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PAPER

AI Model-Blockchain Integrated Decentralized Smart Grid Framework as a Pedagogical Model for Future Engineering Technology Education

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ABSTRACT

Industry 4.0 is a term that depends on many underlying technologies. One of the most important technologies is these key technologies that are aimed at changing the current energy infrastructure. Digital key technologies, like blockchain, smart grids, and artificial intelligence (AI), are among the technologies that provide the base of transformation towards Industry 4.0. Smart grids provide real-time monitoring and integration of distributed renewable energy sources. AI will assist in the analysis of large data sets regarding energy consumption. Blockchain provides secure and decentralized networks that mechanically facilitate financial transactions via smart contracts and enable transparent trading of energy. However, with the advancements in technology, engineering education will increasingly be demanded to give students interdisciplinary skills reflecting the integration of many elements within modern energy systems. Traditional methods of teaching usually treat the above technologies as separate disciplines when, in Industry 4.0 environments, students need to have an understanding of how the different cutting-edge technologies fit together within real-world energy system management situations for there to be interdisciplinary learning opportunities. This paper aims to provide engineering students with an opportunity to gain hands-on experience that bridges between theoretical academic knowledge and practical application of key technologies within Industry 4.0. To facilitate the objective, the paper suggests an integrated AI–Blockchain smart grid framework that integrates blockchain-enabled decentralized energy trading with deep learning (DL)-based electrical demand forecasts to close this gap. The framework is considered a practical use case that comes with the theoretical and implementation aspects to allow engineering students to gain overall knowledge. The framework incorporates three layers: the first layer is the data source, which collects operational data from the smart grid environment. The second layer, the analysis, is an analysis of data using DL algorithms that forecast future electricity aspects. The last layer, the decentralized control, regulates and manages decentralized electricity trading by calculating the dynamic price of electricity using smart contracts on the blockchain network. Framework architecture and implementation details and components are comprehensively discussed to feed the literature with the required aspects of key technologies' integration. Finally, the paper discusses

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expected outcomes and future direction and opens issues towards continuing the research in this important area and provides students with associated interdisciplinary skills.

KEYWORDS
smart grid, deep learning (DL), blockchain, energy trading, dynamic pricing, engineering education, Industry 4.0

1 INTRODUCTION

The rapid advances in Industry 4.0 technologies have revealed new opportunities for the energy sectors. Modern energy systems use smart grids for real-time monitoring of energy, as well as enabling intelligent ways of managing energy consumption. Smart grids also provide a means to integrate renewable energy sources into electric grids [1]. In addition to smart grids, blockchain technology offers a secure, decentralized infrastructure for trading energy transparently with other parties using smart contracts [2]. On the other hand, artificial intelligence (AI) provides powerful methods for processing and analyzing large data sets, as well as for improving forecasts of electricity usage. The increasing importance of these technologies within the context of today's digital energy systems makes them an important component of both engineering and technology education [3]. Despite their increasing importance, the advancements in energy key technologies came with their own challenges to engineering education because modern engineering education needs to include state-of-the-art digital technologies within contemporary learning environments. A new educational approach that goes beyond traditional classroom learning and provides practical experience in understanding new technologies such as blockchain, AI, and smart grid technology is required in order to prepare the workforce of the future. Today, it is essential that engineering students develop interdisciplinary skills to understand how these technologies work [4]. These technologies are closely interconnected and can be practically deployed, making them fundamental components in shaping intelligent and decentralized energy systems in the context of the 21st century.

However, most of the current research has focused on each of these technologies individually; specifically, blockchain technology has mostly been studied in relation to peer-to-peer energy trading, whereas DL techniques have primarily been studied in relation to forecasting electricity demand [5]. There has been very little research conducted on how these technologies may be incorporated into a unified framework, particularly in an educational setting where their combined use and interactions would be very evident. This paper suggests an integrated AI–Blockchain smart grid framework that blends blockchain-enabled decentralized energy trade with DL-based electrical demand forecasting to meet this need. The framework has a layered architecture. The first layer is the data source layer, which collects operational data from the smart grid environment, such as environmental indicators, electricity generation, and consumption. The second layer, the analysis, uses DL algorithms to forecast future electricity usage based on historical usage data from the data source layer. The last layer, the Decentralized Control, regulates and manages decentralized electricity trading by calculating the dynamic price of electricity using smart contracts on the blockchain network. In addition to its technological contribution, the suggested framework functions as an instructional model intended to facilitate the teaching of Industry 4.0 technologies. The framework offers an organized setting where educators and learners can investigate how blockchain-based decentralized control mechanisms, AI-based decision-making models, and smart grid data sources interact.

The proposed framework offers a valuable experimental platform suitable for academic environments and university laboratories, achieved through the construction of the system using Ethereum smart contracts and Python-based DL tools. This platform encourages experiential learning and makes it easier for students and teachers to understand how cutting-edge digital technologies are used in modern energy systems. This makes it easier for students to learn about Industry 4.0 concepts in engineering and technology classes. The main contributions of this study are:

- Establishing a novel theoretical framework that coordinates smart grids, AI, and blockchain technologies in the support of engineering technology education and students' understanding of contemporary energy systems and Industry 4.0 technologies.
- Building a smart grid framework that uses both AI and blockchain technology. This includes a GRU-based model for predicting electricity demand and Ethereum-based smart contracts for dynamic pricing and decentralized energy trading.

2 RELATED WORKS

The evolution of Industry 4.0 has had an enormous impact on how engineering is taught and how modern energy systems are constructed, resulting in a dramatic increase in the implementation of intelligent and digital technologies throughout numerous industries. Numerous studies have demonstrated the importance of integrating emerging technologies into educational settings to improve students' learning experiences and prepare them to address complex, real-life problems. Smart grid systems are one of the key examples of this type of technology; they are now fundamental to today's energy infrastructures, allowing for two-way movement of electricity (bidirectional energy flow), monitoring and control of energy in real-time, and efficiently employing renewable energy in energy systems. At the same time, deep learning (DL) has become widely used because of its ability to analyze large-scale datasets and accurately predict outcomes, especially for applications such as predicting energy demands and optimizing energy systems. Additionally, blockchain technology has created a decentralized and secure way to conduct energy transactions, providing security and trust with regard to energy transactions through smart contracts. Therefore, these technologies create unique opportunities for innovative educational models that combine theoretical and hands-on educational experiences, preparing the next generation of engineers to work in a world of intelligent and decentralized energy systems. One example of this type of study is in [6], where the authors studied the impact of transforming engineering education as a result of global challenges such as COVID-19 and VUCA environments and subsequently developed the idea of Curriculum 4.0—which emphasizes the importance of adaptive thinking, innovative thinking, and the use of AI in decision-making. In the same manner, the authors highlight the importance of integrating other emerging technologies, such as AI, Big Data, and the Internet of Things (IoT), into engineering education to provide students with the necessary 21st-century competencies. The significant amount of research conducted into pedagogical innovations for teaching engineering and technological progress in smart energy systems results in an unfortunate lack of research into combining these areas. There also seems to be no comprehensive framework to integrate AI, blockchain-based energy trading (BET), and smart grid technologies (SG) together in an educational environment. While AI has been widely applied in adaptive learning systems, and blockchain has been extensively researched in decentralized energy markets, only a few studies have examined how AI and BET can be used together as a practical learning resource for supporting experiential and problem-based learning (PBL) in engineering education. This study aims to address the gap in existing literature by proposing a framework that combines SG technologies as data sources, demand forecasting based on a decision-making model, and BET as a method of decentralized control within a pedagogical environment. The proposed framework will create an interactive and application-focused learning platform that will enable engineering students to explore real-world challenges relating to the management of energy, decentralized markets, and Industry 4.0 technologies. Table 1 contains a summary of the most applicable research studies. To confirm there is a gap in research for the three technologies (AI, SG, and Blockchain) from a pedagogical point of view, the researchers performed a keyword search for AI, Smart Grid, Blockchain, and Pedagogical using five different academic databases (IEEE Xplore, Wiley, Springerlink, and IOPscience, ScienceDirect), as shown in Figure 1. The results of this search produced no studies that integrated these four concepts into one research framework. In light of this need, this paper develops an imaginative framework for integrating AI and Blockchain into a Smart Grid system that also functions as an interactive learning environment for engineering students to explore the potential synergy between Blockchain, AI, and SG technologies through the design of intelligent, decentralized energy systems. Moreover, [7] discussed how ICT supports sustainability, enhances teaching and learning, and develops student collaboration and technical skills. AI has been identified as an essential tool for contemporary educational delivery. Furthermore, [8] researched AI utilization in education and identified significant barriers to using AI, including data quality and data reliability; they also suggested using a combination of AI and human support for increased learning outcomes. Similarly, [9] has assessed AI's potential at K-12 levels of education and described how AI is useful in creating adaptive learning systems and supports special needs students through personalized technologies. Additionally, [10] indicated that AI-based adaptive learning systems considerably increase student academic performance and satisfaction through providing personalized learning paths designed to meet student needs. As for pedagogical approach, PBL is considered an effective instructional method within engineering education by [11], and PBL effectively develops entrepreneurial competencies (e.g., perceived behavioral control), therefore improving innovation and employability. In the study of [12], it will be seen that methodologies in induction (including PBL within PBL) can support learners in achieving a greater level of engagement in their education than traditional teaching methods and will allow learners to utilize their academic development in an environment that provides more real-world experiences. At the same time as noting the above developments in relation to education, there has been a lot of progress made in smart energy systems and decentralized energy market systems. [13] provides an overview of how AI Energy Intelligence and Management Systems can help increase environmental sustainability through improving the monitoring and data collection capabilities of UAV technology and UPT capabilities with AI. [14] describes how they developed a blockchain P2P Energy Trading Framework for Microgrid environments which has increased transparency, efficiency, and reliability within decentralized energy markets. Finally, [4] defines the development of the DeepCoin framework, which uses blockchain and DL technologies for secure, verifiable, and reliable data verification for energy trading in a smart grid system. While these advances mark great accomplishments, the author notes that these advances do not address the existing knowledge deficits in the field.

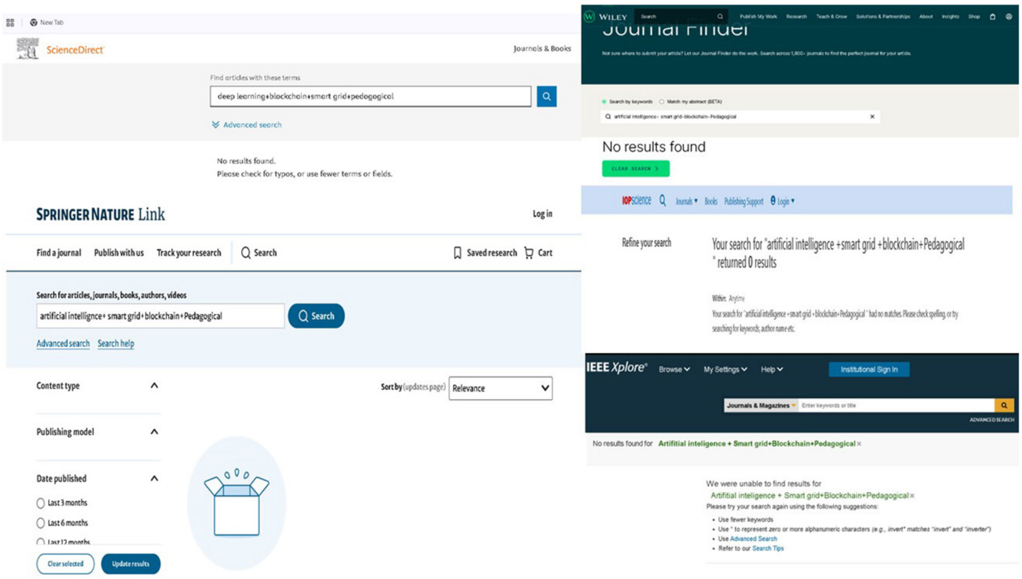

Fig. 1. Search results obtained from major academic databases, including IEEE Xplore, Wiley Online Library, SpringerLink, IOPscience, and ScienceDirect

Table 1. Related works summary

Ref.	Focus Area	Method/Approach	Key Contribution
[6]	Education 4.0	Curriculum 4.0 + Tech Labs	Developed curricula focused on Industry 4.0 skills such as adaptive thinking and AI-based decision-making
[15]	Education 4.0	Systematic Review	Highlighted the integration of AI, Big Data, and IoT in engineering education
[7]	Education and ICT	Analytical Study	Emphasized the ICT role in sustainability and improving students' technical and collaborative skills
[8]	AI in Education	Systematic Review	Identified challenges in AI adoption and stressed human–AI collaboration for better learning outcomes
[9]	AI in Education	Systematic Review	Demonstrated AI role in adaptive learning and supporting students with special needs
[10]	Adaptive Learning	AI-based Learning Systems	Improved academic performance through personalized learning environments
[16]	PBL	Experimental Study	Enhanced innovation, entrepreneurial skills, and employability through PBL
[17]	PBL and Inductive Learning	Review/Meta-Analysis	Improved problem-solving skills, student engagement, and application of knowledge in real-world contexts
[18]	Smart Energy + AI	AI-driven Systems	Improved energy monitoring, management, and sustainability using AI technologies
[14]	Blockchain + Smart Grid	P2P Energy Trading	Enhanced transparency, efficiency, and reliability in decentralized energy trading
[4]	AI + Blockchain (DeepCoin)	Framework Development	Improved security and data integrity in smart grid energy trading systems

3 BACKGROUND

This section will discuss and provide a brief background about the Industry 4.0 key technologies of this study. Blockchain, smart grid, and AI are among the technologies that provide the base of transformation towards Industry 4.0. Smart grids provide real-time control, in addition to the integration of distributed renewable energy sources. AI will assist in the analysis and make easy decision-making based on large data sets regarding energy consumption and the grid environment. Blockchain provides secure and decentralized networks that mechanically facilitate financial transactions and node management via smart contracts and enable transparent trading of energy [1].

3.1 Smart grids

Smart grids represent an evolution from traditional electrical power systems through the integration of advanced technologies such as smart sensors, automated control systems, and advanced information and communication technology in the power grid. Unlike traditional power grids, which are based on one-way power transfer from large, centralized generators to users, smart grids provide two-way transmission of electrical energy and information, allowing for real-time monitoring of the grid and better energy management [19].

The smart grid consists of several components, including things such as smart meters, sensors, communication networks, and smart control systems in Figure 2. Smart grids can detect problems, automatically rectify them, and improve the grid's reliability via self-healing and adaptable control methods. Smart grids achieve this through their continuous collection and analysis of data pertaining to the grid's condition. Additionally, smart grids promote flexibility and decentralization in power systems by permitting traditional methods of electric power transmission to utilize distributed generation resources like solar and wind [20].

From an engineering education standpoint, engineering students require knowledge of smart grid technologies so they can gain a complete understanding of the interrelationships among intelligent control systems, data-driven monitoring and management of the electrical grid, and the integration of renewable energy sources.

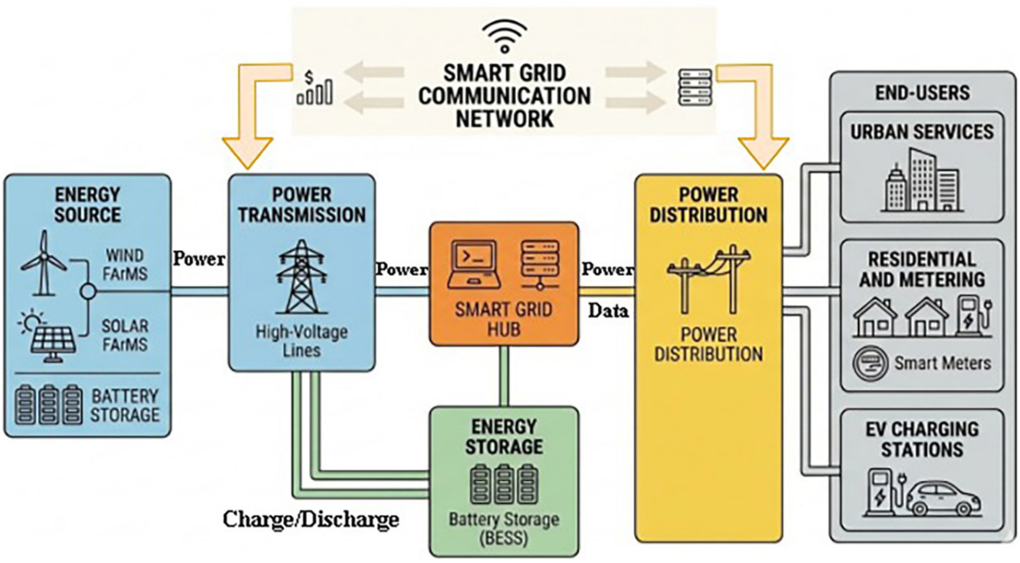

Fig. 2. Smart grid illustration

3.2 AI

Artificial intelligence is defined as a computational system that can perform activities typically performed by the intellect of a human (learning, reasoning, and decision-making) [21]. As such, in modern engineering applications, AI techniques, particularly machine learning (ML) and DL, are often used to analyze large data sets, identify patterns, and produce prediction models for complex systems such as the smart grid [22], as shown in Figure 3. ML and DL enable the use of collected data from digital platforms, smart meters, and sensor networks to assist in forecasting, classification, and intelligent decision-making. As an example, DL models, RNNs, and LSTMs have been utilized very effectively in energy management systems and projects related to forecasting electric demand [23].

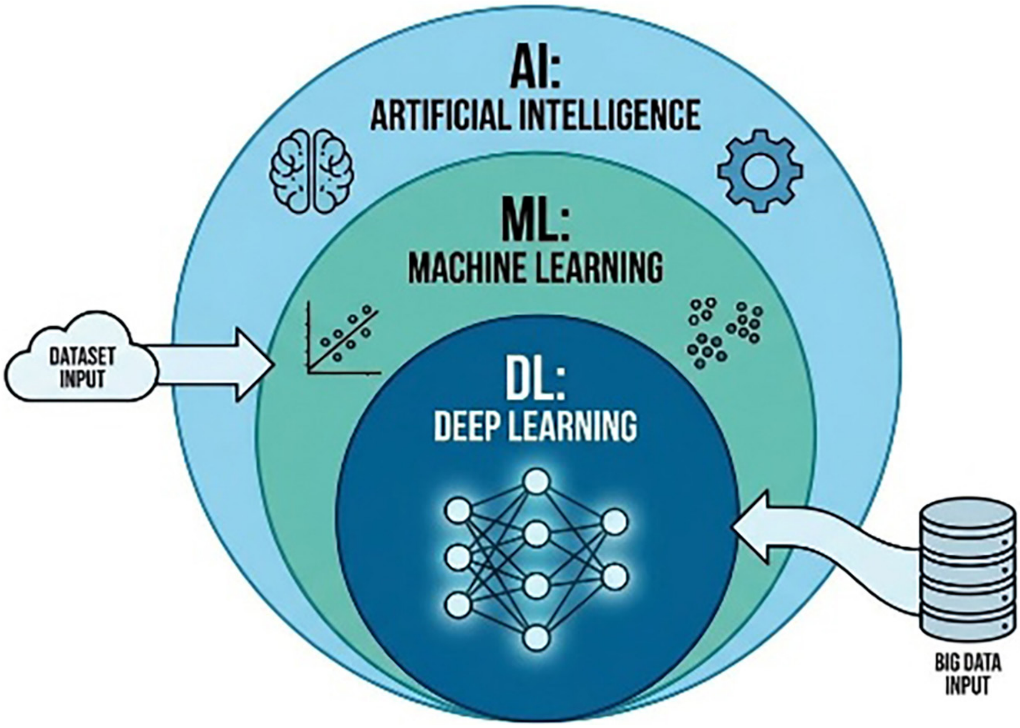

Fig. 3. AI intelligence techniques

Studying AI allows students to gain the essential computational Savitzky-Golay analytical skills needed for modern-day engineering, as far as their respective fields of study are concerned [24]. It also assists the student in understanding how data-driven models can support decision-making in complex systems. Furthermore, it fosters students' awareness of critical issues concerning data ethics, data privacy, and the ethical and responsible use of AI technologies.

3.3 Blockchain technology

Blockchain technology is a decentralized digital ledger that uses dispersed network nodes to securely and transparently record transactions in tamper-resistant blocks [20] shown in Figure 4. Through smart contracts written in languages like Solidity, blockchain enables safe peer-to-peer energy trading and automated market operations in contemporary energy systems [25]. The useful uses of blockchain technology have been extended beyond cryptocurrencies to include energy markets, supply chains, and digital services, thanks to platforms like Ethereum and Hyperledger Fabric [26].

As a result of learning about blockchain, engineering students gain knowledge of an array of key concepts in relation to blockchain technology, such as how distributed ledger technology offers security in a multi-party (decentralized) environment; the impacts of decentralization on business models; and how smart contracts can be automatically executed without manual intervention. Furthermore, learning about blockchain provides engineering students with opportunities to build real-world applications related to smart energy systems and also enables them to develop a secure smart contract system [27].

4 AI-BLOCKCHAIN DECENTRALIZED SMART GRID FRAMEWORK

4.1 Framework architecture

This system will be built upon 3 'layers,' that is, a Data Source Layer (where operational data is collected from the smart grid) and an Analysis Layer (that examines the collected data using DL algorithms against historical usage data in order to predict future electricity usage). The last layer (Decentralized Control) regulates and manages the decentralized electricity trading process by calculating the price dynamically at the point of sale through Smart Contracts available on Blockchain platforms. Each 'layer' has distinct functionality that provides seamless integration of intelligent analysis with data collection and decentralized market operation for the trading of electricity between consumers and producers.

a) **Data Source Layer:** In the proposed system architecture, the smart grid will also be where the data source is created (where data about produced and consumed electricity comes from) by the collection devices (smart meters and various types of sensors) generating large amounts of data due to the number of smart meters and sensors in today's smart grid, and because of the introduction and integration of renewable energy sources such as wind and solar into smart grid electricity production models. The data from the smart grid provides critical input to the other upper modules in the architecture framework. Thus, the smart grid is responsible for collecting data from the electric smart grid (electric part) and communicating that data to all other modules for further analysis (for purposes of smart energy management) and processing to obtain consumption/usage data, as well as to allow students to develop an understanding of the types of renewable energy systems and the ways they generate and use data in today's energy infrastructure from an engineering education perspective.
b) **Analysis Layer:** An analysis layer is the framework layer that predicts future demand for electricity using data collected from smart grids. The first layer examines historical usage data to determine expected electricity usage through the use of the specific model with DL computations, where the DL is useful for modeling time series patterns. This analysis layer outputs expected demand values that inform the pricing of electricity and facilitate the exchange (trade) of energy. The purpose of this element is to educate students about how DL models can analyze energy data and allow for more informed decision-making in the energy production and delivery process.
c) **Decentralized Control Layer:** The third part of this framework is the blockchain's decentralized control layer, which helps run the system to trade energy in a decentralized manner. The people in the energy market can communicate with

each other safely and in a manner that is open, without having to rely on central control (trust) by using two proposed smart contracts, the price and management contracts. Smart contracts help to regulate how trades occur in the proposed system. The management contract manages energy trading between producers, consumers, and prosumers, while the Pricing Contract calculates the dynamic price of electricity based on demand for and supply of electricity. The decentralization provided by the third part of this framework also provides an educational model for students to learn how blockchain technology can help automate and decentralize the energy market. Figure 5 illustrates how the proposed framework is bringing together the use of blockchain technology, DL, and smart grid data into one unified platform.

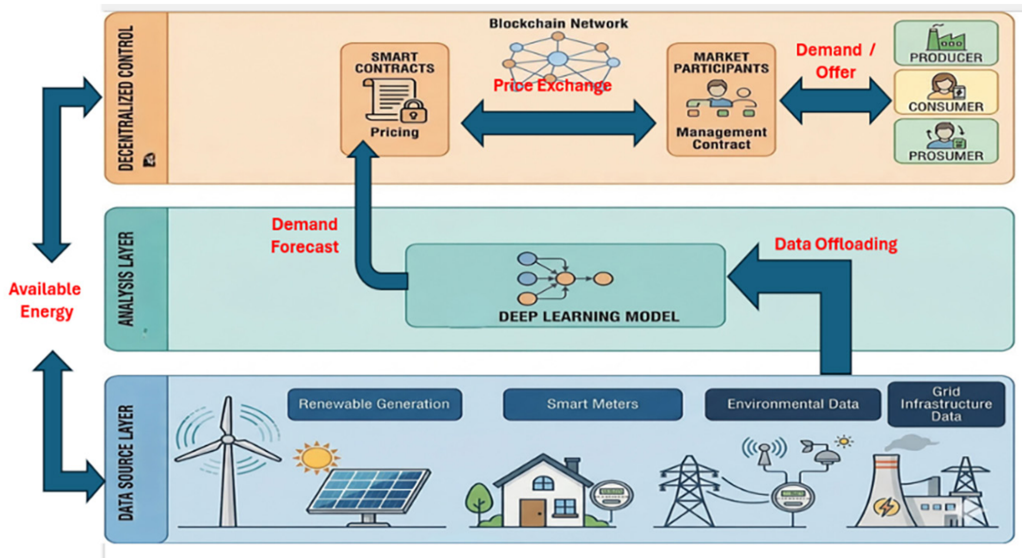

Fig. 4. Suggested framework architecture

First, preprocessed smart grid data is used to train a GRU-based model that can predict future electricity demand. After that, an oracle mechanism sends the predicted values to the blockchain [28]. A dynamic pricing smart contract uses the relationship between supply and demand to set electricity prices. These prices are then used in a decentralized market to make energy trading safer. Every transaction is recorded on the blockchain to make sure that the data is accurate and open. From an educational point of view, this framework shows how modern energy systems can successfully use decentralized technologies and AI.

4.2 Dynamic pricing model

The inverse pricing function presented below is adopted as a baseline model for dynamic electricity pricing [29]

$$P\_raw(t) = \alpha + \beta(D(t)/S(t))$$

Where $P\_raw(t)$ is the electricity price at the time slot t. $D(t)$ is the forecasted demand from the grid, $S(t)$ is the total available supply from all power sources.

α is the base price, which is the minimum price that equals the cost of generation on kw/h. Finally, β, The sensitivity coefficient that gathers the effect of failure in the network, temperature, and all other available data from the grid.

To enhance price regulation and better align the model with real-world practices in Iraq and some Middle Eastern countries, where local gasoline generators operated by private suppliers provide electricity in the absence of a government grid supply, a maximum reference price is used *P_gen* is introduced. This parameter represents the cost per kilowatt-hour charged by local energy providers.

Accordingly, the pricing model is adjusted such that the final electricity price is determined as the minimum between the inverse pricing output and the local generator price. This approach ensures cost efficiency and protects end users from excessive pricing, as shown in the final formula, which has been adopted in the paper.

$$P(t) = min(P\_gen, \alpha + \beta(D(t)/S(t)))$$

5 FRAMEWORK IMPLEMENTATION

The proposed framework combines blockchain smart contracts for decentralized energy trading with demand forecasting based on DL to make a smart grid energy management system. Blockchain smart contracts manage dynamic pricing and trade between market players. A DL model, on the other hand, uses past smart grid data to predict how much electricity will be used. This approach lets the smart grid's forecasting models, pricing systems, and energy trading operations work together automatically.

5.1 Dataset

This study used the Smart Grid Real-Time Load Monitoring Dataset (SGRT-LMD), which is available to the public through [30]. The dataset has about 50,000 records with a time resolution of one minute. It includes real-time electrical load monitoring data collected from 2018 to 2020. The dataset includes a number of operational characteristics related to smart grid monitoring, such as measurements of voltage, frequency, and electrical load demand.

5.2 Data preprocessing

The DL forecasting module was made in Python, using scientific libraries like TensorFlow, Matplotlib, NumPy, and Pandas for processing data. Before training the model, several preprocessing methods were used to improve the quality of the data. The GRU filter smoothed the time-series data while keeping its underlying trend. The input variables were then scaled between 0 and 1 using Min–Max normalization, which improves the performance of the neural network model. The dataset is divided into two parts: one for training and one for testing. This was to see how well the model could make predictions. The timestamp feature was changed into structured temporal features like hour, day, month, and weekday so that patterns in electricity use over time could be found. The missing values in the data were filled in with the average value mechanism.

Because DL for time series data requires work with sequential data, the dataset was turned into time-series sequences using a sliding window technique. The model learned how past data affected the next load value by using a window size of 48 time steps. Once the sequences were generated, data shuffling was disabled to preserve the chronological order of the time series and prevent information leakage from future observations.

5.3 DL algorithm

Using historical smart grid data, a DL forecasting model based on GRU was put into practice to forecast electricity demand. The final prediction is produced by fully linked layers that come after two stacked GRU layers with 128 and 64 hidden units, respectively. The model can capture intricate temporal correlations in the time-series data thanks to this architecture. The Adam optimization approach was used to train the model, utilizing Mean Squared Error (MSE) as the evaluation metric and MSE as the loss function [31][32]. An Early Stopping technique was used during training to prevent overfitting, enabling the model to automatically cease training when validation results ceased to improve. Mini-batches of 64 samples with a 20% validation split were used to train the model. The GRU model aims to predict how much electricity will be needed. The code structure in Figure 5 is meant to help students learn the basic steps of DL by defining the model architecture.

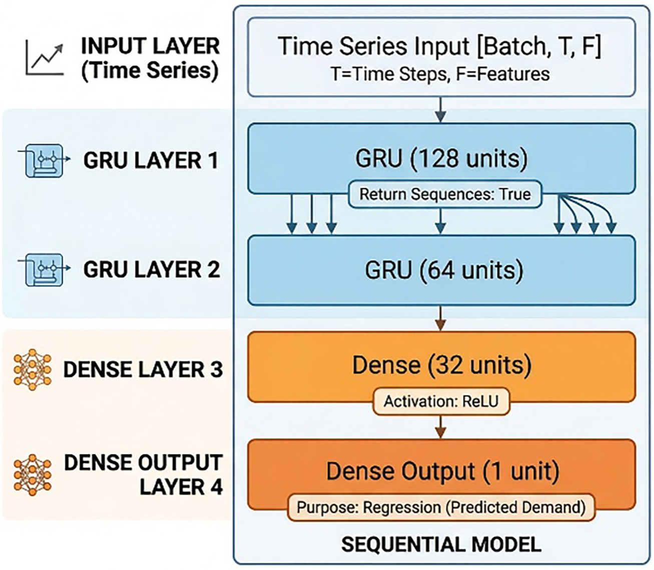

Fig. 5. GRU model summary

Once the GRU forecasting model had been trained, the testing dataset was used to make predictions. An inverse normalization process was used to put the predicted values back on their original scale because Min–Max scaling had already been used to standardize the input data. This step makes it possible to look at the forecasting results in a meaningful way by changing the electrical load values back to their real unit (kW). The real test values were also put back on their original scale so that it would be easier to compare expected and actual electricity demand.

5.4 Blockchain platform and development environment

The Ethereum platform was used to create the blockchain layer in the suggested framework because of its robust support for decentralized applications and smart contracts. Smart contracts that automate energy trading and dynamic pricing mechanisms in the decentralized smart grid market were made with the Solidity programming language. We used some blockchain platforms to make testing and development easier, as follows:

- The Go-Ethereum (Geth) client was used to implement backed Ethereum. During the practical implementation phase, the use of Geth presented several technical challenges that significantly affected the workflow [33]. One of the primary issues was the complexity of configuring a private blockchain network, along with the need to manually manage accounts and private keys. In addition, compatibility issues arose between different versions of Geth and integration libraries such as Web3.py within the Python environment.
- Based on the above, GUI Ganache is selected to implement Ethereum, which also can give developers a place to test and use smart contracts on a local blockchain [34]. The main challenges were the limited level of control over advanced configuration parameters in the graphical interface, such as custom gas limits, block time intervals, and network settings. This restriction reduced the ability to simulate specific experimental conditions required for the proposed framework. In addition, the GUI version exhibited stability issues during extended experimental sessions.

Finally, the implementation is done using a local blockchain network with Ganache CLI, as shown in Figure 6. The CLI-based method makes it easy to use Remix IDE, which is used to build smart contracts using the Solidity programming language [35], as shown in Figure 7. This process is achieved by setting up a local RPC server at http://127.0.0.1:8545. This gives the experiment a controlled, developer-focused environment that is similar to real-world blockchain infrastructure, where they can deploy and interact with energy trading contracts. Then, the web3 library is used to let Python talk to smart contracts and blockchain transactions [36]. This made it easier for other apps to work with the blockchain network. This let them use the blockchain network while it was still being tested and developed.

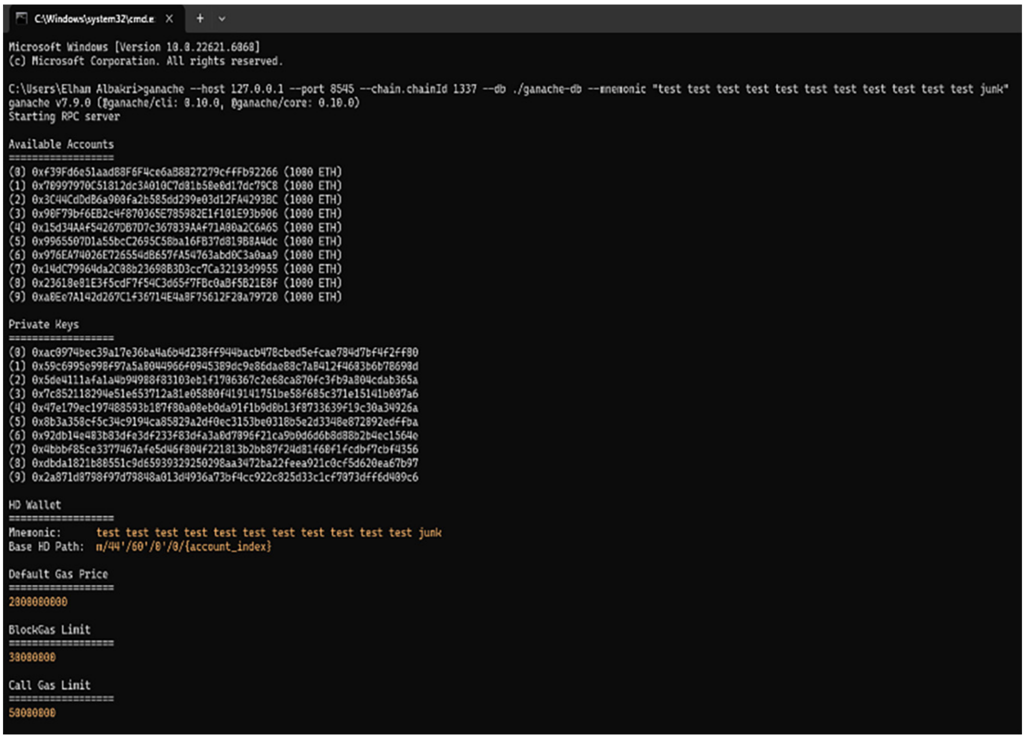

Fig. 6. CLI ganache

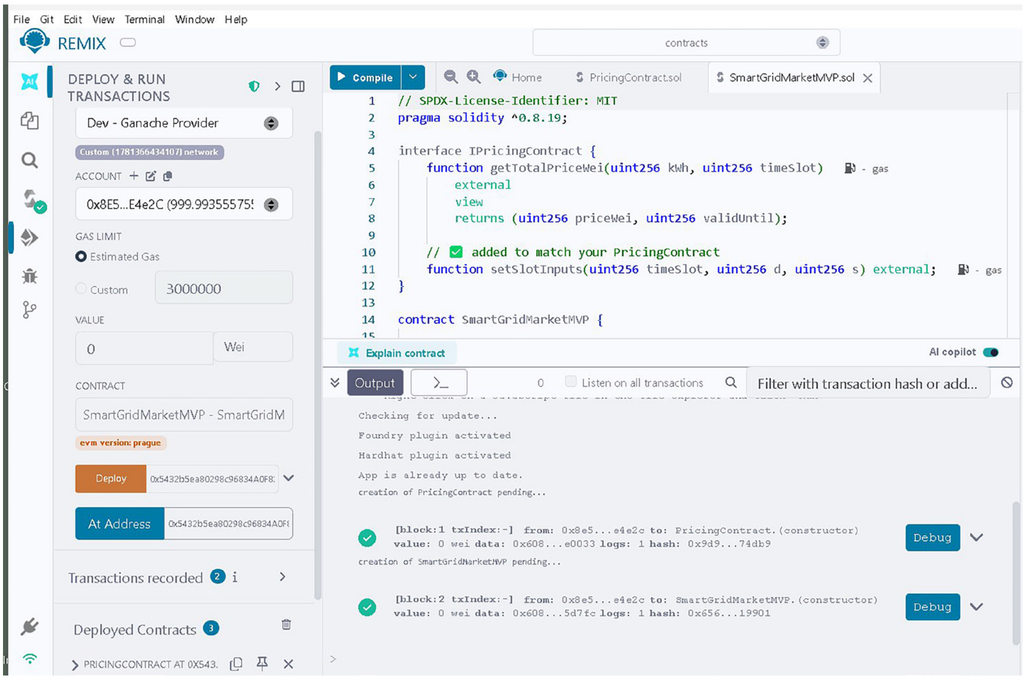

Fig. 7. Remix IDE

In this implementation, two smart contracts have been developed. The first contract is dynamic pricing, and the second is the energy trading management contract.

a) **Dynamic Pricing Contract:** A dynamic pricing contract is used to figure out how much electricity costs right now. The contract has some important variables, like the baseline price, the day and night sensitivity coefficients, and the highest price that is allowed. It also learns about the market, like what the demand and supply are likely to be.

   The contract splits the hours of the day and night into two groups based on Iraqi local time and uses the right sensitivity coefficient to figure out the price. The price is based on how much demand there is compared to how much supply there is. The price goes up when there is more demand for electricity than there is supply. The BET system has clear and automatic prices because there is a price cap that stops the final price from going above the cap.

b) **Energy Trading Smart Contract:** An energy trading management smart contract is developed to make sure that producers, consumers, and prosumers all work together to run the decentralized energy trading process. People can only trade energy if they have permission, and the contract says who can sign up to do so. Energy producers make offers that include the energy and time frame that are available, while consumers make requests for the demand.

   The dynamic pricing contract gives the contract the price after adding up the available supply. An escrow mechanism is used to temporarily lock in the payment after a purchase order is accepted. This is done to make sure that the settlement is safe. The deal is done when the payment is sent to the seller after it has been checked. This process shows how blockchain smart contracts can make financial transactions clear and run decentralized energy markets without human intervention.

5.5 Energy trading process

Figure 8 shows the proposed AI–Blockchain smart grid framework's total operational workflow. The proposed system utilizes automated interactions among market participants and blockchain smart contracts to facilitate the energy trading process.

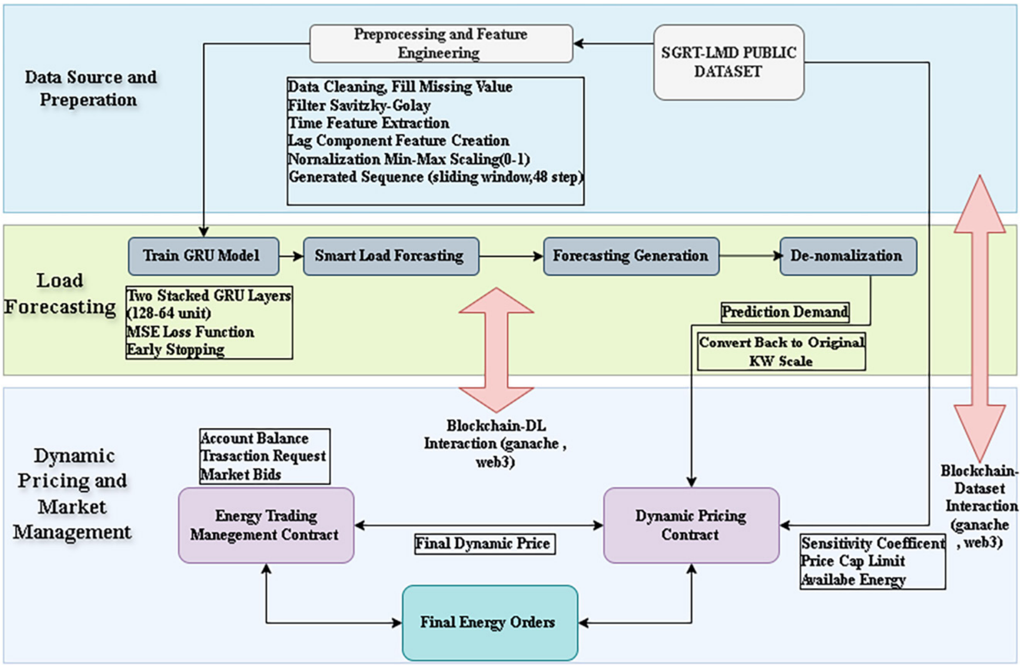

Fig. 8. Implementation underlying techniques

Consumers ask for energy, but energy producers first make offers that include the energy and time slots that are available. The market contract takes the total supply and the expected demand that the DL forecasting algorithm will create and combines them. Based on these inputs, the system gets the energy price from the dynamic pricing contract. Following the creation of purchase orders by customers, the necessary payment is locked in the smart contract via an escrow mechanism after the order is accepted. The decentralized energy trading procedure is finished when the payment is sent to the seller following transaction verification.

5.6 Educational workflow of a BET system

As seen in Tables 2 and 3, this new blockchain- and DL-based energy trading system's operational framework and the process by which it functions are detailed. Table 2 presents the overall workflow of the system and the interactions between participants, while Table 3 provides further detail with a step-by-step breakdown of the various smart contract functions within the system, along with the specific role each participant will play during each stage of execution. The combined information from both Tables 2 and 3 allows us to thoroughly understand the entire pipeline of activities starting with the initiation of the transaction and concluding with its completion (see Figure 1). The first activity performed in the entire transaction process is performed by the administrator when he/she deploys the two key smart contracts (the Pricing Contract and the Market Contract) and connect them so they can function together. The deployment of the two contracts is critical, as it enables the coordinated interaction of the pricing system and trading system. Once all of the required contracts are deployed. The next phase of activity revolves around the producer's and consumer's registration on the system and the administrator verifying their identity to build trust and control access to the decentralized system. After the initial registration phase is completed, the transaction moves into the operational phase. The producer submits their offers for energy amounts they are willing to sell to consumers, and consumers create purchase orders to request energy from producers. The pricing dynamic of the transaction depicts a dynamic price for energy that is calculated by the supply/demand information collected by the Pricing function's market quote through the Pricing contract. Therefore, there is a cohesive relationship between data-driven pricing execution on the blockchain. i.e., the calculated price and the pricing function are based on supply/demand information. Following the calculation of the price, the consumer accepts the order and then provides the required payment (in Ether) for the order. This payment is managed via the smart contract and will provide the participants with an increased level of trust and transparency by executing the payment process as defined within the smart contract. Following the completion of the payment process, the administrator of the smart contract will execute the funds transfer (settlement) from the consumer to the producer, completing the transaction lifecycle.

From an educational perspective, Tables 2 and 3 provide a structured and layered method to explain the system, in that Table 2 illustrates the conceptual workflow, whereas Table 3 provides specific implementation steps outlining the conceptual workflow. Therefore, this dual-level perspective should enhance the learner's understanding of how smart contracts interact and how decentralized energy trading systems operate in the real world.

Table 2. Workflow of BET system and participant roles

Step	From	Function	Description
1	Admin	Deploy Pricing	Deploy the pricing smart contract on the blockchain
2	Admin	Deploy Market	Deploy the market contract and link it to the pricing contract
3	Producer	register	Register the producer in the system
4	Consumer	register	Register the consumer in the system
5	Admin	setVerified	Verify and approve registered accounts
6	Producer	submitOffer	Submit an energy offer for selling
7	Consumer	createOrder	Create a request to buy energy
8	Admin	quoteFromPricing	Calculate the price based on supply and demand
9	Consumer	accept (with ETH)	Accept the order and send payment (ETH)
10	Admin	settle	Transfer payment to the seller and complete the trade

Table 3. Complete trading cycle transaction details

Details	Block Number	Block Timestamp UTC	Tx Hash	From	To	Gas Used	Value Wei	Nonce
Submit Offer Seller_0	93	2026-03-24T20:33:29+00:00	40237ca5901f2e43d20e6c95b86584beba52f702e8df04…	0x95cED938F7991cd0dFcb48F0a06a40FA1aF46EBC	0xCfEB869F69431e42cdB54A4F4f105C19C080A601	87430	0	19
Submit Demand Buyer 0	94	2026-03-24T20:33:29+00:00	db48c930feb8ecd52fa624847ae345cc127c338498c04d…	0x22d491Bde2303f2f43325b2108D26f1eAbA1e32b	0xCfEB869F69431e42cdB54A4F4f105C19C080A601	80932	0	13
Submit Demand Buyer 1	95	2026-03-24T20:33:30+00:00	229f8f708d09a3d73c64ba895957c3543c98f682233685…	0xE11BA2b4D45Eaed5996Cd0823791E0C93114882d	0xCfEB869F69431e42cdB54A4F4f105C19C080A601	65932	0	13
Submit Demand Buyer 2	96	2026-03-24T20:33:30+00:00	49082529fba605930b5fc90158e66275b20fb8368534d7…	0xd03ea8624C8C5987235048901fB614fDcA89b117	0xCfEB869F69431e42cdB54A4F4f105C19C080A601	50932	0	12
Push Slot Inputs	97	2026-03-24T20:33:30+00:00	8cb44f4d1e9def509ef9c75741843b1bd6b7e8691e7321…	0xFFcf8FDEE72ac11b5c542428B35EEF5769C409f0	0xCfEB869F69431e42cdB54A4F4f105C19C080A601	158163	0	12
Push *Pgen* Cap	98	2026-03-24T20:33:30+00:00	738af4b35b87dbddb31d5f32536be4a7dfb2c60dc9cac8…	0xFFcf8FDEE72ac11b5c542428B35EEF5769C409f0	0xCfEB869F69431e42cdB54A4F4f105C19C080A601	54559	0	13
Place Order Buyer 0	99	2026-03-24T20:33:30+00:00	7904d440b8183e07f2708754f77b941adec925a1b37783…	0x22d491Bde2303f2f43325b2108D26f1eAbA1e32b	0xCfEB869F69431e42cdB54A4F4f105C19C080A601	194281	61419850102210500	14
Accept Order Seller 0	100	2026-03-24T20:33:30+00:00	505211593e2d7182a79bfe91779b8e3537502e84e15a80…	0x95cED938F7991cd0dFcb48F0a06a40FA1aF46EBC	0xCfEB869F69431e42cdB54A4F4f105C19C080A601	64778	0	20

6 DISCUSSION

6.1 Pedagogical guide for framework implementation

a) **Python–Blockchain Compatibility:** The applied implementation of this proposed framework demonstrated that there were some compatibility limitations between various versions of Python, as well as between the various tools used to develop the blockchain. An effective set of configurations was developed, which utilized version 3.10.9 of Python in conjunction with version 0.8.19 of Solidity, resulting in effective interoperability between the Python environment and Ethereum-based computer languages (Solidity) through the use of Web3.py. This demonstrates how important it is when working on such a hybrid solution involving blockchain technology and AI, a final solution for educational purposes, yet having to deal with many variables of software configurations associated with developing a hybrid system.

b) **Integration with the AI Forecasting Module:** Merging DL and blockchain technology into smart grid infrastructure is difficult due to the vastly different environments in which each of these two technologies operates. To perform forecasting work, DL models depend on large amounts of data, ongoing computational power, and changing software environments. However, smart contracts on the blockchain operate in a determined and separate environment that does not allow smart contracts to directly gain access to external data or run complicated ML models. As a result, predictive intelligence cannot be applied directly to blockchain energy markets.

The proposed framework resolves this issue by separating the forecasting from the blockchain yet maintaining secure communications between them. An off-chain GRU-based DL module is used to analyze historical operational data from the smart grid to create projections for future electrical demand. Running the forecasting model off-chain allows for all of the computing resources and data processing capabilities necessary to perform accurate forecasting. Since smart contracts on the blockchain do not have direct access to external data, the framework introduces an oracle mechanism to bridge this gap. As a result, the oracle functions as a trusted intermediary used to securely pass the projected demand values created from the DL model to the blockchain network. Consequently, the off-chain produced forecasting intelligence is able to be used by the on-chain system without violating the constraints of the blockchain.

6.2 Pedagogical integration model for engineering technology education

The framework serves as an experiential learning model that integrates theoretical principles into practical, real-life applications of Industry 4.0. By interacting with data from the smart grid, students will gain the knowledge to analyze energy consumption patterns and use these patterns to make data-driven decisions. Students will gain skills in training and validating models by training a GRU-based forecasting model within the DL layer's framework and performing evaluations on it. Finally, the blockchain layer will allow students to research how engineering systems connect to digital markets and safe decentralized technologies by creating a decentralized exchange of energy using Solidity smart contracts.

7 CONCLUSION

This study presented a novel AI-Blockchain smart grid framework that aims to deliver a better understanding and engineering experience education within Industry 4.0. The framework smart grid data analytics, DL-based demand forecasting, and blockchain-enabled decentralized energy trading. The proposed architecture illustrates the integration of new Industry 4.0 technologies within a unified system to facilitate intelligent energy management and the establishment of decentralized electricity markets. The proposed framework is built within a three-layer architecture. First, smart grid data is the main source layer of information for a GRU-based DL model layer that predicts how much electricity will be needed in the future.

Then, blockchain smart contracts use the predicted demand values to figure out dynamic electricity prices within the decentralized control layer. This lets producers and consumers trade energy automatically. This integration makes it clear, safe, and automatic how the market works, and it shows how data-driven forecasting and decentralized control systems can work together. From an educational point of view, the framework is a way for people to learn about smart grids, AI, and blockchain technologies all at once. The proposed model helps engineering students understand how modern digital technologies work together in real-world energy systems. It also helps them develop the analytical, computational, and system integration skills they will need in Industry 4.0 settings. The proposed framework aims to close the gap between theoretical research and real-world application by providing a structured architecture that combines advanced energy technologies and supports hands-on learning in engineering education.

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