Journal of Parallel and Distributed Computing 143 (2020) 148–166

Contents lists available at ScienceDirect

J. Parallel Distrib. Comput.

journal homepage: www.elsevier.com/locate/jpdc

Blockchain and AI amalgamation for energy cloud management: Challenges, solutions, and future directions

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ARTICLE INFO

Article history:
Received 28 March 2020
Received in revised form 27 April 2020
Accepted 11 May 2020
Available online 22 May 2020

Keywords:
Blockchain
AI
Energy cloud management
Smart grid

ABSTRACT

In the recent years, the Smart Grid (SG) system faces various challenges like the ever-increasing energy demand, the enormous growth of renewable energy sources (RES) with distributed energy generation (EG), the extensive Internet of Things (IoT) devices adaptation, the emerging security threats, and the foremost goal of sustaining the SG stability, efficiency and reliability. To cope up these issues there exists, the energy cloud management (ECM) system, which combines the infrastructure for energy, with intelligent energy usage and value-added services as per consumers demand. To achieve these, efficient demand-side forecasting and secure data transmission are the key factors. The energy management issues pose extreme gravity in finding sustainable solutions by using the blockchain (BC) and Artificial Intelligence (AI). AI-based techniques support various services such as energy load prediction, classification of the consumer, load management, and analysis where the BC provides data immutability and trust mechanism for secure energy management. Therefore, this paper reviews several existing AI-based approaches along with the advantages and challenges of integrating the BC technology and AI in the ECM system. We presented a decentralized AI-based ECM framework for energy management using BC and validate it using a case study. It is shown that how BC and AI can be used to mitigate ECM with security and privacy issues. Finally, we highlighted the open research issues and challenges of the BC-AI-based ECM system.

1. Introduction

With the advent of large-scale IoT devices, advancements in cyber–physical systems, and other electric devices, the demand for energy is growing at a rapid pace in comparison to the energy sources in the modern energy distribution system, i.e., SG. The conventional EG sources such as coal, nuclear, and thermal power plants are limited in nature. Probably, the generation of energy from RES such as solar, hydro, and wind energy can play a significant role to fulfill the consumer energy demands. Traditionally, the conventional and RES sources generates the energy at the supply side and distribute it to the consumers at the demand-side. Managing the increasing energy demands at the supply side is restricted due to the SG infrastructure constraints and limited resources. So, the other way to manage the energy at the demand-side is by the usage of the distributed RES, which is known as energy cloud. It raises new challenges to the SG system, such as the management of this local distribution of energy at the demand-side. The main emphasis of SG is to facilitate the local production of energy by the prosumers (the one who can produce and consume energy) and consumption [94] by consumers using peer-to-peer (P2P) energy trading to reduce the burden on SG during the transmission losses, technical losses, and non-technical losses [101].

The continuous usage of energy generates a huge amount of data through the smart meters (SM) and advanced metering infrastructure (AMI) in SG. This motivates the management of energy at the demand side and plays a significant role to have the demand-side ECM [106]. The emergent technologies such as AI and BC have a good potential to transform the SG system. AI can provide energy estimation of the consumers by analyzing the data collected from the SMs. These estimations can serve as the monetary benefit for the consumers of the ECM system towards a demand-side flexible marketplace.

The energy data can be integrated with personal data of the consumers (only consumes energy) and prosumers like data collected from smartphones or card payments. Energy firms can act

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https://doi.org/10.1016/j.jpdc.2020.05.004
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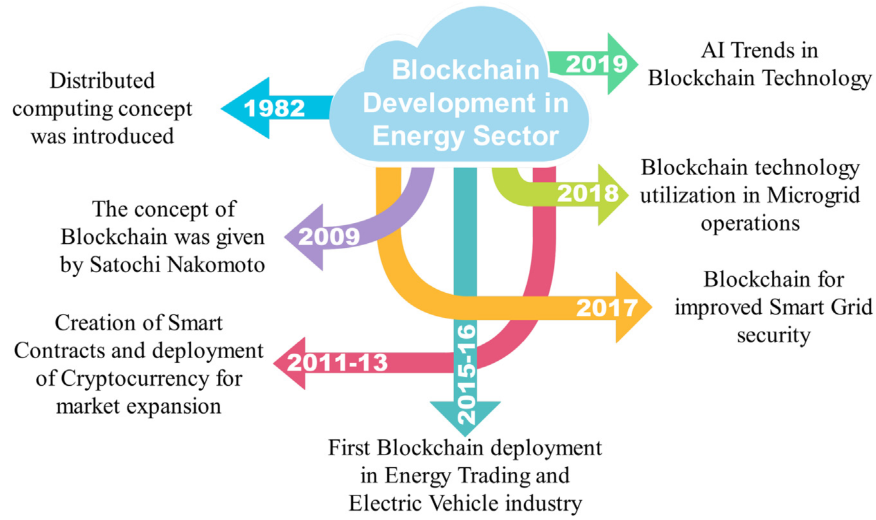


Fig. 1. Timeline of BC evolution in energy sector.

as data vendors for this prediction and AI can be used to estimates the lifestyles of consumers and classify it into categories. AI assists consumers in predicting the dynamic price change in each hour, which steer the use of household appliances such as AC, refrigerator, and washing machine to a specific time (at lowest energy prices). For example, AI offers the energy optimization by adjusting the heating effect at the residential houses in Finland [14]. AI can help to solve the issue of heating and cooling in a cold country like Finland and the USA. AI also offers various services in the energy sector, such as data digitization, demand forecasting, Resource management, Energy storage facilitation, system failure prediction, and prevention.

AI can revolutionize the SG across the globe. It reduces the risks, the manual work, and improves the energy data management [51]. Though before the bright future, AI has to deal with a lot of challenges, such as lack of practical expertise and outdated infrastructure before revolutionizing the SG system [13]. AI prediction helps to estimate the energy demands. After getting the accurate forecast results, the energy supply is required at the consumer end. With the outdated SG infrastructure, this is rarely possible to meet the high demand for energy in real-time, which introduces P2P energy trading at the demand-side using the ECM system. There are various techniques available for the management of energy clouds, such as cloud computing (CC) and fog computing (FC) [16,91]. Both CC and FC use a centralized architecture for ECM. Though CC and FC have several advantages even then, they have the single-point-failure, security, and privacy issues for P2P energy trading in the ECM system. To secure P2P energy trading, BC is one of the prominent solutions. To ensure the improvement in continuous load prediction, a BC provides the complete transparent system between the seller and buyer [69]. Compared to other technologies, BC showed a breakneck pace in the development of the energy industry. A brief time-line of the advent of BC and its utilization in the energy sector is shown in Fig. 1. It shows the introduction of distributed computing concept, introduced in the 1990s and various stages of its development till today [110,112].

AI algorithms (such as ANN and SVM) in P2P energy trading allow the upsurge of microgrids interconnection. They enhance energy production and energy sale directly to prosumer's neighbors. The integration of BC and AI makes the SG more democratic, transparent, and provides mindful use of energy. It reduces the cost of energy, reduces electricity bills, promotes green energy, and incentivizing the understanding of advance metering infrastructure (AMI), IoT, and RES technologies [115,143]. This integration provides energy data forecasting with real-time alerts that can help the SG system to detect and resolve issues as soon as possible.

1.1. Scope of the survey

We conduct a comprehensive survey of various survey articles related to ECM. The opportunities and challenges related to the security and privacy aspects of ECM were discussed in [62]. Several surveys have been conducted in the different application areas of energy management, such as AI-based Load Profiling (LP) and demand response [27,154]. To the best of our knowledge, most of the surveys have highlighted the application of AI in ECM and the application of BC in ECM independently and the integration of both is not explored yet. The proposed survey covers the solution taxonomy and BC-enabled secure AI-model ECM system framework. The proposed framework mitigates the utmost security issues such as energy information disclosure, network traffic congestion, eavesdropping, data modification, Sybil, spoofing, replay, and DoS attacks.

Only few researches focused on non-intrusive monitoring of load using disaggregation algorithms [41,156]. AI methods for non-technical loss (NTL) detection in ECM were reviewed in [4] based on SM data, though the NTL issues were discussed in detail in [161]. The consumer behavior was explored using an AI algorithm. Load prediction is the major application area of the AI-based ECM system. AI enhances the prediction of demand accuracy using load data of SMs. The recent developments in the area of load prediction were critically studied in [58], and various AI techniques for load prediction were discussed in [32]. While AI techniques provide accurate prediction and classification for the consumer demand, the BC is used for distributed management of energy in SG [110]. For example, Pop et al. [117] presented an architecture based on the BC for demand response verification.

Aitzhan et al. [5] combined BC with a decentralized energy trading network for privacy preservation. Guan et al. [48] proposed and data aggregation scheme and privacy-preserving for the ECM system. To handle the security issues and classify the cyberattack, a deep neural network was proposed by Zhou et al. [161] in the SG. Several research proposals have been explored in energy management [3,39,76,106,127], which still need further exploration. So, we present this survey to mitigate the energy management issue at the demand-side. Table 1 presents the summarization of these surveys and their differences in comparison to the existing proposals.

Table 1
Comparison between the proposed and existing surveys on energy management.

Author	Year	Description	Benefits	Findings
Wang *et al.* [154]	2015	Discussed various AI-based load profiling techniques and its application to demand response in ECM system	In-depth survey on challenges of ECM system along with their solutions	Need to secure the ECM system along with energy prediction
Hu *et al.* [62]	2016	Discuss the security challenges and opportunities in ECM system	Parallely considered both security issues in energy management and big data analytics. Identified the vulnerable surfaces of energy management	Not discussed in detail about the non-technical loss detection at demand-side, need to secure energy management system
Chicco *et al.* [28]	2016	Discussed the customer behavior analysis using AI techniques	Application areas of ECM are discussed, also highlighted the challenges in designing efficient and cost effective techniques for customer behavior analysis	Trust between customer and SG need to be ensured, uncertain costs need to be predicted at the deployment phase of the technique,
Ahmad *et al.* [4]	2017	AI-based non-technical loss detection has been discussed in detail	To save the energy and reduce the EG burden on Smart grid	Need to secure the non-technical loss detection methodology
Glauner *et al.* [161]	2017	Discussed the challenges of non-technical loss detection using AI	In-depth survey on challenges of non-technical loss detection in ECM along with their solutions	Not discussed the security aspect of the non-technical loss detection in ECM system
Yang *et al.* [153]	2017	Discussed the usage of BC technology in decentralized energy management	Presented a framework to manage energy over Internet in a decentralized way	Not discussed anything about the load prediction and load balancing
stepfant *et al.* [127]	2018	Present a survey on BC-based energy management for collective self-consumption	In-dept discussion on demand-side energy management in ECM	The implementation aspect of the BC based ECM architecture is not discussed in detail
Javied *et al.* [69]	2018	Presented the strategic energy management technique for cloud infrastructure	In-dept discussion on cloud-based energy management	Considered the centralized infrastructure having single point of failure
Musleh *et al.* [110]	2019	Present a survey on BC Applications in ECM system	Detailed discussion on the existing frameworks	The energy prediction using AI is not discussed with the existing BC based framework.
Johanning *et al.* [76]	2019	A critical survey of disruptive Potential of BC in peer-to-peer energy Trade in ECM system	Detailed discussion on the existing BC based frameworks	Need to include energy prediction to manage the demand-response using BC based framework
Erturk *et al.* [39]	2019	Discussed the benefits and risks of BC technologies in ECM system	Highlight the existing BC based frameworks and its benefits	Need to include demand prediction at demand-side to mitigate the demand-response issue
Miglani *et al.* [106]	2020	A survey on challenges and solution of BC for Internet of Energy management	Exhaustive discussion of BC application in ECM system	The AI aspect and implementation of the BC based framework is not discussed in detail
Ahl *et al.* [3]	2020	Explore the BC for the ECM system with the case study of Japan	A case study is discussed to show the effectiveness of the BC applicability in ECM	The energy prediction to manage the demand-response using BC based framework is not discussed in detail
Proposed survey	2020	Survey the potential of AI and BC in the ECM system and proposed BC-based AI-model architecture to mitigate demand-side of load management	The integration of BC and AI mitigates the security and privacy issue along with energy management issue at demand-side. Also, reduce the EG burden on SG.	–

1.2. Motivation

The foremost motivations of this survey are as follows:

- The significance, security requirement, and deployment of ECM are one of the major focuses to investigate this area. The organizations like DeepMind, Verv, NEXTracker, Verdigris, and many more are participating much in the development and deployment of ECM for efficient management of energy with a high level of security. This creates interest between the researchers across the globe and motivates us to accomplish this study.
- The existing literature mostly focused on conventional ECM, BC-based ECM, AI-based ECM, and very limited literature exists, which focused on AI integrated BC-based ECM system. Hence, there is a need to highlights the integration of AI and BC-based secure ECM systems.
- Researchers working in the ECM field will get motivated from this systematic and comprehensive survey to make the ECM system efficient, secure, and cost-effective.

1.3. Research contributions

In this paper, we present a rigorous survey on BC and AI-based energy management for ECM. We highlight the various challenges in both the energy management schemes and their solutions. In view of aforementioned discussion, following are the main contributions of this paper.

- We present a structured and systematized survey on security issues in existing BC and AI-based energy management for SG systems.
- We highlight the benefits by integration of BC and AI techniques in developing a new ecosystem of decentralized ECM and presented a solution taxonomy.
- Then, we proposed a decentralized and secure integrated architecture of ECM.
- Finally, we highlight the various open issues and future recommendations to ensure secure and reliable ECM.

1.4. Survey organization

The structure of the survey is as shown in Fig. 2. Section 2 provides the background of ECM, AI, BC, and its integration. In Section 3, we highlighted the bibliometric analysis used for the survey. In Section 4, we discuss the proposed BC-based AI ECM architecture. Section 5 discusses the proposed taxonomy and its layers. In Section 6, we discuss the open issues and challenges of ECM and present a case study in Section 7. Finally, Section 8 concludes the paper.

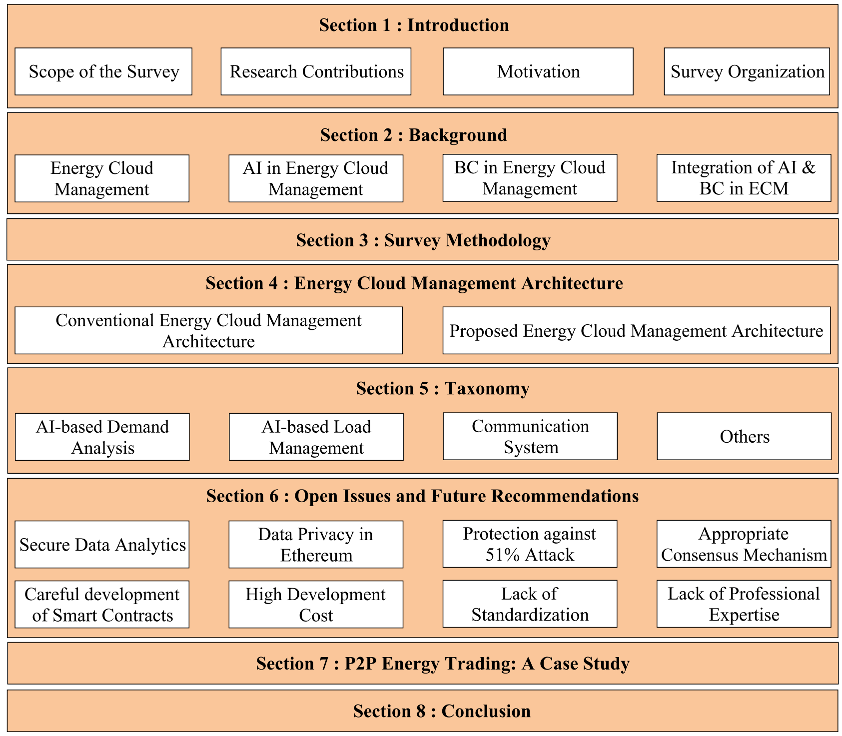


Fig. 2. Roadmap of the survey.

2. Background

This section focuses on the background and importance of ECM, AI, BC, and their integration to secure the energy data shared among the consumers and the SG. This section is bifurcated into four subsections. Firstly, we discuss the importance and significance of ECM and its market value in the coming years. Secondly, we discuss the usage of AI in ECM for energy load forecasting. In the third subsection, we focused on the significance of BC in ECM for secure energy management and sharing among the consumers and prosumers. At last, we highlight the usefulness of the integration of AI and BC in ECM for accurate forecasting and better security.

2.1. Energy cloud management

It is similar to the cloud computing architecture that helps to increase energy-efficiency by managing the demand and supply of consumers in the SG system [15]. It efficiently distributes the energy resources among the consumers. The evolution of energy cloud from centralized to distributed generations is as shown in Fig. 3. The essential components of the energy cloud are demand response, advanced systems to manage interoperability among different SGs, energy storage, and energy efficiency [18,101]. It has a wider scope and acceptability in all energy sectors (renewable and non-renewable). As per the report of *Markets and Markets*, the global market size of energy cloud was USD 5.12 billion in 2016 and it can grow up to USD 15.18 billion in 2021 [103].

2.2. Artificial intelligence in energy cloud management

AI becomes essential in the energy sector and having a great potential in designing the future energy systems. So, AI becomes a technological trend that has the capability to transform any business sector. AI algorithms can handle Terabytes or even Petabytes of heterogeneous data (structured or unstructured) [52]. It can

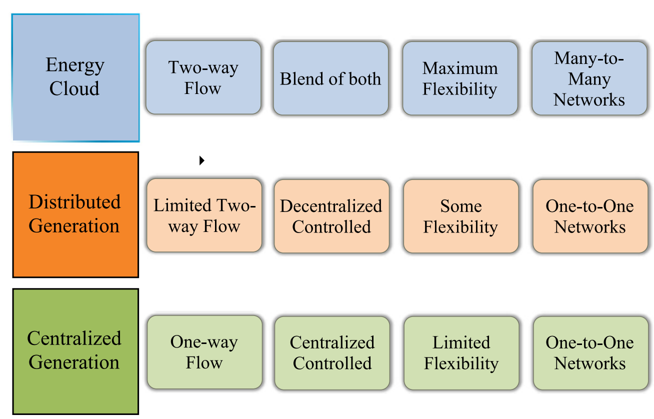


Fig. 3. Evolution of energy cloud.

identify the patterns from the data to make predictions or recommendations. AI in the energy sector created a boom and each firm is moving towards its adoption for balancing the energy demand and supply appropriately. AI algorithms help to manage the energy demands and supply, forecast the consumer energy needs through the SM installed at each consumer side, and recommend the energy usage patterns to the consumers that can help to reduce their energy bills. The global market of AI in energy management was $4439.1 million and is forecasted to $12,200.9 million by 2024 [114]. AI helps to improve the SG stability, predict the energy flow, analyze large amount of data, and increases the system efficiency [90]. Many startups around the world has been initiated that are using the power of AI in managing the energy. The details of few of the companies are as shown in Table 2.

2.3. BC in energy cloud management

BC is an influential technology devised by Satoshi Nakamoto in 2008. It is a sequential chain of blocks connected through the

Table 2
Startups working in energy management using AI techniques [47].

Company	Country	Vision
AppORchid	USA	Using deep learning and natural language processing to understand the behavior of the SG under any condition
Alpiq (Grid-Sense)	Switzerland	It focused on understanding the consumer behavior which helps in optimizing the energy consumption
Siemens	Germany	It focused on optimizing the combustion of gas in turbines
Hazama Ando	Japan	Designed an AI-based smart energy system for energy management
DeepMind	UK	It is owned by Google and is used to reduce energy consumption of their data center
NEX-Tracker	USA	Using AI to increase the energy production with easier management and quick operations
Upside	UK	Working on AI-based algorithms that can manage the demand response of all devices which are running parallely
GE energy	USA	Using AI techniques to increase the efficiency of wind turbine with lower maintenance
Verdigris	USA	Using AI in managing the electricity signals of the building based on the type of equipment
Open energy	UK	Using AI and machine learning algorithms for managing the demand side responses

hash value of previous block [24]. A block can contain information like header, index of the block, timestamp, current block hash, previous block hash, and the transactions. BC is a peer-to-peer (P2P) distributed ledger in which each member has a copy of the whole ledger. It is categorized as public, private, and consortium chains [105]. A Public BC is completely decentralized ledger whereas, the private and consortium BCs are centralized (owned by one organization) and semi-decentralized respectively. BT has various benefits such as decentralization, no third-party involvement, transparency, traceability, and anonymity.

In view of the above mentioned benefits, BC technology has gained the interest of firms which are dealing with energy management. BC has proved one of the most remarkable innovations of the era in energy sector. Many organizations across the globe are investing much in acquiring the BT for secure ECM. Different forecasting bodies such as BIS [57], Mordor Intelligence [66], Zion Market Search [162], and Global Market Insights [64] has predicted the energy demands up to next 5 years as shown in Fig. 4. The most useful application of BC in the energy sector is secure energy trading [130].

Both the prosumers and consumers can participate in energy trading over the BC network as a seller and buyer respectively. BC provides transparency, immutability, and security to the energy data. The energy trading process is entirely automatic through the execution of smart contracts (SC) without the involvement of any third-party organization. Some of the crucial benefits of involving BC in the energy sector are (i) reduced energy bills due to transparency in BC, (ii) instant access to energy data (peer-to-peer energy trading), (iii) no data modification attack (immutability), and (iv) instant payment settlements using SCs.

To purchase or trade energy over the BC network need cryptocurrencies. Some of the most usable cryptocurrencies for energy trading are Matrexcoin, EnergiToken, KWHCoin, and many more. Table 3 shows the comparison of energy cryptocurrencies over the parameters price, BC type, the country used, and market capitalization.

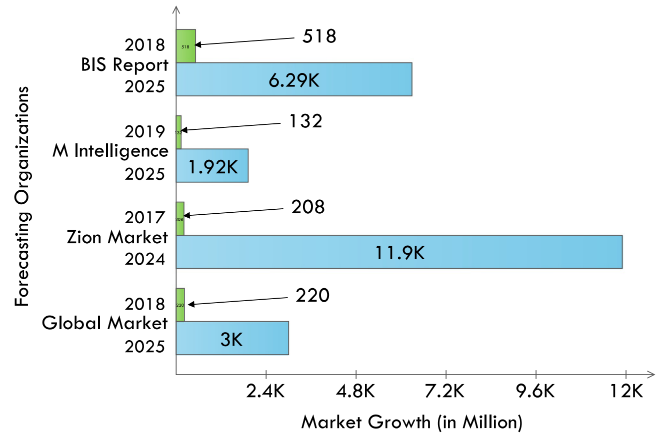


Fig. 4. Forecasting of blockchain in energy sector by the different organizations.

2.4. Integration of AI and blockchain in energy cloud management

The integration of AI and BC technology with ECM is one of the most researchable areas. The AI-based ECM system has various decision-making results, which can be utilized by different entities in a different way, such as energy price prediction for energy suppliers and consumers. The consumer will focus on reducing his energy bills using AI-based price prediction, whereas the energy supplier analyses the same price precision data to increase his profits. From this integration, ECM will get benefited in different areas such as energy yield predictions, increase RES usage, improve energy performance (By choosing smart policies), grid management (to handle multiple sources of energy), distributed energy trading and many more. The Few of the benefits of integration areas as follows [122]:

- *Increased Security*: Transactions (or information) in BC are inherently secured through the encryption techniques. It is quite useful in storing the personalized energy trading data. Researchers across the globe are working on developing AI algorithms to process the encrypted data without exposing it [65]. AI also helps to predict the possible security breaches in advance.
- *Decision Accuracy*: AI enables the computers to think like humans for efficient decision making. Transparency characteristic of BC helps AI to analyze the energy data securely to make an intelligent decision on energy management. It also ensures the analyzed energy data (stored as a transaction in a BC) is temper-proof which increases the decision accuracy at demand side energy management.
- *Information Tracing*: BC helps the participating members to trace the decisions made by AI on the energy data in ECM. This helps in auditing process with high confidence and trust as the data is temper-proof [44].
- *Decentralized Intelligence*: BC is a temper-proof decentralized system, whereas the AI is an intelligent system. It allows to distribute intelligence among all systems of the participating members [23].

3. Survey methodology

This section discusses the detail procedures and methodology opted for this study as shown in Fig. 5. Following the various steps mentioned in Fig. 5 leads to a systematic literature review [83,84,102].

We have used authenticated online sources such as IEEEXplore, ACM Digital Library, Springer, and Science Direct (Elsevier)

Table 3
Comparison of energy cryptocurrencies developed by different countries [60].

Cryptocurrency	Price	Market capitalization	Country used	BC type
Matrexcoin (MAC)	USD 0.01088	USD 187.31k	NA	Ethereum
EnergiToken (ETK)	USD 0.00010	USD 178.67k	UK	Ethereum
KWHCoin (KWH)	USD 0.00001	USD 9.47k	USA	Ethereum
WePower (WPR)	USD 0.00544	USD 3.31M	Estonia	Ethereum
Grid+	USD 0.03113	USD 1.22M	USA	Ethereum
Energo (TSL)	USD 0.00016	USD 96.82k	China	QTUM
SolarCoin (SLR)	USD 0.01026	USD 588.4k	NA	Own BC
SunContract (SNC)	USD 0.01568	USD 1.92M	Republic of Slovenia	Ethereum
Power ledger (POWR)	USD 0.05281	USD 22.65M	Australia	Ethereum
Klimatas (KTS)	USD 0.01300	USD 9.39k	The Netherlands	Own Blockchain
Energycoin (ENRG)	USD 0.00099	USD 121.1k	NA	Own BC
Pylon Network (PYLNT)	USD 0.36415	USD 196.06k	Spain	Ethereum

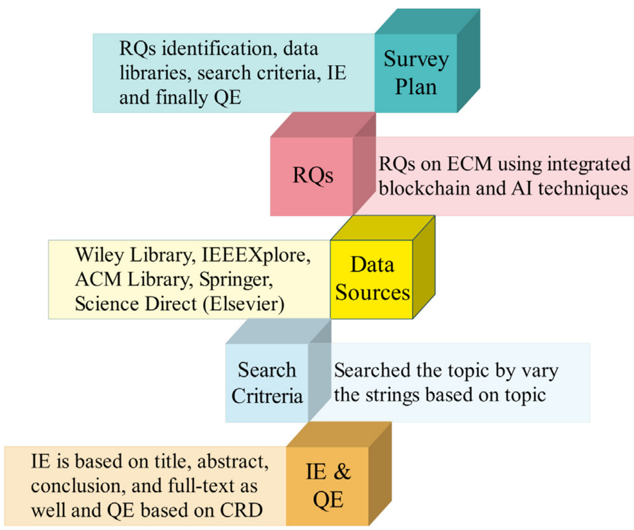


Fig. 5. Steps to be followed in conducting the survey.

Table 4
Quality evaluation questions.

Q. No.	Description of question	Answer
Q1	Does the research paper highlight the security and privacy issues in ECM and its mitigation techniques?	YES
	The papers add an overview of security and privacy issues in ECM where the word "security and privacy issues" are not being used. Are such papers excluded from the literature survey?	NO
Q2	Do the abstract, title, and full text of research paper describe the "security and privacy issues of ECM"?	YES
	Have the abstract, title, and full text of research paper described the security and privacy issues in ECM?	NO

to search the existing literature using different set of keywords like "energy cloud management" ("demand response management" AND "energy load management" AND "energy load prediction" AND "block chain in load management"). Initially, we found the literature on supply side and demand side demand response management (DRM). Later, we found the papers on AI-based future load forecasting for energy demand at the SG. Finally, the literature on BC-based secure energy management was found. In the proposed survey, we have identified the relevant literature on a different aspect of energy management in the ECM system, such as AI-based energy usage prediction, AI-based load management, secure communication system, and consumer data security and privacy. Some of the research questions (RQ) have been recognized alongside their research objectives (RO) for this comprehensive and systematic survey as follows:
RQ1: What are the issues and challenges in ECM system?
RO1: It aims to explore issues and challenges in the ECM system.
RQ2: What are the issues that mitigate using AI-based techniques and its benefit in the ECM system?
RO2: It is expected to search each issue which has been addressed using the various existing mechanism to ensure efficient AI-based ECM system.
RQ3: Which types of attacks exist and how to address those attacks?
RO3: It is expected to search each attack and address the identified attacks using various existing mechanisms and BC technology to ensure a secure ECM system.
RQ4: What are the benefits of integrating BC and AI techniques to improve the effectiveness of the ECM system?
RO4: It aims to recognize different parameters used to evaluate the effectiveness of the ECM system while integrating BC and AI.
RQ5: What are the different solutions that exist in for ECM system?
RO5: It is expected to classify the entire literature and look for a better solution of identified issues in the ECM system and compare the existing solution with the proposed solution.

Our search procedure was iterative until the scope of the search gets narrow down. Based on the outcome, we started filtering out the papers under inclusion–exclusion (IE) criteria based on abstract, conclusion, title, and full-text. Then, we come up with 110 publications that are either directly or indirectly related to our research.

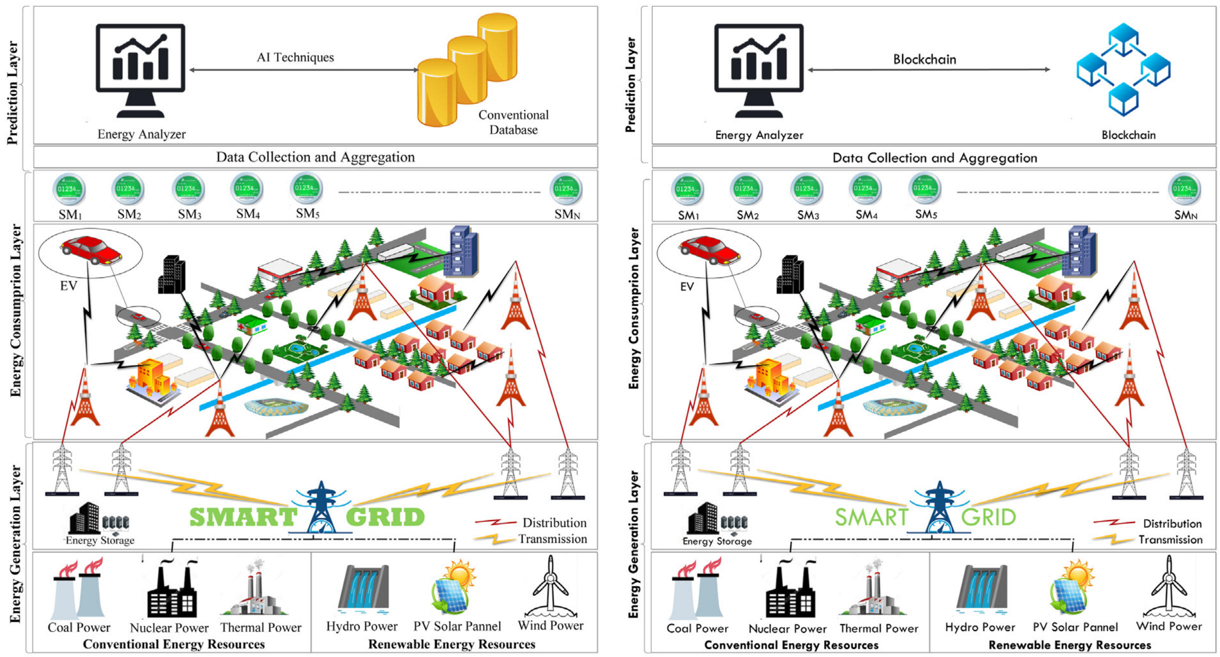
The quality evaluation was carried out on the identified research papers as per the guidelines of *Database of Abstracts of Reviews of Effects* (DARE) and*Center for Reviews and Dissemination* (CRD) [83]. Various quality questions are given in Table 4 which are used to select the quality research papers.

4. The energy cloud management architecture

This section discusses the conventional and BC-AI-based energy management architectures. The detailed description of these architectures are as follows:

4.1. Conventional energy cloud management architecture

The aim of an ECM architecture is to manage, predict, and secure the energy demands of the consumers. Many authors across the globe are working on it and presented their proposed systems, which are based on either BC or AI techniques, as mentioned in Table 1. Figs. 6 and 6b show the AI-based and BC-based conventional ECM architectures respectively with the following layers (i) EG layer, (ii) energy consumption (EC) layer, and (iii) prediction layer. Description of these layers are as follows:



(a) AI-based energy management.

(b) Blockchain-based energy management [19].

Fig. 6. Conventional demand-Side energy management systems for SG.

4.1.1. The EG layer

Energy is a key driver for the working of all household appliances, commercial systems, and EVs. Generating an excessive volume of energy is crucial, as more number of consumers are using large number of electrical appliances and EVs at the same time. So, this arises the need for smart energy distribution system, that fulfill the energy needs of consumers efficiently and appropriately. A SG along with the EG sources (such as conventional and renewable) of the layer can take care of aforementioned increased energy demands. Conventional EG sources include coal, nuclear, and thermal power plants, whereas hydro, PV solar panel, and wind are the renewable sources. The amount of energy generated from the EG sources is stored in the SG's local energy storage system. A SG can transmit the stored energy to the energy distribution points, which can further distribute to the consumers. An advanced metering infrastructure (AMI) at SG can take care of appropriate distribution of energy without any wastage.

4.1.2. The EC layer

This layer comprises of consumers and prosumers of energy, which can be residential or commercial in nature. They utilize energy for the functioning of their electrical appliances, machines, and EVs. The energy demand of each different consumer varies and is based on their frequency and time of appliances usage. So, to meet out the varying energy demands of the consumers, a SG at EG layer plays a vital role. A SM is installed at each residential and commercial site that keep record of the energy usage of the respective consumer. A SM is sharing its data with AMI at the supply side (SG side) for the proper distribution of energy.

4.1.3. The prediction layer

As the population is increasing, the number of electrical appliances is also increasing, which arises the need for a huge generation of energy. But due to the availability of limited EG infrastructure, the demanding energy needs of all consumers cannot be fulfilled. But, in another way, it can be managed so that consumers cannot be able to feel short of energy. This would be possible only if the supply side knows the future energy needs of the consumer. So, the function of the prediction layer is to forecast the energy requirements of the consumers using AI algorithms. The appropriate amount of energy can be distributed to the consumer at appropriate time only if we know about their energy needs prior. This layer collects the energy data from SMs and aggregates it for prediction. The energy analyzer component of this layer, as depicted in Fig. 6a along with AI techniques, performs the energy prediction and stores the results into cloud infrastructure, which is more vulnerable to security attacks [9,17]. The architecture in Fig. 6b uses a BC to store the consumer's energy analysis data, which strengthens the security and establishes the trust [54].

As per the literature, many researchers around the world have given either AI-based or BC-based ECM solutions. A very few discussion on the integration of these two technologies for ECM in the SG environment. So, in this paper, we propose an architecture based on the integration of AI and BC technologies. It predicts and secures the analysis data for proper energy distribution. The working of proposed architecture is explained in the next subsection.

4.2. The proposed energy cloud management

The conventional ECM systems either predict energy demands or secure the analysis data, but not both. So, we need a system that can do both energy load forecasting and data security. Our proposed system as shown in Fig. 7 is capable of doing both. It collectively works without the involvement of trusted third-party systems. It meets the crucial needs for future energy consumption. The bottom two layers in the proposed architecture are the same as the conventional system, as explained in Section 4.1. The bottom layer is the combination of EG and SG layer, whereas the other layer is the EC layer. The third layer of the proposed system is the prediction layer, which is different from the conventional system's prediction layer.

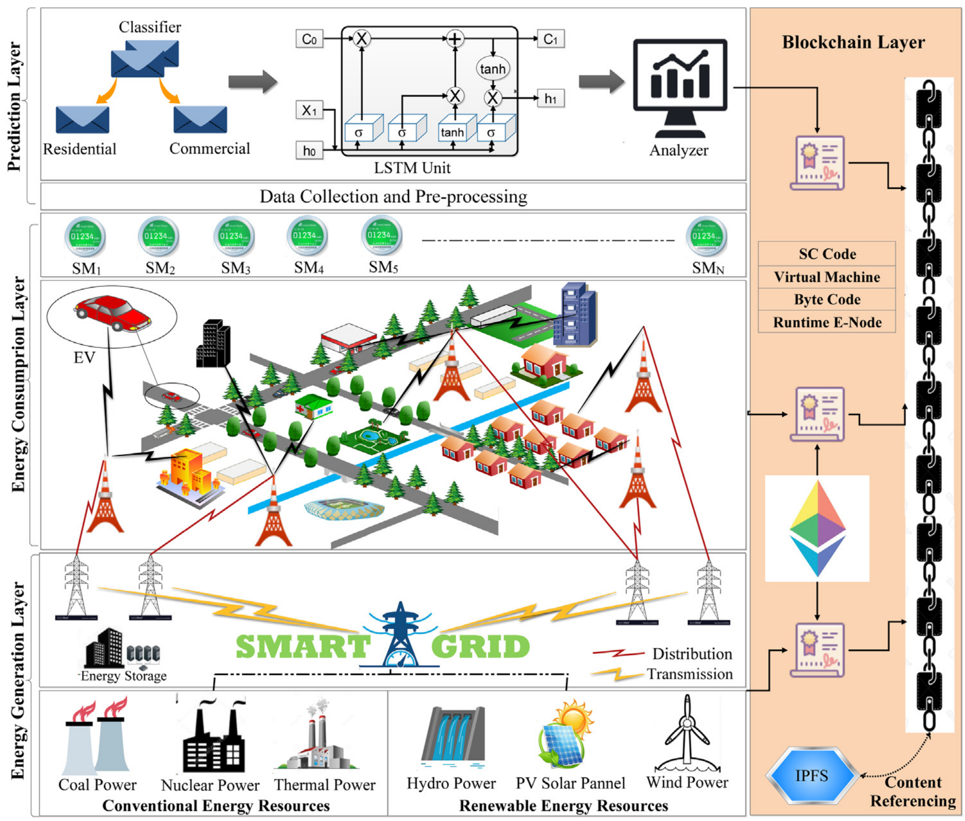


Fig. 7. Blockchain and AI-based energy cloud management architecture.

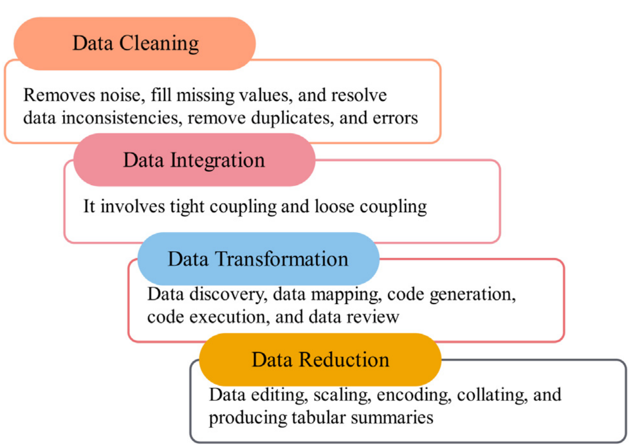


Fig. 8. Data pre-processing steps.

4.2.1. Prediction layer of the proposed system

This layer collects energy data from the consumers SMs at the EC layer and pre-processes it. Data pre-processing involves data cleaning, data integration, data transformation, and data reduction, as shown in Fig. 8. Data cleaning removes the noise from the data, filled the missing data, and resolve data inconsistencies. Data integration combines heterogeneous data from different sources to address the representation conflict; data transformation normalizes and aggregates the data. Data reduction reduces the size of data without affecting its properties for better prediction results.

After pre-processing, the energy data is classified (using traditional algorithms such as decision tree, SVM, random forest, and Bayes theorem classifier) as residential or commercial, because of the huge difference in energy usages in both the sectors. Once the data is classified, it is then fed into the LSTM model for energy load forecasting. LSTM is a sequential learning model for data forecasting and is well suitable for time-series data [53]. It forecasts the energy load consumption of the consumers based on the previous energy data usage. Once the energy data is forecasted, the results are being passed to the analyzer for analysis of bifurcated demands. Finally, the result is stored in the BC as a transaction for security purposes [55].

4.2.2. Blockchain layer

BC is a distributed immutable ledger that maintains the trust among its participating members like prosumers, consumers, and SG. It is common to all three layers of the proposed architecture. The amount of energy generated at the supply side (EG layer) is stored in the BC as a transaction for transparency. All energy usages and demands of the consumers and prosumers are kept into the BC as a transaction for security against the data modification attacks. A data is stored into the BC only if it satisfies the conditions of the digital SC. It eliminates the need for third party systems in order to maintain the trust between the participating members of the BC.

In this paper, we consider an Ethereum (public) BC because of the interoperability issues in the private BC. All prosumers and consumer's energy requests (i.e., purchase and sell) are stored in the BC to maintain the trust, reliability, and security of the data. The reliability and fault tolerance of data is maintained through the consensus algorithms. To store one word in a chain of block is very costly, i.e., ≈ USD 550, which is not affordable. To overcome this cost issue, we store our data in the distributed and immutable IPFS storage.

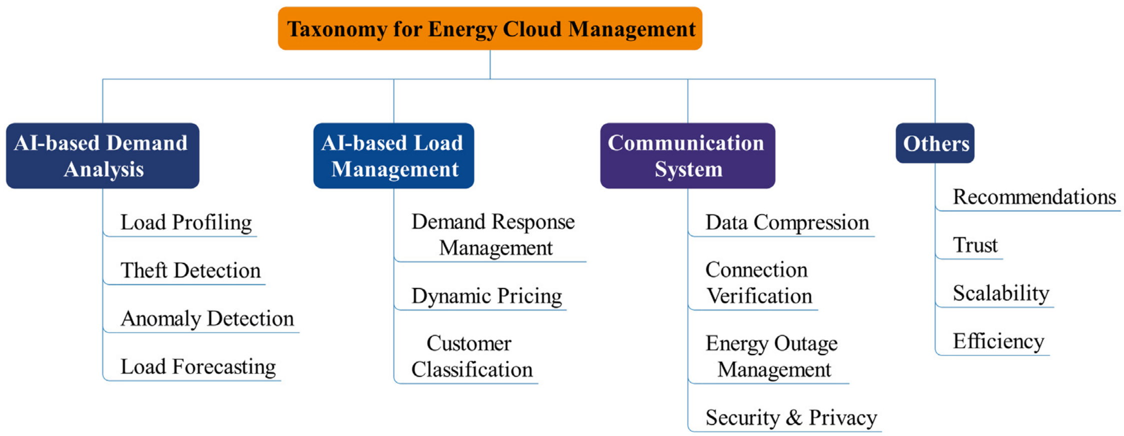


Fig. 9. Taxonomy for energy cloud management.

5. Taxonomy

The detailed taxonomy of ECM is summarized in Fig. 9. The solution taxonomy is categorized based on the collected literature and survey methodology applied using the Kitchenham guidelines. It covers different application areas of the AI integrated BC-based ECM system for the demand side. For example, various demand analysis techniques like LP and anomaly detection are required in the ECM system, so it is discussed in the *AI-based Demand Analysis* subsection. Then, DRM, dynamic pricing, and customer classification is categorized as *AI-based Load management* subsection. Further, the ECM communication infrastructure plays an important role in establishing a good communication system, so it is highlighted in *Communication System* subsection. The rest of the works (not covered in the previous subsection) has been focused in *Others* section. The detailed description of each existing approach is discussed in the following subsections.

5.1. AI-based demand analysis

This section is divided into four aspects of energy demand analysis: (i) load profiling, (ii) threat detection, (iii) anomaly detection, and (iv) load forecasting. The brief description about these aspects are as follows.

5.1.1. Load profiling

It denotes the classification of energy load curves based on consumer energy consumption behavior. It is categorized as direct-clustering and indirect-clustering LP. In case of direct-clustering LP, multiple AI techniques like K-means and hierarchical clustering can be directly applied to SM data [27,154,161]. However, in indirect-clustering, features are extracted before the clustering which includes dimensionality reduction [134], variability, load characteristics, and uncertainty-based approaches. There are few rudimentary problems associated with direct-clustering approach because of the dynamism of the real-time data. So, to dealt with, a dynamic clustering has been proposed in [20], which allows to capture the trends and behavior of LP. However, in indirect-clustering approaches the feature extraction is accompanied before the initiation of the clustering procedure. Dimensionality reduction and Principal component analysis (PCA) are the efficient ways to address an extraordinary dimensionality of SM [85]. PCA discloses the consumption behaviors of different LP and is also used to find the temporal and spatial patterns of LP [26]. The local and global features of SM data are important to find distinctive LP. Then, a mix model clustering method was used to obtain typical LP, and then the variability in residential LP was modeled using Markov decision processes and Markov chain [93]. Further, an unsupervised deep embedding has been for LP clustering and analysis [151].

5.1.2. Threat detection

Energy threat detection (TD) generally belongs to the bad or vulnerable data. A SM data is actually not always a bad data (temporal or unintentional data) but, it can be changed due to non-technical loss in node voltage. Here, the AI-based TD is classified as supervised TD (required labeled SM data) and unsupervised TD (used unlabeled SM data) [131]. Supervised TD consists of two steps: feature extraction and classification [77]. One of the prominent technique that has been comprehensively used in the field of TD is a support vector machine (SVM). An SVM based LP classification and rule-based TD has been elaborated in [33]. Then, a top-down approach based on SVM and decision tree was used in [73]. Further, unsupervised energy TD does not need the labels of consumer's energy data. An optimum-path forest clustering approach was proposed in [79] using Gaussian distribution. Here, the LP is TD if it is more than the threshold value. Then, the unsupervised energy TD method was proposed using the load prediction problem. In this case, if SM consumption is noticeably lower than the predicted consumption, then the TD is marked for the specific consumer [68]. The author Jokar et al. [77] has used SVM to detect various types of anomalies in the ECM system. Nagi et al. [111] also proposed an SVM-based approach to detect frauds on the irregular energy consumption pattern. Then, Depuru et al. [33] presented an SVM model for the classification of consumers as genuine or illegal. In [34], the ANN with SVM both approaches has been used to improve the efficiency of TD [73].

5.1.3. Anomaly detection

In this section, we highlight the unusual energy consumption patterns or missing energy data caused due to the failure of system such as data collection or communication systems. A system usually normalizes the daily energy consumption patterns generated from the SMs of residential or commercial or industrial sites. AI techniques are used for anomaly detection which are classified as a machine learning (ML)-based method or probability and statistic-based method [116]. A SM data is time-series data, so, the research work was concise to low-rank matrix-based, time-series-based, and time-window-based approaches. Further, the energy data cleaning approach was presented in [116] using optimally weighted average for both off-line and online scenarios. Later, the time-series energy data fed as an input to the artificial neural network (ANN) for anomaly detection [6]. Then, energy consumption classification and outlier removal techniques were used to handle data anomaly by Li et al. [95]. From security point of view, the handling of malicious data is also very crucial to prevent security attacks, which has been discussed in detail by Huang et al. [63]. Then real-time anomaly detection

Table 5
Comparative analysis of state-of-the-art approaches for AI-based demand analysis.

Author	Year	Description	Category of load analysis	Benefits	Findings
Koivisto *et al.* [85]	2013	Presented a clustering approach for load modeling in distribution systems	Load profiling	Principal component analysis is used to address the extraordinary dimensions in energy data generate from SM.	–
Chelmis *et al.* [26]	2015	Identified the temporal and spatial patterns of the energy load profile	Load profiling	A big data analytics for DRM and perform load cluster over space and time	Need to secure the proposed approach to restrict against the security threats during data analytics
Jokar *et al.* [77]	2016	Presented an energy theft detection technique using customers energy consumption pattern in advance metering infrastructure (AMI)	Theft detection	In-dept monitoring of abnormalities in energy consumption patterns and suspicious customers are identified using support vector machine	Technical loss need to be incorporate as part of the energy loss detection.
Jindal *et al.* [73]	2016	Presented an AI based technique to detect the theft of energy in ECM system.	Theft detection	A Decision tree and support vector machine based data analytics for theft detection in ECM system. A two-level data processing and analysis approach as the energy data processed by decision tree and fed as an input to the SVM classifier.	A real-time implementation is required for real-time scenarios.
Peppanen *et al.* [116]	2016	Presented an approach to handle bad or missing smart meter energy data through advanced data imputation	Anomaly detection	Identified the missing energy data as well as malicious data	Data security and privacy has not been included during anomaly detection
Araya *et al.* [11]	2017	An ensemble learning framework for anomaly detection in building energy consumption is proposed	Anomaly detection	A pattern-based anomaly classifier and collective contextual anomaly detection has been proposed using sliding window (CCAD-SW) framework which improved the sensitivity by 3.6% and reduced the false alarm rate by 2.7%.	Hybrid base classifiers are required to trained the different energy datasets.
Huang *et al.* [63]	2017	An approach for false data separation for data security in smart grids is discussed	Anomaly detection	Improved data security by removing bad data	Need to emphasis on the consumer privacy during anomaly detection
Stephen *et al.* [128]	2017	A sub-profile models for short term aggregated residential load forecasting approach	Load forecasting	Incorporate the practice theory for energy load forecasting.	Need to include long-term and medium-term load forecast also.
Jian *et al.* [70]	2018	Real-time anomaly detection for very short-term load forecasting	Anomaly detection	Bad data detection in real-time along with energy forecast for short-term.	For long-term forecasting need to be included to check the impact on anomaly detection.
Wen *et al.* [150]	2019	Presented an optimal load dispatch of microgrid community using AI technique.	Load profiling, Load forecasting	Application areas of microgrids are discussed with challenges in optimal load dispatch of solar power and load forecasting. It provides total costs reduction and improved system reliability.	Trust between consumer and smart grid need to be ensured, uncertain costs need to be predicted at the deployment phase of the technique.

was done using ML-approaches for short-term load prediction by Luo et al. [70]. Most of the research has been done using other approaches such as the K-means clustering approach [8], anomaly learning framework [11]. The author Liuet al. has used the Lambda architecture for online anomaly detection on energy consumption, which claimed high proficiency with large energy datasets [97].

5.1.4. Load forecasting

Energy load prediction is widely used in ECM system for efficient distribution of power, support operation, and planning process in SG. The retail and dynamic pricing of energy are also based on the prediction of energy consumption. The accurate prediction of energy consumption is nontrivial at lower levels compared to the top-level (feeder level). In this section, we examine the recent literature for load prediction based on whether the SM data has been used or not. In the lower level of load forecast, the SM data need to be used, whereas the top-level use high/low voltage data, which is required for the prediction. Another classification of load forecast is short-term (seconds or min or hours), medium-term (monthly consumption pattern), and long-tern forecast (yearly consumption or more). There various ML and DL approaches (a subset of AI techniques) such as SVM, auto-regression, ANN, recurrent neural network (RNN), LSTM, and their combinations are highly used in load forecasting [144]. The load forecasting for an educational building has been presented using a self-recurrent wavelet neural network to provide more accurate results compared to the wavelet neural network [29]. Further, a pooling-based deep-RNN was projected to learn spatial data shared between interconnected consumers. It outpaced SVR, ARIMA, and classical deep RNN. A Spatio-temporal load forecasting approach was anticipated by combining the ideas of compressive sensing and data decomposition [135,155]. Then, a shape-based approach for residential house electric energy load curve prediction and clustering has been made in [137]. A residential house load prediction disclosed that the ensembles outperformed compared to the individual prediction from traditional models [128]. Apart from these approaches, there are probabilistic forecasting approaches, which provide more information about future uncertainties compared to the point forecast. The work flow of this approach is as follows: (i) multiple-input generation scenario (ii) application of probabilistic forecasting model and (iii) output by using forecast combination or residual simulation [21,30,152].

Table 5 provides the detailed relative comparison of state-of-the-art approaches for AI-based demand analysis.

5.2. AI-based load management

This section summarized into three aspects of load management: (i) demand response management, (ii) dynamic pricing to meet the consumer energy demand, and (iii) customer classification. The brief description about these aspects are as follows.

5.2.1. Demand response management

DRM is one of the most critical tasks in ECM as it helps to balance the gap between energy demand and energy supply [45,133]. It shaves the valley or peak in load demand in real-time [74]. It delivers manifold benefits to the energy companies and consumers like reduction in energy bills of the consumers, real pricing schemes, load balancing, and increased involvement of the user. The DRM categories as (i) Control mechanism-based DRM programs, (ii) Motivational DRM programs, and (iii) Decision variable-based DRM programs. The control-based DRM programs are further categorized as centralized and distributed programs. The significant difference arises from a decision-making module for the execution of DRM programs. In centralized programs [100], load activation and scheduling are taken at the grid level while considering the number of consumers as a group. This is difficult to control for a larger area, so, a distributed architecture is used to establish a connection between consumers and energy suppliers. It is highly flexible, scalable, and more user friendly with their involvement [42].

The motivational DRM programs are classified as price-based or time-based DRM programs and incentive-based DRM programs. The price-based DRM programs work on the increasing the price of energy with respect to load demand; while the incentive-based DRM programs offer incentives to the consumers by reducing the energy consumption of consumer during peak hours using direct load control [75], demand bidding and emergency DRM programs mechanism [1]. Both methods benefit the ECM system to fill valleys and shave peaks in the load demand. Though, the price-based DRM programs are popular due to factors like time of use (TOU) pricing, critical peak pricing, and real-time pricing [12,38]. The decision variable-based DRM programs decide the schedules of energy in various homes using decision variables. In this scheduling scheme, the activation time is focused according to the requested load in order to choose the energy schedule [157].

5.2.2. Dynamic pricing

The demand for energy can be effectively managed by the pricing scheme. The energy prices classified as two fixed price and operational prices. In the fixed price, a certain amount is charged for per kWh of energy consumed by the consumer. However, it does not meet the dynamic requirement of energy consumption, and variable pricing or time-based pricing approach is required for the ECM system. The variable pricing schemes are ToU, Real-Time Pricing (RTP), and Critical Peak Pricing (CPP). The ToU is used for peak time and non-peak time; here, prices are sophisticated during peak time and comparatively low during the non-peak time [160]. The CPP handles the time of year when there is a high demand for energy compared to the peak-time of ToU. The RTP is based on price forecasting such as hourly pricing and day-ahead pricing scheme. The involvement of consumers helps to provide a better real-time price using a dynamic pricing scheme [82].

5.2.3. Customer classification

The characterizations of the consumers are diligently related to sociodemographic status. A naive challenge is to detect the consumer types according to their LP. The other challenges are recognizing sociodemographic data from LP and predict the energy load shapes using this information. Classification of consumers can be apprehended by a simple classification approach of AI like SVM or K-means clustering. For example, Linear SVM for customer classification has been presented using a non-negative sparse coding method based on usage patterns of LP [146]. This approach classifies the consumers into three categories residents, small and medium-sized enterprises (SME). Then, another work for consumer classification has been done using a fast Fourier transformation [159]. Several research work has been focused on retrieving sociodemographic information of consumers using SM data. A clustering-based approach has been proposed using a Dirichlet process mixture model for residential and commercial LP [46]. Further, multinomial logistic regression, supervised and unsupervised classification approach has been applied to lodge the household appliance characteristics to understand customer behavior [59,104,125].

Table 6 provides the detailed relative comparison of state-of-the-art approaches for AI-based load management.

5.3. Communication system

This section is divided into four aspects of communication analysis: (i) data compression, (ii) connection verification, (iii) energy outage management, and (iv) security and privacy. The brief description about these aspects are as follows.

5.3.1. Data compression

In a SG system, the SM plays a vital role in sensing the consumer's energy data continuously using various sensors and communicates it to the AMI. Hence, a massive volume of energy data is generated at the consumer-site ECM system. To manage these raw data in the database, a well-known method to address the issue of a large volume of energy data during communication is to compress the energy data. The energy data compressed and transmitted over the ECM communication network and later on decompressed on the destination system. The compression technique categorized as a lossy and lossless compression method [126]. Few energy data does not recover back in lossy compression, while in the lossless compression, all energy data is recuperated back after de-compression. In this repute, a common framework for data compression in regard to AMI has been presented in [61]. Then, a singular value decomposition approach has been proposed for lossy energy data compression and achieves spatial compression [31,108]. Further, a sparse illustration method has been employed to decompose LP into linear combinations of several partial energy usages of SM data [147]. There are several other techniques like a fuzzy-based technique for spatial compression, and embedded zero-tree wavelet transform technique for temporal compression that are found in the data compression literature [78,81,99]. More, a non-negative sparse coding method has been used for partial usage load patterns identification and energy data compression sparsely [145].

5.3.2. Connection verification

A communication system is one of the primary elements in the ECM system for handling bi-directional flow of important data like faults, energy load flow, etc., efficiently and reliably. In the ECM system, network connectivity assists energy distributors and energy companies in the decision-making of the energy distribution operation. For connection verification in demand-side, significant work has been carried out with respect to communication mechanism, control mechanism, modeling, and fault detection across the globe from the last decade [67,72]. Nevertheless, insofar as fault diagnosis is apprehensive, a variety of

Table 6
Comparative analysis of state-of-the-art approaches for AI-based load management.

Author	Year	Description	Category of load analysis	Benefits	Findings
Jindal *et al.* [74]	2016	A data analytical approach using support vector machine for DRM in smart grid is proposed	DRM	DRM for residential load using SVM.	Need to test the approach for commercial and industrial energy consumers also in order to verify the effectiveness of the system.
Aalami *et al.* [1]	2016	A nonlinear model for demand bidding and emergency demand response programs	DRM	Regulation of market clearing price-based on nonlinear models for energy demand management	The model is validated through a numerical study, a real-time implementation with performance evaluation is required.
Wang *et al.* [146]	2017	A sparse and redundant representation-based smart meter data compression and pattern extraction	Customer classification	Customer segmentation is based on the energy consumption data.	Data security and consumer privacy need to take care while accessing energy consumption data.
Jindal *et al.* [75]	2018	A data analytical demand response scheme for peak load reduction in smart grid.	DRM	A peak load reduction scheme to manage the residential consumer demand-response. The proposed approach	Need to secure the proposed approach to handle the threats during data analytics
Mousa *et al.* [7]	2019	A prediction model for a day-ahead dynamic pricing system	Dynamic pricing	A probabilistic model is developed to estimate customers response for dynamic price changing which reduces the demand peaks.	The model solely depends on the consumer response, in case consumer does not respond, that scenario needs to be captured in the model.
Kong *et al.* [86]	2019	A demand response program based on elasticity transfer and reinforcement learning for dynamic pricing	Dynamic pricing	The proposed method can maximize the price of the energy service provider and the user by setting the optimal price at a faster rate without consumer.	Emphasis only on the energy provider benefits from increasing prices of energy the benefits for the consumer should be included in the approach.
Singh *et al.* [124]	2019	An improving energy demand management through households socio-analytics for customer classification	Customer classification	Proposed a data analytics approach that couples the socio-demographics, socio-economic, dwelling and occupant behavioral characteristics of energy consumption patterns to derive consumer segmentation for targeted demand-management programs.	Data security need to be emphasize during analytics
Wang *et al.* [149]	2020	A deep reinforcement learning method for demand response management of continuous interruptible load	DRM	Improve demand side resilience, Reducing both the peak load demand and the operation costs on the energy companies premises up to a safe limit.	Need to handle other load programs also like Direct load-control and curtailable load.

procedures available in a communication medium that include either iterative methods or simulation-based approaches [113], or numerical method. Further, the connectivity error rectification approach has been presented in [71] based on the correlation analysis on SM energy data. The topology identification using conditional probability has been articulated as an optimization problem [158]. Likewise, topology identification was accessible as a sparse estimation problem and probabilistic graph model in [136].

5.3.3. Energy outage management

A power outage is the failure in energy supply due to various factors like short-circuit, station failure, and damaged distribution line [49]. It includes notification of location, verification of restoration, and outage. In [138], a two-stage strategy has been discussed to identify the outage area. The author Kuroda et al. [92] presented rapid detection and outage prediction technique using SM-based energy data. Besides, a multiple-hypothesis procedure was projected to distinguish the faulty section on the feeder level [71]. Conversely, a distinctive hierarchical framework has been proposed to detect outage using event data in place of energy usage data [109]. Moreover, issues related to outages, missing data, selection of variables, and multivariate count data have been discussed in [22].

5.3.4. Security and privacy

Security and privacy of energy data is among the significant worries in the ECM system. The ECM needs to develop an extensive communication and computing infrastructure that supports significant situational awareness and permits fine-grained control and command. This should support the main application area of SG, such as DRM and control, energy storage and transportation, and automation of the distribution system. The ECM is a complex system, and it has vulnerabilities and challenges arisen from an amalgamation of physical and cyber systems and other factors like regulatory policy, human behavior, and subsystem interactions. These challenges are categorized as trust, communication, device security, and privacy [87]. The trust can be identified as "the authorized user is accessing accurate data generated by the right device at the expected time, location and communicated using the proper protocol, and the data received at the destination has not been modified" [142]. However, the increasing number of system automation in ECM and system coordination raises a security concern. SG data availability increases the more stringent demands of security on the communication system compared to traditional supervisory control and data acquisition (SCADA) systems. The security deployments are based on broadband communication, Internet technologies, and a non-deterministic communication system, that handles various attacks such as injection attack and Denial-of-service (DoS). The rapid deployment of communication systems with adequate planning and reliable system helps to handle the security threats [123]. For example, security attacks on communication system (jamming channel attack: tampering attack and forgery attack, man-in-the-middle attack, sinkhole attack, Sybil attack, eavesdropping attack), security attacks on data sources (injection attack, physical attack, and service manipulation attack [88]), and other attacks (insider attack, SQL injection, privacy leakage, and distributed denial of service (DDoS) attack) [62,98].

Table 7
Comparative analysis of state-of-the-art approaches for communication system in ECM.

Author	Year	Description	Category of load analysis	Benefits	Findings
He *et al.* [56]	2016	Outage management approach for electric power distribution networks is proposed	Energy outage management	Identification of outage area based on topology analysis and smart meter information was developed.	The outage area identification are effective in 3-meter criterion, which area range should be increased for better outage coverage.
Souza *et al.* [31]	2017	A Data compression technique in smart distribution systems using singular value decomposition	Data compression	Assist the communications infrastructure to cope with the challenge of transmitting a big volume of data that can be exchanged in future SGs.	A lossy compression technique as loss of information is low after energy data reconstruction.
Spiegel *et al.* [126]	2018	Comparative study of lossless compression algorithms to enhance the energy efficiency in smart meters.	Data compression	Proposed a lossless compression algorithm to achieve the best trade off between the compression ratio and computational costs.	Data security not explored much during energy data compression.
Black *et al.* [21]	2018	A probabilistic approach for energy analytics to model energy outages using weather data.	Energy outage management	Used regression analysis to model energy distribution outages and construct a probabilistic view of reliability indices which helps to reveal utility's reliability trend.	The other factors for the energy outage also need to be consider such as system failure, transmission loss and so on.
Pop *et al.* [117]	2018	A decentralized management of demand response programs in smart energy grids using BC.	Security and Privacy	The approach was validated over Ethereum platform with energy consumption and production traces.	The consumer privacy needs to be included in the proposed approach.
Aitzhan *et al.* [5]	2018	A decentralized energy trading through multi-signatures, BC and anonymous messaging streams	Security and Privacy	Implemented a proof-of-concept for decentralized energy trading system using BC technology, anonymous encrypted messaging streams, and multi-signatures, enabling peers to anonymously negotiate energy prices and securely perform energy trading transactions.	A real-time implementation of the proposed approach is required.
Uddin *et al.* [140]	2019	A fault diagnosis and Control in smart grid system	Communication verification	A stochastic analysis approach using Markov model which focused on restoring the system automatically within the minimum possible interval.	Considered only ideal communication medium, i.e., Ethernet.
Roman *et al.* [118]	2019	A protocol for vehicle to grid (V2G) networks in smart grid	Communication verification	Pairing-based authentication protocol for vehicle to grid communication. Handle various attacks for EVs	The simulation of the protocol is required in a network simulator and its adaption for integration in the V2G network for the cloud.
Wang *et al.* [148]	2020	A data compression method using stacked convolution sparse auto-encoder is proposed	Data compression	Reconstruction error and computation time is significantly reduced. Grouping compression is proposed to further improve the compression effect.	Need to focus on this verified relationship to further reduce the computing time for the compressed data.

Further, consumer's privacy can be preserved using various authentication and authorization mechanism [19]. One of the distributed accumulation architecture has been proposed for additive SM data [37]. Then a secure communication protocol has been proposed to prevent disclosure of critical data of consumers [132]. Then, a hidden Markov model-based approach has been used to the trade-off between consumer's privacy and utility requisite by Sankar et al. [120]. Subsequently, the information theory approach has been used to protect consumer privacy [121]. Further, privacy preservation was expressed as an optimization problem [80,89]. Auxiliary, consumer's data privacy can also be managed with an appropriate set of standards and interoperability in place.

Table 7 provides the detailed relative comparison of state-of-the-art approaches for AI-based load management.

5.4. Others

This section covers those aspects which are different from other taxonomy subsections: (i) recommendation for users, (ii) trust, (iii) scalability, and (iv) efficiency. The brief description about these aspects are as follows.

5.4.1. Recommendation for users

In ECM, the energy usage data can help to predict the usage patterns of the consumer using AI-based techniques like CNN, RNN, and others. Based on this, the list of services can be offered by the energy companies to increase revenues and profit. The relevant service for each consumer can be identified by their usage pattern, for instance: In case a user that belongs to the commercial sector can get some benefits on the tariff plan (on bulk energy usage) by using the more energy during festivals [36]. Similarly, if a residential consumer uses the washing machine only mid-day (during peak hour) and staying at home (identified as TV energy utilization is the entire day), then energy companies can offer then incentives applicable to him only if he uses his washing-machine in a non-peak hour [35,139].

5.4.2. Trust

For ECM systems, we consider trust as consumer confidence during specific time-interval, i.e., the authorized user is accessing accurate data to a particular time. The trust is influenced by system design, in case participants are not trustworthy, new methods such as BC, cryptography, and other privacy-preserving techniques should be used beyond the existing monitoring approaches [2,129].

5.4.3. Scalability

With the rise in population, the demand for energy is increasing every day. This is causing the addition of a new user on daily-basis and requires the scalable and secure ECM system.

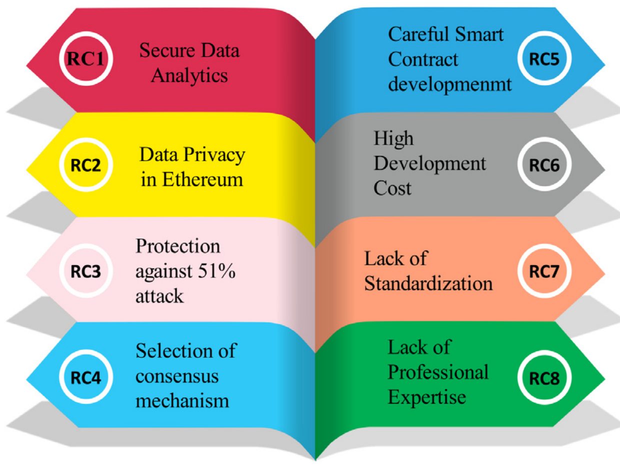


Fig. 10. Open issues and future recommendations.

The scalability of the ECM can be achieved using various technologies such as CC and FC. Though, these technologies having various issues like single-point-failure issues and other security vulnerabilities. So, an emergent technology to mitigate the aforementioned issues is required, such as BC. A BC-based secure and decentralized ECM system support P2P energy trading and the traditional supply of energy as well [40,141].

5.4.4. *Efficiency*

The efficiency is the major factor which requires for efficient management of the energy usage in ECM. It is identified based on several aspects such as productivity, technical, and social aspect. The BC-based secure and decentralized system is proven to be efficient due to the real-time settlement of the energy trading, immutability features, and so on [96].

6. Open issues and future recommendations

This section discusses the future research challenges for combining AI and BC technologies in ECM. Some of the identified challenges in the integration of both technologies in energy management are shown in Fig. 10. The brief description of these future research challenges is as follows.

6.1. *Secure data analytics*

In the proposed system, data analysis is performed after the classification and prediction (using the LSTM model) step at the prediction layer. It is crucial for appropriate and effective energy management. *What if* someone (malicious user) misleads the analysis process by passing fake/dummy/malicious data? In this case, the entire energy management procedure can be deceptive. This is an open research issue that needs excellent attention from researchers around the world.

6.2. *Data privacy in Ethereum*

In our system, we preferred Ethereum (a public BC) to overcome the interoperability issues among the supplier as well as the demand side. The data in Ethereum is publicly available and is easily accessible to all participating members of the BC [10]. This violates the privacy of block data. AI and cryptographic techniques can be helpful in achieving data privacy, but they require high computation power. So, achieving privacy with low computation overhead is an open challenge.

6.3. *Protection against 51% attack*

Decentralization in the BC is vulnerable to 51% attack where more than 50% of the network mining is controlled by the group of miners. This problem generally occurs in public BC like Ethereum [107]. So, there is a need to develop a robust consensus mechanism that takes care of such issue of public BC.

6.4. *Selection of appropriate consensus mechanism*

In the BC system, there exists N number of consensus mechanisms that make the system fault-tolerant on a single common agreement [119]. Different consensus protocols are for different purposes or applications. To select an appropriate consensus mechanism or designing a new one for our application is quite challenging.

6.5. *Careful development of smart contracts*

Smart contracts are the programming codes written in standard languages such as Solidity, Kotlin, and Go [50]. The implementation phase of the SC is very crucial because all software vulnerabilities and bugs can be solved in this phase only. Later, the testing of SC against the security vulnerabilities and software bugs is of utmost importance before its deployment. So, the bug-free development of SC is needed in the growing BC network.

6.6. *High development cost*

BC requires an entirely new infrastructure to achieve integrity and eliminate the need for an intermediary. It also needs high cost in storing a byte or word in the block of a BC. To store one work in a BC requires $\approx$ USD 550, which is too costly. To accommodate maximum words in BC with low cost is a challenge for researchers around the world.

6.7. *Lack of standardization*

To date, no stable standards are being developed by international standard bodies such as IEEE, ITU, 3GPP, and NIST for the BC system. However, many organizations want to deploy BC, but they restrict themselves because of no standardization and guidelines. Standards are required for BC interoperability and governance. The non-availability of BC standards poses the challenges for its adoption.

6.8. *Lack of professional expertise*

As the BC is an emerging field, only few researchers across the globe are working on it to make it stable and adaptable. So, in this field there is lack of professionally experienced BC expertise people. Without the experienced professionals, the development of BC is quite challenging.

7. P2P energy trading: A case study

To validate the proposed BC and AI-based ECM architecture, we present a case study, as shown in Fig. 11. In this case study, we study a BC-based Energy Trading System (BETS) for energy transactions using AI along with peer to peer (P2P) technology [25]. The BETS analyzes energy using SM technology and allowing prosumers (consumer producing energy from its own RES such as Solar PV mounted at rooftop) to track the production and selling of energy in a distinctive transaction. In the P2P energy trading platform, AI and BC provide the upsurge of inter-connected microgrids to handle production of energy directly from RES and to

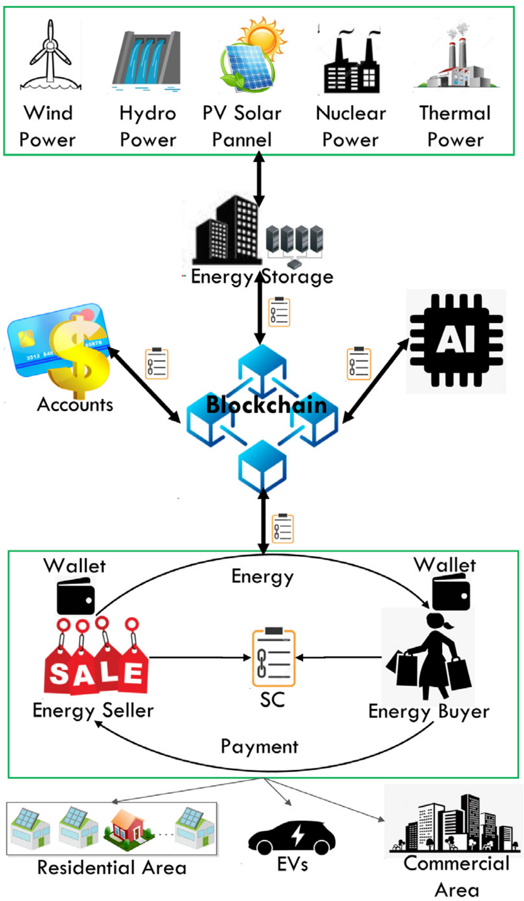


Fig. 11. P2P energy trading: A case study.

sell excess directly to neighbors in a more transparent, secure, and distributed way. It helps to reduce the energy bill, promote green energy, reduce the cost of energy (as the demand for energy from SG will reduce), and give incentives to the prosumers for participation in energy trading.

This BETS uses a DL approach (a subset of AI) and BC is used to complete a reliable P2P energy transaction. This approach comprises five phases, a setup phase (initial phase), agreement phase (establishing agreement between peers), block creation phase, consensus-creation phase, and change view phase. The different energy datasets have been used to evaluate the performance of this system. In this P2P energy trading, communication comprises different entities; these are Energy buyer, Energy seller, BC, and AI. Energy buyers and sellers participate in trading, where energy buyers should have sufficient cryptocurrency (for payment) to fulfill the minimum asset requirement of trading. An energy buyer can be a person residing at an individual house or industry or commercial building located in a Neighborhood area Network (NAN), Building Area Network (BAN), or Home Area Network (HAN). Similarly, Energy sellers can be a person with RES (E.g., Solar PV) or energy companies located in HAN, BAN, NAN.

Initially, the energy seller yields energy from RES and fulfills his own energy needs. After that, with the left energy, the seller publishes his per kilowatt energy per-unit prices on the BETS network. Then, the interested buyer will look upon the published data of a unit of energy and its reserve price. In case the energy buyer has sufficient cryptocurrency balance in his wallet (account in the BC) for energy trading, he sends a purchase request on the BC network with per unit buying price and unit of energy to purchase. Then, the purchase request is validated on the BC network and transaction executed. After that, the seller receives cryptocurrency in his account and sells the energy to the buyer. This P2P energy trading system identifies the frequent seller and buyer and identifies the malicious transactions over the network using AI techniques (E.g., DL-based LSTM model for prediction). A malicious node or block can impact an entire P2P energy trading system. AI-based system can help to figure out the fraudulent transactions and attacks on the network [43]. The study shows excellent system performance compared to the other state of art approaches with a reduction in carbon emissions and energy bills.

8. Conclusion

The ECM system offers many applications to provide energy management in SG for load demand management at the grid. The desire for secure, reliable, and efficient DRM raises the concern for the development of an ECM system with CC infrastructure. However, the single point failure and added security and privacy issues introduce FC in the ECM system. Though FC-based ECM has several unsolved security issues such as authenticity and confidentiality attacks so efficient techniques are required to predict the accurate demand using various AI-based techniques for demand-side prediction for better management of energy in the ECM system. This paper presents a comprehensive and detailed study of AI-based techniques for the ECM system with the integration of BC technology. It highlights the existing research on demand-side related to the ECM system, safety, and security defense mechanisms for energy management. Then, we proposed a decentralized and secure AI integrated BC-based ECM architecture and validated it using a case study based on P2P energy trading. Finally, we presented a solution taxonomy based on the components and behavior of ECM in the demand side. Moreover, the paper ascertains open research challenges and issues for future research directions for the researchers working in the ECM field. In the future, we will explore the AI and BC amalgamation on the load side ECM system. Further, the successful implementation of the ECM system needs to be addressed significantly in the coming years.

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.

Acknowledgments

This work is supported by Visvesvaraya Ph.D. Scheme for Electronics and IT by Department of Electronics and Information Technology (DeiTY), India, Ministry of Communications and Information Technology, Government of India.

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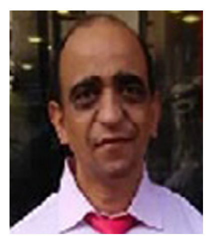

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