IEEE Access
Multidisciplinary | Rapid Review | Open Access Journal

Received January 26, 2021, accepted February 14, 2021, date of publication February 19, 2021, date of current version March 16, 2021.

Digital Object Identifier 10.1109/ACCESS.2021.3060457

Peer-to-Peer Energy Trading Mechanism Based on Blockchain and Machine Learning for Sustainable Electrical Power Supply in Smart Grid

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This work was supported in part by the Energy Cloud Research and Development Program through the National Research Foundation of Korea (NRF) by the Ministry of Science, and ICT (MSIT) under Grant 2019M3F2A1073387, and in part by the Institute for Information and Communications Technology Planning and Evaluation (IITP) Grant by the Korean Government through MSIT (AutoMaTa: Autonomous Management framework based on artificial intelligent Technology for adaptive and disposable IoT) under Grant 2018-0-01456.

ABSTRACT It is expected that peer to peer energy trading will constitute a significant share of research in upcoming generation power systems due to the rising demand of energy in smart microgrids. However, the on-demand use of energy is considered a big challenge to achieve the optimal cost for households. This paper proposes a blockchain-based predictive energy trading platform to provide real-time support, day-ahead controlling, and generation scheduling of distributed energy resources. The proposed blockchain-based platform consists of two modules; blockchain-based energy trading and smart contract enabled predictive analytics modules. The blockchain module allows peers with real-time energy consumption monitoring, easy energy trading control, reward model, and unchangeable energy trading transaction logs. The smart contract enabled predictive analytics module aims to build a prediction model based on historical energy consumption data to predict short-term energy consumption. This paper uses real energy consumption data acquired from the Jeju province energy department, the Republic of Korea. This study aims to achieve optimal power flow and energy crowdsourcing, supporting energy trading among the consumer and prosumer. Energy trading is based on day-ahead, real-time control, and scheduling of distributed energy resources to meet the smart grid's load demand. Moreover, we use data mining techniques to perform time-series analysis to extract and analyze underlying patterns from the historical energy consumption data. The time-series analysis supports energy management to devise better future decisions to plan and manage energy resources effectively. To evaluate the proposed predictive model's performance, we have used several statistical measures, such as mean square error and root mean square error on various machine learning models, namely recurrent neural networks and alike. Moreover, we also evaluate the blockchain platform's effectiveness through hyperledger calliper in terms of latency, throughput, and resource utilization. Based on the experimental results, the proposed model is effectively used for energy crowdsourcing between the prosumer and consumer to attain service quality.

INDEX TERMS Energy trading, energy prediction, predictive analysis, machine learning, blockchain.

I. INTRODUCTION

During the last few decades, the primary energy generation source is non-renewable energy resources, such as coal, natural gas, and oil. Nonetheless, the non-renewable energy sources are becoming costly over time and are difficult to fulfill the load demand of a large population [1], [2]. Similarly, the non-renewable energy resources are not eco-friendly, which indicates that the energy generation process produced high carbon emission [3]–[5]. Therefore, many eco-friendly organizations have emphasized using renewable energy sources (RES), such as solar, wind, tidal, biomass, etc. RES are eco-friendly and are used for producing cheaper energy with less transmission cost [6], [7]. Furthermore, RES

The associate editor coordinating the review of this manuscript and approving it for publication was Ali Shariq Imran.

is also used to contribute to the main grid to meet the grid load demand. The evolution in renewable energy resources opens the door for distributed Peer-to-Peer (P2P) energy trading, such as home and buildings [8]. The P2P energy trading is also referred to as trading between consumer and prosumer. The peers can trade energy with each other without the intervention of any traditional energy distributors, such as grid [9].

The smart grid innovation, such as Distributed Energy Resources (DER) and microgrids, has to change energy generation and consumption in two aspects. Firstly, the addition of a prosumer as a grid participant helps with energy contribution to main grid storage and provides grid decentralization. Second, the modification in utility to service providers from the power retailer, which aims to provide (renting) transmission line to the prosumer. The shifting of the traditional grid to the smart grid requires a trusted energy platform, mathematical model, distributed operations, and control algorithms to facilitate stable grid functions, prosumer interaction, and business model based on intensive [10]–[12].

Crowdsourcing is the large-scale set off for numerous industries and has been implemented in many disciplines, e.g., cyber-physical system, medicine, and engineering system [13]. The main aim of crowdsourcing is to use crowds' services and goods to attain system objectives [14], [15]. Crowdsourcing can also be applicable in the energy sector. We have studied the most prominent crowdsourcing market, i.e., Amazon Mechanical Turk, which facilitates customers to pole their job along with expiry-date and financial rewards. Similarly, the energy crowdsourcing system (ECS) is useful for many scenarios, such as charging and discharging of the battery, electric vehicle charging, meet energy demand(real-time) via renewable energy resources, such as solar panel, wind, and other DER [16]–[20]. These scenarios can be automated by using smart plugs, inverters, and digital meters with the involvement of a power distributor and blockchain implementation.

The conversion in the continual energy system, where prosumer is used for crowdsourcing and expedite in two ways such as:

- A crowdsourcing based energy system that provides grid stability via real-time management of the grid.
- A secure computerized framework (e.g., blockchain) that supports millions of energy trading transactions, such as prosumer to consumer or prosumer to the utility.

Most of the existing studies rely on optimal power flow, which is used to estimate the optimal operational level for a utility to meet the load demand by minimizing the cost of operations [21], [22]. Moreover, blockchain technology is also used by many researchers for providing data security in the energy system. However, the energy system and computerized framework have many shortcomings. Firstly, the existing computerized framework is not scalable in supporting millions of energy trading transactions. Second, there is an ambiguity of how the trading between the peers took place. Finally, how the prosumers and crowdsourcees can adopt the controllable loads and DER. This research study attempted to address the issues mentioned earlier, and the main contribution of this paper is followed as:

- The main aim of this study is to propose an intelligent peer-to-peer energy trading between the prosumer and the consumer.
- The proposed system comprised of smart contract enabled real-time and day-ahead controlling and generation scheduling of DER, controllable loads in order to meet the load demand of smart grid based on reward and agreement.
- The proposed blockchain-enabled intelligent energy trading platform is modeled and implemented using a permission blockchain network called Hyperledger Fabric, which allows the system admin to operate the network, crowdsourcees to manage their accounts, and perform energy transactions within the eco-system.
- The data analytics module is implemented based on data mining techniques to extract the knowledge and hidden patterns important for energy distributors to devise effective decisions and manage energy resources effectively.
- The proposed energy predictive analytics module is implemented based on machine learning techniques to predict the short-term energy demand in order to minimize the delivery cost of electrical energy for consumers.

The rest of the paper is formed as follows. Section 2 describes the start-of-art comparison of energy trading platform based on blockchain and machine learning. Section 3 presents the predictive peer-to-peer energy trading based on blockchain, including an operational model of distributed energy resources, smart contract centric energy trading transaction, and reward model. Section 4 demonstrates the implementation and development scenario. Section 5 presents the results and discussion. Conclusion and future directions of the proposed peer-to-peer energy trading platform are given in Section 6.

II. RELATED TERMINOLOGIES

Many studies focus on integrating the distributed energy resources operation in distributed networks. The operation includes economic dispatch problems, distributed energy resources scheduling, grid frequency maintenance, and load and renewable forecasts. Nowadays, the energy demand and reward pave away the owner of distributed energy resources to contribute to eco-friendly production.

A. ENERGY TRADING AND BLOCKCHAIN SYSTEMS

Blockchain is a distributed ledger technology that relies on a consensus and communication protocol that safeguards the ledger's integrity through connected cryptographically time-stamp block that represents transactions [23]–[29]. The blockchain approach originates after the bitcoin invention, which uses the Proof of Work (PoW) concept. The miner incorporates transactions into tree-based blocks encrypted

TABLE 1. Characteristic of blockchain with various component.

Platform \ Component	Smart Contract	Transactions	Network	Consensus Algorithm	Cryptocurrency	Programming Language
Hyperledger Fabric	Chaincode written in Golang	anonymous	Permissioned	PBFT	No	Java/Node.js
Bitcoin	None	anonymous	Permissionless	PoW	Bitcoin	C++
Ethereum	Smart Contracts written in Solidity	public/private	Permissionless	PoW	Ether	C++

with predefined hash range [30]. Nonetheless, the PoW approach using public ledger has too many shortcomings in privacy, scalability, numbers of the transaction, and energy consumption [31]. During the last few years, many new blockchain technologies have been introduced in order to overcome the shortcoming mentioned above. These technologies include privacy and permission mechanism, consensus mechanism, and smart contracts [31], [32]. The details of these technologies are mentioned below.

- **Privacy and Permission Mechanism**: The blockchain system can be divided into a private and public blockchain. The private blockchain is an invitation-only network managed and administered by a set of registered participants. In permissioned blockchain, only the registered parties can participate in the block creation, while in permissionless blockchain, anyone can participate in the creation of block and consensus mechanism [33]. Therefore the permissionless blockchain is less transparent, less anonymous, and less secure as it depends on the participants' integrity. Likewise, the permissioned blockchain is more secure, high customizability, better scalability, and enhanced access control mechanism [34], [35]. In other words, the private blockchain is more efficient than the public blockchain; therefore, in the presented system, we use Hyperledger Fabric, a permissioned blockchain used for developing blockchain-based application [33], [36].
- **Consensus Mechanism**: The consensus protocol is used to provide consistency and integrity in blockchain and assure the sequence of transactions across the distributed nodes [37]. The existing consensus protocol, like PoW, which is used by the bitcoin, consumes 47.1 teraWatt/hour energy consumption per annual. Moreover, the PoW consensus protocol has many shortcomings in terms of numbers of a transaction, which minimize the chance of using the system in a high-performance environment [38]. Many new consensus protocols have been developed during the last couple of years, e.g., PoS (Proof of Stake) and Practical Byzantine Fault Tolerance (PBFT). Some of these consume more energy, and some of them are used to reduce energy consumption. In this work, we use PBFT, which is used to increase the frequency of transactions between each shared and eliminate the risk of blockchain centralization [39]. Furthermore, the PBFT minimizes energy consumption by removing the hash energy to process the block in blockchain [40].
- **Smart Contract**: A smart contract is a type of computer program which provide the functionality of self-execution, self-verification, and tamper-resistant abilities. Nick Szabo initially developed a smart Contract in 1994. [41]. Smart Contract supports turing virtual machine(VM) and protocol that allow nodes to execute services based on the results of transaction processor function and also provide the facility of sophisticated logic [42]. Smart Contract integrated with offer an efficient and secure platform for both the consumer and prosumer to perform energy trading transaction [43].

Table 1 summarized the consensus protocol feature along with the public and private blockchain platform.

B. MACHINE LEARNING IN MICROGRID

During the past several decades, many machine learning algorithms have been proposed to discover and investigate the massive amount of data's hidden patterns and knowledge.

Nowadays, the enhancement in the machine learning algorithm provides a way to discover hidden information from the large volume of data to construct a predictive model to drive a conclusion [44]–[46]. In every prediction system, the important part is the prediction algorithm that influences the system's prediction result and performance. Deep neural network (DNN) is widely used in computer science, energy management, speech recognition, computer vision, etc. Several researchers use DNN to build a prediction model using several algorithms like data mining and text mining to enhance the system performance. The LSTM is a renowned machine learning approach used to prediction, classifying, and processing using time-series based data [47]–[49].

Utility companies and energy sector decision-makers have claimed that blockchain can solve the challenges of the energy sector. Nowadays, many energy trading platforms integrated with blockchain have been introduced to solve the energy sector problem while providing an eco-friendly environment. The German Energy Agency [50] suggested that the current blockchain technology have the potential to enhance the efficiency of energy sectors and expedite the research and development of IoT based application which boosts the innovation in the P2P energy trading solutions. Furthermore, blockchain technology also facilitates the usage of energy trading by the utility companies and local residential consumer and prosumer, which improve customer costs and services [2].

In the energy trading market, the P2P network model provides and manages consumers and supports the prosumer, which improves traditional energy trading to a flexible energy market. The author in [51], presented a P2P network model that is used to enhance the energy market efficiency. Furthermore, the distributed system also contribute to improving the high rigor demand response signal [52], minimize cost, and boost speed [53]. The energy system endures a transformational change provoked by the upgrading of distributed energy resources and information technology. One of the main challenges of the energy system is digitization and decentralization, which requires the adoption, consideration, and exploration of unique distributed technologies. Blockchain provides a solution to manage and control complex decentralized microgrids and energy systems due to the inherent nature. Integrating consumer participants, small-scale renewables, flexibility services, and distributed generation in the energy sector is challenging. The author in [50] discussed that blockchain technology provides an innovative and secure energy trading system where the consumer and the prosumer can trade surplus energy on a P2P basis. The operating consumer record is stored in tamper-proof, immutable, and transparent smart contracts. The development of such an energy trading platform can provide information on energy cost and price signals to the consumer efficiently.

During the last few years, many blockchain-enabled energy trading platforms have been introduced, which improve the consensus mechanism, cost minimization, energy consumption, and security of personal data. In [54], Brooklyn microgrid, the first blockchain-based energy trading platform, was introduced by the exergy team in April 2016. Similarly, in [55], Sunchain project is presented using Hyperledger Fabric, which provides virtual network support for solar energy and improves energy transactions at minimum cost. The Sunchain startup did not get success as few users involved in sharing the surplus solar energy. The project traces the complete trail of energy generation and sharing. In [56] author presented the interoperable, transparent, and trustless energy trading platform named Power ledger. The Power Ledger is an Australian startup that supports token-based transactions that provide users to receive real-time payment in exchange for energy trading. In [57], the author presented a Pylon network, an open-source P2P energy trading system that complete store record of each energy transaction and provide transparency and security while energy payment. SolarCoin [58] a global incentive solution that provides rewards to prosumers for selling surplus solar energy. The SolarCoin foundation rewards solar energy producers one solar coin for one megawatt/hour of energy. SolarCoin is open-source, decentralized, and decoupled from any government organization. SolarCoin is based on blockchain that creates a P2P network that allows energy trading across the distributed global network. Grid Singularity is an open-source energy trading platform that connects individuals to the marketplace through smart contracts [59]. The author in [60], presented an NRGcoin, an open-source Belgium based energy trading platform that uses individual renewable energy and pays NRGCoin. The NRGcoin is a virtual crypto-currency and easily convertible with euros. Table 3 summarized the comparison of the existing energy trading platforms.

III. LITERATURE REVIEW

The scientific community has produced various techniques concerning optimization in microgrids and effectuate the energy trading process. Optimization is the selection of the best option from a set of available alternatives. Beside Energy optimization is used in other field of sciences such as sustainable smart solutions [61]–[64]. An optimization model [65] is presented to optimize energy trading between two microgrids operating in islanded modes using a central controller. The model meets the power demand for a microgrid and reduces energy production costs. In a study [66], authors have introduced an incentive-based renewable energy sharing technique to meet load demands with surplus energy through which energy is traded among multiple users in a simultaneous manner. An optimal electricity price for energy trading is derived using coalitional game [67]. The model results in balanced revenue for small-scale energy producers and consumers. The study [68] presents a cooperative distributed power generation and trading mechanism to enable multiple prosumers for energy trading in a cost-efficient manner. Besides, various ML [45], [69]–[73] and blockchain techniques can be proven useful in solving prediction to optimization-related issues for energy trading in smart grid [74]–[77]. The author in [78] presented an approach to optimize microgrid based on machine learning. The developed system forecasts the standalone microgrid's security and energy demand. In another study, a hybrid energy management system based on machine learning, fuzzy logic, and multi-objective optimization using linear programming. This system's main purpose is to minimize renewable energy's operational cost while maximizing the energy generation [79]. The author in [80], presented an energy trading system on a vehicle to grid-based on edge computing and blockchain. The efficient and secure trading system is a two-stage model comprised of the Stackelberg leader-follower game and backward induction approach. The model is evaluated using numerical and theoretical analysis. In [81], the industrial internet of thing (IIoT) based blockchain-enabled energy trading is presented known as FeneChain. The FeneChain is a secure energy trading platform based on industry 4.0, which improves and manages energy management in buildings. The following table recapitulates the pros and cons of the state-of-the-art in microgrid energy trading.

IV. INTELLIGENT PEER-TO-PEER ENERGY TRADING

A. CONCEPTUAL SCENARIO OF INTELLIGENT ENERGY TRADING

Figure 1 presents the model of an intelligent peer-to-peer energy trading platform based on blockchain. The smart contract-enabled intelligent energy trading consists of two

TABLE 2. Comparison of energy trading platform.

Platform	Privacy Protection	Pricing Mechanism	Consensus Mechanism	Crypto-Currency	Data Storage Protection	Access Policy	Mining Required
NRGcoin [60]	No	Yes	PoW/PoS	Yes	No	Permissionless/ Consortium blockchain	Yes
Sunchain [55]	Yes	No	PoW	No	No	Permissionless blockchain	No
GridSingularity [59]	Yes	No	PoA	Yes	Yes	Permissionless/ Consortium blockchain	Yes
Exergy [54]	Yes	Yes	PoS	Yes	No	Permissionless blockchain	Yes
SolarCoin [58]	No	Yes	PoS	Yes	No	Permissionless blockchain	Yes
Pylon network [57]	Yes	Yes	PoW	Yes	No	Permissioned blockchain	Yes
Power Ledger [56]	No	Yes	PoW/PoS	Yes	No	Permissionless/ Consortium blockchain	Yes
Proposed System	Yes	No	PBFT	No	Yes	Permissioned blockchain	No

TABLE 3. Critical analysis of machine learning based blockchain-enabled energy trading platform.

Approach	Optimization Technique	Trading model Type	Pros	Cons
[65]	Centrally controlled	Energy Trading between two microgrids	Optimization method adopted to meet demand and response is centrally controlled and reliance on a central entity leads to stability between connected microgrids.	The authors have not focused on issues like uncertainty in energy production and privacy. Limited to only two microgrids.
[66]	Centrally controlled and incentive driven	Connection of multiple users to a same microgrid	The technique adopts two optimization methods (centrally controlled and incentive-driven) which beneficiates in improving accuracy. Also, privacy among the connection is also maintained.	The issues like energy production uncertainty is not focused
[67]	Centrally controlled and game theoretic	Trading among local consumers and prosumers	The employed game-theoretic model leads to an efficiency of optimization model.	Issues like privacy, energy production uncertainty have not been focused.
[68]	Cooperative	Energy Trading between a group of prosumers	Mutual benefit is a key concern for cooperative optimization models that cause model stability.	Similar to [67], issues like privacy, energy production uncertainty are not been focused on.
[82]	Game theoretic and centrally controlled	Energy Trading between microgrids	Privacy is ensured and adopted multileader multi-follower Stackelberg game improves the performance of optimization models.	Uncertainty of energy production is overlooked.
[83]	Game theoretic	Energy trading between multiple prosumers and a single consumer	The model addresses the issue of uncertainty of energy trading between microgrids	The privacy issue has not been addressed.

distinct modules, i.e., real-time and day-ahead energy trading based on pre-processed data and short-term energy prediction. Each node of the proposed platform is used to store and process energy trading data. In this study, we have considered solar energy generation (PV), dispatchable load (e.g., ESS), and shapeable load(e.g., electric vehicle). The energy consumption data from these sources are analyzed using different machine learning and data mining approaches to discover the useful time-series pattern and hidden knowledge from the data to meet future energy demand. The pre-processed data is used for real-time and day-ahead controlling and scheduling of distributed energy resources. Moreover, the discovered time-series features, such as hourly, daily, weekly, yearly, and seasonally, are used to predict the short-term energy demand using machine learning models. Every transaction between the nodes that act as prosumers and consumers is stored in the state database in the form of an Energy trading transaction (ETT). The participants, such as prosumer, consumer, and utility operator, can interact with the system through the client application, which is used for secure energy trading.

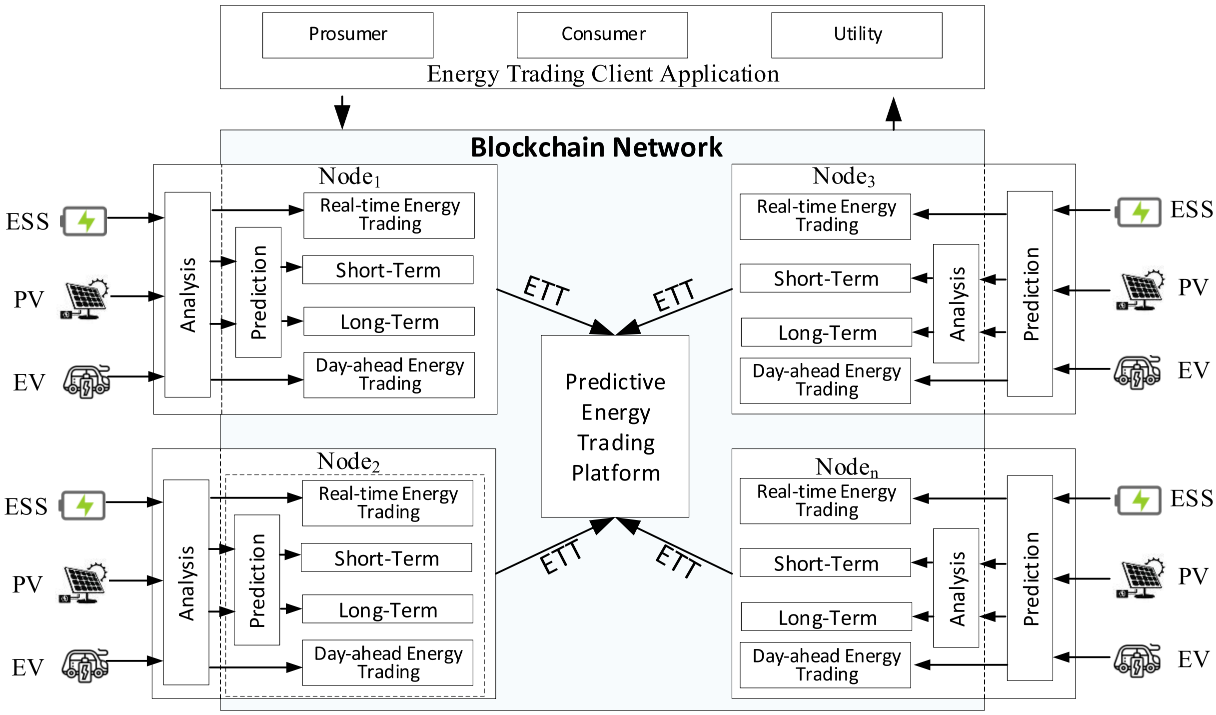


FIGURE 1. Intelligent energy trading platform conceptual scenario.

The communication between the blockchain network and the client application is established through the RESTFul API, which used the HTTP protocol to handle user requests.

B. INTERACTION MODEL FOR INTELLIGENT ENERGY TRADING

The proposed blockchain-based intelligent energy trading workflow is presented in Figure 2. The designed system comprises technical infrastructure that consumes the distributed ledger technology(DLT) and smart contract as a service to the blockchain through a user service framework. The intelligent energy trading platform contains a set of peers or nodes as illustrated in Figure 1, where each peer maintains the ledger copy to sustain the consistency of the distributed ledger technology. The distributed ledger (DL) is responsible for storing the immutable energy trading transactions into the chain of blocks. In contrast, the proposed system data lake maintains and store the information related to distributed energy sources, system participants, and energy trading transactions. The blockchain network store and keep all the modification arise in the data lake. The data lake is considered as an off-chain database that maintains the data related to energy trading transactions and is also used for the data analytics model. Moreover, the proposed system also provides the functionality RESTfull API in order to provide the back-end services to the front-end energy trading client application. Each participant must be enrolled using the identity manager before committing the blockchain network's energy trading transaction. Similarly, the participants, like prosumer, consumer, and utility, can submit the energy trading transaction by retrieving surplus energy from energy sources. Afterward, the energy consumption data is analyzed and used in an intelligent smart contract in order to perform real-time and day-ahead energy trading. Similarly, the analyzed data is also used by a machine learning model to predict future energy demand. Each energy trading transaction data is stored in the blockchain. The notification is sent to the respective user upon the successful energy trading transaction.

C. BLOCKCHAIN MODEL FOR INTELLIGENT ENERGY TRADING

The proposed blockchain-enabled predictive energy trading platform is a modular architecture where each layer is independent of other layers so that the developer can easily modify existing components or new components without changes the rest of the system. The distribution grid network model consists of various distributed energy resources, e.g., solar energy and dispatchable loads connected via a bus transmission line. Each node in the grid distributed network is equipped with distributed energy resources such as shapeable loads, dispatchable loads, and solar energy with the ability to generate and consume energy. Finally, each bus is used to connect the grid with a node in order to consume and transmit energy. The blockchain-based energy trading service layer provides several features of blockchain such as identity management, API Interface, distributed ledger, P2P communication, and consensus manager. The distributed ledger comprises synchronized, shared and replicated digital data distributed across the blockchain network where all the network participant maintains their ledger replica. Furthermore,

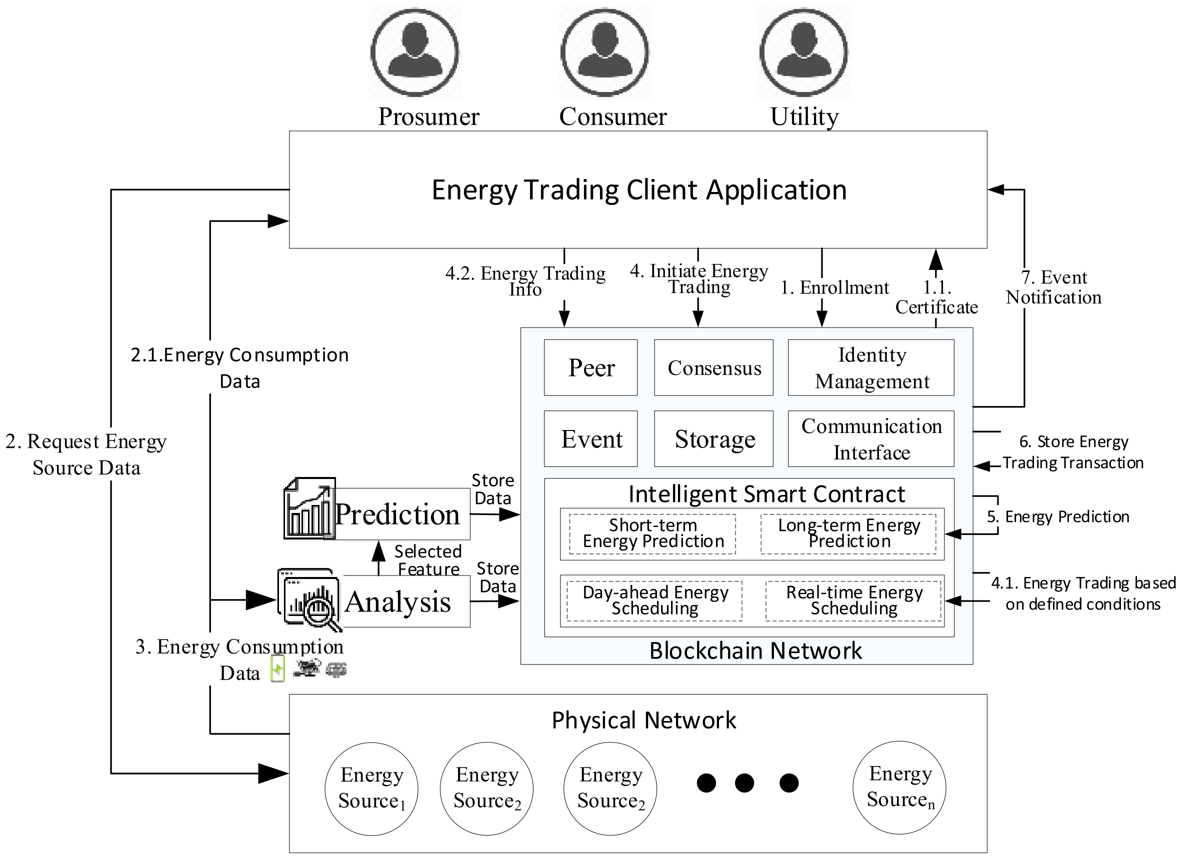


FIGURE 2. System workflow of the intelligent blockchain based energy trading platform.

the distributed ledger also provides secure data storage capability to store microgrid configuration and energy consumption and generation between the consumer and prosumer. Any modification in the ledger is reflected in all the replicas in a minute or seconds. The blockchain's ledger can be permissionless or permissioned, concerning anyone or an approved network member who can run a peer and validate the transaction. The smart contract is a chaincode triggered by the client application to perform defined operations. We defined several transaction processor functions such as the Real-time reward model and Day-ahead scheduling, to name a few. The smart contract is initiated and install on every peer within the blockchain network. The application programming interface is used to visualize the back-end blockchain services managed and accessed through a client application. Similarly, the application layer provides the services to render the services-oriented data from the distributed network model. Lastly, the system's users are prosumer, consumer, and utility operators responsible for selling, buying, and managing the distributed energy resources. The prosumer in the proposed system aims to sell the distributed energy resources to the utility or consumer. Similarly, the consumer is the one who consumes the energy, whereas the utility operator is responsible for managing the distributed energy resources of the user based on mutual consensus. The layered architecture of the proposed system is presented in Figure 3.

We have used a single feeder based on a radial distribution network linked with utility-scale renewable and traditional generation in a blockchain-based predictive energy trading platform. We consider a scenario where crowdsourcees are connected at the feeder level with n-buses modeled as tree graph structure (T_n, T_L). The T_n is the set of nodes connected on the lines $T_L \subseteq (T_n)^2$. The T_n in the radial distribution network can be defined as $T_n = \{U_n \cup L_n \cup C_n\}$, where U_n denotes utility-scale power generation attached to the feeder; C_n which connects with buses containing user who agree for energy crowdsourcing. L_n denotes load on buses.

The crowdsourcer is the residential building or house equipped with distributed energy resources like PV, WT, and ESS. The crowdsourcer in C_n also act as a participant in the proposed system which is of two types, i.e., $CType_1$, $CType_2$. $CType_1$ are the user responsible for committing a day-ahead market (weekly or monthly) according to the plan assigned by the grid operator. The grid/operator, in return, provides benefits in terms of bill discounts or social-economic incentives. Similarly, $CType_2$ users are responsible for committing a real-time decision and notification based on the task assigned by the operator/grid, e.g., charging and discharging of electric vehicle based on the location of the user and grid physical state. In other words, the $CType_1$ users contribute with the day-ahead policies as per the grid/operator suggestion, whereas $CType_2$ is aimed to provide real-time support. The

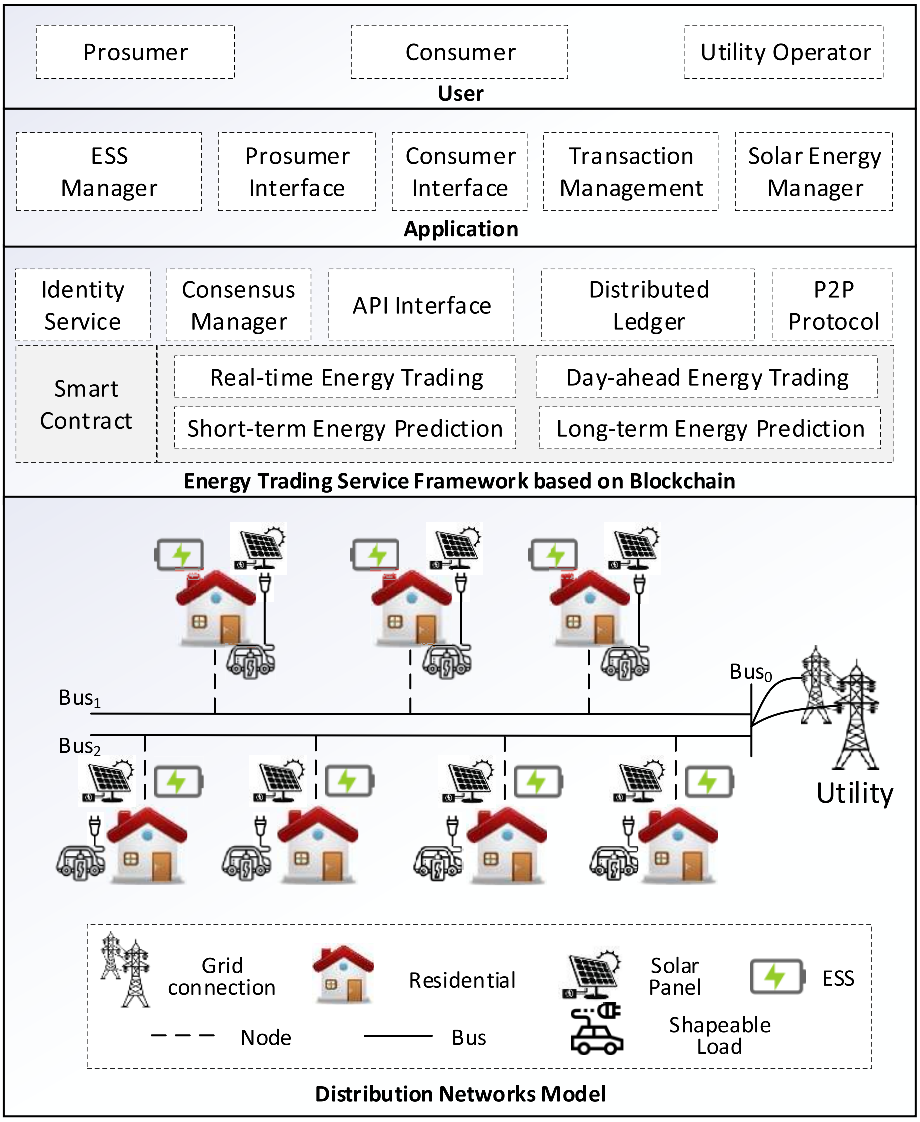


FIGURE 3. Block diagram of energy trading and distribution network model based on blockchain.

proposed blockchain-based radial distribution network model is presented in Figure 3.

The proposed system also support energy trading transaction and is of two types, i.e., ET_{Type1} and ET_{Type2}. The ET_{Type1} is used solely between the crowdsourcees ($CType_1$ and $CType_2$) and the grid. In ET_{Type1} transaction, the crowdsourcees act as prosumer and feed the utility/grid with the power generated from the distributed energy resources. Likewise ET_{Type2} is only committed between the $CType_2$ users. In ET_{Type2} transaction, the user $CType_2$ can trade energy with each other generated from distributed energy resources. The flow of transaction, according to the crowdsourcees, are shown in Figure 4.

D. OPERATIONAL MODEL OF DISTRIBUTED ENERGY RESOURCES

In the proposed system, we consider a scenario in which energy is generated from multiple sources, e.g., energy storage system, dispatchable, and non-dispatchable generation. The dispatchable energy generation is generated by the grid/utility to meet the energy load demand. In contrast, non-dispatchable energy generation includes renewable energy sources like wind power and solar power.

1) SOLAR ENERGY GENERATION

In this article, we consider only solar power as a non-dispatchable energy source. Let assume that index $\in T_n$ represents the distribution system and the time period is denoted by t. The solar power generation is formulated as $S^{pow}_{index,t}$ for bus index $\in C_n$ at time t. The $CType_1$ crowdsourcees feed the $S^{pow}_{index,t}$ into the grid, but the controlled authority only lies with the grid. Likewise, the $CType_2$ crowdsourcees have the choice to feed the $S^{pow}_{index,t}$ to grid or sell or trade it locally with other $CType_2$ crowdsourcees.

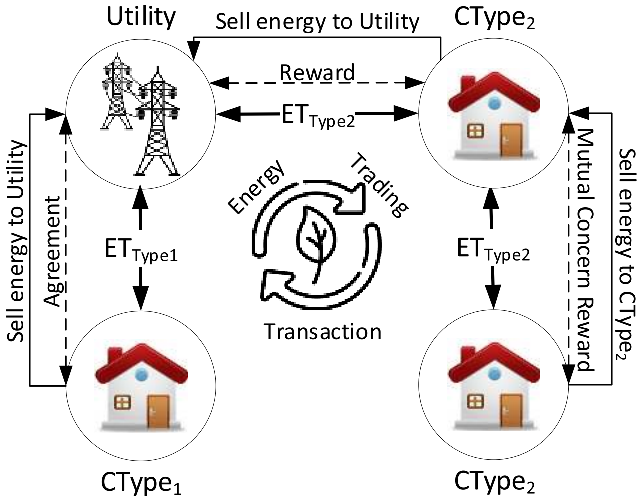


FIGURE 4. Energy trading transactions types.

2) DISPATCHABLE LOADS

The dispatchable loads are the batteries that are used to withdraw or inject energy. The output of the battery is formulated as $B^{pow}_{index,t}$ where $index \in C_n$. The $B^{pow}_{index,t}$ can be positive or negative, which implies the power is injecting or withdrawn from the battery. The operational model of the battery can be expressed as

$$En^{pow}_{index,t} = En^{pow}_{index,t-1} + CB^{pow}_{index,t,K_{in}} - DB^{pow}_{index,t,K_{out}} \quad (1)$$
$$B^{pow}_{index,t} = DB^{pow}_{index,t} - CB^{pow}_{index,t} \quad (2)$$
$$0 \leq DB^{pow}_{index,t} \leq B^{pow}_{index,t,rel} \quad (3)$$
$$0 \leq CB^{pow}_{index,t} \leq B^{pow}_{index,t,inj} \quad (4)$$
$$En^{pow,min} \leq En^{pow}_{index,t} \leq En^{pow,max} \quad (5)$$

In the above model, the $En^{pow}_{index,t}$ represents the battery's energy at time t. K_{in} and K_{out} denotes the efficient constant of the charging and discharging of the battery. The $DB^{pow}_{index,t}$ and $CB^{pow}_{index,t}$ is the discharging and charging of battery. The net power $B^{pow}_{index,t}$ is calculated by subtracting the battery discharging and charging power. The $B^{pow}_{index,t,rel}$ and $B^{pow}_{index,t,inj}$ is the discharging and charging limitation power of the battery. In the designed system, we modeled the dispatchable load into a single vector variable as $Q^{pow}_{index,t}$: $S^{pow}_{index,t}, En^{pow}_{index,t}, DB^{pow}_{index,t}, CB^{pow}_{index,t}$.

3) SHAPEABLE LOADS

In the proposed system, we consider the shapeable load as an electric vehicle that takes fixed power input 24 hours. The shapeable load can be formulated as

$$V^{s}_{index,t} = P^{s}_{index,t} + iX^{s}_{index,t} \quad (6)$$

where index $\in L_n$ which implies load on bus. The electric vehicle is defined with constant energy demand $En^{s}_{index,dem}$ for 1 day. The $P_{index} + iX_{index}$ is the power flow in the bus index to $index_n$. Furthermore the electric vehicle must be contented between start and end time represented as $t_{index,st}$ and $t_{index,end}$ respectively. The electric vehicle model can be defined as

$$En^{s}_{index,dem} = \sum_{t=1}^{l} V^{s}_{index,t} \Delta t \quad (7)$$
$$V^{s}_{index,t} = for t=0, 1, \ldots, t_{index,st}, t_{index,end}, \ldots, l \quad (8)$$
$$V^{s,min}_{index} \leq V^{s}_{index,t} \leq V^{s,max}_{index} \quad (9)$$

where the time-horizon length is denoted by t, Δt denotes time interval. we modeled shapeable load into single vector that can be represented as $Q^{s}_{index,t} = V^{s}_{index,t}$.

The net power injection for every bus index at time interval t can be formulated as presented in Equation 10. Let assume that for every buses in the network we defined $Q_t = (Q^{s}_{index,t}, Q^{pow}_{index,t})_t$ as a vector variable which is used to control variables related to shapeable loads and batteries. For crowdsourcees $CType_1$ and $CType_2$ we divide the controlling vector Q_t into Q_1 for $CType_1$ and Q_2 for $CType_2$. Likewise for solar energy $S^{pow}_{index,t}$ we defined R variable.

$$PI_{index,t} = S^{pow}_{index,t} + B^{pow}_{index,t} - P^{s}_{index,t} \quad (10)$$

In the proposed system, the crowdsourcees configuration and desire parameter, e.g., eagerness to sell energy, criterion relevant to load, batteries, and solar panel are disseminate with the utility/operator.

E. SMART CONTRACT CENTRIC ENERGY TRADING TRANSACTION AND REWARDS DESIGN MODEL

This section discussed different types of energy trading transactions and defined a reward mechanism that urges the crowdsourcees to participate in the design platform. The proposed system comprised of two energy trading transaction, i.e., ET_{Type1} and ET_{Type2}. These types of transactions are committed between the crowdsourcees and the utility. Furthermore, the design system supports P2P energy trading between the prosumer and the consumer and prosumer and the utility, while awarded crowdsourcees with an incentive so that they can contribute to the energy trading eco-system. The proposed system supports two types of algorithms for crowdsourcees, i.e., day-ahead scheduling and real-time reward model. In day-ahead scheduling, we consider the energy load demand, solar energy forecast, and crowdsourcees day-ahead energy trading transaction scheduling. Similarly, in the real-time reward model, the $CType_2$ users get rewarded by selling the surplus energy either to the grid or other $CType_2$ users in order to full their load demand. The details of these two algorithms along with users and transaction type are presented in Table 4.

1) DAY-AHEAD ENERGY SCHEDULING

In day-ahead scheduling, the distributed energy resources of $CType_1$ users' is controlled by the utility as per the agreement signed on the mutual concern. Similarly, the $CType_2$ has a choice to participate or not in the crowdsourcing process based on the offered rewards. The $CType_2$ can trade the

TABLE 4. Energy trading transaction types along with corresponding user and algorithm.

Transaction Type	Seller	Buyer	Cost	Algorithm
ET_{Type1}	$CType_1$	Utility	Agreement	Day-ahead scheduling
ET_{Type1}	$CType_2$	Utility	Reward	Real-time reward model
ET_{Type2}	$CType_2$	$CType_2$	Mutual Concern	Day-ahead scheduling

surplus solar energy either to the utility or other $CType_2$ users if the offered reward is sufficient in the hour-ahead or real-time markets. Furthermore, for $CType_2$ users, the output energy from dispatchable loads $B^{pow}_{index,t}$ and solar energy $S^{pow}_{index,t}$ where index $\in CType_2$ are not managed by the utility. Therefore, if $CType_2$ made decision to not to trade energy with other $CType_2$ users as mentioned in ET_{Type2} then these parameter are set to zero in (10) as presented in (11).

$$S^{pow}_{index,t} = B^{pow}_{index,t} = 0, index \in CType_2 \tag{11}$$

In other cases, the seller and buyer can trade energy based on the energy supply-demand request. The energy trading request for $CType_2$ users can be expressed as $EnergyTradingTransaction(Q_2, R)$.

2) REAL-TIME REWARD MODEL

In the real-time reward model, the $CType_2$ users are rewarded whenever the surplus solar energy is trade to meet the grid's energy demand load. In this model, the real-time energy services are provided like charging electric vehicle and real-time energy trading, which is used to meet the real-time load demand using surplus solar energy. In exchange for these services, the crowdsourcees will get rewarded based on the amount of energy unit. The amount of energy trade in terms of net power can be computed as

$$P^{net}_{index,t} = S^{pow}_{index,t} - P^{s}_{index,t} + B^{pow}_{index,t}, index \in CType_2 \tag{12}$$

In (12), the shape load that consumes energy can be reduced from the surplus solar energy afterward; the computed net power can be used to trade either to $CType_2$ users or grid. If the ($P^{net}_{index,t} \leq 0$) then the crowdsourcees has no energy to sell at time interval t. Similarly if the ($P^{net}_{index,t} > 0$) then the crowdsourcees have surplus solar energy to trade either with grid or other $CType_2$ users.

V. ENERGY TRADING ANALYTIC MODEL

This study introduces an integrated operational model of blockchain-enabled intelligent energy trading platform that contemplate an immense domain of distributed energy resources, energy trading transaction, and several types of crowdsourcees in a distributed network. The main aim is blockchain-enabled secure energy trading based on energy crowdsourcing between the prosumer and the consumer and intelligent energy model to predict energy utilization to meet short term energy demand. In other words, the proposed system is divided into two modules, the secure blockchain-based P2P energy trading and intelligent energy prediction model to fulfill energy demand in a distributed network.

A. SMART CONTRACT ENABLED PREDICTIVE ANALYTICS MODEL FOR ENERGY TRADING

The proposed approach is evaluated using real-time data from smart grid institute Jeju, South Korea. The dataset contains time-series energy consumption(MW) data. The dataset consists of 116,189 energy consumption records from the time period of 2002 to 2018. The proposed energy data analytics model consists of an input layer, energy data pre-processing, energy predictive analysis, performance analysis, and validation layer, as shown in Figure 5.

First, the data is prepared for the analysis models; the final dataset contains two features: time(hr) and energy consumption. The raw data is transformed into reliable data using different data pre-processing techniques and statistical measures. In the start, all redundant records from the energy consumption dataset are identified and removed. Hence this reduces dataset size and also the computation cost of data analysis. Similarly, the tuples with the missing values are also removed from the dataset. The missing values represent that the energy consumption tuples don't have date-time or energy consumption data for the specific record. The time-series attribute, which represents the time and date of the energy consumption data, is used to extract the underlying time-series hidden patterns to predict the short term energy prediction. The short-term and long-term analysis enable to plan and minimize the cost of delivering electrical energy for consumer and thus is significant to economize power engineering. Furthermore, accurate electricity consumption prediction is essential for policymakers to formulate electricity supply policies such as meet load demand.

The next layer is the energy data analysis layer, which uses descriptive data analysis methods to find hidden patterns from the pre-processed dataset. The extracted features using descriptive analysis can effectively enhance machine learning models' training process for short-term and long term energy prediction. Time-series pattern discovered using descriptive analysis is short-term energy analysis such as hourly and daily energy consumption and long-term energy analysis such as weekly, monthly, yearly, and seasonally. These extracted features are used as input to the proposed predictive analysis models. Descriptive and predictive analysis will enable accurate prediction to minimize the cost of delivering electrical energy for the consumer. We proposed Bi-directional Long Short Term Memory (Bi-directional LSTM) predict the short and long term energy prediction in a predictive analysis approach. A Bidirectional LSTM consists of two LSTMs: one for input in a forward direction and the backward direction. LSTM is a type of RNN that recognizes value after a random layoff. LSTM is useful to process, classify,

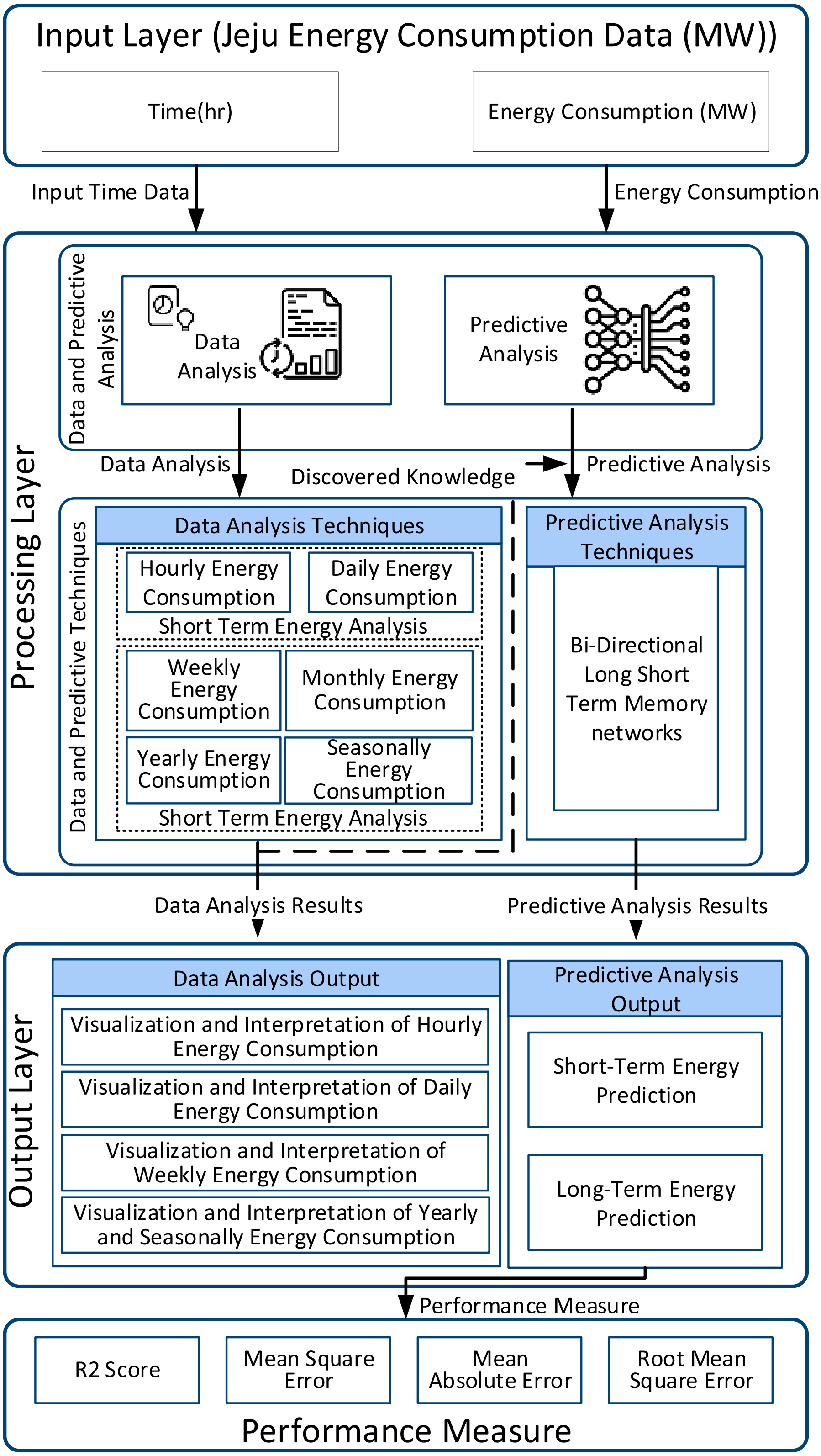


FIGURE 5. Proposed model of the blockchain-based predictive energy trading.

and predict the time-series energy data. Every node specifies the neuron of an individual time step. Every block in LSTM contains self-connected solo or multiple memory cells and multiplicative entities, such as input and output gates. These layers present continuous analog of reading, write, and reset transactions for the memory cell. Similarly, the RNN training

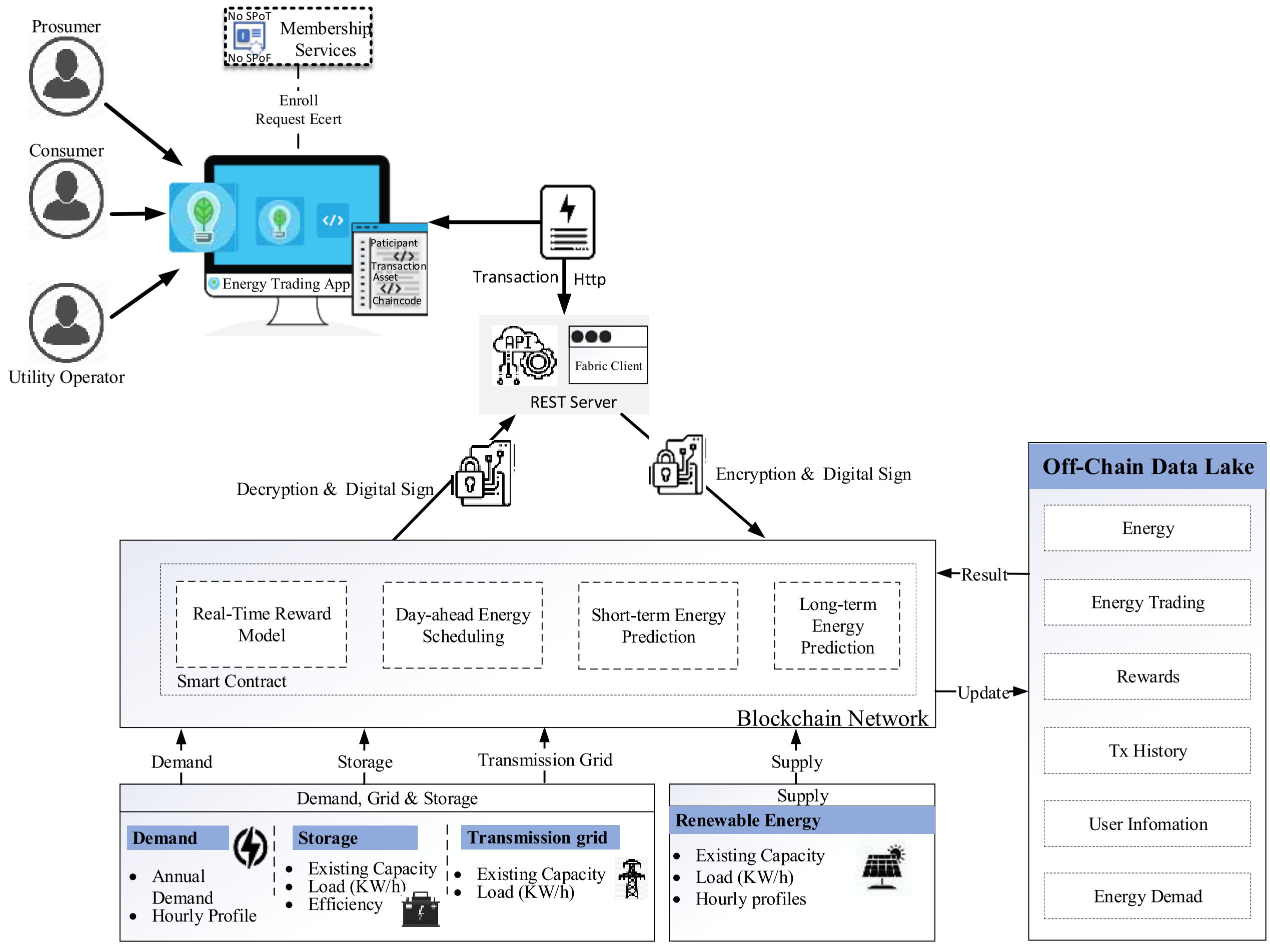


FIGURE 6. Predictive energy trading platform implementation and use-case deployment.

process consists of a forward and backward pass. The RNN forward pass is similar to multi-layer perception with a solo layer. Likewise, the backward pass is the same as propagation through time which is used to compute weight derivative for RNN.

The final layer is the energy prediction performance measure, as the problem discussed in this paper is a regression problem. Therefore, we will evaluate the proposed time series-based prediction models in terms of R2 score, Mean square error, mean absolute error, and root means square error.

VI. IMPLEMENTATION ENVIRONMENT OF THE INTELLIGENT ENERGY TRADING PLATFORM

Figure 6 presents the case study's development environment for the proposed blockchain-enabled predictive energy trading platform and shows the link between the distributed grid network and the blockchain network. The distributed grid network consists of distributed energy resources used to buy and sell surplus solar energy. In the design system, we use Hyperledger Fabric, an open-source framework, to develop a blockchain-based application. The predictive energy trading blockchain network consists of four peers, an orderer node running as an image in the container. Each peer in the blockchain network consists of data storage and smart contract to record the transaction block to the ledger. We have used CouchDB, which acts as a state database, and support enriches queries used to retrieved customized data from the database. The data record in the state database is in key-value format, and the datatype is JavaScript Object Notation (JSON). Furthermore, the composer-rest-server is used to generate the RESTful API that exposes the distributed grid network services like real-time reward model, day-ahead scheduling, to name of a few, to the client application through client SDK. The blockchain is based on distributed ledger technology, where each block in the network is cryptographically secured to form a block sequence of transactions. Practical Byzantine Fault Tolerance (PBFT) is installed on the orderer node to maintain the ledger consistency. Moreover, the orderer node runs independently of the peer process and arranges the transaction in FCFS(first come, first serve) order across the entire blockchain network. Finally, the system user gets a notification from the blockchain network in case of the transaction response.

TABLE 5. Smart Contract modeling for predictive energy trading platform.

Type	Component	Description
Assets	Energy	Energy asset is used for trading of energy data from utility to consumer and prosumer. We define two types of energy solar and utility.
	Reward	The reward is the asset used as incentive in exchange of energy while trading.
	SolarEnergy	Solar energy is the energy generate from solar panel.
	EnergyStorage	The energy storage system (ESS) is an asset used for storing energy.
	EnergyTrading	The energy trading represents the energy trading record of each user that are equipped with solar panel.
	Utility	The utility is the source of energy generation that records the information of grid utility.
Participant	Utility Operator	The utility operator is responsible for selling energy to prosumer and consumer.
	Prosumer	Prosumer is the person who generate energy and sell to consumer and utility.
	Consumer	Consumer is the person who consumed energy from the grid and utility.
Transaction	EnergyToReward	Convert energy into rewards based on per Unit price ($).
	ET_{Type1}	CType1 can sell the surplus solar energy to utility based on the agreement. CType2 users can sell the surplus energy to utility in real-time based on reward model.
	ET_{Type2}	CType2 users can only sell surplus solar energy to CType2 users to meet the demand load.

A. SMART CONTRACT MODELING OF PREDICTIVE ENERGY TRADING PLATFORM

The smart contract in the designed system is implemented using an open-source framework and toolset to facilitate the development of the blockchain applications. The smart contract is model as Business Network Archive (.bna), which comprises assets, participants, transaction processor function, access control rules, and query definition. The assets are services, goods, or property, which are the smart contract and modified based on the defined transactions. Participants can also interact with assets that are directly linked with task and identity across the entire blockchain network. The participants can perform a particular operation like create, delete, update, and reading on assets to perform user-specific tasks. We define multiple assets like solar energy, shapeable loads, dispatchable loads, utility, ESS, reward, and energy, to name a few used to perform a specific task in the proposed system. Like assets, participants are also defined in the smart contract as a part of a business network whose responsibility is to submit transactions and interact with assets. The prosumer, consumer, and utility operator are the participant defined in the blockchain network. The transaction processor function specifies logical actions performed on the assets defined as a part of a smart contract. In the proposed system, we develop a transaction processor function in JavaScript language. In the design system, we defined multiple transaction functions that include, but are not limited to, a real-time reward model, day-ahead scheduling, energy trading, and transfer rewards. In the real-time reward model, the $CType_2$ participants sell the surplus solar energy to other participants types(i.e., utility and $CType_2$) in exchange for rewards. In a smart contract, we defined an access control rule in order to provide authorization and authentication to the user of the system within the blockchain network. Each participant in the specified network has the privilege to access certain types of resources across the entire blockchain network. Lastly, queries are written in a bespoke language as a separate file in the smart contract. The queries are used to fetch customized data based on the user-defined operation from the world state database. Table 5, summarized the types and definition of the assets, participants, and transaction processor function.

In this work, we use Hyperledger Composer to create a smart contract(`.bna`) which is further used in developing the representational state transfer application program interface RESTful API. The composer-rest-server is used to generate the platform-independent RESTful API and provide interoperability between the platform worldwide. In the presented system, the RESTful API is used to connect the client application, and the blockchain back-end service like energy trading, scheduling, and managing distributed energy resources, to name a few. Generally, the RESTful API is comprised of three-part, i.e., resource, verb, and action. The resource is the HTTP request, while verbs execute a singular resource, like, PUT, POST, GET, and DELETE. The RESTful API works based on HTTP based protocol where the request header consists of the following parameters such as media type, verb, and base URI. The media type represents the transition state element, e.g., Application/JSON. In contrast, the URI determines the path of the data request, e.g., a POST request to the resource like `/api/EnergyTrading` will update the assets in the registry in the encrypted form. Table 6, summarized the RESTful API used in the proposed system.

B. TRANSACTION PROCESS OF PREDICTIVE ENERGY TRADING PLATFORM

The energy trading platform aims to enable monitoring, managing, originating, and trading distributed energy resources in a decentralized manner. Hyperledger Fabric blockchain is

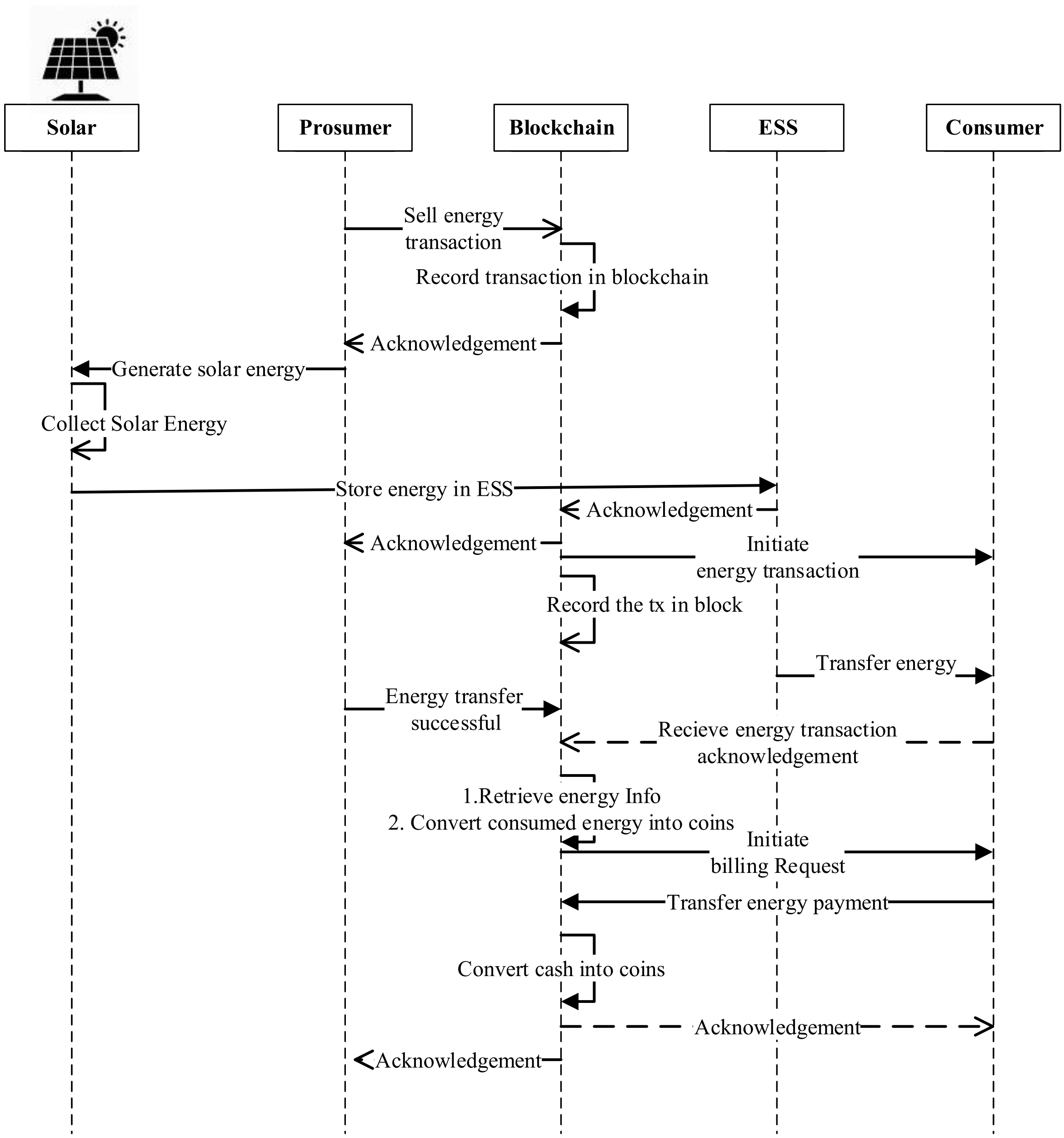


FIGURE 7. Execution process for the predictive energy trading platform between Prosumer to Consumer.

used to streamline the distribution, tracking, and trading of energy. The smart contract automates the processes without third-party intervention. The residential can either be the prosumer who produces the energy or the consumer who purchases the energy. The execution process between $CType_2$ users of the proposed predictive energy trading platform is presented in Figure 7.

In this transaction ET_{Type2}, the $CType_2$ users are divided into two types, i.e., prosumer and consumer. Prosumer monitors the energy status collected from the solar panel. Prosumer invoked energy transactions to record the amount of energy from the solar panel into the blockchain and stored it in the energy storage system (ESS). The user sells the energy stored in the ESS based on mutual concern. The consumer can get available energy on the market by sending a query request to the blockchain. To purchase the energy, the consumer invokes the energy purchase transaction, and the ESS transfers the corresponding energy to the consumer. Once the required energy is successfully transferred to the consumer, the reward model will be initiated by the smart contract. The smart contract converts the required energy into coins. Afterward, the payment is sent to the prosumer account and also notified both prosumer and consumer.

In prosumer to Utility energy transaction ET_{Type1}, the utility request the energy demand to meet the load demand. The system will notify the prosumer to start an energy trading

TABLE 6. RESTful API for blockchain-enabled predictive energy trading platform.

Operation	Action	URI
ESS Management	All	/api/ESS
Prosumer Management	All	/api/Prosumer
Consumer Management	All	/api/Consumer
Utility Management	All	/api/Utility
Solar Energy Management	All	/api/SolarEnergy
Moneypool	All	/api/Moneypool
Real-time Reward Model	Get,Post	/api/RealTimeReward
Day-ahead Scheduling	Get,Post	/api/DayScheduling
Blockchain Network Text	Get	/api/system/ping
Identity Issue of participant	Post	/api/SystemIdentities/issue
Retrieve Identities	Get	/api/System/identities
Fetch historian records	Get	/api/System/historian

process. The surplus solar energy will be transferred to the utility in exchange for reward based on mutual concern and agreement. The surplus solar energy is stored in the ESS using the blockchain platform. On a successful transaction, the notification is sent to every participant of the system. The energy is converted into a reward based on the per-unit price. Afterward, the reward is transferred to the prosumer money pool, and an acknowledgment is sent to the prosumer and utility.

VII. DEVELOPMENT ENVIRONMENT

The tool and technologies used in the proposed intelligent energy trading blockchain platform are summarized in Table 7. The proposed system development environment is segregated into two parts, i.e., the intelligent energy trading blockchain network and the front-end client application. In the back-end blockchain network, we have used the Intel central processing unit with 3.0 GHz computation power. Similarly, the operation used is Ubuntu Linux 18.04 *LTS* with the run-time support of docker composer and engine. The docker composer is used to configure the docker container and docker image in the Ubuntu operating system. Furthermore, Hyperledger Fabric $V - 1.2$ is used to develop a blockchain network, which supports intelligent smart contract construction. The smart contract is furthered managed using the administrator's command-line tool to deploy the proposed intelligent energy trading chaincode. Likewise, the participant uses the front-end intelligent energy trading application, like consumer, prosumer, and utility operator, to consume the back-end blockchain services, such as secure energy trading, energy prediction, and energy reward/incentive model. The web application is implemented using multiple programming languages, such as HTML, CSS, JavaScript, and Node.js and the JQuery, Notify.js, and Bootstrap library.

The blockchain-enabled intelligent energy trading web-interface is presented in Figure 8. The proposed system prototype is implemented using the Hyperledger Fabric framework. The developed interface provides the functionally of complete CRUD operation on Prosumer, Consumer, and Utility operator. Moreover, the `Records` dashboard shows the energy trading record and the renaming energy and energy

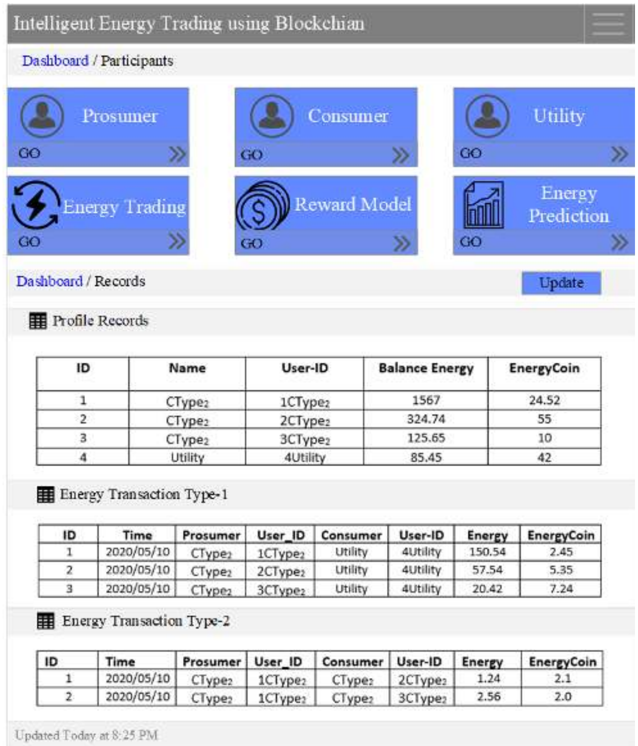


FIGURE 8. Web application for intelligent energy trading blockchain platform.

coins. The proposed model support two types of energy trading transaction, i.e., ET_{Type1} and ET_{Type2} which is also shown with Type-1 and Type-2 transaction along with consumer and prosumer details. The dashboard also provides the energy prediction functionality that uses the computed features to predict the future energy load and demand. Finally, the update button fetches the updated energy trading transaction records through the RESTful API.

VIII. RESULTS AND DISCUSSION

A. DESCRIPTIVE ANALYTICS

Descriptive analysis is used to process the data and convert it into meaningful knowledge. In contrast, the energy load dataset is used to predict short-term energy load prediction. In the proposed descriptive analytics model, we have collected the Jeju, South Korea energy consumption data from the mid of 2002 to 2018. The data is stored on an hourly basis. In order to perceive the data hidden knowledge, we carry out a descriptive analysis of energy data. We analyze the energy consumption data into short-term and long-term. In short-term, we consider hourly (9a), and daily (9b) analysis, similarly, for long-term we consider, weekly (11a), monthly (11b), and yearly (11c), and quarterly (11d) analysis.

As stated earlier, in short-term energy consumption analysis, we examine the hourly and daily energy consumption in Mega Watt(MW) as shown in Figure 9. The Figure shows the relationship between the hours of the day and energy consumption. In Figure 9 (a) shows whereas 9 (b) shows day-wise analysis. The hourly analysis shows that energy consumption

TABLE 7. Development environment for the proposed patient vital sign monitoring.

Name	Component	Description
Intelligent Energy Trading Blockchain Network	CPU	Intel(R) Core(TM) i5-8500 CPU @3.00GHz
	Operating System	Ubuntu Linux 18.04 LTS
	Docker Engine	Version 18.06.1-ce
	Docker Composer	Version 1.13.0
	IDE	Composer Playground
	Programming Language	Node.js
	Hyperledger Fabric	Version 1.2
	Node	Version 8.11.4
	Database	Couch DB
	Memory	12 GB
Intelligent Energy Trading Blockchain Web application	Operating System	Window 10
	Browser	Chrome, Firefox, IE
	Programming Language	HTML, CSS, JavaScript, Node.js
	Library/Framework	Notify.js JQuery, Bootstrap

increase from the morning slot of the day. The maximum energy load at 6 PM is 62000 MW, whereas the minimum energy load is 41500 MW at 3 AM midnight. Similarly, in the case of Day Wise analysis, the x-axis of the graph represents the day of the week, and the y-axis represents the energy consumption.

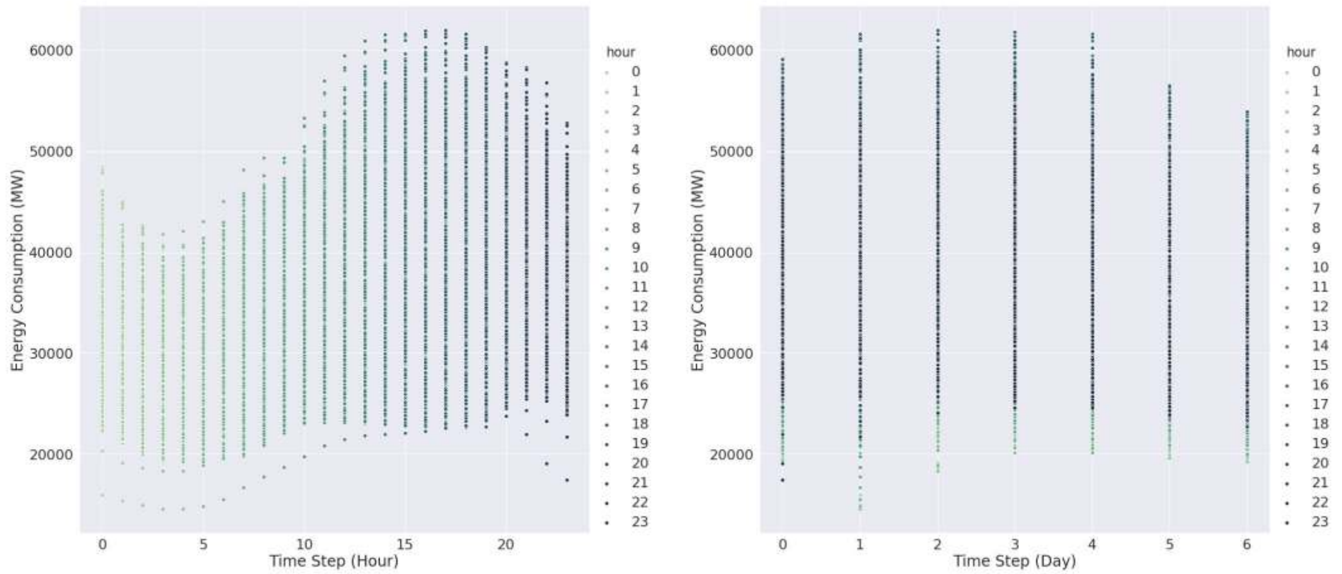
As stated earlier, in long-term energy consumption analysis, we analyze the energy consumption distribution based on the season. Seasonally energy consumption analysis is given in Figure 10. The analysis results are categorized into four seasons of the year, winter, summer, spring, Autumn. It is evident from the graph that the energy load is more in winter and the least in autumn.

Finally, we consider weekly, monthly, yearly, and quarterly analysis of energy consumption, as shown in Figure 11. Figure 11-(a) represents weekly analysis, Figure 11-(b) represents monthly analysis, Figure 11-(c) represents yearly analysis, whereas Figure 11-(d) represents quarterly analysis. Y-axis in Figure 11 represents energy consumption, whereas X-axis represents weekly, monthly, quarterly, and yearly distribution. The figure's illustration shows that the energy load is high in the last quarter of the year when the temperature is cold outside.

B. PREDICTIVE ANALYTICS

In this section, we present the predictive analysis performed on the energy consumption blockchain data. Predictive analysis methods are used to predict future events based on historical event data. Previously, predictive analysis is used for optimal decisions and making effective policies [44], [84], [85]. For predictive analysis, we propose a prediction model based on Bi-directional LSTM. We also trained other models such as LSTM, RNN, Random Forest, and XGBoost for long and short-term energy prediction. The proposed prediction mechanism considers user preference parameters and parameters discovered during descriptive analysis. Firstly we prepared the data for building our proposed model. Apart from traditional data processing techniques, we also applied the data partitioning approach to split the data into training and testing energy consumption datasets. The split ratio of the training and testing dataset is 70-30 %, 70 % of the energy consumption data is used for training, and 30 % data is used for testing purposes. Furthermore, we consider the time of data instances while splitting the dataset; for instance, the energy consumption data from 2002 to 2017 is used as a training dataset, and the remaining instances of 2018 are used for testing purposes. In terms of the number of instances, training set instances are 110,000, and the testing set is 6189 instances. Now, we discuss the experimental environment of the proposed blockchain-enabled predictive energy trading platform. The proposed system's experiment is carried out on tensor flow version 1.15.0, python, hardware configurations included 24 GB RAM and core-i7 processor. However, minimum configurations could be followed per the requirement of tensor flow and python integrated development environment such as anaconda. As stated earlier, the dataset consists of 116,189 data instances from the time period of 2002 to 2018. Each instance of energy consumption data depicts the hourly energy load of south Korea. Table 8 summarized the proposed blockchain-enabled predictive energy trading platform's implementation and experimental setup.

Figure 12-(a) present the comparison between the actual and predicted energy prediction data using the RNN model. We used the RNN model for the energy consumption sequence of data; each energy consumption sample data can be assumed to be dependent on previous energy consumption sample data. As RNN is recurrent, it repeats the same



(a) Hourly analysis (b) Day Wise analysis

FIGURE 9. Short-term energy consumption analysis based on hourly and daily analysis (2002-2018).

TABLE 8. Implementation and experimental setup.

Parameters	Description
Operating System	Window 10
System Configuration	Core i3-2150 3.56 GHz
Memory	24 Gigabyte
Programming Language	Python
Development Toolkit	PyCharm

function for input energy consumption data, while output energy consumption data depends on the past computation of energy consumption data. RNN used its internal state called memory for processing the sequence of input energy consumption data. Figure 12-(b) present actual and predicted energy consumption in term of power consumption data using the LSTM model.LSTM model for energy consumption prediction is trained using Backpropagation Through Time series data of the energy consumption. LSTM is a type of RNN that can address difficult sequence problems such as energy consumption prediction from time-series data to achieve the best results than other traditional regression approaches. Forget Gate decides what energy consumption information to forget and throw away from block-based on conditions. Input Gate decides which input energy consumption sequence should be used to update the state of the memory. Output gate used the status of input and memory block to determine the output energy consumption sequence. As discussed earlier, a Bidirectional LSTM consists of two LSTMs: one for input in a forward direction and the second for the backward direction. Figure 12-(c) present the comparison between the actual and predicted energy prediction data using Bidirectional LSTM Model. For evaluating the accuracy of these models, we used regression model performance matrices such as R2 score,

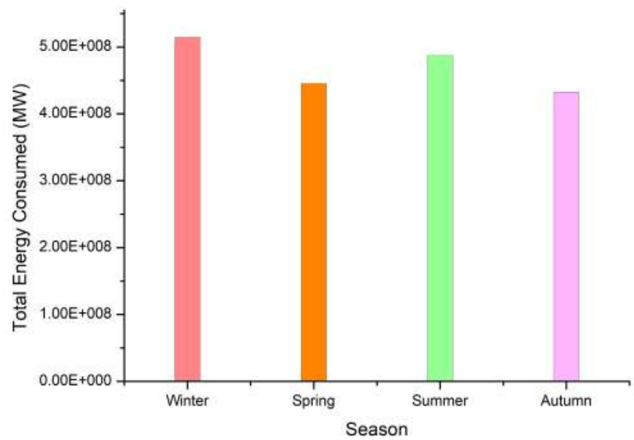
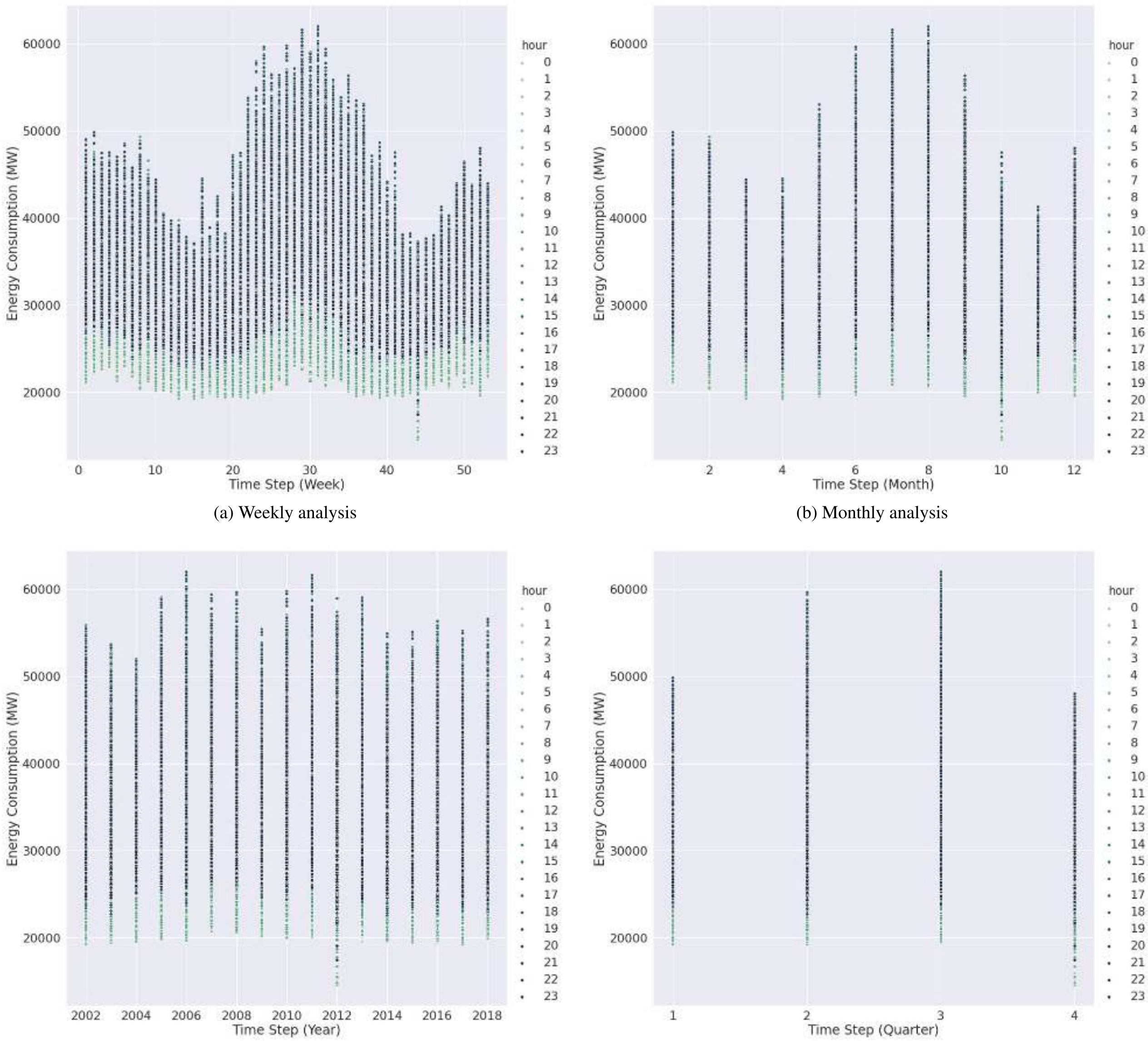


FIGURE 10. Seasonally energy consumption analysis.

mean square error, mean absolute error, and root mean square error, mean absolute percentage error. We also trained other traditional regression models to compare the accuracy of LSTM and RNN, such as XGBoost and random forest. Comparative analysis of the proposed model with these models is discussed in detail in the performance analysis section.

C. PERFORMANCE ANALYSIS

In this section, we conducted numerous tests in order to assess the performance of the proposed blockchain-enabled predictive energy trading platform. We have considered several performance measures, such as throughput latency, and resource utilization, and block size. For simulation, we have used an open-source framework known as Hyperledger Calliper, which evaluates the blockchain performance. Similarly, some parameters have been defined for the experiment, i.e., four



(a) Weekly analysis (b) Monthly analysis

(c) Yearly analysis (d) Quarterly analysis

FIGURE 11. Long-term energy consumption analysis based on Energy Consumption Data of the years(2002-2018).

peer and solo orderer nodes. In this study, we evaluate the throughput in two ways, i.e., read and transaction throughput. Equation 13 define the formulation of transaction throughput, which indicate the number of invoked transaction in a defined time. In the case of read throughput, the number of read operations is calculated in a blockchain using an Equation 14. The overall throughput is measured by differing the transaction send rate with an arbitrary configuration of machine utilization. The read transaction throughput is accessed with an arbitrary send rate of 500 tps to 3000 tps, whereas the transaction throughput is measured by a varying send rate of 200 tps to 1300 tps as shown in Figure 13.

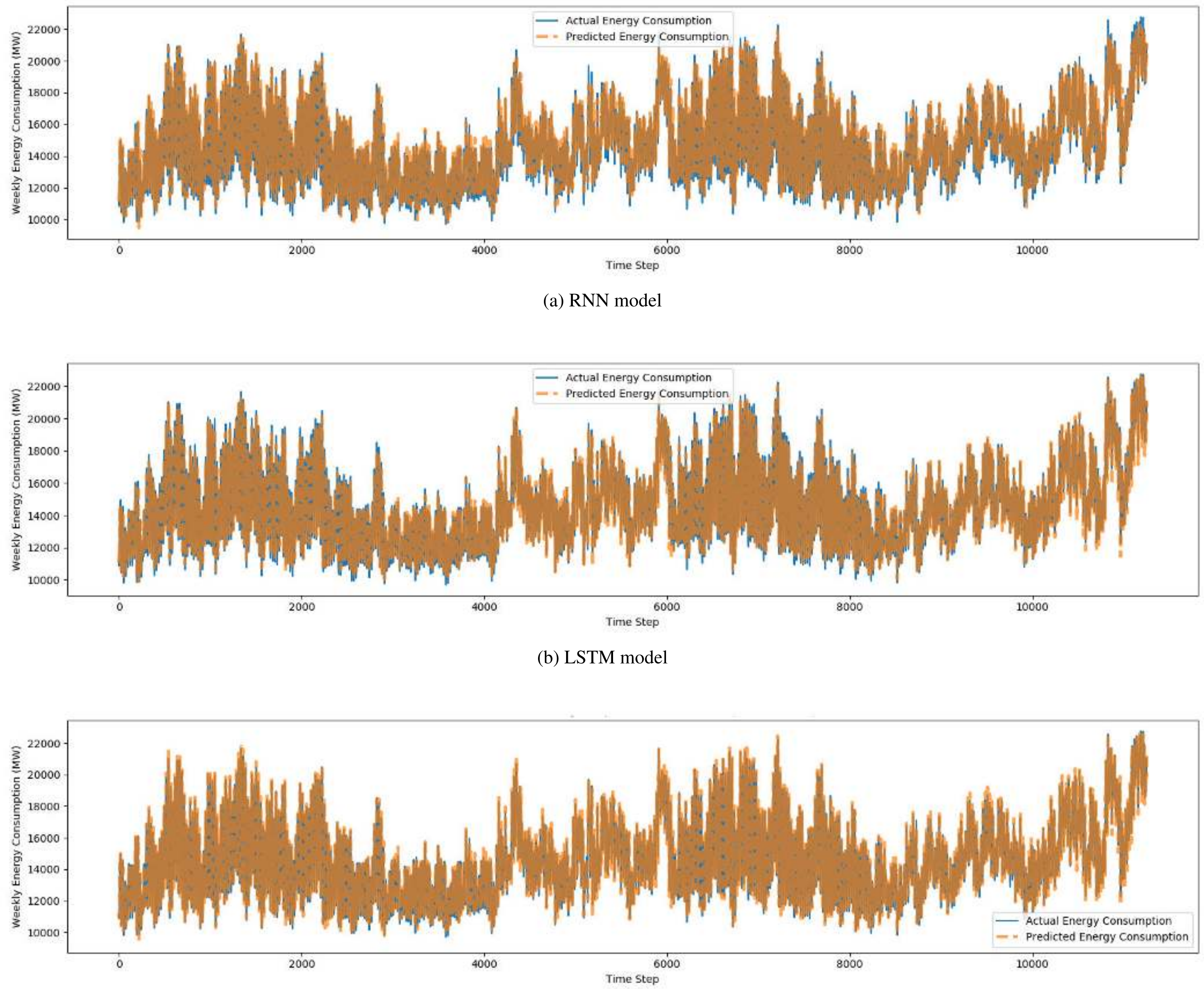
In Figure 13a, the transaction throughput is investigated with the transaction send rate of 500 to 3000 transaction per second. The throughput increases with the increase of the transaction send rate. The transaction throughput decreases after the optimal send rate of 2500 *tps*. Similarly, in the case of transaction throughput, as shown in Figure 13b, the throughput increases after the optimal send rate of 1100 *tps*.

$$TT = \frac{TCT}{T_{sec}} \tag{13}$$

where TT denotes transaction throughput, TCT represents the total committed transaction, and finally, the T_{sec} is the time.

$$RTT = \frac{TRO}{T_{sec}} \tag{14}$$

Likewise, RTT stand for read transaction throughput and TRO denotes total read operation, and finally the T_{sec} is a time per second.



(a) RNN model

(b) LSTM model

(c) BD-LSTM model

FIGURE 12. Comparison of proposed Bidirectional LSTM approaches with traditional deep learning approach for energy consumption Prediction.

The transaction latency in the proposed system is measure in two ways, read and transaction latency, as shown in Equation 15 and 16, respectively. The total time required to execute the transaction in a blockchain network is called transaction latency. The transaction latency consists of transaction broadcast, submission, and consensus time. Likewise, the transaction round trip time is computed as the time response of transaction from submission to the execution, as mentioned in Figure 14.

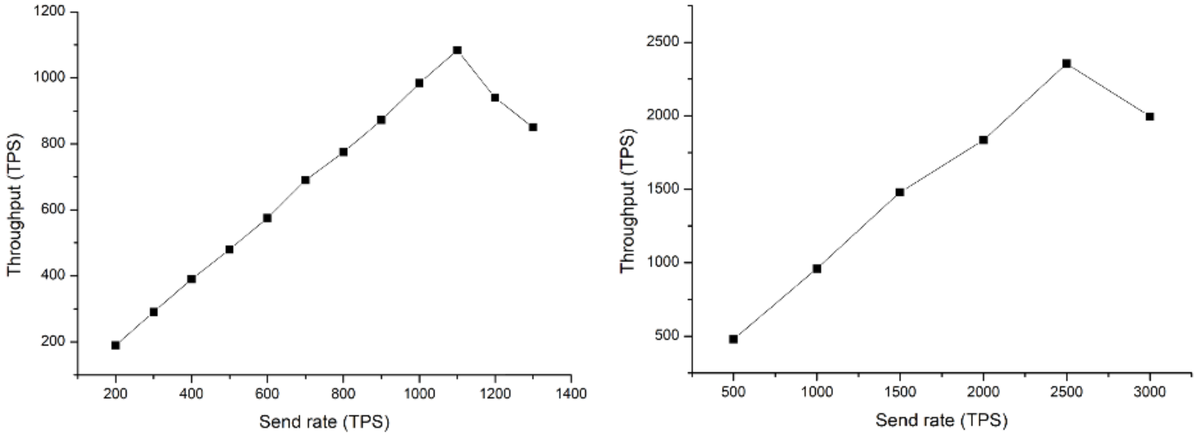
Figure 14a illustrate the transaction latency of the proposed blockchain-enabled predictive energy trading platform, which increases as the number of user request increase in the blockchain network. It is investigated from the graph that the transaction latency rise after the optimal transaction sends rate of 1100 transaction per second. Likewise, in Figure 14b, the read latency is measured as varying the transaction send rate from 500 tps to 3000 tps with arbitrary machine utilization resources. It is estimated from the graph that read latency increases comparatively less as the send rate increase. However, the read latency notably increased with the rise of the send rate after 2500 transactions per second.

$$RL = TRTT - TI_T \tag{15}$$

where RL is the read latency, transaction round trip time is denoted by TRTT, and TI_T represents the invoke transaction latency.

$$TL = (TE_T \times NT_T) - TI_T \tag{16}$$

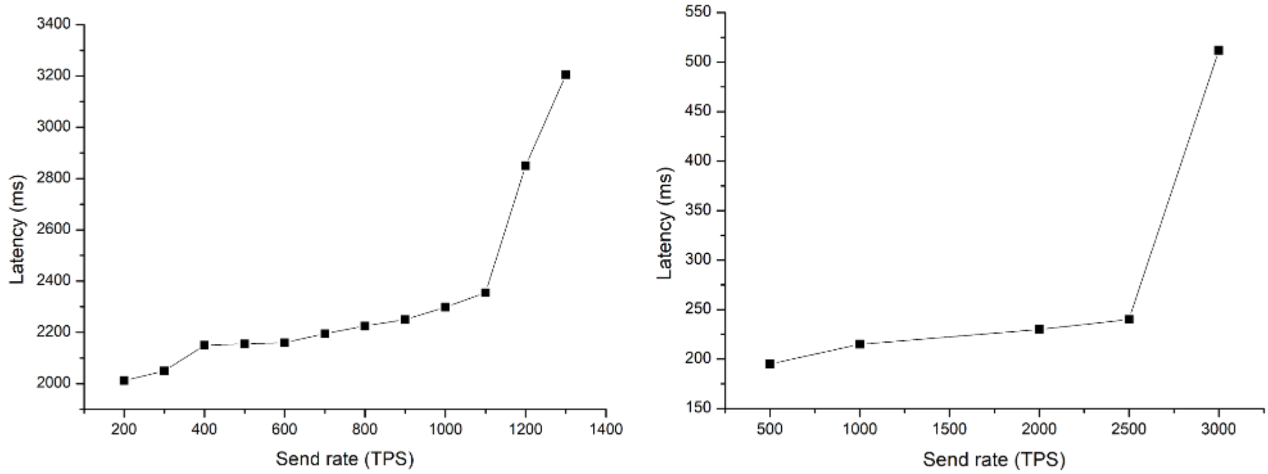
Similarly, transaction latency is represented as TL, TE_T denotes as transaction execution time, NT_T is the network



(a) Transaction Throughput

(b) Read Throughput

FIGURE 13. **Transaction Throughput analysis.**



(a) Transaction latency

(b) Read latency

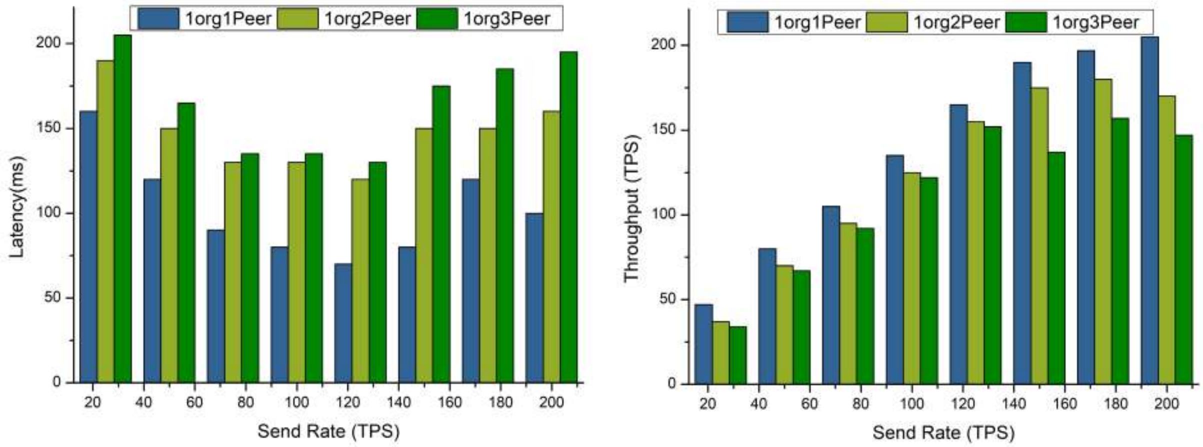
FIGURE 14. **Transaction latency analysis.**

threshold time, and finally, the transaction invokes time is denoted as TI_T.

The intelligent peer-to-peer energy trading platform's performance is also evaluated by changing the number of endorser peers in terms of latency and throughput. The endorser peer is responsible for endorsing the transaction once it is proposed. The endorser peer contains the chaincode, which is used to endorse the transaction when it is triggered. Figure 15 demonstrates the performance of the proposed platform by varying the number of peer nodes. Figure 15a shows the proposed platform's latency by changing the number of peer nodes with a send rate between 25-200 transaction per seconds. It is investigated from the results that increasing the number of peers node will increase the network latency. Furthermore, the network traffic volume is also increased by increasing the number of peer nodes, which conclusively decreased the proposed network throughput, as shown in Figure 15b.

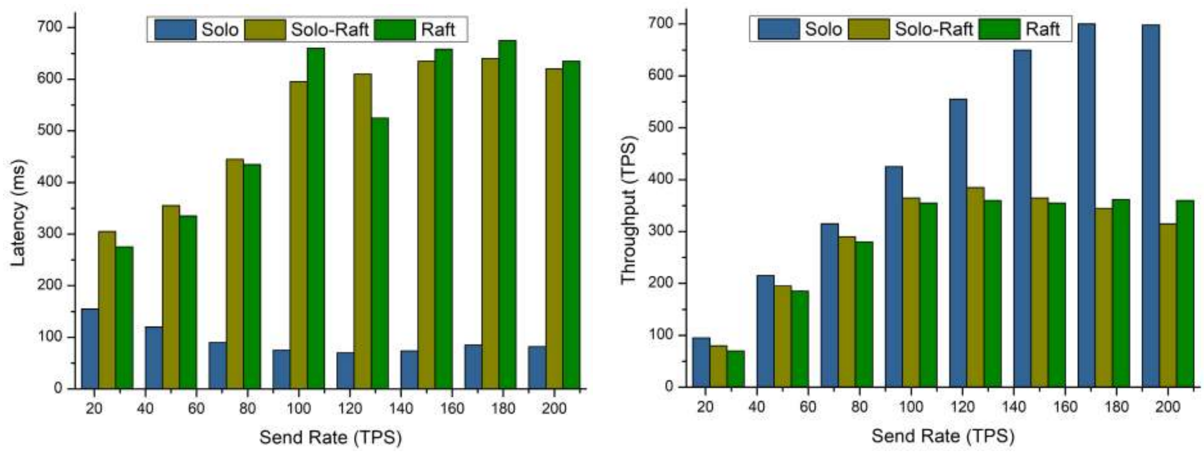
Similarly, the performance of the proposed system is also accessed by changing the ordering service in terms of latency and throughput, as shown in Figure 16. In Hyperledger Fabric, the ordering service is responsible for transactions order. We have considered three types of ordering services in the proposed system: solo, solo-raft, and raft over different send rates between 25-200 transactions per second. It is found from the graph that the solo ordering service has less latency as compared to solo-raft and raft because of the extra processing of transaction layer security (TLS) among the peer nodes. Figure 16a presents the orderer node latency over the different send rates. Likewise, the throughput of solo ordering service is higher than the solo-raft and raft because the solo ordering service contains a single node and doesn't require additional TLS support in processing, as shown in Figure 16b.

The performance of the proposed system is also evaluated in terms of resource utilization. The Hyperledger Calliper with five rounds is used for the experimental environment. The average memory and CPU utilization of a peer node in the network is recorded as 92.21 MB and 4.65 %, respectively. Likewise, in the case of the orderer node, the average CPU and memory utilization is noted as 1.20% and 24.5 MB,



(a) Latency (b) Throughput

FIGURE 15. Impact of varying peer node with different transaction rate.



(a) Latency (b) Throughput

FIGURE 16. Impact of varying ordering service with different transaction rate.

respectively. Lastly, the machine and memory utilization for certificate authority is reported as 1.50 % and 5.1 MB. Table 9 summarized the resource used in the proposed system in terms of the memory and CPU.

In this section, we evaluate the performance of the energy consumption prediction models in terms of a regression performance measure, such as R^2 score, Mean Square Error(MSE), Mean Absolute Error(MAE), Mean Absolute Percentage Error(MAPE), and Root Mean Square Error(RMSE). First, we explain these measures in detail.

1) **R^2 score** is also known as coefficient of determination (CoD) and used for evaluating regression model using statistical measures. The formulation of R^2 is given in Equation 17

$$R^2 = 1 - \sum_i \left(\frac{y_i - \hat{y}_i}{y_i - \mu}\right)^2 \tag{17}$$

2) **Mean Square Error** is used to eliminate the below zero values and determine the average among the predicted and the actual values. The formula of Mean Square Error is given in Equation 18

$$MSE = \frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{n} \tag{18}$$

3) **Mean Absolute Error** is used for evaluating the performance of the regression model which determine the deviation among the actual and predicted values. The formulation of Mean Absolute Error is given in Equation 19

$$MAE = \frac{\sum_{i=1}^{n} |y_i - \hat{y}_i|}{n} \tag{19}$$

4) **Root Mean Square Error** is used for regression model to determine the error rate and accessed whether the size of target is same as the size of error. It is computed by taking square root of Mean Square Error as given in Equation 20

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} |(y_i - \hat{y}_i)|^2}{n}} \tag{20}$$

TABLE 9. Utilization of resources of proposed blockchain platform.

Name	CPU (max %)	CPU (avg %)	Memory (max)	Memory (avg)	Traffic In	Traffic Out
peer0.com	12.44%	5.59%	106.6 MB	98.5 MB	4 MB	4.2MB
peer1.com	17.09%	6.24%	93.5MB	85.7 MB	4.3 MB	5.2 MB
peer2.com	15.02%	4.56%	110.5 MB	92.21.3 MB	5.6 MB	10 MB
peer3.com	0.00%	5.54%	90.8 MB	85.8 MB	4.8 MB	5 MB
orderer.com	4.95 %	1.20%	34.5 MB	24.5 MB	5 MB	10.6 MB
CertificateAuthority_0	0.00%	1.50%	5.5 MB	5.1 MB	546 B	0 B
CertificateAuthority_1	0.00%	2.00%	5.2 MB	5.2 MB	430 B	0B

TABLE 10. Comparison of the proposed approach with state of art prediction methods.

Model	RMSE	MAE	R2	MAPE
RNN	567.585	422.277	0.947	2.977
LSTM	519.95	377.245	0.956	2.611
Random Forest	1064.23	1328.23	0.45	14.77
XGBoost	793.1	943.43	0.51	9.91
Proposed Model	419.047	284.616	0.971	1.98

Mean Absolute Percentage Error (MAPE) is used to compute an average deviation found in energy consumption value from actual energy consumption value. MAPE is calculated by dividing the sum of absolute differences between the actual and predicted energy consumption by the machine learning algorithm we applied in this study with the total number of energy data records such as n.

$$MAPE = \frac{100\%}{n}\sum_{t=1}^{n}\left|\frac{e_t}{y_t}\right| \tag{21}$$

We present the performance comparison of the smart contract enabled predictive analysis using state of the art predictive analysis method RNN, LSTM, and Bi-directional LSTM. The energy prediction analysis models are evaluated in two steps. First, we compare RNN, LSTM, and Bi-directional LSTM in terms of MAE, MSE, RMSE, and MAPE. The second step of the prediction performance analysis is R^2 score. Table 10 presents the performance analysis comparison of proposed Bi-directional LSTM and sate of art prediction methods in MAE, MSE, RMSE, R^2 and MAPE. The models' prediction performance shows the robustness of the proposed prediction model based on Bi-directional LSTM for long-term and short-term energy predictions. Proposed approach regression score in term of R^2 score is more as compared to the previously used state of the art prediction methods.

IX. CONCLUSION AND FUTURE DIRECTION

In this research, we proposed a blockchain-enabled predictive energy trading platform that is based on the integration of machine learning and blockchain model. The proposed platform comprises three modules, i.e., intelligent peer-to-peer energy trading, data analysis, and smart contract-enabled predictive analysis. Predictive analysis is made using deep learning approaches based on RNN, LSTM, and Bi-directional LSTM for predicting short-term and long-term energy demand. The predictive peer-to-peer energy trading platform is developed based on a permission blockchain network known as Hyperledger Fabric, which provides the functionality of securing crowdsourcees energy trading transaction records and real-time energy trading, day-ahead energy trading, predictive short-term energy results, and personal user records in a decentralized manner. It also provides support of energy reward and incentive model in case of successful energy trading transaction. The proposed predictive energy trading platform is implemented based on PBFT to address the issue of security, interoperability, transparency, accountability, and reliability. Similarly, an interactive front-end application is developed, which is used to expose the blockchain back-end services through RESTful APIs. For experimental analysis, we have used Hyperledger Caliper in order to evaluate the performance of the proposed system. The results show that the proposed predictive energy trading platform performs better in terms of latency and throughput. Secondly, the data and smart contract-enabled predictive analytics module are designed using several data mining and machine learning approaches where the data is taken from the renewable energy department of Jeju province, Republic of Korea. The hidden and discovered patterns are useful to minimize the cost of electrical energy consumption for customers and are very important to economize power engineering. The proposed data exploration is based on the comprehensive analysis of 116,189 energy consumption data instances over the time-span of 16 years (2002-2018). Furthermore, the smart contract-enabled predictive analytics model aimed to develop an intelligent prediction model using RNN random forest, XGBoost, and LSTM to predict the short-term energy demand. The prediction results show that the LSTM has the minimum MAPE value compared to other machine learning models using time-series data. In the future, we can improve the performance by integrating the hybrid machine learning model to make the system robust. Furthermore, in the future, we may consider other features, such as humidity, temperature, and wind speed, which can be selected using optimization algorithms.

CONFLICT OF INTERESTS

The authors declare that there is no conflict of interest regarding the publication of this paper.

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