International Journal of Science and Research (IJSR)
ISSN: 2319-7064
Impact Factor 2023: 1.843

AI - Based Smart Energy Consumption Prediction for IoT - Connected Homes

Omkar Reddy Polu

Department of Technology and Innovation, City National Bank, Los Angeles CA
Email: *omkar122516[at]gmail.com*

Abstract: ***As smart homes are becoming more and more adopted by IoT technology, so are energy consumption levels increasing, which requires for intelligent and practical energy management solutions. The Smart Energy Consumption Prediction System is an AI powered, IoT, machine learning (ML), blockchain and edge computing integrated system to predict dynamically the consumption of energy. In the proposed system, the deep learning models including LSTMs, Transformers, and hybrid AI models are applied to real time energy consumption forecasting. Furthermore, optimization based on reinforcement learning is used for automation of energy scheduling aiming for the input of minimum cost with minimal power wastage. This is supplemented with a blockchain - based peer to peer (P2P) energy trading system that will allow for decentralized and secure energy transaction between smart home users. Federated learning is used to scale the system and achieve privacy, in order to train decentralized AI to multiple households without data leakage. It is integrated with edge computing in order to process the streaming sensor data with minimum latency and do away with cloud computing. Real world datasets are evaluated on the system, with, more accurate predictions, lower energy demand and cost savings. Ultimately, this research lays the groundwork for future AI enabled energy management solutions with respect to smart city infrastructure, and the smart city infrastructure of the future, as it aligns with the sustainable development goals.***

Keywords: AI - driven energy management, IoT, deep learning, smart homes, energy prediction, blockchain, edge computing, federated learning, reinforcement learning, peer - to - peer energy trading.

1. Introduction

The smart homes with an IoT enabled have rapidly become increasing common to modern living allowing automation and real time control on appliances and energy consumption. The growth of the number of connected devices, however, results in a greater usage of energy and so to develop intelligent energy management systems is necessary. The conventional energy monitoring solutions currently available are not able to be predictive and as such energy is not utilized in an efficient manner and at a high cost. To tackle this issue, smart energy prediction models based on the AI were gaining popularity as they are providing real time predicted data, the adaptive energy optimization and automated decision making.

This research proposes an AI based Smart Energy Consumption Prediction System using machine learning (ML), deep learning (DL), edge computing and blockchain for the purpose of energy efficiency in the IoT Connected Homes. By proposing the system to combine advanced AI models including LSTMs, Transformers, hybrid architectures used to make accurate prediction of energy usage. The appliance scheduling is optimized via reinforcement learning to lower the level of unnecessary power consumption. Additionally, the smart home is integrated with blockchain P2P energy trading and can buy and sell excess energy in a secure manner.

This research tries to bring up a next generation smart energy management framework by combining federated learning for privacy in AI, edge computing for real time processing, and blockchain for secure transaction. It is tested using real world datasets and its capability to disrupt energy efficiency, cost reduction, as well sustainability in IoT powered energy environments is demonstrated.

2. Literature Survey

Smart energy management has advanced greatly by including these IoT, AI, and blockchain technologies. The traditional energy prediction methods like statistical models (ARIMA, regression models) have been widely adopted, however, these methods are not good enough to interpret such complex and/NR non linear energy consumption. To address this, researchers have also tried to use the methods of machine learning (ML) and deep learning (DL). Results show that the LSTMs and Transformer models performed better than the other conventional methods in time series energy forecasting, as the former can learn the long time series dependencies.

Apart from prediction, reinforcement learning (RL) algorithms for dynamic energy optimization are applied to automate appliance scheduling based on the variations of the demand and cost. Other researchers have also studied blockchain based peer to peer (P2P) energy trading systems where secure and decentralized energy transaction is ensured. But it is not easy to scale, be private, and be efficient computationally. Looking at the challenges and the analysis of Federated Learning as a technology worth exploring through its portfolio of applications, Federated learning (FL) has been identified as a promising approach to train AI models on distributed data from IoT. Additionally, smart energy computing has been investigated with regard to latency reduction.

Existing approaches are found to be limited and it is necessary to have an integrated AI based framework which involves deep learning, reinforcement learning, blockchain and federated learning for designing an efficient, secure and adaptive smart energy management system in the context of IoT enabled homes.

a) Traditional Energy Consumption Prediction Methods

Typically, prediction of traditional energy consumption was based on statistical and econometric approaches. A number of the time - series energy data have been subjected to techniques, such as Autoregressive Integrated Moving Average (ARIMA), Multiple Linear Regression (MLR), Holt - Winters Exponential Smoothing, and Seasonal Trend Decomposition. These models are capable of conducting the short term energy forecast using the historical trends so they are suitable for the basic energy monitoring. However, they have some inherent challenges in managing nonlinear type of consumption patterns, lack of data, and the dynamics of IoT enabled smart homes.

As the complexity of modernises energy consumption pattern is due to consumer behavior, applicable on weather conditions, energy consuming equipment, and renewable energy integration, the weaknesses of statistical models are exposed. Moreover, they struggle in adapting to the problem at hand, suffer from the inability to process large-scale real-time data and usually do not generalize well across different household energy usage profiles. Additionally, these methods require the human - in - the - loop to perform manual engineering and the presence of extensive domain experts to minimize their runtime. The efficiency of these methods thus diminishes when applied to large scale automated applications.

To overcome those challenges, researchers have moved to AI - based prediction of energy models that, through learning complicated relations of data, do not demand as much precise physical processes. AI based model has become an essential cornerstone of modern smart energy management solutions due to the great improvement in prediction accuracy aided by transition from traditional to machine learning and deep learning techniques.

b) Machine Learning and Deep Learning Approaches

Machine learning (ML) and deep learning (DL) have had a revolutionizing effect on the energy consumption prediction through the facility to extract features automatically, adapt through learning, and perform decision at runtime. One of the early ML models like Random Forest, Gradient Boosting Machines (GBM), Support Vector Machines (SVM), etc. did not perform better than standard statistical models, but did better than them in terms of accuracy, yet these approaches still did not perform well with long term dependencies and dealing with the large scale IoT data processing.

In the past, models based on Long Short-Term Memory (LSTM), Gated Recurrent Units (GRU) or Transformer based architectures have achieved a very good energy prediction. Specialized recurrent neural networks like LSTMs and GRUs are able to effectively capture temporal dependencies and thus, energy forecasting is a perfect use case for them. Over the past few years, they've somehow also demonstrated that Transformer - based models, initially conceived for natural language processing (NLP), can be more efficient when exploiting long range dependencies compared to LSTMs.

Additionally, Hybrid AI models (such as LSTMs and CNNs with attention mechanism) have subsequently increased the prediction accuracy. The second class of model is the ones which are able to process high dimensional energy data and account for the external factors such as weather conditions and can also adapt themselves in dynamic consumption patterns. Despite such problems as high computational requirements, lack of interpretability, and energy efficient deployment, they still remain open research areas.

While the IoT devices are becoming faster and smart now, researchers also do not want their models to become slower, and hence are concentrating on the deployment of such ML/DL models on IoT devices itself to reduce latency as well as boost real time energy monitoring capabilities.

c) Reinforcement Learning for Energy Optimization

Since machine learning can only improve energy prediction, reinforcement learning (RL) takes it one step further by automating energy consumption by intelligent decision making and automated scheduling. Autonomous energy management takes place by adapting appliance usage in a dynamic manner, according to the real time factors including electricity pricing, demand response policies, and occupancy patterns, using RL.

Both Deep Q Network (DQN) and Proximal Policy Optimization (PPO), as well as Advantage Actor Critic (A2C), have been used sucessfully in energy management problem. In these models, they learn an optimal policy for energy efficient scheduling that maximizes reward signals such as cost savings and reduced carbon footprint as an environment is interacted with.

A significant number of studies have demonstrated that the performance of RL based systems is superior to traditional rule-based energy optimization methods, in reducing cost of energy, achieving minimum peak demand as well as effective management of various distributed energy resources, such as solar panels and battery storage. Also, multiagent RL (MARL) has been devised to allow energy usage be optimized in several smart homes in a community grid.

Similar to other areas, RL has also a list of its challenges that include high sample complexity, difficulty in convergence, and high-quality reward functions. By integrating xai techniques with rl, the interpretability can be better integrated with the real-world smart home applications.

d) Blockchain - Based Energy Trading

More and more people are investing their time and effort exploring this secure, decentralized energy trading option in smart grids through blockchain technology. Adopting the rise of peer to peer (P2P) energy trading, households that have renewable energy sources such as solar panels can directly sell extra electricity to other users without the use of the traditional utility providers. These transactions get automated by such blockchain based smart contracts with transparency, security and trust.

Overly, the writers propose the use of Ethereum based smart contracts and platforms such as Hyperledger Fabric for decentralized energy marketplaces that enable users to engage in real time bidding and energy exchange. It is known that blockchain can add resiliency to the grid, reduce reliance on centralized systems, and promote sustainable energy consumption in a study.

At the same time, scalability, high energy consumption and transaction latency are the key limitations on blockchain based energy trading. Proof of Work (PoW) consensus mechanism used in Bitcoin and Ethereum are computationally expensive, hence their inability to work in energy application. Now that we more or less know how oracles et al are contributing to blockchain decentralization failures in terms of slow transaction speeds for energy trade, research is being done on energy efficient consensus mechanisms such as Proof of Stake (PoS), Delegated PoS (DPoS) and Practical Byzantine Fault Tolerance (PBFT) to improve blockchain scalability for energy trading.

Despite the limitations of blockchain integrated smart grids, it is being adopted, and efforts must be put in by more towards enhancing transaction speed, decreasing costs, and propose AI based dynamic pricing strategies for real time energy trade.

e) Edge Computing and Federated Learning for Smart Energy

IoT connected smart homes generate huge amount of energy data in real time along with all these data processing, privacy, latency with high volume of energy data generated from IoT connected smart homes. Currently, traditional cloud based AI models are very dependent on the network, are insecure and come with additional operational costs. In order to tackle this problem, the researchers view edge computing and federated learning (FL) as the essential enablers for operationalizing distributed AI based energy management.

In edge computing, AI processing is brought closer to the data source where we deploy the models to IoT gateways, smart meters, embedded devices (Raspberry Pi, Jetson Nano, Google Coral). By virtue of this, it reduces cloud dependency and thus faster response times, low latency energy predictions and real time optimisation. Edge AI has also been proven to improve power efficiency and security, and it is therefore an appropriate avenue for scalable energy monitoring.

Federated Learning (FL) goes a step further and still allows training of an AI model without sharing the raw data in the training phase itself. FL allows us to collaborate on learning from sensitive energy data through our data sovereignty and compliance with regulations such as GDPR without centralizing the very sensitive data.

Challenges such as heterogeneous device performance, communication overhead, model synchronization however need to be addressed before large scale FL becomes widely adopted to smart grids. Secure aggregation of AI models formed through the combination of FL with blockchain is an area of research that has great potential for improving energy prediction and optimization in IoT connected homes.

3. Materials and Methods

The proposed AI Based Smart Energy Consumption Prediction System for IoT Connected Homes consists of a set of multiple advanced technologies such as machine learning (ML), deep learning (DL), reinforcement learning (RL), blockchain, edge computing, and federated learning, which can be used to manage energy by adopting this approach. The materials and methodologies used to develop the system and design of the system are described in this section.

Sensors and smart meters that monitor real time energy consumption are put in place as part of a network of IoT sensors and smart meters, which make up the hardware infrastructure. The set of these sensors include Zigbee based smart meters, ESP8266/ESP32 based Wi - Fi enabled power monitors, and LoRaWAN based remote sensing devices to monitor appliance level energy usage. Context information includes additional environmental sensors (for example, temperature, humidity and motion sensors) and they can have impact on the energy consumption. Data is collected and preprocessed locally through a central IoT gateway such as Raspberry Pi 4 or an NVIDIA Jetson Nano and sent to the cloud or edge servers.

This software architecture has various layers including data acquisition, data preprocessing, prediction using AI, optimization, and energy transaction using blockchain. The first one is the data acquisition layer that collects the real time energy consumption data from IoT devices using MQTT and HTTP protocol. The preprocessing layer takes care of the raw data and cleans them by offering missing data, outlier and noise treatment with the help of data normalization and anomaly detection techniques. A Generative Adversarial Networks (GANs) based data augmentation is carried out to provide synthetic data for training robust AI models on time series data.

Taking advantage of the deep learning techniques, mainly LSTM networks, GRU, and Transformer models; the energy consumption prediction model is based on AI driven prediction model. The models are trained on real world datasets such as UK - DALE, Pecan Street and Smart datasets. LSTM and CNN based feature extraction are combined together to capture both temporal dependencies and spatial correlations on energy usage data as an energy usage hybrid model. Finally, a hyperparameter optimization is performed using Bayesian optimization, grid search, etc.

Reinforcement learning (RL) is applied for energy optimization and to learn how to develop an intelligent energy agent, able to dynamically schedule appliance usage for energy optimization. An RL model based on a Deep Q - Network (DQN) is trained to learn the best optimizing energy saving strategies from an environment simulated using OpenAI Gym. These state inputs to the agent include the real time electricity pricing, occupancy data, and the predicted energy demand, and there actions include turning off of appliances, reducing HVAC usage and scheduling power intensive tasks and duty during off peak hours. With reward functions that advocate energy savings and cost savings, the RL model is trained.

By using blockchain module, this secures and decentralized peer to peer (P2P) energy trading among IoT connected homes. A blockchain framework based on Hyperledger Fabric is deployed to handle transactions between prosumers (prosumers, whose peer enjoys excess solar energy) and consumers. The smart contract written in Solidity is used for automated energy pricing, payment processing and transaction validation. It eliminates the need of intermediaries lowering energy costs and promoting the trading of sustainable energy. Energy efficient consensus mechanism like Delegated Proof of Stake (DPoS) or Byzantine Fault Tolerance (BFT) are applied to address the scalability issues in case of blockchain.

Edge computing is integrated in the system to enhance real time energy forecasting and decision making. Using TensorFlow Lite and ONNX Runtime, the AI models are optimized for edge inference, which means they can be measured on Raspberry Pi or NVIDIA Jetson locally to make energy predictions. It reduces the latency and dependence on cloud service. However, federated learning (FL) is also conducted with Google's TensorFlow Federated (TFF) to simultaneously use multiple smart homes in training AI models without directly sharing raw energy data, ensuring data and privacy security.

Multiple performance metrics (Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Energy Savings Ratio (ESR) and blockchain transaction latency) are used for evaluating the system. Finally it is shown that the results outperform baseline machine learning models (XGBoost, Random Forest and ARIMA) using deep learning based forecasting. We deploy the system in a Smart home environment to monitor its power savings, its ability to save costs and energy effective usage of appliances in the system over a period of three months.

This research integrates AI, Io, blockchain and edge computing for scalable and secured and private smart energy management solution in IoT home. Other future enhancement includes multi agent reinforcement learning (MARL) for community level energy optimization, Explainable AI (XAI) for model interpretability, energy predictions in ultra low latency using 5G enabled edge network.

4. Results and Discussion

To evaluate the effectiveness of the proposed AI - based Smart Energy Prediction Consumption System (AISEDPS) for IoT - connected home using real world energy datasets such as UK - DALE, Pecan Street, and Smart* datasets, the prediction of the energy usage, appliance scheduling scheduling, and secure energy transactions for IoT - connected home were assessed. An IoT smart home test environment with real time energy consumption data of different household appliances was made and its evaluation was done here. It is shown that the improved accuracy in energy forecasting, the savings in cost and energy, and the system efficiency have significant advantages compared to traditional energy management techniques.

Historical energy consumption data were trained & tested against the deep learning based forecasting models such as LSTMs, GRUs and Transformer automotive models. RMSE, MAE and MAPE were used to evaluate the performance of the proposed model. Results showed performances of Transformer - based model from 3.8% of MAPE to LSTM and GRU with 4.5% and 5.2% respectively. Also, the hybrid LSTM - CNN model further improved accuracy with a MAPE of 3.5% as CNN can extract the appliance level of energy consumption pattern. However, the traditional machine learning models such as XGBoost and ARIMA performed quite poorly and significantly worse with MAPE exceeding 8%, and these failed to capture the complex energy usage trends. These show that the deep learning models especially hybrid architectures can effectively predict energy demand in IoT connected homes with high accuracy as compared to conventional models.

It showed good performance on energy scheduling and cost reduction by an RL agent trained using its Deep Q Networks (DQN), Proximal Policy Optimization (PPO). Finally, the RL based system was tested under real time electricity pricing conditions and with maximum costs reduced. Evaluation show an average of 15 - 20 % of reduction of peak energy consumption by shifting of high energy tasks like dishwashers, washing machines, etc. to off peak hours. Furthermore, the use of RL - based optimization resulted in average electricity bill reduction by 18% as opposed to a rule based energy scheduling system. Experiment results show that DQN requires more episodes (5000) to learn effectively compared to PPO (3000) on energy management indicating that policy gradient based RL methods are more suitable for energy management. RL based optimization results in both adaptive and intelligent approach for minimizing energy costs incurred to households as well as effective energy use.

Block validation was then performed by developing a Hyperledger Fabric based P2P energy trading system with the permission to homes secured with surplus solar energy electricity to be sold to neighbors. In order to test the transaction efficiency, scalability and security, the system was tested. The transaction latency was found to be 1.2 seconds on average, which is much lower than other traditional PoW based blockchain networks like Ethereum, which makes it fine for trading digital energy in real time. A multi sign verification scheme was applied to avoid transaction signature mishandling, and smart contract execution success rate was 98.7%. Through buying surplus renewable energy at lower rates than the grid electricity prices, households engaged in blockchain based trading of energy saved 12 percent more compared to charging grid electricity. The following findings prove that a blockchain based energy trading provides a viable choice compared to conventional energy distribution methods as it offers secure, decentralized and affordable transactions for electricity.

These results of implementing edge AI and federated learning (FL) for energy prediction and optimization provided both improvements to the system efficiency, privacy as well as latency. On IoT gateways, real time energy forecasting was achieved at 3.2 times faster edge AI inference speed as compared to cloud based AI processing. With federated learning, federated devices did not transmit raw energy data to central servers for training, while Federated Learning improved data privacy. The accuracy of the FR model was 95 percent of the accuracy of centralized deep learning models on energy prediction, which validated that FR is effective in privacy preserving energy prediction. Such results support the need for edge computing and FL when smart energy management needs to be real - time and secure for large scale IoT deployments.

To evaluate its superiority, the proposed system was compared in terms of performance with existing rule based, statistical and traditional ML based energy management approaches. ARIMA and regressions based models improved these forecasts by 40% compared to deep learning models. In rule based scheduling systems, they saw 7% savings, versus 18% savings in an RL based energy optmization systems. There is 12% savings from blockchain - enabled P2P energy trading, which is not available in a centralized grid - based energy distribution. With edge AI, we achieved 68% reduction of the inference latency compared to traditional cloud based processing. Conclusively, these comparisons validate the fact that integrated AI, blockchain, and edge computing based approach have significantly better effectiveness than using traditional energy management techniques.

The results of this study indicate that IoT connected homes utilizing an AI driven energy management can save a lot of efficiency and cost. A scalable, private, and decentralized energy optimization system is formed by integrating deep learning, such as RL, blockchain, and federated learning. In the future such as explainable AI (XAI) etc. can be added to improve transparency in relation to energy decisions done by energy this can also be covered with multi agent reinforcement learning (MARL), 5G networks with the capability of ultra low latency energy monitoring and prediction and AI powered dynamic pricing models for real time energy cost optimization which will come into play in smart grids.

5. Conclusion and Future Enhancement

It has been demonstrated that AI based smart energy consumption prediction of IoT connected home can provide better accuracy in energy prediction as well as improved energy optimization and reduced cost by integration of state of the art technologies like deep learning, reinforcement learning, blockchain, edge computing and federated learning. The system successfully predicted energy demand based on the real time energy consumption data from IoT sensors by using the machine learning techniques, with the accuracy much better than the traditional statistical methods. For long term dependencies and appliance level consumption pattern, deep learning models, especially the Transformer based architecture and hybrid LSTM CNN outperformed traditional forecasting methods, leading to significant reduction in the prediction errors. Additionally, it further enhanced the energy efficiency through the reinforcement learning based optimization module wherein the appliances are dynamically scheduled based on real time electricity pricing and occupancy pattern, resulting in large savings for the user.

The development of blockchain based peer to peer (P2P) energy trading has been proposed on the basis of distributed energy distribution in a decentralized way. Through this, smart contracts were implemented on a Hyperledger Fabric blockchain framework to maintain the transparency and buy in trust between the transactions and decrease the dependence on centralised power grids. It was evaluated and found out that the addition of blockchain to the system will provide more cost savings by the possible expenditure of surplus energy at lower amounts. However, scalability and energy balance challenges to the scalability, transaction latency and energy balance consensus mechanisms has to be tackled to widely adopt blockchain. There is more research to be conducted around integrating energy efficient models of the blockchain such as Proof of Stake (PoS) and Byzantine Fault Tolerance (BFT) to speed up the transaction and reduce computation overhead.

Finally, edge computing and federated learning enabled deployment of privacy preserving as well as low latencies energy prediction. As opposed to relying on cloud based AI models, the system was able to process the energy data locally and increase the pace of inference three times. In addition to this, the privacy was then enhanced further by Federated learning i. e training of AI models across various smart homes without sharing raw data and hence ensuring the security of data and also compliance with the privacy regulations. In the context of energy forecasting, the effectiveness of federated learning indicates that future implementations may incorporate more advanced techniques, such as personal federated models which are the algorithms that can be personalized to individual household consumption pattern without compromising privacy. Nevertheless, further optimisation is needed in large scale federated networks as the challenges include communication overhead and model synchronisation.

The promising results had raised the need for further enhancements in the system to provide higher scalability, robustness and adaptability to the system. For the sake of transparency and interpretable predictions, the prediction models could be integrated with explainable AI techniques (also known as XAI), so that users will understand the reasoning of why energy is forecasted and why appliances are scheduled. Marl can be used to deploy optimization capability to a whole community or smart grid network consisting of a group of agents who must collaborate to balance energy in demand and supply dynamically. An approach allowing to manage the energy of the whole neighborhood and the whole city would be more holistic but that would be beneficial primarily for a single household.

As 5G technology is being adopted, future improvements may consist of facilitating ultra low latency energy monitoring and control with high speed network connectivity. Incorporating AI driven dynamic pricing models can go a step further and bring in more energy cost optimization by adapting electricity rate in a real time manner, depending on the consumption patterns, peak time of demand, or availability of renewable energy. Further, energy saving recommendations developed within adaptive energy management systems by incorporating behavioral analytics would be able to perfect recommendations about energy saving based on the user preferences and their interactions in the past.

Smart energy management, however, continues to be prey to sustainability, and future study need to exploit the combining of forecasting models for renewable energy so as to improve the use of solar and wind energy. Also, AI can be used in predictive maintenance for IoT connected appliances that would aid energy conservation by detecting redundancy and hence saving energy. More studies could take place to bring the system reliability up even more and keep the system proactively managed by incorporating AI - driven anomaly detection to handle faulty appliances or strange consumption patterns.

Finally, I find that I have successfully shown that AI driven smart energy consumption prediction systems can completely transform our IoT connected homes with an optimized AI driven prediction, intelligent optimization, and decentralized energy trading. The current example demonstrated that efficiency and cost reductions are achieved; however, the AI, blockchain and edge computing will continue to improve the system's likelihood and capability. One can say that future research needs to contemn existing challenges, scale up, and integrate emerging technologies to develop a full guts autonomous and sustainable energy management system of smart homes. Such intelligent systems will contribute largely to global energy efficiency goals, and carbon footprints reduction and towards a smarter, more sustainable living environments.

References

[1] Y. Natarajan et al., "Enhancing Building Energy Efficiency with IoT - Driven Hybrid Deep Learning Models for Accurate Energy Consumption Prediction, " Sustainability, vol.16, no.5, p.1925, 2024.
[2] B. Abu - Salih, "Blockchain - enabled Peer - to - Peer Energy Trading, " Energy Reports, vol.7, pp.6983 - 6992, 2021.
[3] M. Bharadwaj and S. Sarda, "Energy Prediction using Federated Learning, " arXiv preprint arXiv: 2301.09165, 2023.
[4] Q. Yang and H. Wang, "Privacy - Preserving Transactive Energy Management for IoT - Aided Smart Homes via Blockchain, " IEEE Internet of Things Journal, vol.8, no.4, pp.2346 - 2356, 2021.
[5] T. Cioara et al., "Smart Grid Management using Blockchain: Future Scenarios and Challenges, " IEEE Access, vol.9, pp.124827 - 124843, 2021.
[6] M. M. Alenazi et al., "Energy Efficient Neural Network Embedding in IoT over Passive Optical Networks, " IEEE Transactions on Green Communications and Networking, vol.5, no.1, pp.274 - 284, 2021.
[7] S. P. K. R. et al., "IoT Data Fusion and AI for Enhanced Energy Efficiency in Smart Homes, " Journal of Ambient Intelligence and Humanized Computing, vol.12, pp.6575 - 6587, 2021.
[8] M. A. Hossain et al., "Applications of Blockchain Technology in Peer - to - Peer Energy Trading: A Review, " Energies, vol.14, no.3, p.734, 2021.
[9] M. Andoni et al., "Blockchain Technology in the Energy Sector: A Systematic Review of Challenges and Opportunities, " Renewable and Sustainable Energy Reviews, vol.100, pp.143 - 174, 2021.
[10] F. A. Rahman et al., "Peer - to - Peer Energy Trading: A Review of Enabling Technologies, " Renewable and Sustainable Energy Reviews, vol.141, p.110701, 2021.
[11] J. Guerrero et al., "Decentralized P2P Energy Trading under Network Constraints in a Low - Voltage Network, " IEEE Transactions on Smart Grid, vol.10, no.5, pp.5163 - 5173, 2021.
[12] M. A. Kabir et al., "A Blockchain - Based Peer - to - Peer Energy Trading Framework for Community Integrated Energy System, " Energy Reports, vol.6, pp.288 - 299, 2020.
[13] S. K. Rathor and J. Saxena, "A Comprehensive Review on AI - Based Solutions for Energy Management in Smart Buildings, " Journal of Building Engineering, vol.44, p.103299, 2021.
[14] M. A. Hossain et al., "A Review on Artificial Intelligence and Machine Learning for Energy Management in Smart Grids and Smart Buildings, " Energies, vol.14, no.9, p.2414, 2021.
[15] A. S. Hafiz et al., "Blockchain - Based Peer - to - Peer Energy Trading: A Comprehensive Review, " IEEE Access, vol.9, pp.36191 - 36207, 2021.