption in ARIMA models is stationarity. Use distinction to make the information static if it is not already stagnant. Removing the prior data from the present data is the process of differentiation. Divide the information into sets for both training and testing. Determine the ARIMA model's phases (p, d, and q). The moving average level is denoted by q, the differencing phase by d, and the autoregressive rate by p. These rankings can be ascertained via statistical approaches, evaluation, or testing. To help you make decisions, you may also utilize the plots of the autocorrelation function

(ACF) and partial autocorrelation function (PACF) [355]. Create the ARIMA framework equation using the selected orders as a guide. $A_t = \varphi_1 A_{t-1} + \varphi_2 A_{t-2} \ldots \varphi_p A_{t-p} + \varepsilon_t - \Theta_1 \varepsilon_{t-1} - \Theta_2 \varepsilon_{t-2} \ldots - \Theta_q \varepsilon_{t-q}$; where A_t is the present load, $\varphi_1, \varphi_2 \ldots . \varphi_p$ are AR coefficients, ε_t is the error term at interval t, Θ_1, $\Theta_2 \ldots \Theta_n$ are coefficients of MA. Refine the ARIMA model using the education and instruction set. Calculate the autoregressive and moving average parameters using methods such as maximum probability estimates. Evaluate the effectiveness of the ARIMA model using the evaluation set. Common assessment criteria are things like MAE, MSE, and RMSE [356]. Employ the developed ARIMA algorithm to estimate the energy needs that are anticipated. Make use of the framework to forecast the load for each additional step in the estimation frame. Build the peer-to-peer energy trading platform with the ARIMA load forecasting model included. With other participants in the peer-to-peer energy trading network, exchange load forecasts [357].

In confronting temporal variations and trends in short-to medium-term instances, ARIMA models provide a flexible and effective tool for load forecasting; nevertheless, meticulous parameter tweaking is essential.

9.8. Genetic algorithm

Genetic algorithms are algorithms for optimization that draw inspiration from the laws of selection and inheritance. This is a brief explanation on how to use a genetic algorithm for forecasting load in P2P energy trading. In the setting of peer-to-peer energy trading, define the load forecasting problem. Indicate the objective parameter you wish to optimize [358]. Selecting or creating a load forecasting model that illustrates the connection between past data and anticipated energy demands. Create a genetic algorithm that optimizes the selected load forecasting algorithm's characteristics. This entails specifying the genetic drivers (crossover, mutation), the selection method, and the depiction of individuals (possible alternatives) [359]. Draw possible solutions (people) as chromosomes, with each gene denoting a characteristic of the load prediction algorithm. Genes come together to generate a possible remedy. Describe an objective criterion that assesses a possible solution's effectiveness. Start a population of putative answers (chromosomes) at arbitrary. For the load forecasting approach, a set of variables is represented by each chromosome. Use genetic algorithms to generate fresh generations of possible solutions, such as crossover and mutation. While mutation adds minor adjustments to each individual solution, crossover integrates data from two parental responses. Employing the specified goal operation, assess each possible solution's viability within the population. A solution's accuracy in estimating load is shown by its efficacy level. Choose folks for the following generation according to their level of health. Give preference to solutions that meet the load forecasting task requirements [360]. Establish termination conditions for the genetic algorithm, like converging to a steady solution, reaching a certain fitness limit, or a limit number of generations. From the last iteration of the genetic algorithm, extract the characteristics or parameters of the most effective option. Incorporate the load forecasting algorithm with these optimized settings. Utilizing the optimized variables and past information, retrain the load forecasting model. Forecast future energy loads using the learned model. Incorporate the genetic algorithm-optimized predicted load models into the peer-to-peer energy trading platform. Forecasted load data is available to participants for use in making decisions [361].

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.

9.9. Support vector machine

In load forecasting, Support Vector Machines (SVM) entail building a model to identify the hyperplane that optimally divides points of data, optimizing the gap among various categories. The following is a detailed instruction on how to use SVM for load forecasting: At periodic times, compile past data on energy output or consumption. Prepare and clean the data [362]. Determine the pertinent characteristics that affect the generation or utilization of energies. Divide the data collection into sets for testing and training. Make sure that the characteristics have comparable ranges by scaling them. Because SVMs respond to the size of the input features, standardization or normalization can be required. Select the right kind of SVM for the load forecasting problem at hand: Ideal for linear connections is the linear SVM [363]. Kernel technique for non-linear SVM: To capture intricate interactions, use non-linear kernels such as the radial basis function (RBF) kernel. Utilizing the training data and the decided-on characteristics, train your preferred SVM algorithm. In light of the previous data, the SVM will learn how to relate the input characteristics to the desired factor (the power load). Utilizing the testing set, assess the SVM model's performance. MAE, MSE, and RMSE are examples of common assessment measures. Create load projections for upcoming time periods using the SVM model that has been trained. To obtain forecasts, provide input characteristics for the selected forecasting period. Include the SVM load forecasting model in the network for peer-to-peer energy trading. Share load forecasts with other members of the peer-to-peer energy trading community. Members can better plan and manage their energy-related tasks when there is open communication [364,365].

When working with intricate and non-linear interactions, SVMs offer a reliable method for load forecasting; nevertheless, meticulous parameter adjustment is necessary.

9.10. Adaptive demand

Adaptive demand projection is the process of proactively modifying models to adapt to shifting situations and continually updating projections based on actual time input [366]. At regular periods, compile historical statistics on energy output or utilization. Prepare and disinfect the information. Identify the pertinent elements that might affect the need for energy [367]. These elements might include time-based trends, the state of the weather, holidays, or any other pertinent element in the context of P2P energy trading. Divide the dataset into sets for testing and training. Select or create a forecasting model that allows for flexibility. Models that provide incremental updates, online learning, and condition-based changes are examples of this [368]. Establish a continuous learning process that updates the model often with fresh data. This may entail gradual parameter changes, online instruction, or recertification on a regular basis. Utilizing the testing set, assess the adaptive demand forecasting model's effectiveness. Include the framework for adaptive demand estimation in the peer-to-peer energy trading system. Share load forecasts with other members of the peer-to-peer energy trading community [369].

Although there are infrastructural issues, adaptive demand forecasting improves load forecasting accuracy by continuously modifying estimates in real-time, increasing energy management system effectiveness.

9.11. Expert systems

In order to generate predictions and judgements, expert systems in load forecasting incorporate human skills into a rule-driven framework. This is an explanation regarding how to use an expert system for load forecasting in P2P energy trading: Collect specialist knowledge, this contains data about user behavior, time-based trends, the state of the climate, and any other pertinent elements [370]. Create a set of guidelines based on the information you've learned. The connections between the qualities that have been found and how they affect energy consumption should be reflected in these regulations. At regular periods, compile historical statistics on energy output or consumption. Make sure the information has features and timestamps from the knowledge source

[371]. Prepare and disinfect the data. Create an inference engine that processes the supplied data using the knowledge base's principles. Using the data collected as a basis, the inference engine executes the rules to forecast future energy loads. Think about adding fuzzy logic to the expert system if there's ambiguity or complicated interactions among variables. Fuzzy logic enables the rules to express inaccuracy and ambiguity. Use past data to educate the expert system, if relevant [372]. Optimize rule settings according to historical results to raise the system's accuracy. Utilizing a verification set of information, verify the expert system. Analyze how it fared with respect to measures like remembering, reliability, and accuracy. To evaluate the framework's capacity for generalization, test it on a separate testing set. Share load forecasts with other members of the peer-to-peer energy trading community. Think about including human specialists in the system's decision-making processes. Integrating expert judgement into the projection procedure, managing unusual circumstances, and fine-tuning algorithms may all benefit from human participation [373].

Expert systems include human knowledge to provide interpretable conclusions and important insights into load forecasts. However, they may not be able to respond to changing conditions without ongoing input from experts.

9.12. Artificial neural network

A computerized model called an Artificial Neural Network (ANN) is modelled after the way the neural networks in a person's brain are organized and operate [341]. The input layer, a number of hidden layers, and an output layer are only a few of the linked nodes, or "neurons," that make up the system [374]. This is a detailed tutorial on predicting load with artificial neural networks (ANNs) for peer-to-peer energy trading: At regular periods, compile historical statistics on energy output or consumption. Prepare and disinfect the information. Evaluate and pick the important elements that might affect the need for energy. The neural network will use these properties as input parameters [375]. Partition the information into sets for testing and training. Select the neural network's design, taking into account the number of layers, each layer's quantity of neurons, and the activation parameters. Employing the training set, train the neural network. Through analyzing the past data, the network discovers deeper trends and correlations [376]. To alter the network's weights, use optimization procedures such as stochastic gradient descent. Try varying the pace of learning, quantity of batches, and number of periods, among other hyperparameters, to determine the best configuration that maximizes the efficiency of the learning system. Utilizing the testing set, assess the learned neural network's efficiency. Predict the demand for a future time interval using the neural network that has been trained. Share load forecasts with other members of the peer-to-peer energy trading network [377].

When working with irregular trends, ANN are an effective tool for load forecasting; nevertheless, proper model tweaking along with data constraints are essential.

9.13. Fuzzy logic control

Utilizing language parameters and principles to reflect risks and inaccurate data, fuzzy logic in load forecasting facilitates more adaptable and human-like making choices. Here's a detailed explanation for how to use fuzzy reasoning for load prediction in peer-to-peer energy trading: Determine whether fuzzy sets are appropriate for the given input variables [378]. Terms in language such as "low," "medium," and "high" are represented by fuzzy sets. To transform clear value inputs into fuzzy sets, apply fuzzification. To find out how much a given input value corresponds to each fuzzy set, employ function membership. Create a rule basis that outlines the connections among the fuzzy sets of input parameters and the fuzzy ranges of outcomes that are produced (energy load). Usually, rules are written in the "IF-THEN" style, with each rule representing an area of professional expertise [379]. Put in place an inference engine that creates fuzzy output sets by processing the fuzzy rules. The fuzzy rule outputs may be aggregated using a variety of inference techniques. To transform the fuzzy output settings into a sharp output value, employ defuzzification. At regular periods, compile historical statistics on energy output or consumption. Prepare and disinfect information. Divide the data collection into sets for training and testing purposes. Utilizing the training data, refine the rule basis. Modify the rules and roles to increase the fuzzy logic system's reliability [380]. With the use of a validation set of data, validate the fuzzy logic system. Analyze its performance with respect to measures like recall, accuracy, and precision. To evaluate the system's capacity for generalization, test it on a separate testing set. Connect the load forecasting system with fuzzy logic to the peer-to-peer energy trading platform [381].

Share load forecasts with other members of the peer-to-peer energy trading network.

By using reasoning that feels human to address unpredictability, fuzzy logic provides a reliable method for load forecasting; nevertheless, careful rule development and input from experts are necessary.

The best load forecasting strategy depends on a number of factors, including the specific characteristics of the data, the size of the network, and the goals of the prediction project. Every technique has advantages and disadvantages. Regression models function effectively where there are clear linear relationships between the predictor elements. Exponential smoothing techniques may be used to improve time series data by producing weighted averages that adapt to changing patterns. Autoregressive techniques are very useful for time series forecasting, especially when utilizing stationary information. Genetic algorithms are a useful adaptive optimization technique for complex, non-linear situations. An artificial neural network can effectively extract complex relationships and trends from datasets. Support vector machines are useful for both non-linear and linear forecasting challenges, especially in multidimensional spaces. When dealing with data that has uncertainties and insufficient details, fuzzy logic performs effectively. The best approach will change based on your data's specifics and the requirements of your load forecasting task. Trying out several tactics and even combining a few different approaches can significantly improve precision and adaptability. Consider factors like interpretability, processing power, and the amount of available historical data while choosing the best course of action for your circumstances. It's usually a good idea to try out a few different approaches and see which works best in the particular situation as shown in Table 7.

10. Scheduling techniques in P2P energy trading

10.1. Linear programming

An optimization issue with linear constraints and an objective variable to minimize or maximize is formulated using linear programming in load scheduling. There are several processes involved in applying linear programming to implement load scheduling in HEMS inside a P2P energy trading paradigm [382]. Here's a detailed how-to: Establish decision variables that reflect each home's energy production and usage throughout certain time periods, let $A_{x\,y}$ be the energy consumed/produced by home x during time interval y; Establish the objective function by considering your objectives, such reducing the total price, Reduce $K = \sum_{x,y} P_{xy}.\, A_{x,y}$, where P_{xy} is the price of energy of home x during time interval y; Determine and clarify constraints like energy balance, $\sum_{x}.\, A_{x,y} = Demand\, y$ for all y, where $Demand\, y$ is the total demand during time bracket y; Compile the constraints and the goal function into a linear programming model, Reduce $K = \sum_{x,y} P_{xy}.\, A_{x,y}$ subject to $\sum_{x}.\, A_{x,y} = Demand\, y$ for all y, $A_{x\,y} >= 0$ for all x, y; Employ tools or solvers for linear programming to determine the best values for the choice variables in order to minimize the objective function and

Table 7
Characteristics of different forecasting approaches used in P2P energy trading.

Method	Process	Feature	Application	Pros	Cons
Multiple regression	Historical data to predict future energy consumption	Utilizes statistical analysis to create a model	Smart homes and IoT devices	Provides understanding of complicated relationships	Correct input data are required for reliable forecasts.
Exponential Smoothing	Time series forecasting method	Assigns exponentially decreasing weights to past observations to predict values	Demand forecasting	Ideal for data with seasonality and patterns.	Less reliable long-term forecasts
Iterative reweighted least-squares	Data point weights are iteratively adjusted.	Useful for robust regression	Frequently employed in reliable regression analysis	Efficient in dealing with outliers	Compared to conventional least-squares regression, take more iterations to converge.
Autoregressive	Data from a time series based on previous linear estimations	Captures serial correlation in data	Widely used in economics, finance, and signal processing	Effective for predicting and modelling time-dependent data	Complicated temporal patterns might not be captured
Moving average	Determines the data points' average inside a sliding frame.	Identifies trends and shows patterns in changing data.	Trend analysis and demand forecasting	Gives a precise illustration of data patterns.	Lag behind quick changes and can skew data at the time series' edges.
Autoregressive moving-average	Analyze data by taking into account both previous values and a moving average of previous errors.	Provides a versatile method for capturing intricate temporal patterns	Time-series modeling	Flexible for handling different data formats	Require significant computational resources
Autoregressive integrated moving-average	Combines Autoregressive, integration, and moving-average components to model and forecast time-series data.	Addresses periodicity and patterns	Removing trends in demand forecasting	Suitable for many different types of complicated time-series data	Without extensions, long-term patterns could not be properly captured.
Genetic algorithms	Involves the evolution of a population	Search a vast solution space and adapt to find optimal solutions	Parameter adjusting for complex problems with multiple variables	Handle multiple objective functions and solution spaces	Require fine-tuning of parameters
Support vector machine	Find a hyperplane that maximizes the gap between classes while classifying the data	Effective for high-dimensional data	Widely used in classification tasks	Robust against overfitting	Limited suitability for multi-class problems
Adaptive demand	dynamically modifies forecasts in response to changing circumstances	Machine learning algorithms	Demand prediction, and pricing strategies,	Improved responsiveness to changes	Difficulties in interpreting dynamical frameworks
Expert systems	knowledge bases and inference engines	Rule-based reasoning	Areas that demand specialized expertise	Expert-level assessments	Restricted to the extent of available knowledge
Artificial neural network	Inspired by the human brain	Deep learning competencies for recognizing complicated patterns	predictive modeling.	Incredibly good at managing unstructured data	Often lacks interpretability
Fuzzy logic	Based on degrees of truth requires the use of linguistic variables and membership functions	Human-like approach to decision-making	Uncertain environments	Imitate human reasoning in ambiguous situations.	May not always follow conventional logic

meet the constraints [383]. Put into practice the ideal timetable that the linear programming method yielded. The schedule will show when each household should generate or use energy in order to satisfy demand at the lowest possible cost or in accordance with other predetermined goals [384]. Energy trades and price in the trading process can be taken into consideration by expanding the linear programming model. Keep a close eye on the amount of energy produced and used, and modify the plan as necessary to account for variations in demand, the availability of clean energy sources, and other variables [385]. While linear programming is an effective technique for scheduling and resource allocation optimization, it is important to take into account its assumptions and potential drawbacks when attempting to capture non-linear connections.

10.2. Mixed-integer linear programming

A mathematical optimization method called mixed-integer linear programming (MILP) mixes numerical decision variables and linear programming [386]. It is used to resolve optimization issues where certain decision variables must take integer values but others can use continuous values. To identify the best solutions that adhere to both linear restrictions and discrete selection criteria. The objective product and limitations in MILP are both linear, whereas the result variables are consistent, numeric, and scalar. This is especially helpful for scheduling issues that need specific choices, like turning on or off devices. The following steps outline how to use MILP to perform load scheduling in P2P energy trading: Determine the decision-making factors [387]. Let $A_{x,y}$ be the continuous parameter that shows how much energy participant x generated or used throughout the given period of time y, $B_{x,y}$ be a binary variable that indicates the presence or absence of participant x device is on ($B_{x,y} = 1$) or off ($B_{x,y} = 0$) during interval y; Indicate limits for device states, such as binary limitations, manufacturing capacity, and equilibrium of energy, energy balance constraints: $\sum_x . A_{x,y} = Demand\, y$ for all y, Capacity production constraints: $A_{x,y} < capacity_x$ for all $x\, and\, y$, Binary limitations: $A_{x,y} \le M.\, B_{x,y}$ for all $x\, and\, y$, $A_{x,y} \ge M.\, B_{x,y}$ for all $x\, and\, y$; Create a mixed-integer linear programming model by combining the goal function with the restrictions. Reduce $K = \sum_{x,y} P_{xy}.\, A_{x,y}$ subject to $\sum_x . A_{x,y} = Demand\, y$ for all y, $A_{xy} \le capacity_x$ for all $x\, and\, y$, $A_{xy} \le M.B_{xy}$ for all $x\, and\, y$, $A_{xy} \le m.B_{xy}$ for all $x\, and\, y$, $B_{xy}\, belongs\, to\, \{0, 1\}$ for all $x\, and\, y$, $B_{xy} \ge 0$ for all $x\, and\, y$; To determine the best solutions for both continuous and binary decision variables, utilize programs or algorithms for mixed-integer linear programming; Apply the best timetable that was found by solving the mixed-integer linear programming problem. This timetable will specify when every participant should generate or use energy, as well as when to turn their gadgets on and off, in order to satisfy need at a price that is affordable [388,389].

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

10.3. Nonlinear programming

In order to address optimization issues when the goals or limitations are nonlinear, or do not have a linear connection. Finding the best values for decision factors in nonlinear programming entails maximization or minimization of an objective function while adhering to an array of restrictions [390]. The following procedures outline how to use non-linear programming to accomplish load scheduling: Describe the variables used in decisions, let A_{xy} energy produced or consumed by every participant x in time period y; Establish the goal function that has to be optimized. Non-linear connections, including quadratic costs or non-linear efficiency curves, may be present in this function, for instance, to use a quadratic cost function to minimize the entire cost: Reduce $K = \sum_{x,y} P_{xy} \cdot (A_{x,y})^2$; Indicate any limitations, including production capacity, energy balance, and any other non-linear connections, Constraint on energy balance: $\sum_i A_{xy} = Demand_x$ for all j, Limitation on production capacity: $A_{xy} \leq capacity_x$ for all x, y; Incorporate the restrictions and the objective function into a NLP model, Reduce $K = \sum_{x,y} P_{xy} \cdot (A_{x,y})^2$ subject to $\sum_i A_{xy} = Demand_x$ for all j. $A_{xy} \leq capacity_x$ for all x, y. Any other nonlinear limitations: $A_{xy} \geq 0$ for all x, y; To determine the ideal values for the choice variables that minimize the desired variable while meeting the restrictions, use software [391,392]. This schedule takes into account non-linear cost functions or limitations and will suggest when every participant should generate or utilize energy to satisfy the need. Keep a close eye on the amount of energy produced and used, and modify the plan as necessary to account for variations in demand, the availability of sources of clean energy, and other variables [393].

Because non-linear interactions are taken into account, non-linear programming improves load scheduling accuracy and provides a more accurate optimization method for situations involving complex system dynamics.

10.4. Mixed-integer non-linear programming

Optimization is extended to accommodate both discrete and non-linear continuous decision variables in load scheduling through the use of Mixed-Integer Non-Linear Programming (MINLP) [394]. The steps below describe how to achieve load scheduling using MINLP: Indicate parameters A_{xy} illustrates generation/utilization, and B_{xy} as binary factors presenting gadgets states; Create a non-linear, mixed-integer value function, reduce $K = \sum_{x,y} P_{xy} \cdot (A_{x,y})^2$, taking into account non-linear interactions; Incorporate limitations such as energy balance $\sum_x A_{xy} = Demand_y$, generation capacity $A_{xy} \leq capacity_x$, and binary limitations $A_{xy} \leq M \cdot B_{xy}$; Incorporate the restrictions and the goal value into a mixed-integer non-linear programming framework [395,396]. Utilize solvers for mixed-integer non-linear programming to determine the best A_{xy} as well as B_{xy} values, carrying out the plan for effective load control in peer-to-peer energy trading [397].

By taking into account non-linear connections as well as discrete selections, MILNP improves load scheduling accuracy and provides a potent method for optimizing a variety of scheduling options.

10.5. Particle swarm optimization

In order to simulate social behavior, Particle Swarm Optimization (PSO) in load scheduling iteratively modifies a population of solutions (particles) depending on their specific and collective effectiveness [398]. The following procedures outline how to use PSO to accomplish load scheduling: Each particle should be represented as a possible load schedule, with every participant's energy generation and use quantities for every period of time being contained in the position vector A_x; Create an objective function, such as minimizing the total cost by assessing the healthiness of every particle in light of the price of energy and limits. Establish the velocities of a swarm of particles based on the optimization process and initialize them with randomized schedules [399,400]. Particle swarm optimization (PSO) methods are used to iteratively update particle locations and velocities in order to converge towards optimum load schedules. Use the best-performing particle's optimum schedule to regulate load effectively in peer-to-peer energy trading [401].

While PSO is a reliable method for load scheduling and resource allocation optimization, it requires careful parameter adjustment to get the best possible outcomes in dynamic circumstances.

10.6. Genetic algorithm

In load scheduling, Genetic Algorithm (GA) simulate natural selection by gradually developing a population of possible solutions through crossover, mutation, and selection [402]. The following procedures outline how to use GA to accomplish load scheduling: Show all participants as a chromosome with possible load schedules encoded in it. Genes correspond to each participant's energy generation and use levels during certain time intervals [403]. Create a fitness function to assess each person's schedule according to goals like cost reduction and fulfilling limitations like productivity and energy utilization. Create a population of people with arbitrary load schedules at the beginning. Utilize genetic processes (mutation, crossover, and selection) to develop the population via successive generations, giving preference to more suited schedules. To control load in peer-to-peer energy trading, apply the load schedule embodied by the fittest individual found after a predetermined number of generations [404,405].

In complicated circumstances, genetic algorithms can be an effective optimization method for load scheduling; nevertheless, it is important to take into account their sensitivity to parameters and computing needs.

10.7. Simulated annealing

Simulated annealing is a probabilistic optimization approach that draws inspiration from the metallurgical annealing procedure [406]. By mimicking the slow cooling and consolidation of a material, it is used to determine the general optimal of a complex expression. A description of the use of simulated annealing in load scheduling for peer-to-peer energy trading is provided here: Each possible load schedule should be represented as a state, with each state representing the energy production and consumption values for every participant across certain intervals of time [407]. Develop an objective function to assess the fitness of each state in light of energy prices, restrictions (such as production capacity and demand fulfilment), and any other pertinent variables. Use a load schedule that is based on heuristics or randomness to start the present state. Establish the starting temperature and the cooling settings. Accept fewer ideal solutions with a probability based on the Metropolis criteria as you iteratively move between states [408]. As per the cooling schedule, lower the temperature. After the simulated annealing process, execute the load schedule that was derived from the final state. The peer-to-peer energy trading system's load management should be effectively addressed by this timetable [409].

For optimization situations where a global optimum exists in a complicated solution space, the simulated annealing approach provides for an equilibrium among exploration and exploitation. When load scheduling is involved, it can be especially helpful in situations where there are intricate and non-linear interactions between restrictions and variables.

10.8. Colony optimization

Using pheromone trails, Ant Colony Optimization (ACO) in load scheduling simulates ant foraging behavior to discover optimal solutions repeatedly [410]. In P2P energy trading, ACO might be utilized in load scheduling as follows: Provide hypothetical load schedules as solutions, each of which encodes the energy production and consumption values for every participant across certain time periods. Create an objective function to assess each solution's fitness in light of energy costs, restrictions (such as production capacity and demand fulfilment), and any other pertinent variables [411]. Set up ant agents so they may create load schedules. Specify variables like visibility, pheromone concentrations, and other tuning factors. Use ant agents to create load schedules in an iterative manner. Ants use probability to choose time periods for each member depending on visibility and pheromone levels in order to construct solutions [412]. Pheromone levels should be updated in accordance with the caliber of built solutions. Use the load schedule that was derived from the ant colony's best solution as an effective way to control load in the peer-to-peer energy trading system [413].

Tasks with discrete choice factors and a vast scope of solutions benefit most from the application of ant colony optimization. It facilitates the testing of several schedules in the framework of load scheduling and gradually moves closer to the best options. The algorithm's success depends on the tuning of variables like the exploration-exploitation balancing and the pace at which pheromones evaporate.

10.9. Evolutionary algorithms

Computing techniques called evolutionary algorithms are influenced by evolutionary biology. They emulate the concepts of natural selection, reproduction, and mutation to address optimization and search issues [414]. The following is a basic overview of how load scheduling in peer-to-peer energy trading may be handled using evolutionary algorithms: Possible load schedules should be represented as people within a population, wherein each individual represents the energy production and consumption for every individual during predetermined periods. Develop an objective function that assesses each person's fitness in relation to energy prices, restrictions (such as production capacity and need fulfilment), and any other pertinent variables [415,416]. Create a population of people with arbitrary load schedules at the beginning. Explain genetic operators like mutation and crossover. Use genetic operators to iteratively develop the population over several generations. Based on fitness, choose individuals for reproduction, perform crossover and mutation procedures, and replace those who are less fit with the new progeny. Use the load schedule that the fittest person in the last generation provided to control load in the peer-to-peer energy trading system effectively [417].

With taking into account computing needs and configurations of parameters, evolutionary algorithms provide a potent optimization tool for load scheduling, especially in complicated circumstances.

10.10. Adaptive neural fuzzy inference system

A computer model called the Adaptive Neural Fuzzy Inference System (ANFIS) blends fuzzy logic with neural networks to provide a hybrid modelling and inference method [418]. Developing prognostic and decision-making platforms that can manage complex and ambiguous data linkages requires the usage of ANFIS. In P2P energy trading, ANFIS might be utilized as follows: Establish input parameters for things like production and utilization, battery power, market rates, and player interests. The connections among the input variables and ideal trade schedules should be represented by linguistic variables and fuzzy sets. Create an ANFIS architecture that reflects the intricate connections among the trading schedules and the input parameters [419]. To train the ANFIS model, utilize prior information and optimization goals. The ANFIS model adjusts to diverse circumstances as it gathers data, taking into account participant interests and market dynamics. Once trained, the ANFIS model may anticipate real-time or predicted data to estimate the best trading schedules for forthcoming periods [420]. The ANFIS model may be regularly updated with fresh data to increase its precision and flexibility in response to shifting market dynamics and energy trends. The P2P energy trading interface should incorporate the trained ANFIS model so that users may get suggestions for the best trading times depending on their energy profile and goals [421].

Although careful evaluation of the information and model settings is necessary, ANFIS is a strong tool for load scheduling, giving flexibility and precision in modelling irregular interactions.

The selection of optimization methods for load scheduling in P2P energy trading is contingent upon the particularities of the issue, the intricacy of the restrictions, and the intended qualities of the solution. Every method has advantages and could be appropriate in certain situations. Here is a quick rundown of some possible applications for some of the approaches listed: For issues where there are linear connections among each variable, LP is applicable. Excellent for load scheduling optimization in situations where both objectives and limitations can be expressed linearly. In order to accommodate discrete choice variables, MILP enhances linear programming. Suitable in situations when load scheduling necessitates making binaries or numeric judgements, such switching on or off equipment. NLP useful in solving nonlinear relationship difficulties. Appropriate in situations when complicated, non-linear restrictions or objectives are included in the load scheduling issue. MINLP handles issues including non-linear connections as well as discrete and continuous decision factors. Fit for intricate load scheduling situations involving a variety of decision factors. PSO works well for optimization issues with lots of possible answers. Appropriate for load scheduling in dynamic settings requiring extensive solution space exploration. GA works well for issues with several objectives and a big solution area. Appropriate for load scheduling in situations when there are conflicting objectives and an ideal solution that might not be unique. SA works especially well in situations involving wide search spaces and challenging terrain. Appropriate for load scheduling when it's necessary to investigate other options and break free from local optima. CO is appropriate for combinatorial optimization issues and resembles the foraging behavior of colonies. Potentially useful for load scheduling issues involving intricate relationships between several devices. Natural selection serves as the inspiration for several optimization methods included in EA. Appropriate for load scheduling in situations with complicated connections and a variety of solution spaces. ANFIS for simulating intricate systems. Appropriate for load scheduling issues where ambiguous or unclear linkages exist between factors. The particulars of the load scheduling problem, the data at hand, the computing capacity, and the intended trade-offs between exploration and exploitation all influence the strategy that is used. It's usually a good idea to try out a few different approaches and see which works best in the particular situation as shown in Table 8.

11. Futuristic P2P energy trading approaches

11.1. Energy internet

Electricity is the only sort of energy that the smart grid technology can handle (see Table 9). However, energy may also be produced from several sources, including thermodynamic, chemical, and electromagnetism ones [422]. All forms of energy sources will be included in future energy exchanges, not simply electrical energy. The novel electrical system that emerges from this link is referred to as Energy Internet Center [423] is intended to be an online network for power connections that combines all types of power sources in a publicly accessible link equivalent to the Internet we are all familiar with. Additionally, Energy Internet is anticipated to offer versatile energy scheduling, mutual flow of power, energy conversion, and routing features that are not offered by the current smart grid systems [424]. A typical Energy Internet System is

Table 8
Characteristics of different scheduling approaches used in P2P energy trading.

Method	Process	Feature	Application	Pros	Cons
Linear programming	Create a linear limitation and goal to operate and optimize to get the best result	Fit for issues involving linear correlations	Basic load scheduling situations, ideal resource allocation.	Quick convergence and excellent fit for linear issues	Only applicable on linear relationships
Mixed-integer linear programming	Consists of linear restrictions and binary or numeric variable choices	Manages discrete choice variables	Equipment toggle choices and load management	Supports numeric or binary values	Discrete decision-making leads to increased complexity
Nonlinear programming	Create and resolve nonlinear functional optimization issues.	Fit for issues with nonlinear goals or limitations	Nonlinear relationship-based load scheduling under intricate circumstances.	Adaptable to nonlinear issues	Perhaps not guaranteeing global responses
Mixed-integer non-Linear programming	Nonlinear functions, discrete and continuous decision variables to solve optimizations	Handles issues with a variety of variable kinds.	Combining continuous and binary/integer decision-making with load scheduling.	Adaptable, manages a range of factors	More intricate
Particle swarm optimization	A crowd of particles iteratively searches the solution domain	Suitable for expansive and dynamic answer spaces	Exploration-oriented issues and load scheduling under dynamic situations.	Ease of use and flexibility in changing conditions	Local optimal conditions might converge
Genetic algorithm	Selection, crossover, and mutation are all parts of population-based optimization.	Appropriate for issues with a variety of solution spaces	Load scheduling with several competing goals	Able to handle a variety of solution spaces and resilient to local optima	Requires a lot of computation
Simulated annealing	Based on metallurgical annealing	Good for investigating a range of options	Include complicated, non-convex solution spaces in load scheduling.	Exploration-focused and robust.	Tuning parameters might affect this
Colony optimization	Ant colonies build outcomes in an iterative manner	Fit for situations involving combinatorial optimization	Combinatorial choices for load scheduling	Adaptable to various combinatorial issues	Parameter tweaking sensitivity
Evolutionary algorithms	A large class of naturally evolving optimization algorithms	Adaptable to a wide range of optimization issues.	Scheduling loads with various specifications	Solves a variety of issues and global optimization	Vulnerability to variables and processing expense
Adaptive neural fuzzy inference system	Hybrid learning algorithm	Enable the integration of knowledge by experts	Control systems and pattern recognition	Interpretability through fuzzy rules	Requires sufficient data for training and overfitting

made up of energy levels, communication and information technology, and power routers like the computerized grid. The most crucial component of the energy Internet, permitting both power and information flow transmission, is the power router, according to Ref. [425]. The relevance of energy Internet as a promising technology for peer-to-peer energy trade has been explored in energy internet is a developing system, nevertheless, and its associated notions haven't yet been firmly defined, making it an intriguing subject for future research [426].

11.2. SDN

Energy routers, like the computerized grid router, are crucial in allowing P2P DET by offering crucial features such as bilateral flow of energy, energy conversion, routing, and distribution scheduling [427]. To achieve worldwide reliability in the power system, however, good administration of interconnected power routers, flexible routing arrangements, and effective interaction and collaboration between energy routers are absolutely necessaries has been suggested by a number of studies as a viable way to handle the intricate networking infrastructure of smart grids [428]. SDN networking permits centralized control and flexible settings of network equipment and structures, in contrast to conventional networks that operate via decentralized control and fixed settings. SDN does this by isolating the method of decision-making (Control Plane) from the network's delivering mechanism (Data plane) [429]. A centralized software regulator comprises the Control Plane. Through open AP Interfaces, the centralized program controller enables management of many networks' equipment from just one point and flexible network topologies. The administration of power routers was not covered in earlier research, which largely recommended SDN-based connectivity for enhanced efficiency and for attaining desirable QoS in current smart grid networks [430,431].

11.3. Federated learning

Data science's significance is becoming more and more obvious as storage and computational power become more powerful. A cooperatively decentralized safe technology called federated learning (FL) was created to solve the problems of data silos and vulnerability [432]. In decentralized machine learning environments, it is described how numerous users collaborate while using a variety of centralized databases. A decentralized machine learning strategy called federated learning enables multiple gadgets or node edges to cooperatively train a single model while maintaining localized data. By allowing training without centrally gathering raw data on a computer, it allays privacy concerns. Instead, just the model upgrades are shared and the model is modified on every gadget [433]. FL might be utilized as follows: The local datasets are maintained by each member in the P2P energy trading infrastructure. Members use their local datasets to train a local energy trading model that takes into account variables such as energy production, consumption, pricing, and environmental factors. Players communicate their model modifications (gradients) to a central server or aggregator rather than exchanging raw data. To update the worldwide energy trade framework a centralized server compiles the system's upgrades from various players [434]. Data confidentiality and integrity are preserved since it stays on participants' devices. The only thing traded are model upgrades. Then, without disclosing sensitive information, the global model is utilized to optimize trading techniques among participants. As each participant's local model records their unique energy profile and choices, the federated method enables the use of customized trading techniques [435].

Federated learning in peer-to-peer energy trading improves privacy, encourages cooperation, and enables real-time response to fluctuating energy circumstances while maintaining the localization of confidential information.

Table 9
Characteristics of different futuristic approaches used in P2P energy trading.

Method	Process	Feature	Application	Pros	Cons
Energy internet	Decentralized energy management with a framework akin to the internet	Instantaneous tracking, decentralization, and price volatility	Mutual energy exchange, adaptive load balancing	Effective use of resources and incorporation of green energy	Infrastructure demands and legislative difficulties
SDN	Network supervision is centralized using capable of programming	Network customization, centralized control, and optimized Quality of Service (QoS).	Distributing the load evenly, virtualizing networks	Effective dialogue and flexible network	Difficulty of the initial configuration.
Federated learning	Model accumulation, revisions, and training locally on participating gadgets	Decentralized learning and maintaining confidentiality.	Participant-specific load scheduling.	Cooperative learning and privacy preservation	Excessive communication
Reinforcement learning	Agent develops decision-making patterns that maximize cumulative rewards.	Delayed rewards, sequential decision-making, and trial-and-error	Autonomous vehicles and recommendation systems	Adaptable to shifting circumstances and dynamic surroundings	It can be difficult to design and train appropriate reward functions.
Metaverse	Participants engage in energy associated tasks in virtual surroundings	Realistic environments and user experiences	User involvement and load scheduling through virtual instruction.	Interactive and easy to use	Difficulties in adopting technology.
Digital twin technology	Making a virtual replica of a physical thing, system, or procedure	Enables testing, optimization, and testing without impacting the actual item	Grid optimization, predictive maintenance, smart cities	Innovation, remote monitoring and sustainability	Complex Implementation, data security and Integration, initial investment and maintenance
Artificial Intelligence	Gaining knowledge from data and making decisions	Learning, automation, scalability and personalization	Natural language processing, computer vision and autonomous vehicles	Accuracy, data analysis, personalization and safety	Data dependency, bias, complexity and ethical Concerns
Electric vehicle	Grid-to-Car and Car-to-Grid, respectively	Optimizing EV range and usefulness, facilitating two-way power transfer	EV charging and discharge with variable load management	Grid assistance and green energy inclusion	Restricted grid connectivity, structures and depletion of batteries
Data science	Obtaining information and understanding from data	Interdisciplinary, data-centric, predictive and descriptive	Predictive maintenance, process optimization, and demand forecasting.	Using data-driven insights to make better decisions	Resource-intensive and data quality
Internet of Things	Connecting devices to the internet	Devices can interact with central systems and with one other.	Security, energy management and Predictive maintenance	Enhances security through monitoring and immediate alerts	Handling massive quantities of data and expanding IoT systems.
Cloud computing	Utilize online computer resources and services.	On-demand access scalability, resource pooling, self-service and broad network access	Analytics and data processing on the cloud.	Accessible, offers robust backup and recovery solutions.	Security concerns, downtime, data transfer costs and vendor Lock-In

11.4. *Reinforcement learning*

A machine learning training approach called Reinforcement Learning (RL) rewards desired behavior and penalizes undesirable one. A reinforcement learning agent typically has the capacity to sense and understand its surroundings, act, and learn via experiences [436]. How RL may be used in peer-to-peer energy trade is as follows: In the P2P energy trading system, each member is portrayed by an RL agent. gradually, these agents acquire the ability to choose which energy to trade. The state contains data on market pricing, historical trade data, battery levels, energy output, and consumption. It records each participant's present situation. The RL agents' decisions on whether to trade energy, what amount to trade, and whether to utilize or preserve it might all be actions [437]. Establish a reward function that represents the participant's goals, such as increasing profit, lowering expenses, attaining energy independence, or lessening the impact on the environment. RL agents engage in actions and rewards with the environment (the power market). Through failures and successes, they discover the best trading strategies for maximizing long-term cumulative gains. To make the best trade decisions, agents strike a balance between exploitation (using tried-and-true methods) and exploration (attempting novel strategies). Applying reassurance participants get the ability to independently optimize their trading techniques while taking into account real-time data and personalized objectives by learning P2P energy trading [438,439].

P2P energy trading can benefit from Reinforcement Learning's dynamic approach, which provides flexibility and optimization capabilities. However, careful evaluation of training data and exploration methodologies is essential.

11.5. *Metaverse*

The term “metaverse” implies to a shared, immersive, and permanent three-dimensional virtual environment with numerous users that connects across numerous digital platforms and melds with the actual world so that people may interact in actual time while they buy, perform tasks, and lounge out together [440]. Ways the metaverse might impact peer-to-peer energy trade is as follows: Users in a metaverse might engage in peer-to-peer (P2P) energy trading through digital spaces where they can converse and practice energy exchanges. Real simulations of energy generation, utilization, and trade may be found in the metaverse, enabling users to see the results of their trading choices in a fluid virtual setting. The effectiveness and reliability of P2P energy trading might be increased by participants working together in the metaverse to make judgements about trade that are all based on common knowledge and current information [441]. Energy market information might be made visible in a metaverse, enabling players to gain insight into market circumstances and make wise trading decisions. Users could discover regarding the fundamentals of energy trading on the metaverse's teaching platform. Within the metaverse, virtual communities might emerge around shared energy objectives, stimulating discourse, information exchange, and P2P energy trade. Ways the metaverse might impact peer-to-peer energy trade is as follows: Construct virtual worlds in the metaverse wherein users may participate in energy trading marketplaces that resemble actual energy transactions. Enable users to carry out peer-to-peer energy trading agreements in a virtual setting by integrating smart contracts into the metaverse. Provide simulated load prediction and scheduling situations in the metaverse so that users may see and adjust their production as well as consumption approaches in a virtual environment [442]. Utilize the metaverse as a teaching tool to give people immersive, engaging experiences that teach them regarding environmentally friendly methods, load sharing, and conserving energy. Investigate cutting-edge metaverse interfaces used to visualize and interact with real-time energy data, enabling more informed P2P energy trading decisions [443].

It is noteworthy that the successful use of load scheduling and forecasting in peer-to-peer energy trading in a metaverse calls for developments in virtual reality technologies as well as blockchain-based systems (for safe and fair operations). These innovations are always changing as of the previous revision, so for the most up-to-date information, make sure you keep up with the latest advancements.

11.6. Digital twin technology

In order to enable real-time monitoring, evaluation, and optimization, digital twin technology includes building a virtual copy or simulation of a real-world system, process, or item. In 2002, Michael Grieves was the one who initially proposed the concept of DT. The explanation followed in his "Digital Twin." He believed that by using the data of the actual equipment, an online unit and subsection reflecting the features of the physical item could be created in a virtual (informational) environment [444]. Digital twin technology is used in P2P energy trading to model, track, and optimize energy trades in a decentralized and localized energy market using virtual clones of real assets, such as energy generation and consumption devices. Ways digital twin technology may be employed in peer-to-peer energy trading is as follows: Each power producing or consuming item used in the process of trade might have a digital twin in P2P energy trading [445]. Actual asset and information monitoring is made possible by digital twins. The digital twin can offer current data on the asset's energy production or consumption, which is crucial for figuring out how much energy is available for trade. Forecasting and past statistics may be used to estimate patterns in energy production or consumption using digital twins. In order to identify the most productive and economical trading methods, optimization algorithms may be deployed to digital twins. The procedure can be facilitated by digital twins by enabling parties to see the state and accessibility of energy from diverse resources in actual time. Digital twins can use smart agreements to streamline energy trading procedures [446]. These smart contracts can be triggered by digital twins via real-time information they gather. The possible risks connected with energy procurement transactions can be evaluated via digital twin simulations of various situations. The efficiency of resources may be tracked and servicing requirements can be discovered with the use of digital twins. By the usage of these digital twins, traders and other players may see how the energy market is doing and how their assets are doing by using an interface that is easy to use. Participants will find it simpler to comprehend and take part in the trading method as a result [447].

A comprehensive and fueled by data strategy to load scheduling is offered by the integration of digital twin technology into peer-to-peer energy trading platforms. Better choice-making, real-time modifications, and the network's efficient use of energy assets are all made possible by it. Like any technology, its actual use may vary depending on the framework, demands, and developments in digital twin characteristics.

11.7. Artificial intelligence

Artificial intelligence (AI) is the capacity of a machine or a robot operated by a computer to perform duties typically performed by humans because they call for intellect and judgement [448]. The use of AI in peer-to-peer energy trading may be demonstrated herein: Compile past information on generation, utilization, weather trends, and other pertinent variables. Use artificial intelligence (AI) methods to examine the information and find patterns, that include machine learning tools. Create forecasting algorithms with AI to estimate supply as well as demand for energy. The period of day, the climate, and past trends in consumption are just a few of the variables that these models may adjust for. Employ optimization methods powered by AI to find the best load scheduling techniques [449]. These algorithms have the ability to take into account real-time data and dynamically modify schedules in order to successfully integrate clean energy sources, reduce costs, and stabilize the grid. Blockchain technology and AI together can provide safe and transparent peer-to-peer energy exchanges. AI-powered smart contracts have the ability to automate and enforce energy trade agreements under specified parameters.

Permit consumers to independently decide on generation, trade, and utilization by utilizing decentralized AI techniques [450]. This promotes a P2P energy trade network that is adaptable and autonomous. Put into practice machine learning models with continuous training and situational adaptation capabilities. This enables the system to adjust its load scheduling tactics in response to changing energy trends and user input over time. Provide simple interfaces that take use of AI-driven insights to help players decide on resource optimization, energy trade, and load allocation [451].

An energy ecosystem with more efficiency, adaptability, and sustainability might be possible with AI-driven load scheduling in peer-to-peer energy trading. Better resource management, monetary savings, and the grid's incorporation of green energy supplies can all be facilitated by the technology. To put AI into practice, energy specialists, technological programmers, and AI experts would work together to create and execute reliable systems that are customized for certain P2P energy trading networks.

11.8. Electric vehicle

EV (Electric Vehicle) technology encompasses various concepts, including V2G (Vehicle-to-Grid) permits electric automobiles to send extra power back to the grid when required in addition to using the grid to charge their batteries [452]. EVs can serve as interim energy storage devices thanks to this power's bidirectional flow. G2V concept concentrates on how EVs and the electrical grid contact by adjusting charging schedules such that either the EV owners and the grid profit. An inventive method of energy management is introduced by using electric vehicles (EVs) for load management in P2P trade of energy. Here's a quick rundown: Establish an intelligent recharging system so that electric vehicles may interact with the energy trading system [453]. Bidirectional energy transfer should be supported by this network, allowing EVs to return energy to the grid in addition to charging it. Make use of Vehicle-to-Grid (V2G) technology, which makes it possible for EVs to interact actively with the energy infrastructure. When demand is high, EVs may help the system by feeding additional power back into it at peak hours. Establish two-way connectivity between the peer-to-peer energy trading network and EVs. Through this connection, EVs may get price and signal data obtained from the grid and modify their charging and discharging schedules in response to current circumstances [454]. Develop methods that plan the powering and draining of devices, maybe based on AI or optimization approaches. Provide EV owners with benefits to engage in peer-to-peer energy trading. monetary rewards, cost savings on recharging, or prizes for utilizing smart charging and discharge systems to support grid stability are a few examples of this. Empower EVs with additional assistance mechanisms for the grid in times of emergency or high demand. This could entail concerted attempts to release energy that has been hoarded for the good of the larger society [455].

The optimal use of clean energy assets, load balancing, and grid reliability can all be facilitated by the bidirectional features of electric vehicles (EVs), particularly when combined with V2G technology.

However, standardization of procedures, regulatory backing, and cooperation among players in the energy and automobile sectors would be necessary for effective execution.

11.9. Data science

Data science is a field of study that works with enormous amounts of data using novel methods and tools to identify hidden patterns, extract valuable knowledge, and make judgements [456]. It seems to utilize data science inside the P2P energy trading architecture: Gather information from a range of resources, such as past generation and utilization of energy, meteorological data, player behavior, and market pricing. Make that the information is correct, up-to-date, and system-representative. Clearing up the information and put it in a manner that is appropriate for examination. This might involve encoding variable types, normalizing scales, and managing missing data. To learn more about the links, structures, and trends in the data, use interactive analyses of data. Key aspects and the fundamental patterns may be understood by applying statistical evaluation and visualization tools. Create predictive models that estimate energy pricing, supply, and demand by utilizing machine learning techniques [457]. Regression modelling, ensemble approaches, and time series projection techniques can be used to create precise simulations. To optimally plan energy demands, use optimization methods. Taking into account a variety of limitations and goals, optimization methods such as mixed-integer programming and linear programming can assist in balancing demand as well as supply for energy. Utilize algorithms that learn to support load scheduling choices. Based on past data and current knowledge, these algorithms are able to suggest the best scheduling tactics. Put in place continuous tracking systems that gather and evaluate data continually [458]. This makes it possible for the network to adjust its load plans in response to evolving circumstances, guaranteeing flexibility in response to shifts in supply, demand, or other variables. Create a feedback loop so that models may be updated and improved over time in response to fresh data. Through this iterative approach, the system may gradually improve the precision of load scheduling forecasts and adjust to changing trends [459].

While taking into account data quality and computing needs is critical, data science plays a significant role in enhancing P2P trade in energy, enabling better precision and effectiveness.

11.10. Internet of Things

The Internet of Things (IoT) is the interconnection of sensor and actuator technologies for the following purposes: providing standard features for the particular equipment; implementing data investigation; and demonstrating information within a cloud system [460]. IoT is based on the concept of a "smart environment" that uses ICT to improve management, security, facilities, and a variety of other industries. IoT can be used in the P2P energy trading setting: IoT-enabled smart meters may offer each member of the P2P trading network updated information on their energy output and usage. Actual information regarding energy supply, demand, and prices may be transmitted via IoT devices. By autonomously altering energy use depending on inputs from the power system or marketplace, IoT devices may support demand response programs [461]. IoT-enabled renewable energy sources can offer real-time information on energy production that is used to balance supply and demand and make it easier to trade extra energy. Energy storage facilities may be managed by IoT devices, ensuring the best possible use of the energy for commercial or domestic purposes. IoT gadgets can streamline trading choices depending on established criteria when they are combined with AI methods. Blockchain technology and IoT together enable safe, computerized, and open interactions. Utilizing intuitive interfaces, IoT gadgets may offer consumers real-time information about their trade and energy usage operations. To optimize energy use and prevent grid congestion, IoT devices can track patterns in use of energy and allocate loads through different appliances and gadgets. Analysis of IoT-generated data can reveal patterns of use, forecast future power requirements, and alert users to possible trade possibilities. The efficiency, openness, and ecological responsibility of the energy market are all improved by integrating IoT technology into peer-to-peer energy trading. It enables automated activities, instantaneous choices, and improved incorporation of green energy sources [462,463].

Quality of information and computation. needs must be taken into consideration; however, data science plays a critical role in providing greater precision and effectiveness in P2P household power management.

11.11. Cloud computing

Cloud computing is the provision of various computer services via the internet. Instead of controlling and owning physical hardware and software, people are permitted to access computer resources, such as processing power, storage space, databases, links, and programs, via internet servers located in data centers [464]. Here are a few examples whereby cloud computing may be applied to peer-to-peer energy trading: Utilize internet-based databases for archiving vast amounts of past and present information about the generation of energy, utilization, and market circumstances. Participants may easily access, retrieve, and share data when it is stored on the cloud. Utilize the cloud's flexibility to manage intricate calculations and load scheduling optimization techniques [465]. This is especially helpful whenever demand is at its highest and more computer resources could be needed. Analyze real-time data via sensors, intelligent meters, and other Internet of Thing's devices using cloud-based data mining technologies. This makes it possible to decide on load scheduling in a timely manner using the most recent data. Utilize based on the cloud machine learning methods to develop forecasting models for price, generation, and demand for energy. By adding complex analytics, such models can improve the load scheduling algorithms' efficiency [466]. Manage distributed renewable energies, by integrating cloud-based systems. DER use may be optimized in load scheduling choices with the aid of cloud services. Use blockchain technology on cloud computing platforms to guarantee safe and open peer-to-peer energy transfers. Smart agreements may be enabled via cloud-based blockchain technologies, which eliminates the requirement for a centralized authority. Employ software on the cloud to provide remote oversight and management of energy systems and equipment. The ability to view and control one's energy resources from any location encourages versatility in load scheduling for participants. Provide cloud-based collaborative systems where P2P energy traders may exchange data, work out deals, and optimize load schedules as a group. Cloud-based cooperation improves member interaction and cooperation. Employ cloud-based applications that follow compliance guidelines and data protection laws. Maintaining safekeeping of private data in peer-to-peer energy trading is crucial. Reduce expenses by using cloud services on a pay-per-use basis. As a result, P2P energy trading networks may adjust their size in response to demand, guaranteeing economical resource use [467].

Although connection and security issues must be taken into account, cloud computing's flexibility and actual time characteristics help residential energy management systems estimate and schedule loads more effectively.

12. Mathematical modeling

12.1. HEMS's P2P load scheduling methodology is subject to stochastic and failure assessment

By considering activities in various connected energy resources and equipment, the proposed stochastic modelling of a HEMS attempts to establish the optimal forecasting and scheduling solutions. As a result, the scheduling and prediction problems may be quickly resolved. In this scenario, as shown in Fig. 21, the projected supply source, i.e., $U^j(t)$, may be modified according to the projected Load requirement $R^j(t)$ by minimizing the Impeded demand/requirement I(t). For this, a closed-loop control system is modelled, as shown in Fig. 21.

To analyze these two anticipated parameters, the closed-loop architecture combines projected load requirement $D^p(t)$ and source response $U^j(t)$. To provide an ideal balance of load across multiple sources of energy, a controlled load flow between source supply and load requirement is required. For this reason, $U^j(t)$ and $R^j(t)$ needs to be synchronized.

$$U^j(t) = R^j(t) + s_o \tag{1}$$

s_o on the other hand, is a constructed standby/spare backup that is basically a source supply obtained from HEMS. In this case, the influence of $U^j(t)$ and $D^j(t)$ is assessed by continuously altering b_o and the returning demand R(t) using HEMS. $U^j(t)$ and $R^j(t)$, thereafter achieve synchronized equilibrium.

A delay time frame, referred to as the mean delay or latency (m_l), is used to evaluate the stated case and take potential outcomes into account. m_l can be interpreted as,

$$m_l = \lambda_{k1} \tag{2}$$

The design mainly covers a single time in (2). Equation (2)'s more general version is expressed as

$$m_l = \frac{1}{p}\sum_{i_1=1}^{p_1} \lambda_{k1} \tag{3}$$

As a result, k_1 stands for a closed-loop delay, and p_1 is the effect of this disruption on a synchronized network. In addition, it is anticipated that Casualness $C_R(t)$ is included in the energy network together with the actual demand $R^g(t)$ in order to manage reaction to demands in actual/genuine time.

$$R^g(t) = R^j(t) + C_R(t) \tag{4}$$

By adding the m_t model from (3) into (4)

$$R^g(t) = R^j(t) * \left(\frac{1}{p}\sum_{k_1=1}^{p_1} \lambda_{k1}\right) + C_R(t) \tag{5}$$

Constant monitoring implementing a probabilistic closed-loop paradigm, as shown in Fig. 21, (5), can be summarized as follows.

$$R^g(t) = \sum_{k=1}^{p} \left\{ R_k^j(t) * \left(\frac{1}{p}\sum_{k_1=1}^{p_1} \lambda_{k1}\right) + C_{R_k}(t) \right\} \tag{6}$$

where $C_R(t)$ signifies the random variation among $R^g(t)$ and $R^j(t)$ and it may be found using an auto-correlation stochastic technique, i.e.

$$C_R(t) = X\left\{R^g(t) * R^j(t)\right\} \tag{7}$$

when, $R^g(t) \rightarrow R^j(t)$, the random deviation(t)→0, Its synchronous robustness is achieved as

$$U^j(t) = R^j(t) \tag{8}$$

Similar to how the genuine or real source supply $U^g(t)$ are anticipated to be synchronized with the past $U(t-1)$ and $U^j(t)$, with the addition of some casualness $C_R(t)$, while considering developing response trends in instantaneously.

$$U^g(t) = U(t-1) + U^j(t) + C_U(t) \tag{9}$$

Consequently, to maintain load flow balancing between load requirement and source supply features $U(t-1)$ is a regulating parameter that instantly restores a closed-loop feedback system to the earlier time period. As shown in, a HEMS manages $U(t-1)$ to provide an optimal $U^g(t)$ by including delay in (9), resulting in

$$U^g(t) = \left\{ U(t-1) * \left(\frac{1}{p}\sum_{k_1=1}^{p_1} \lambda_{k1}\right) + U^j(t) * \left(\frac{1}{p}\sum_{k_1=1}^{p_1} \lambda_{k1}\right) + C_U(t) \right\} \tag{10}$$

(10) can be presented as a closed loop feedback system in a broad sense.

$$U^g(t) = \sum_{k=1}^{p} \left\{ U(t-1) * \left(\frac{1}{p}\sum_{k_1=1}^{p_1} \lambda_{k1}\right) + U^j(t) * \left(\frac{1}{p}\sum_{k_1=1}^{p_1} \lambda_{k1}\right) + C(t) \right\} \tag{11}$$

wherein $C_U(t)$ is the self-correlating stochastic method that may be used to determine the arbitrary deviation between $U^g(t)$ and $U^j(t)$.

$$C_U(t) = X\left\{U^g(t) * U^j(t)\right\} \tag{12}$$

Additionally, when $U^g(t) = U^j(t)$ the random variation $C_U(t) = 0$, which achieves an equal power across $U^g(t)$ and $U^j(t)$, assures dependability in HEMS.

$$U^g(t) = U^j(t) \tag{13}$$

The controlling factor $U(t-1)$ must be ideally tuned to equalize power throughout $U^j(t)$ and $R^j(t)$ in order to entirely minimize a $C_U(t)$, i.e., $C_U(t)$ tends to zero.

$I(t)$, which can be represented as, is a Impeded demand expression that represents the power shortfall.

$$I(t) = A^g(t) - U^g(t) \tag{14}$$

while $A^g(t)$ is the Articulate demand, that needs to be constantly satisfied at particular periods to enable the best load managing. balancing response and the demand. The $I(t)$ occurs, when

$$A^g(t) > U^g(t) \tag{15}$$

By adding an m_l in (19)

$$I(t) = \left\{ \left(A^g(t) - U^g(t)\right) * \left(\frac{1}{p}\sum_{k_1=1}^{p_1} \lambda_{k1}\right) \right\} \tag{16}$$

(16) is generalized by converting it.

$$I(t) = \sum_{k=1}^{p} \left\{ \left(A^g(t) - U^g(t)\right) * \left(\frac{1}{p}\sum_{k_1=1}^{p_1} \lambda_{k1}\right) \right\} \tag{17}$$

$I(t)$ will continue to keep the feedback mechanism active and articulate any Accumulated or backlogged demand M(t) to the infrastructure. It will still be connected using a closed loop delay, or λ_{c1}. The equation for the Accumulated demand M(t). Will thus be represented in the form of $I(t)$, together with the multiplier for the particular closed-loop equivalent delay, as given in (14).

$$M(t) = A^g(t) - U^g(t) \tag{18}$$

$$M(t) = \sum_{c1=1}^{p_1} \left(\frac{1}{\lambda_{c_1}}\right) * \left(\left(A^g(t) - U^g(t)\right)\right) \tag{19}$$

(19) is now written as

$$M(t) = \sum_{c1=1}^{p_1} \left(\frac{1}{\lambda_{c_1}}\right) * \left\{ \sum_{i=1}^{p} \left(\frac{\left(A^g(t) - U^g(t)\right)}{p}\right) * \left(\frac{1}{p}\sum_{k_1=1}^{p_1} \lambda_{k_1}\right) \right\} \tag{20}$$

The reserve or standby $s(t)$ may be written as

$$s(t) = U^g(t) - A^g(t) \tag{21}$$

while into the reserving phase

$$U^g(t) < A^g(t) \tag{22}$$

By adding delay

$$s(t) = \{U^g(t) - A^g(t)\} * \left(\frac{1}{p}\sum_{k_1=1}^{p_1}\lambda_{k1}\right) \quad (23)$$

(23) generalized into

$$s(t) = \sum_{k=1}^{p}\left\{\{U^g(t) - A^g(t)\} * \left(\frac{1}{p}\sum_{k_1=1}^{p_1}\lambda_{k1}\right)\right\} \quad (24)$$

The criteria should be specified if there are reserve $s(t)$ requires.

$$s_o < s(t) \quad (25)$$

Utilizing a HEMS, the $U^g(t)$ has to be raised. By doing this, $I(t)$ will be lowered and s_o and $s(t)$ will be as close as possible to one another. The stepping-up restriction's method can be used to do this task; instead, if

$$s_o > s(t) \quad (26)$$

The following procedure is to decrease $U^g(t)$) such that s_o and $s(t)$ are as close as possible to one another. The approach of scaling down limits can be used to achieve this. While escalating restrictions exist

From (9), $U(t) - U(t-1)$ may be written as

$$s_o \leq U^j(t) + C_U(t) \leq S(t) \quad (28)$$

In this situation, the fundamental problem is to consistently sustain the backlogged/Accumulated demand, or M(t), This may be done by employing a HEMS to reduce $C_U(t)$. To do this, we must control the value of s_o in accordance with the progressive up and down specifications from (25) and (26) in order to synchronize it to $s(t)$. As a result of minimizing $C_U(t)$, (28) may be written as

$$s_o \leq U^j(t) \leq (t) \quad (29)$$

The synchronization of $U_j(t)$ and $R_j(t)$ may be done using (1), i.e.,

$$s_o \leq R^j(t) \leq s(t) \quad (30)$$

From (30), it is evident that the load flow equilibrium between demand and response has been achieved. In this situation, HEMS will not only provide the best load flow equalization across the various energy sources and equipment, but it will also act as an energy reserve to compensate for RER instability.

12.2. Peer-to-peer homes energy management level

P2P homes energy management level is used to sequentially optimize the performance of each pair of residences in linked activity. The HEMS system, placed inside each house, and the data accessible in the data cloud are used at this level to optimize the performance of the projected house pairings as follows.

A joint optimization procedure is used for each pair of homes, home (A) and home (B), to decide (1) the minimum daily power price for each couple 'P_{P2P}', (2) the 24-h profiles for the optimum scheduling of the shiftable gadget in the home (A) and home (B) [$Sch_{gad_{opt}}(k,t)^{P2P(A)}$, $Sch_{gad_{opt}}(i,t)^{P2P(B)}$] respectively, and (3) the 24-h profiles for the power exchanged between each coupled homes within the residential community $U_{ex_{opt}}{}^{A\rightarrow B}$.

The cost function for a linked home "P_{P2P}", may be written as follows.

$$P_{P2P} = \sum_{p=A,B} P_{home}{}^{p} \quad (31)$$

$$P_{home}{}^{p} = P_{battery_{deg}} - P_{home_{ex}} \quad (32)$$

$$P_{home_{ex}} = \begin{cases} \Delta T * \sum_{to}^{T} f_{ex\ exp}(t) * U_{ex}{}^{A\rightarrow B}(t), U_{ex}{}^{A\rightarrow B}(t) > 0 \\ \Delta T * \sum_{to}^{T} f_{ex\ imp}(t) * U_{ex}{}^{A\rightarrow B}(t), U_{ex}{}^{A\rightarrow B}(t) < 0 \end{cases} \quad (33)$$

where $P_{home}{}^{P}$ is the total power cost of home no. (p) (£), $P_{battery_{deg}}$ is the daily battery degradation cost of the battery located at house no. (p) (£), $C_{home_{ex}}$ is the daily price of the shared energy between home (A) and the coupled house (B) in the residential community, $f_{ex\ exp}(t)$ is the power export tariff for the energy exchanged across the coupled houses (£/kWh), $f_{ex\ imp}(t)$ is the electricity import tariff for the power exchanged among coupled homes (£/kWh), $U_{ex}{}^{A\rightarrow B}(t)$ is the power flow between home (A) and home (B) (kW).

The connection limits between the linked houses are introduced using the following limitations; To guarantee that the power exchanged between the residences at any particular time goes only in one way, constraint (38) is utilized.

$$U_{ex}{}^{A\rightarrow B}(t) = -U_{ex}{}^{B\rightarrow A}(t) \quad (34)$$

Mobility losses, which may be described as, can affect the exchange of energy among two homes.

$$U_{losses}{}^{A>B}(t) = \eta_{losses}{}^{A>B}(t) * U_{ex}{}^{A>B}(t) \quad (35)$$

$\eta_{losses}{}^{A>B}(t)$ is the transmission efficiency (%), $U_{losses}{}^{A>B}(t)$ is the power loss (kW) during the transfer of power among homes (A) and (B), and this value is modified by the community administrators according to the distance among homes in the area. When energy is moving from home (A) to home (B), the energy received by (B) in absolute terms is equal to the energy that leaves house (x), less transit losses, as shown in (36).

$$U_{ex}{}^{A\rightarrow B}(t) = U_{losses}{}^{A\rightarrow B}(t) + U_{net-ex}{}^{A\rightarrow B}(t) \quad (36)$$

$$\delta_+(t) = \begin{cases} U_{ex}{}^{A\rightarrow B}(t) > 0, 1 \\ U_{ex}{}^{A\rightarrow B}(t) \leq 0, 0 \end{cases} \quad (37)$$

$$\delta_-\ (t) = \begin{cases} U_{ex}{}^{A\rightarrow B}(t) < 0, 1 \\ U_{ex}{}^{A\rightarrow B}(t) \geq 0, 0 \end{cases} \quad (38)$$

$$\delta_+(t) + \delta_-\ (t) \leq 1 \quad (39)$$

$$U_{ex,max}(t) * \ \delta_+{}^{A>B}(t) \geq U_{ex}{}^{A>B}(t) \quad (40)$$

$$U_{ex,max}(t) * \ \delta_-{}^{A>B}(t) \geq U_{ex}{}^{A>B}(t) \quad (41)$$

wherein $\delta_+(t)$ is a Boolean parameter; that is, it equals 1 if power flows from home (A) to home (B) at time t and 0 otherwise. Neg(t) is a Boolean parameter, meaning that it equals 1 if the energy at the time is zero. Flows from the home (B) towards the home (A) at period t and alternatively, zero. The maximum value for the power exchanged among $U_{ex,max}(t)$ and home (A) and home (B), with the option to change this value, unless otherwise specified, this value is set to zero.

The power balancing equation for each of a set of homes that operate as a connected system must be rewritten as in (42–44),

For home (A):

$$U_{battery}{}^{A}(t) - \ U_{ex}{}^{A\rightarrow B}(t) = U_{load}{}^{A}(t) + U_{ex\ gad}{}^{A}(k,t) - U_{RER}{}^{A}(t) \quad (42)$$

For home (B):

$$U_{battery}{}^{B}(t) - \ U_{ex}{}^{B\rightarrow A}(t) = U_{load}{}^{B}(t) + U_{ex\ gad}{}^{B}(k,t) - \ U_{RER}{}^{B}(t) \quad (43)$$

For home A and home B:

$$U_{battery}{}^{p}(t) - U_{losses}{}^{A>B}(t) - U_{losses}{}^{B>A}(t) = \sum_{p=A,B} U_{load}{}^{p}(t) + U_{ex\ gad}{}^{P}(i,t) - U_{RER}{}^{P}(t) \quad (44)$$

A set of optimum control factors $Sch_{gad_{opt}}(k,t)^{P2P(p)}$, $U_{ex_{opt}}{}^{A\rightarrow B}(t)$.] are produced by solving the optimization problem for a connected pair of homes, home (A) and home (B). Where the homes (A) and (B) are represented by the numbers n. In contrast to operating separately, the result produced by the collaborative optimization method must provide a better circumstance. The following set of limitations must be met before an agreement may be reached

$$P_{home}{}^{A}\left(\left[U_{ex_{opt}}{}^{A\rightarrow B}(t)Sch_{gad_{opt}}(k,t)^{P2P(A)}\right]\right) < P_{home}{}^{A}\left(\left[Sch_{gad_{opt}}(k,t)^{single(A)}\right]\right) \tag{45}$$

$$P_{home}{}^{B}\left(\left[U_{ex_{opt}}{}^{B\rightarrow A}(t)Sch_{gad_{opt}}(k,t)^{P2P(B)}\right]\right) < P_{home}{}^{B}\left(\left[Sch_{gad_{opt}}(i,t)^{single(B)}\right]\right) \tag{46}$$

12.2.1. Selection level

From the P2PEML findings, the Selection factor is used to sequentially choose the most probable pair of houses: select pairs of homes from available pairs $p_{homes} * (p_{homes} - 1)/2$, where the P_{P2P} function value is less than the total of each price function $P_{home}{}^{single(A)}$.; The pair with the greatest % decrease in household energy price is chosen from among these viable couples (e.g. couple i, j).

The selection process is carried out in the data cloud, where the selection level identifies all the potential pairings of homes and generates the final ideal settings in data arrays to be ready for calling from the HEMS platforms in each home. Subsequently, each house's HEMS framework retrieves the final decisions $[Sch_{gad_{opt}}(k,t)^{P2P(A)}, U_{ex_{opt}}{}^{A\rightarrow B}(t)]$, from the selection hierarchy (data cloud) and applies these final settings. The lowest layer of the HEMS framework in-house (A) receives this profile and uses the rule-driven regulator to establish the ideal power configuration for the battery degrading. The shiftable devices in home (A) are controlled by appliance scheduling profiles called " $Sch_{gad_{opt}}(k,t)^{P2P(A)}$", which are delivered instantly to each equipment in household (A).

13. Simulations and result

In single line diagram as shown in Fig. 22 there are three clusters, as each cluster composed of 200 homes (peer). Based on formulation of load forecasting mathematical model we assume that the power demand $D_{peer}{}^{U}(t)$, of every home (peer) in each cluster is 5kw. Hence, power requirement $D_{cluster}{}^{U}(t)$ of each cluster is 1000 kw respectively. So, total load $D_{cluster\ T}{}^{U}(t)$ equals 3000 kw. To maintain the $D_{cluster}{}^{U}(t)$, of each cluster we have to perform the scheduling among clusters. Whenever, one cluster is in power shortage the other two clusters transfer power (see Fig. 23).

If other two clusters are unable to supply power, then power storage bank, RER or utility supply power to maintain balance between demand and supply. In order to validate our presumptions, we took into account three different scenarios.

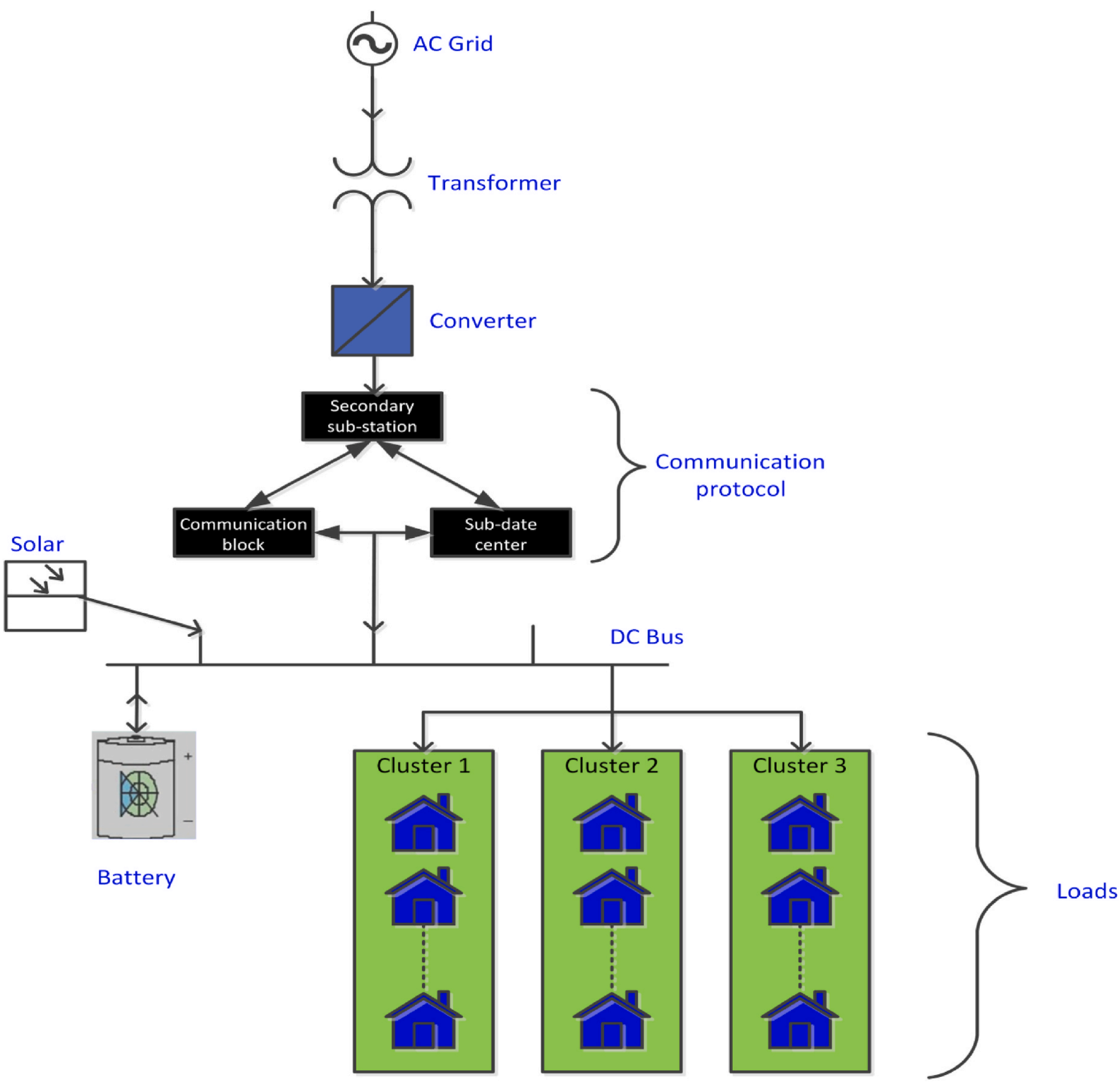

Fig. 22. Single line diagram of HEMS cluster mode.

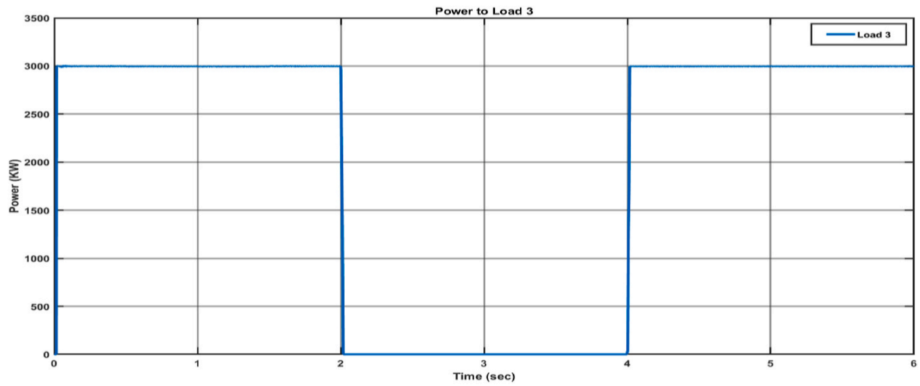

Fig. 23. Power to load 1.

13.1. Case 1

Load of $D_{cluster\ 1}{}^{U}(t) = 1000$ kw are required for cluster 1, having two clusters, RER, battery and utility supply. To verify and explain the scenario in Fig. 22 for power balance through simulation result. Fig. 26 depict three separate case studies that we took into consideration. Fig. 26 illustrates the phenomenon. When each of the three clusters indicated in Fig. 26 are operational. An unexpected power short fall will occur at (0s–1s), (1.5s–2s), (3.5s–5s) as shown in Fig. 26. Its predicted supply need should be $U^{j}(t) = 1000$ kW, however its actual/genuine supply $U1^{g}(t) = 0$ at given intervals. Therefore, this circumstance will result in failure in cluster 1 if appropriate corrective action is not performed. Because of this, the actual supply $U1^{a}(t)$ must be raised in accordance with our anticipated supply need, i.e., $U1^{g}(t) = U1^{j}(t)$, in order to satisfy our forecast demand requirement of $U1^{j}(t)$. This condition will thus be present in cluster 1. Performing so, we can easily eliminate the power issue in cluster 1 by achieving a balanced power between $= U1^{j}(t)$, and $D1^{j}(t)$. This may be accomplished by utilizing clusters of the HEMS integrated smart transmission network, RER, or utility supply. The procedure can be executed by transferring extra active power from the other clusters at interval (0s–0.5s) from cluster 3 $(U3^{g}(t) = 3000\ kw)$, at (0.5s–1s) either from cluster 2 $(U2^{g}(t) = 3000\ kw)$ or cluster 3 $(U3^{g}(t) = 3000\ kw)$, at (1.5s–2s) from cluster 3 $(U3^{g}(t) = 3000\ kw)$, at (3.5s–4s) from cluster 2 $(U2^{g}(t) = 3000\ kw)$, at (4s–5s) either from cluster 2 $(U2^{g}(t) = 3000\ kw)$ or cluster 3 $(U3^{g}(t) = 3000$ kw), as shown in Fig. 26.

13.2. Case 2

Load of $D_{cluster\ 2}{}^{U}(t) = 1000$ kw are required for cluster 1, having two clusters, utility supply RER and battery storage. To explain and justify the scenario in Fig. 26 for power equilibrium through simulation result. Fig. 26 shows three case studies that we took into account. Fig. 26 shows the phenomenon. When each of the three clusters indicated in Fig. 26 are operational. At cluster 2, an unexpected power short fall will occur at (0s–0.5s), (2.5s–3.5s) as shown in Fig. 24. Its forecasted supply need should be $U2^{j}(t) = 1000$ kW, however its actual supply $U2^{g}(t) = 0$ at given intervals. Therefore, this circumstance will result in failure in cluster 2 if appropriate corrective action is not performed. Because of this, the actual supply $U2^{g}(t)$ must be raised in accordance with our anticipated supply need, i.e., $U2^{g}(t) = U2^{j}(t)$, in order to satisfy our forecast demand requirement of $U2^{j}(t)$. This condition will thus be present in cluster 2. Performing so, we can easily eliminate the power issue in cluster 2 by achieving a balanced power between $U2^{j}(t)$ and $D2^{j}(t)$. This may be accomplished by utilizing clusters of the HEMS integrated smart transmission network, RER, or utility supply. The procedure can be executed by transferring extra active power from the other clusters at interval (0s–0.5s) from cluster 3 $(U3^{g}(t) = 3000\ kw)$, at (2s–2.5s) either from cluster 1 $(U1^{g}(t) = 3000\ kw)$ or cluster 3 $(U3^{g}(t) = 3000\ kw)$, at (2.5s–3.5s) from cluster 1 $(U1^{g}(t) = 3000\ kw)$, at (5s–6s) from cluster 1 $(U1^{g}(t) = 3000\ kw)$, or cluster 3 $(U3^{g}(t) = 3000$ kw), as shown in Fig. 26.

13.3. Case 3

Load of $D_{cluster\ 3}{}^{U}(t) = 1000$ kw are required for cluster 3, having two clusters, utility supply RER and battery storage. To explain and justify the scenario in Fig. 26 for power equilibrium through simulation result. Fig. 26 shows three case studies that we took into account. Fig. 26 shows the phenomenon. When each of the three clusters indicated in Fig. 26 are operational. At cluster 3, an unexpected power short fall will occur at (2s–4s) as shown in Fig. 25. Its forecasted supply need should be $U3^{j}(t) = 1000$ kW, however its actual supply $U3^{g}(t) = 0$ at given intervals. Therefore, this circumstance will result in failure in cluster 3 if appropriate corrective action is not performed. Because of this, the actual supply $U3^{g}(t)$ must be raised in accordance with our anticipated supply need, i.e., $U3^{g}(t) = U3^{j}(t)$, in order to satisfy our predicted

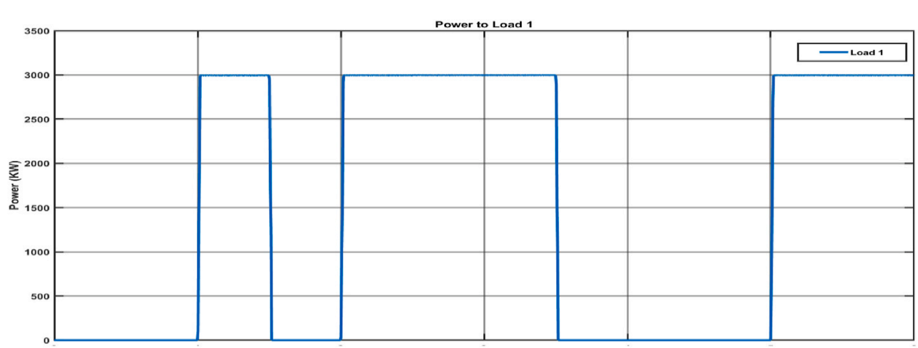

Fig. 24. Power to load 2.

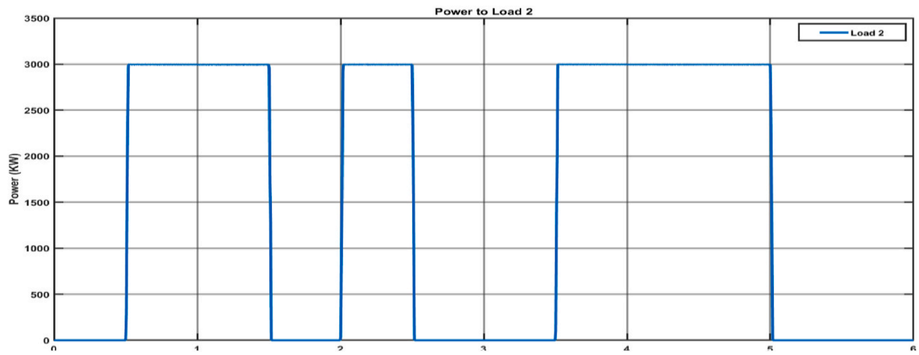

Fig. 25. Power to load 3.

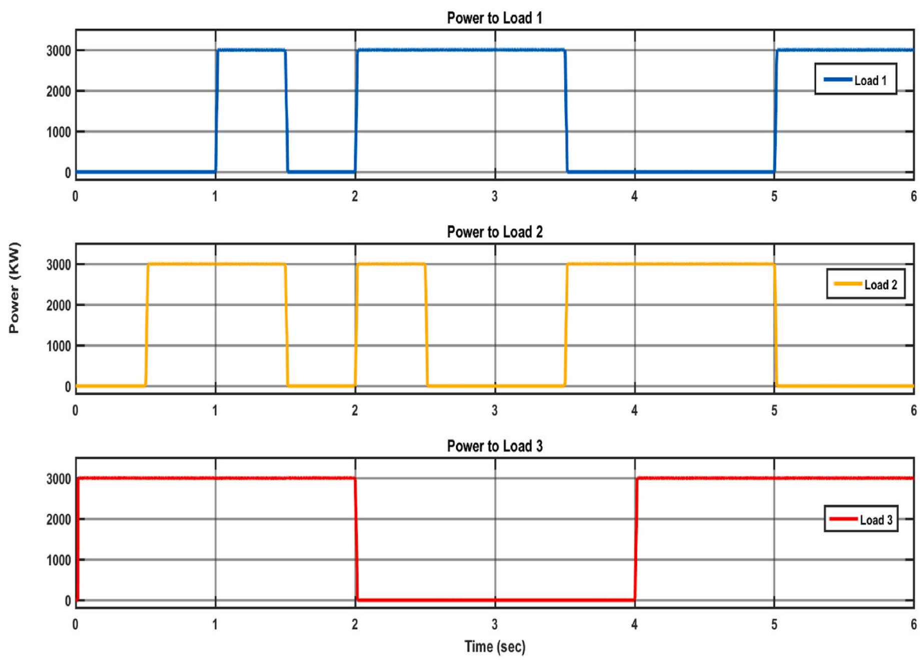

Fig. 26. Power to load 1, load 2, load 3.

demand requirement of $U3^j(t)$. This condition will thus be present in cluster 3. Performing so, we can easily eliminate the power issue in cluster 3 by achieving a balanced power between $U3^j(t)$ and $D3^j(t)$. This may be accomplished by utilizing clusters of the HEMS integrated smart transmission network, RER, or utility supply. The procedure can be executed by transferring extra active power from the other clusters at interval (2s–2.5s) from cluster 1 $(U1^g(t) = 3000\ kw)$ or $(U2^g(t) = 3000\ kw)$, at (2.5s–3s) either from cluster 1 $(U1^g(t) = 3000\ kw)$, at (3s–3.5s) from cluster 1 $(U1^g(t) = 3000\ kw)$, at (3.5s–4s) from cluster 2 $(U2^g(t) = 3000\ kw)$, as shown in Fig. 26.

A simulation model for the P2P HEMs load scheduling framework that is both reliable and optimum is also suggested in order to critically analyses the P2P HEMs network, resulting in smart communities that make cities smart.

To confirm the efficacy of our provided framework in actual time, we will contrast our suggested HEMS stochastic and fault evaluation approaches with a HEMS case investigation and actual model. The system developed for this study has been implemented as a component of a pilot project at a testbed residence of the Smart Campus Green & Smart Building Park, Benguerir, Morocco. The scope of this project includes. A 3.75 kwh grid-connected photovoltaic power structure, variable loads, essential loads, and 6.4 kWh of stored energy batteries are all present. The proposed HEMS structure is based on two complementary regulate methods: demand-side administration, which plans and supervises flexible equipment for the optimal load profile modulation, and supply-side administration, which timetables and regulates power transport among generation, utilization, and conserving agents. The primary determinants of energy flow management are grid power costs, user preferences, and data predictions (such as photovoltaic power and weather). The two developed control algorithms are combined in an AI-based multiple-purpose optimization technique to simultaneously maximize comfort factor and minimize costs. A flexible operating approach for the system is shown in Fig. 27. It is evident that a " Tracking Unit" gathers and keeps the information gathered from the various sensors and meters in a database. The "Information Administration Section," which includes a sub-module devoted to forecasting, includes the database as one of its components. The data is visualized using a "Human–Machine Interface" (HMI), which offers extensive insight into the system's past, present, and future aspects. Via the HMI module, the user can additionally interact with the system by specifying a desired level of convenience. These comprise the dynamic part of the optimization problem that the "Decision-Making Module" is meant to resolve, along with the measured and anticipated data. Actuators are controlled by a "Implementation Module" which provides them with instructions in a collection of adjusting points. The optimization algorithm's results after determining the optimal way to run the system. Based on this

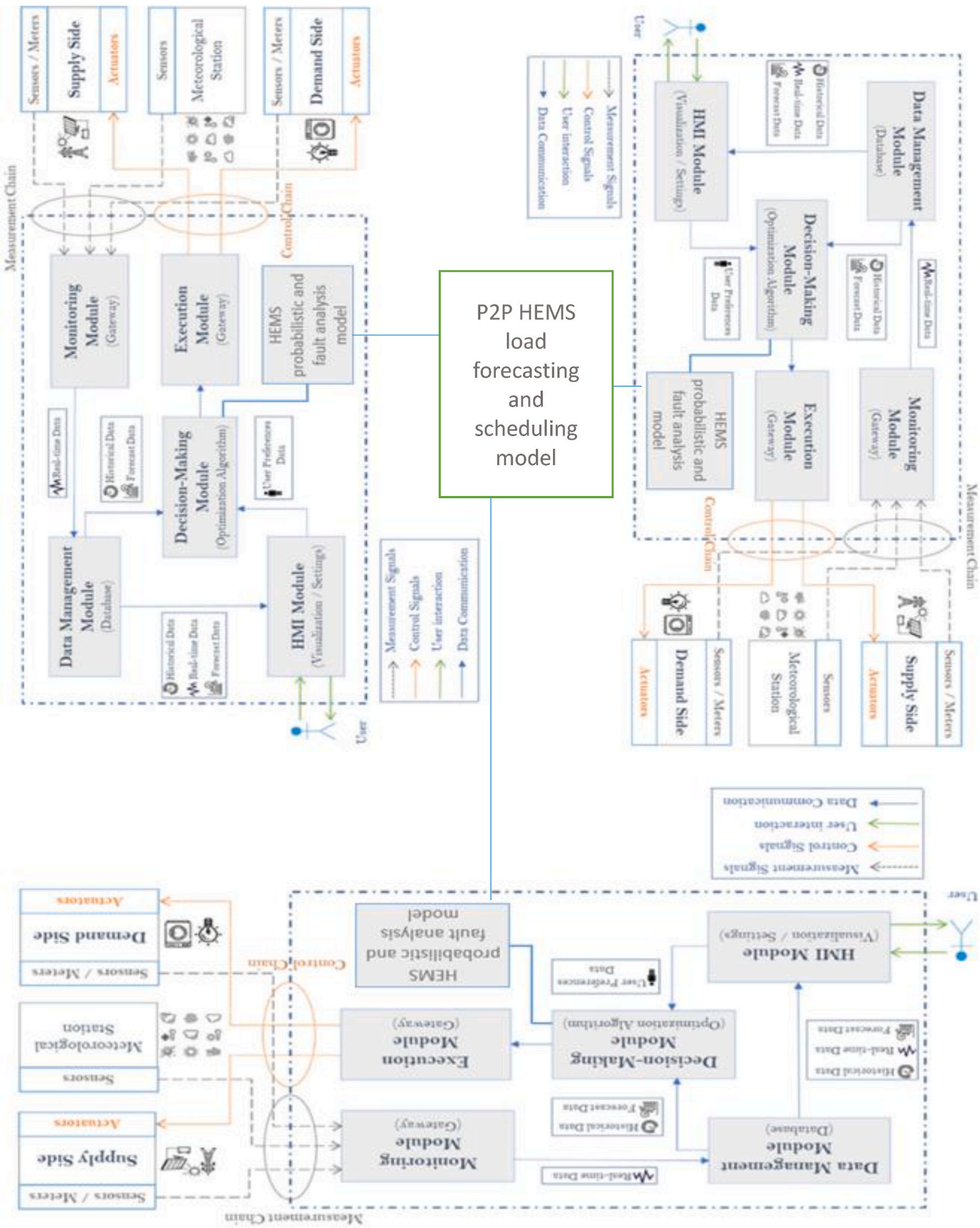

Fig. 27. A modular functional architecture of the case study P2P HEMS.

description, it is significant that the structure uses a measurement chain and a control chain to operate in a closed loop. The unified HEMS section that follows will contain information on the general physical architecture. The focus will then shift to the decision-making module, with control strategies being developed to monitor both demand and supply [468].

The supply and demand side management can be satisfied if we incorporate our suggested general P2P HEMS stochastic and failure assessment models with the decision-making module, as seen in Fig. 27. This will balance demand and generation. The objectives of optimization are to minimize costs and maximize user comfort, taking into account electricity pricing, consumer preferences, and predictions for solar energy production. Our proposed model can be applied to a wide range of real-world situations and case studies because it can balance various demand and supply scenarios by implementing an uncooperating backup.

14. P2P challenges

P2P energy trading is an advanced technique allowing consumers

Table 10
Summary of P2P energy trading structure, procedure, market design, trading platform, trading algorithm, pricing mechanism, existing and futuristic P2P approaches and our work. Note: PY: published year; TD: Trading Structure; P: Procedure; MD: Market Design; TP: Trading Platform; TA: Trading Algorithm; PM: Pricing Mechanism; PA: P2P Approaches; GT: Game Theory; B: Blockchain; S: Simulation; O: Optimization; A: Algorithm; DA: Distributed Algorithm; C: Consensus; MMD: Multi market driven; MR: Multiple Regression; ES: Exponential Smoothing; IRLS: Iterative Reweighted Least-Squares; AR: Autoregressive; MA: Moving Average; ARMA: Autoregressive Moving-Average; ARIMA: Autoregressive Integrated Moving-Average; GA: Genetic algorithm; SVM: Support Vector Machine; AD: Adaptive Demand; ES: Expert Systems; ANN: Artificial Neural Network; FL: Fuzzy logic; LP: Linear Programming; MILP: Mixed-Integer Linear Programming; NLP: Nonlinear Programming; MINLP: Mixed-Integer Non-Linear Programming; PSO: Particle Swarm Optimization; GA: Genetic Algorithm; SA: Simulated Annealing; CO: Colony Optimization; EA: Evolutionary Algorithms; ANFIS: Adaptive Neural Fuzzy Inference System; EI: Energy internet; SDN: SDN; FL: Federated Learning; RL: Reinforcement Learning; M: Metaverse; DDT: Digital Twin Technology; AI: Artificial Intelligence EV: EV (V2G & G2V); DS: Data science; IoT: Internet of Things; CC: Cloud Computing; Reference: Ref.

PY	Duration	TS	P	MD	TP	TA	PM	GT	B	S	O	A	DA	C	MMD
2016	2012–2016	✓	×	×	×	×	×	✓	×	×	×	×	×	×	×
2017	2011–2017	×	×	×	×	✓	×	×	×	×	×	×	×	×	×
2017	2010–2017	×	×	×	×	✓	×	✓	×	×	×	×	×	×	×
2018	2011–2018	×	×	×	×	×	×	✓	✓	×	×	×	×	×	×
2018	2010–2018	✓	×	×	×	✓	×	×	✓	×	×	×	×	×	×
2019	2011–2019	✓	×	×	×	×	×	✓	×	×	×	×	×	✓	✓
2020	2012–2020	✓	×	✓	✓	×	×	✓	✓	×	×	✓	✓	×	×
2020	2010–2020	✓	×	✓	×	×	×	✓	✓	×	✓	×	✓	×	×
2021	2012–2021	×	×	×	✓	×	✓	✓	✓	✓	×	×	×	×	×
2021	2013–2021	✓	×	×	×	×	×	✓	✓	×	×	×	×	×	×
2022	2012–2022	✓	✓	✓	×	×	×	✓	✓	✓	✓	×	×	×	×
2023	2014–2023	×	×	✓	✓	✓	×	✓	✓	×	×	×	×	×	×
Our work	Up to 2024	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

MR	ES	IRLS	AR	MA	ARMA	ARIMA	GA	SVM	AD	ES	ANN	FL	LP	MILP
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×	×	×	×	×	×	×	×	×	×	×	×	×	×	×
✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

NLP	MINLP	PSO	GA	SA	CO	EA	ANFIS	EI	SDN	FL	RL	M	DTT	AI
×	×	×	×	×	×	×	×	×	×	×	×	×	×	×
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×	×	×	×	×	×	×	×	×	×	×	×	×	×	×
✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

EV	DS	IoT	CC	REVIEW	Ref
×	×	×	×	Highlight the structure and compatibility characteristics of modules for P2P energy trading.	[482]
×	×	×	×	The emphasis of the paper is on business models that function analogous to providers in the electrical market.	[483]

(*continued on next page*)

Table 10 (*continued*)

EV	DS	IoT	CC	REVIEW	Ref
×	×	×	×	Three representative market paradigms proposed by researcher.	[484]
×	×	×	×	Give a thorough analysis of current demand response optimization models in P2P network.	[485]
×	×	×	×	To identify and classify the essential components and technologies involved in P2P energy trading	[486]
×	×	×	×	To recognize and categories the essential components and innovations involved in P2P energy trading.	[487]
×	×	×	×	This report summarizes and analyses the global evolution of peer-to-peer energy trading.	[488]
×	×	×	×	Discuss the technological techniques that have been widely employed to overcome the issues with P2P transactions.	[489]
×	×	×	×	This study presents an overview of P2P energy trading that is required to comprehend the present methods, difficulties, and next research.	[490]
×	×	×	×	The paper covers how various issues are handled within the four tiers of P2P architecture.	[491]
×	×	×	×	This article offers a thorough examination of current P2P energy trading investigation and execution efforts.	[492]
×	×	×	×	This study examines the P2P technology in developing nations while also analyzing current business strategies and trade regulations.	[293]
✓	✓	✓	✓	Comprehensive survey with critical analysis of the structure, procedure, market design, trading platform & algorithm, price mechanism, (method, process, applications, pros and cons) futuristic and Optimal load forecasting and scheduling control strategies for P2P energy trading in HEMS clusters. A simulation model for the P2P HEMs load scheduling framework is presented that is both reliable and optimum is also suggested in order to critically analyze the P2P HEMs network, resulting in smart communities that make cities smart.	Our work

Table 11
P2P energy trading limitations and challenges.

Open research Challenges	limitations
Different pricing frameworks, intricate regulatory frameworks, and constrained price freedom as a result of current market constraints	How to resolve pricing arrangements, and legislation?
Maintaining regulatory compliance while striking a balance between pricing transparency and effectiveness	How to approach Pricing approaches, marketplace regulations, equilibrium liability, and infrastructure limitations?
Making sure the platform can manage a high number of subscribers and operations while maintaining scaling, speed, and protection	How to Sustain a high volume of users and transactions?
Absence of regulations and protocols for compatibility across many platforms and infrastructure	How to provide compatibility between various P2P energy trading systems, gadgets, and industry players?
Tackling cybersecurity threats, guaranteeing adherence to confidentiality laws, and fostering player confidence in data safety protocols	How to safeguard the confidentiality and protection of members' private information, financial transactions, and electrical data?
Incorporating peer-to-peer trading into the current grid architecture while maintaining grid stability and guaranteeing grid dependability in the face of variable renewable energy production	How to provide reliability of the grid, frequency oversight, voltage supervision, and system rebalancing?
Obtaining forward funding for innovation in technology, electrical grid improvements, and clean energy initiatives	Where to provide Making investments?
Solving issues with cost, authenticity, and trustworthiness	How to recognize and acceptance of the consumers?
Guaranteeing each participant's equitable participation in the market. Tackling issues with manipulation of markets and exploitative behavior	How to provide supremacy and sovereignty in the Marketplace?

and businesses to proactively purchase and sell power among each other (see Table 10). Usually, transactions are facilitated via decentralized technology. P2P energy trading has several advantages but also confronts certain challenges as shown in Table .11: P2P energy trading might not be appropriate to the current energy regulations. Hence, the regulatory system must change to accommodate peer-to-peer trading while maintaining reliability and consumer safety [469]; It can be challenging to integrate P2P energy trading with the current energy system. Technologies must be developed by utilities to control the variations in energy generation and utilization that P2P trading might cause [470]; P2P energy trading depends on players exchanging data, such as rates and consumption trends. In order to gain users' confidence, it is crucial to guarantee the confidentiality and safeguarding of this data [471]; Various P2P energy trading structures may make use of distinct requirements and technology. It can be challenging to achieve interoperability across various platforms, making it hard for members of one platform to conduct commerce with users of others [472]; The framework must be capable to handle growing numbers of transactions as P2P energy trading expands to incorporate more players, which might put an added burden on current systems [473]; P2P trading usually functions best in connection with energy-storing technologies like batteries. However, numerous prospective players may find it difficult to enter due to the price and lack of access to these technologies [474]; It is difficult to create a fair and effective market structure for P2P energy trading. A difficult balance must be struck when choosing price structures, taxes, and rewards that promote participation while preventing market manipulation [475]; It can be difficult to persuade customers to take part in peer-to-peer energy trading. Many people are unwilling to alter their energy usage patterns because they are unknown with the idea [476]; P2P energy trading requires reliable internet access along with accessibility to smart meters. Establishing P2P trading may not be feasible in places with inadequate infrastructure [477]; It is difficult to assure that P2P energy trade benefits all participants, especially vulnerable and low-income groups. Avoid circumstances in which only a small group of people can benefit [478]; It might be difficult to create a viable business strategy for P2P energy trading networks. While providing people with competitive rates, they must make money [479]; The concepts of decentralization and fair competition may be undermined by monopolistic behavior as a result of the rise of dominating firms in the P2P energy trading industry [480]. P2P energy trading must become a viable and inclusive choice for the future of energy distribution by working together with stakeholders, including authorities, energy companies, technology vendors, and customers, to find answers to these problems [481].

15. Conclusion

With the growth of dispersed energy resources over the past few decades, delivery networks have altered. Energy generation and utilization have undergone significant change. Proliferating energy consumers have taken on a significant role in energy production, enabling a more open and decentralized system. Facilitating the transition to a P2P marketplace to include prosumers into the electrical network is a study area that many scientists have concentrated on. P2P energy trading is a key strategy for increasing the adaptability of the energy system for a low-carbon energy transition. Additionally, P2P enables the expansion of household usage of green power. Energy management is now a service that aims to use energy effectively and responsibly in expert configurations. HEMSs reduce the overall electricity generation and utilization of homes by anticipating and planning ahead for the use of household devices. This article provided an overview of HEMS in P2P energy trading and discussed the need for load forecasting and scheduling in P2P intelligent environments to ensure the whole power structure operates smoothly. This paper aims to provide researchers with a general understanding of the various concepts in P2P energy trading including structure, procedure, market design, trading platforms, trading algorithms, P2P approaches, forecasting and scheduling strategies in P2P framework. This article discusses upcoming developments in P2P technology and the way it may impact HEMS operations in the coming years. The P2P HEMS load prediction and scheduling framework is offered with a probabilistic and fault evaluation that upholds load flow balance between need and supply between three P2P clusters as result shown via simulation. A simulation model for the P2P HEMs load scheduling framework that is both reliable and optimum is also suggested in order to critically analyze the P2P HEMs network, this enables a more intelligent, more integrated, and adaptive metropolitan future, and this convergence heralds a pivotal age in urban history. Peer-to-peer (P2P) energy trading integrated into a smart city architecture is a novel and revolutionary method to energy management. By introducing decentralized, centered around communities' methods, this paradigm improves energy adaptability, empowers locals, and advances sustainability's overarching objectives. Thus, the path to smart living entails not just redesigning the city but also how people engage with and perceive their residences in the bigger picture of a smart city. Future work and P2P challenges are also highlighted. The results of this review can help researchers, decision-makers, and business advocates create new energy policies and procedures for decentralized energy programs.

16. Future work

In the subject of smart electricity structures, peer-to-peer energy trading is one of the new and well-liked study fields, as shown by the research papers. P2P energy trading offers a number of promising opportunities for the possible future of energy delivery: P2P energy trading enables residents and neighborhoods to take authority over their energy usage and generation. It promotes energy autonomy and regional independence by allowing households with clean energy sources to sell surplus power to neighbors directly; The grid integration of clean energy sources can be facilitated through P2P trading. It enables users to effectively sell excess clean energy, which lessens dependency on fossil fuels and helps to create an improved sustainable energy balance; P2P networks can increase the energy grid's robustness by facilitating local energy trade. The societies can continue to trade power locally amid grid outages or disasters, thereby decreasing exposure to centralized failures; P2P energy trading is becoming more widely used, which may result in lower greenhouse gas emissions. It promotes the use of clean sources of energy and lessens the need for power produced from fossil fuels; P2P energy trade can increase the availability of energy in neglected regions in both developed and developing areas. Off-grid populations may exchange locally produced energy using P2P technologies to lessen energy poverty; P2P trading allows consumers to bargain prices via local producers rather than depending entirely on centralized utility rates, therefore protecting them against changes in energy prices.

CRediT authorship contribution statement

Ali Raza: Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Investigation, Data curation, Conceptualization. **Li Jingzhao:** Writing – review & editing, Writing – original draft, Supervision, Resources, Methodology, Investigation, Conceptualization. **Muhammad Adnan:** Writing – review & editing, Supervision, Resources, Investigation, Data curation. **Ijaz Ahmad:** Writing – review & editing, Writing – original draft, Software, Data curation, Conceptualization.

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.

Data availability

Data will be made available on request.

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