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RESEARCH ARTICLE

A Testing Framework for Blockchain-Based Energy Trade Microgrids Applications

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ABSTRACT Distributed energy generation disrupts traditional energy markets by blurring the line between producers and consumers and enabling the emerging prosumers to trade energy in per-to-peer transactions. Blockchain technology automates peer-to-peer energy trades in a distributed database architecture that achieves security and cost-effectiveness using cryptographic hashing and consensus-based verification. Before its deployment, an energy blockchain trading application needs to be tested in a virtual environment that is analogous to the real-world setting to ensure correct implementation and identify potential obstacles and opportunities. This study suggests executing such a testing within a framework that integrates a Geographic Information System (GIS) environment with an Agent-Based Modeling (ABM) simulation platform. The application of this testing framework to a case study of solar Photovoltaic (PV) energy trade among household peers in in Doha, Qatar, shows how the integration of the GIS environment offers a detailed analysis of transactions in local housing community markets. The ABM simulation reveals that population density, energy market prices, and household proximity significantly influence residential PV energy trading in Qatar. The ensuing simulation environment provides a decision-support platform for designing and implementing decentralized trading systems based on blockchain technology, and high-performance computing can enhance model performance for scalable energy blockchain analysis in Qatar and beyond.

INDEX TERMS Spatial temporal access, social simulation, power grid, artificial intelligence, solar energy, blockchain technology, agent based modelling, energy marketplace.

I. INTRODUCTION

By blurring the traditional distinctions between energy producers and consumers, the emergence of distributed energy generation, particularly through residential and commercial photovoltaic (PV) applications, has altered the energy landscape giving rise to the prosumer as a new player in the energy market (Fig. 1). Blockchain technology presents a promising option to enable prosumers to join the energy market in a secure and cost-effective manner. The blockchain makes it possible for consumers, prosumers, and utilities to participate in effective energy trading by automating direct energy transactions within a distributed database architecture based on cryptographic hashing and consensus-based verification. To guarantee the correct utilization of blockchain-empowered energy exchanging frameworks, it is fundamental to test them in a virtual environment that reenacts realistic circumstances. In this study, a testing framework is proposed that integrates agent-based modelling with Geographic Information System (GIS) technology [1]. The framework aims to simulate and analyze the behavior of prosumers, utilities, and other energy market players in a virtual environment. This will allow for the identification and testing of potential issues and challenges that may arise in the implementation of blockchain-enabled energy trading systems.

The traditional energy market has always been characterized by a clear distinction between energy producers and consumers. Producers, such as power plants, generate electricity and sell it to consumers through utilities, who act as intermediaries. However, with the emergence of distributed

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energy generation, particularly through residential and commercial photovoltaic (PV) applications, this traditional model is being disrupted. Distributed energy generation refers to the production of electricity by small-scale systems, such as rooftop solar panels, that are installed on or near the premises of consumers. This has given rise to the concept of the 'prosumer' - a hybrid of producer and consumer - who is both a producer and a consumer of energy. Prosumers are able to generate their own electricity and also sell any excess energy back to the grid. This blurring of the lines between producers and consumers has altered the energy landscape, giving prosumers a new role in the energy market. As a result, there is a need for new technologies that can facilitate the participation of prosumers in the energy market in a secure and cost-effective manner. This is where blockchain technology comes into play.

Blockchain technology, which was originally developed for the cryptocurrency Bitcoin, is a decentralized, distributed ledger that records transactions in a secure and transparent manner. It has the potential to revolutionize the energy market by enabling direct energy trading between prosumers, consumers, and utilities without the need for intermediaries. By automating direct energy transactions within a distributed database architecture based on cryptographic hashing and consensus-based verification, blockchain technology makes it possible for consumers, prosumers, and utilities to participate in effective energy trading. This not only reduces transaction costs but also increases the efficiency and transparency of the energy market. However, to ensure the correct utilization of blockchain-enabled energy trading systems, it is essential to test them in a virtual environment that simulates realistic scenarios. This is where the proposed testing framework, which integrates agent-based modelling with Geographic Information System (GIS) technology, comes into play.

Agent-based modelling is a computational technique that simulates the behavior of individual agents within a system, while GIS technology allows for the visualization and analysis of spatial data. By integrating these two technologies, the testing framework aims to simulate and analyze the behavior of prosumers, utilities, and other energy market players in a virtual environment. The testing framework will allow for the identification and testing of potential issues and challenges that may arise in the implementation of blockchain-enabled energy trading systems. For example, it can simulate the behavior of prosumers who may try to manipulate the system for their own benefit, or the impact of sudden changes in energy demand or supply.

Furthermore, the framework can also be used to analyze the potential benefits and drawbacks of implementing blockchain technology in different regions with varying energy market structures. This will provide valuable insights for policymakers and energy market stakeholders to make informed decisions about the adoption of blockchain technology. There have been several studies that have successfully integrated ABM and GIS in energy trading analysis. One of the earliest studies that integrated ABM and GIS in analyzing blockchain-enabled energy trading systems was conducted by [2]. The authors developed a framework that combines ABM, GIS, and blockchain technology to simulate and analyze the behavior of prosumers and utilities in a decentralized energy market. The framework considered various factors such as geographical location, energy demand and supply, and peer-to-peer energy trading among prosumers. The results of the study showed that the use of blockchain technology in energy trading can lead to a more efficient and transparent market, with reduced costs for consumers. The integration of ABM and GIS allowed for a more detailed analysis of the market, taking into account the spatial and behavioral aspects of energy trading. Similarly, in [3] proposed a similar framework that utilized ABM and GIS to simulate a blockchain-enabled energy market. The study focused on the impact of different energy policies on the behavior of prosumers and utilities, such as feed-in tariffs and carbon taxes. The results showed that blockchain technology can facilitate the integration of renewable energy sources into the grid and promote a more sustainable energy market.

For example, a study by [4] used this approach to analyze the impact of renewable energy integration on electricity markets. The study found that incorporating spatial factors into ABM can improve the accuracy of market forecasts and enable the identification of potential market inefficiencies. Another study by [5] used ABM and GIS to analyze the impact of spatial factors on the trading behavior of wind farm operators. The study found that spatial factors, such as proximity to transmission lines and wind resource availability, significantly influenced the behavior of these operators. This information can be used to develop strategies to improve the efficiency of wind energy trading. In addition to these studies, several software tools have been developed that integrate ABM and GIS for energy market analysis. For example, the Energy Market Agent-Based Model (EMMA) developed by the National Renewable Energy Laboratory (NREL) is a powerful tool for simulating energy markets and analyzing the impacts of policies and technologies.

Despite their potential, ABM and GIS have certain limitations that hinder their effectiveness in energy market analysis. One of the main challenges is the lack of data availability and quality. ABM requires detailed data on individual agents and their behavior, which may not be readily available. Similarly, GIS requires accurate and up-to-date spatial data, which may be lacking in some regions. This can lead to biased and inaccurate results. Moreover, ABM and GIS are computationally intensive and time-consuming. Developing and running complex simulation models can be a daunting task, and it may take a long time to get results. This can be a barrier for policymakers who require timely and actionable information to make decisions.

To overcome these limitations, we propose a new approach that integrates Machine Learning (ML) techniques with ABM and GIS. ML is a subset of Artificial Intelligence that focuses on developing algorithms and statistical models that can learn from data and make predictions or decisions. By incorporating ML techniques, we can address the data availability and quality issues of ABM and GIS. ML algorithms can analyze large datasets and identify patterns and trends that may not be visible to human analysts. This can provide a more comprehensive understanding of energy markets and their dynamics.

A case study involving the power network of the Education City Community Housing (ECHH) Complex in Doha, Qatar (Fig. 2), demonstrates the functionality of this testing environment. The testing environment enables stakeholders to analyze day-to-day energy use and generation by simulating the spatiotemporal trading characteristics of local energy markets. This fosters a deeper comprehension of market dynamics that supports the development of decentralized energy markets.

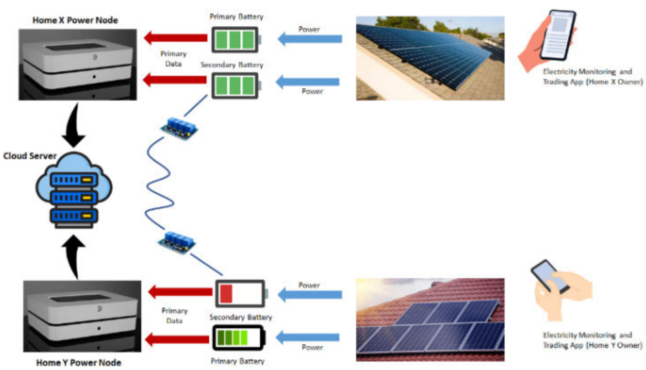


FIGURE 1. Education City Community Housing (ECCH) lot#1 (top) and lot#2 (bottom). The ECCH involves two closes by bundles, with an amount of 623 homes. One principal substation supplies 15 auxiliary substations that give capacity to the ECCH homes through the power network [1].

The paper is structured as follows. Section II provides background information data on power markets, microgrids, blockchain innovation, local area sunlight based, and energy blockchain systems. The methodology, including the data and models used, is outlined in Section III. In Section IV, the results of the experiments are discussed, and in Section V, the conclusion is made. Table 1 contains a list of the terms utilized in the paper.

II. BACKGROUND

A. POWER TRADING MARKETS

Ordinarily, energy trade ocurrs through the intervention of mediators, e.g. utilities [2], [3]. This practice adds unnecessary costs and complexity to the energy trading process. Decentralized energy markets (Fig. 3) offer eminent benefits, such as a likely 40% expansion in effectiveness and versatility compared to traditional trading frameworks [6]. Prosumers can either consume the energy they produce or sell it in the energy market that integrate regulatory frameworks such as the feed-in tariff and net metering [3].

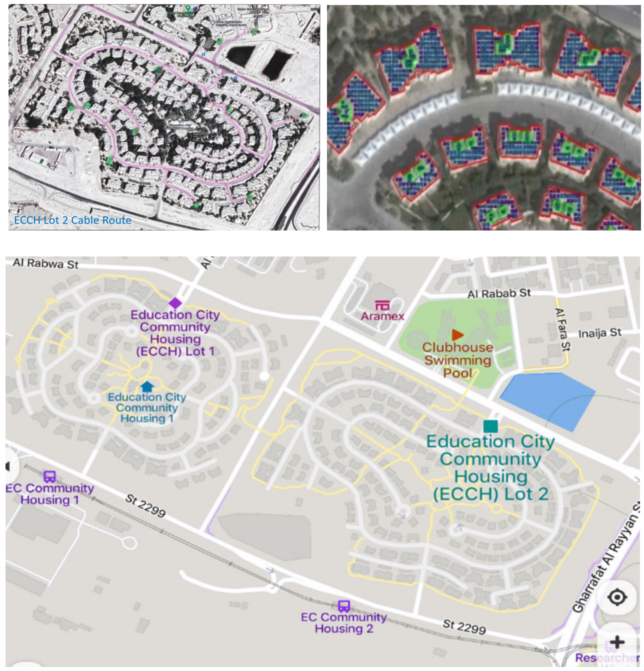


FIGURE 2. Education City Community Housing (ECCH) lot#1 (top) and lot#2 (bottom). The ECCH involves two closes by bundles, with an amount of 623 homes. One principal substation supplies 15 auxiliary substations that give capacity to the ECCH homes through the power network [1].

TABLE 1. Terminologies used in the paper [1].

Terminology	Meaning
PV	Photovoltaic
ABM	Agent Based Model
ECCH	Education City Community Housing
GIS	Geographic Information System
DER	Distributed Energy Resources
CHP	Heat/cooling and Power
PoW	Proof of Work
PoS	Proof of Stake
US	United States
POWR	Power Ledger
P2P	Peer-to-Peer
TE	Transactive Energy
EBCE	Energy Blockchain Community Ecosystem
IoT	Internet of Things
CAS	Complex Adaptive Systems
EBCE	Energy Blockchain Community Ecosystem
RPV	Rooftop Photovoltaic
HVAC	Heating, Ventilation, and Air Conditioning
PMU	Phasor Measurement Units
GCC	Gulf Cooperation Council
RET	Renewable Energy Technologies
API	Application Programming Interface
BCS	Blockchain Community Ecosystem
MMR	Mid-Market Rate
SDR	Supply Demand Ratio
DBMS	Database Management System
OPF	Optimum Power Flow

B. MICROGRIDS

As demonstrated in Fig. 4, the decentralization of energy systems is driven by the integration of renewable energy, energy storage, and demand response in local power systems

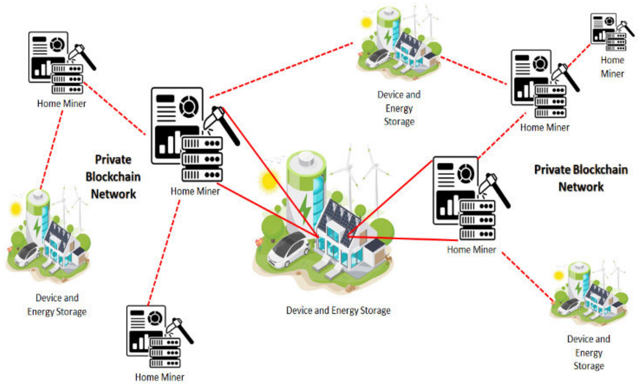


FIGURE 3. Decentralized exchange marketplace based on blockchain.

known as microgrids [7]. Aging power networks in urban areas struggle to meet the increasing demand, making infrastructure enhancement through cable and substation replacement costly and complex. Urban microgrids provide a cost-effective solution by meeting rising demand without compromising power quality and network reliability. Urban microgrids centrally manage Distributed Energy Resources (DER) like solar PV, small wind turbines, and conventional generators using controllers [8]. These controllers ensure secure and optimal power dispatch from diverse sources by managing local demand effectively. The addition of DER assets enables microgrids to handle increasing power demand while maintaining efficiency and reliability.

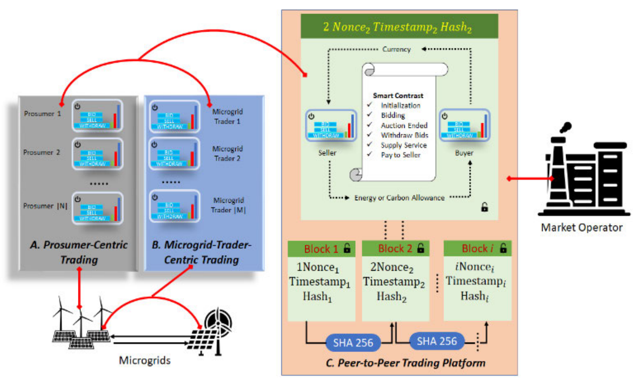


FIGURE 4. Cost-effective multiuser microgrids.

Operational microgrids include the Marcus Garvey Village,[1] University of Texas at Austin,[2] Brooklyn,[3] Milford, and Borrego Springs in the United States,[4] and the Power Matching City in the Netherlands.[5] Monitoring and control systems optimize power production, consumption, and minimize costs and emissions, as demonstrated by the Borrego Springs microgrid [1]. Accurate load, renewable resources, and storage forecasts aid in resource utilization and cost reduction.

Larger microgrids with enhanced monitoring and control systems achieve better optimization outcomes. Microgrid sizes vary, ranging from single building nano grids to groups of buildings in campuses, neighborhoods, and commercial/government structures. Multiple microgrids can coexist in an urban area, each with its power demand and supply. A multiuser microgrid configuration enhances resource utilization through expanded power exchange. For example, employing Combined Heat/Cooling and Power systems achieves 80% efficiency by matching peak loads with demand [8]. Exporting excess power to neighboring microgrids during peak periods maximizes efficiency. Microgrids with storage capabilities can benefit from purchasing power at reduced prices during abundant generation from neighboring microgrids. Proximity minimizes power transfer losses, yielding efficient and cost-effective multiuser microgrids [14].

C. ENERGY BLOCKCHAIN

Electricity markets traditionally operate through daily or short-term auctions, where all energy is sold at a uniform market-clearing price, regardless of varying offers and bids [9]. The emergence of blockchain technology offers new opportunities for cost-effective energy trading, removing intermediaries and enhancing security and resiliency. The blockchain enables peer-to-peer energy trading using a distributed consensus algorithm, eliminating the need for a central governing entity. Transaction data is stored in a decentralized, time-stamped, and encrypted digital database called a blockchain. Cryptographic hashing ensures privacy and transaction integrity, while distributed databases enhance resistance to hacking. Consensus mechanisms like proof of work [10], [11] or proof of stake prevent denial of service attacks and enable fault tolerance. Transactions in the blockchain are associated with "smart contract" code, defining the transaction terms. Transactions are grouped into blocks, and each block contains a hash linking it to the previous block.

To join the blockchain, a block's transactions must be confirmed by a computer node, verifying time, amount, and participants through a consensus algorithm. Proof of work (PoW) and proof of stake (PoS) are the two most widely used consensus algorithms in blockchains [10], [11], [12]. In PoW, a computer node competes to solve a numerical problem associated with adding a block to the blockchain, and the first node to find a solution receives a reward. In PoS, the validating node is selected from a pool based on random selection, wealth, or seniority.

Peer-to-peer energy transactions that are both secure and automated are made possible using blockchain technology in energy applications. As a result, there will be less friction and the price of electricity trading will go

[1] Marcus Garvey Village | Enel X.
[2] Microgrid | Center for Electromechanics (utexas.edu).
[3] Brooklyn Microgrid | Community Powered Energy.
[4] Borrego Springs: California's First Renewable Energy- Based Community Microgrid | California Energy Commission.
[5] Power Matching City – Smart Circle (smart-circle.org).

down. Effective blockchain microgrid pilots exist in the US and Australia, with projects being worked on in Thailand, Malaysia, Japan, Turkey, Italy, Slovenia and Germany. The Brooklyn Microgrid is a notable real-world application of energy blockchain [6]. It establishes a local energy marketplace using a private blockchain and smart meters called TAG-e G2. The project aims to enable automatic transactions between local energy producers and consumers, driven by rooftop solar installations.

While these initiatives demonstrate the successful implementation of local energy markets with blockchain, challenges remain. The existing solutions have yet to fully address physical grid constraints and ensure data integrity in transactive energy marketplaces. Further development and refinement are needed to overcome these issues and realize the full potential of blockchain in energy systems. Existing energy blockchain solutions lack efficient market solutions, overlook grid properties affecting transaction costs and power stability, lack in-ledger transaction verification, and lack interoperability with IoT protocols. The proposed framework in this paper addresses these issues by modeling the electricity network, forecasting supply and demand, considering power loss [1], and adopting an industrial IoT architecture with standardized interconnection between energy blockchain platforms using protocols like LwM2M and CoAP.

D. COMMUNITY SOLAR

Energy blockchain solutions are essential for promoting the development of community solar business models, particularly in countries like Qatar that have been slow in adopting distributed renewable energy (Fig. 5). Community solar, also known as shared solar, involves solar energy installations collectively owned by community members and third parties, enabling multiple consumers to share the generated electricity. Community solar has emerged as an alternative model for residential and commercial PV adoption, addressing concerns about utility revenues, PV ownership costs, and equitable deployment subsidies [1]. In the United States, community solar installations reached 1,523 MW in 2018, experiencing a compound annual growth rate of 200% between 2015 and 2017 [7]. The Rocky Mountain Institute projects that community-scale solar power could reach a capacity of 30 GW by 2020 [15].

In countries like Qatar, where a majority of the population consists of expatriates without long-term residency, and citizens enjoy free electricity, community solar presents an ideal solution for residential PV adoption. This study focuses on the ongoing development of a Blockchain Community Solar Ecosystem within Qatar's Education City Community Housing (ECCH) complex. It aims to achieve technical objectives in four key areas: microgrid infrastructure, IoT architecture, energy blockchain application, and regulatory framework. The microgrid infrastructure component involves the design and implementation of a computational microgrid model with integrated hardware for the ECCH complex's power system.

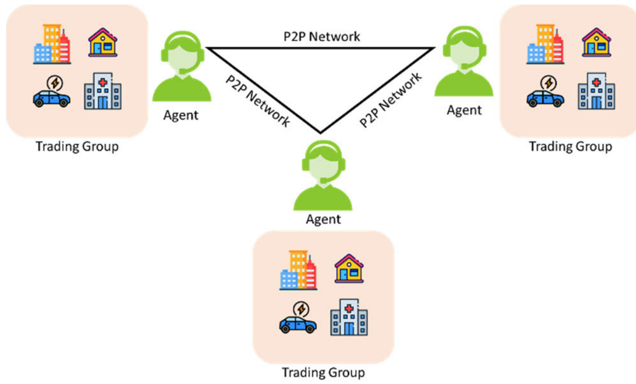


FIGURE 5. Simplified community solar paradigm.

It includes smart meters, residential solar PV systems with energy storage (based on a 5 kW PV system with 10 kW storage), a solar cadaster for estimating rooftop PV potential in Education City (Fig. 6), and EV charging stations connected to the microgrid's monitoring and control system.

Interconnectivity inside the energy blockchain environment is laid out through the plan and execution of an IoT reference engineering, taking on industry guidelines like LwM2M and CoAP [16]. By fostering the concept of a Blockchain Community Solar Ecosystem, this study ushers a novel way to produce and consume solar energy in Qatar through the creation of a secure, decentralized energy market where households in Community Solar neighborhoods can sell or purchase solar energy from one other. This system could also be used to improve the efficiency of energy production and consumption in Qatar. This could also help to reduce energy costs in the country, as producers and consumers would be able to access cheaper solar energy from each other.

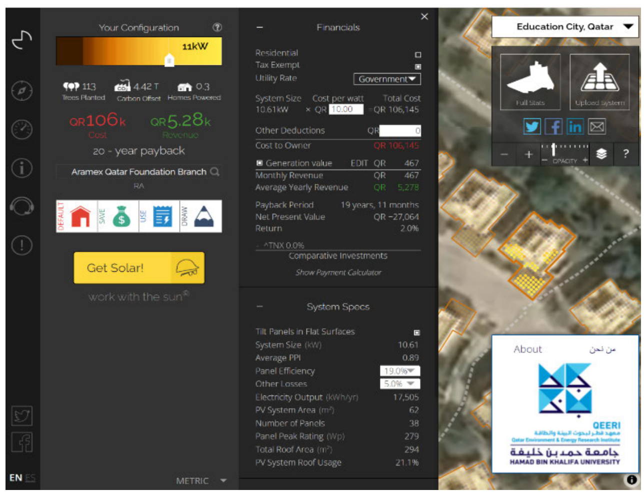


FIGURE 6. Sample output of solar cadaster application for education city.

E. MODELLING ENERGY BLOCKCHAIN ECOSYSTEMS

The primary contribution of this study is the development of a virtual environment that utilizes a Complex Adaptive

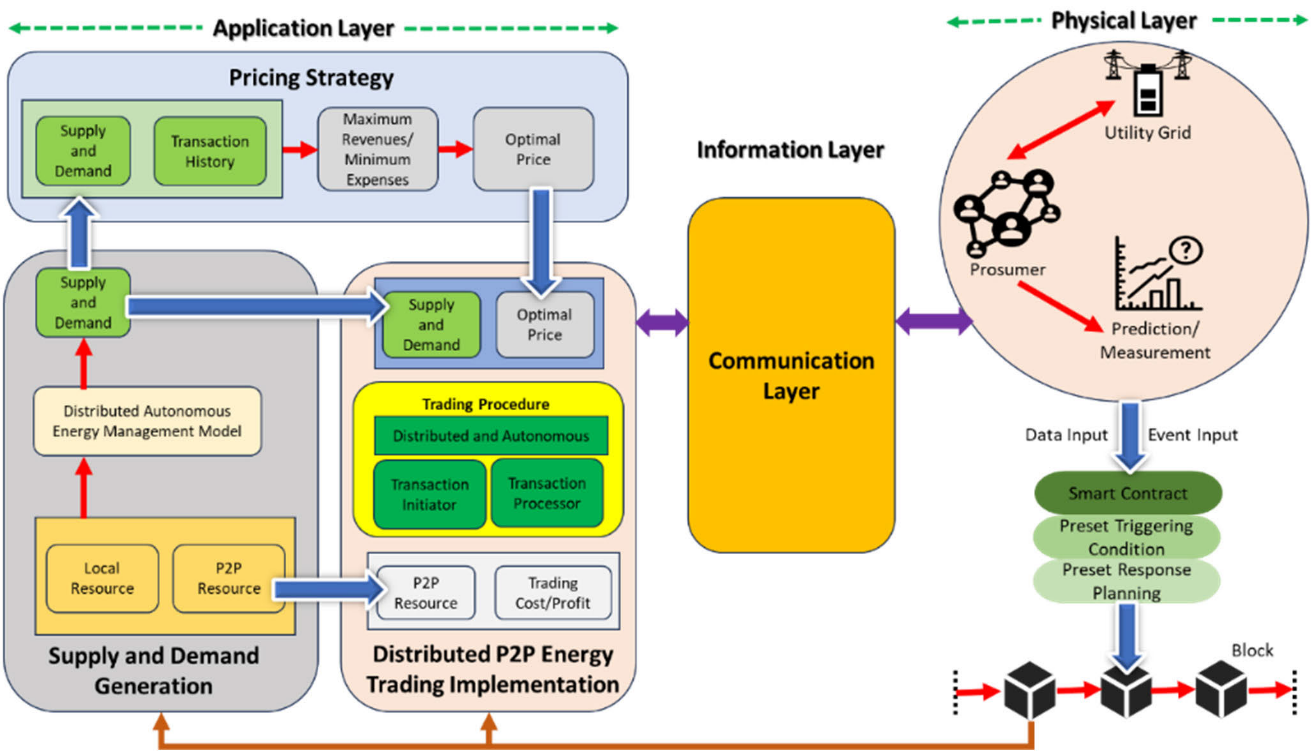


FIGURE 7. Proposed blockchain-enabled distributed P2P energy trading framework.

System (CAS) approach to test and validate the secure and fair trading of energy within a blockchain community solar ecosystems. The collective behavior of semi-autonomous agents that evolve and adapt to a changing environment is modeled as a CAS [13]. ABM simulations implement CASs by modeling the interaction of individual agents to explore their evolving behaviors.

Decentralized electricity markets have been studied with the help of equilibrium models [14], game theory [7], [10], human-subject research [9], and agent-based models [10]. Traditional supply and demand principles are based on equilibrium theory, which may not take into account the complexities of decentralized energy markets that encompass goals other than economic equilibrium (such as environmental considerations). Decentralized electricity markets may not be adequately described by game theory, which focuses on zero-sum games. Human-subject experiments provide behavioral insights, but they consume a lot of resources. ABM addresses these limitations by allowing automated simulations of autonomous agents with multifaceted utility functions that take into account a variety of constraints and make it easier for new traits to emerge.

In recent years, ABM has gained popularity for modeling decentralized energy markets. For instance, [10] used agent interactions and ABM to predict the behavior of energy market ecosystems, which are complex adaptive systems. [1] utilized smart contracts to implement a similar strategy for trading locally produced energy. Reference [11] used ABM to model a blockchain-and-Byzantine fault tolerance consensus-based financial market ecosystem. The proposed approach utilizes ABM to establish a versatile environment for testing the feasibility of an energy blockchain ecosystem inside Qatar's social, financial, and environmental setting [17].

ABM offers greater flexibility in representation, allowing agents to represent individuals or aggregate structures within the reference system across different spatial scales and time horizons. This choice depends on the level of abstraction used by the modeler [18], [19], [20]. However, most agent-based models of decentralized energy markets do not fully utilize the capabilities offered by ABM. For example, they often employ simplistic and discrete located agents without reference to realistic geospatial mapping strategies. To address these limitations, we propose a simulation methodology that combines a powerful Geographic Information System (GIS) approach with data mining to create explicit and multilevel spatial models within the ABM framework.

F. DISCUSSION

Traditional GIS models are based on centralized databases, where a single authority controls the data. This model has limitations in terms of data quality, as the data may be outdated, incomplete, or inaccurate. It also raises concerns about data security, as a single point of failure can compromise the entire system. Moreover, traditional GIS models lack transparency, as the data is controlled by a single entity, making it difficult for users to verify the authenticity of the data. To overcome these limitations, various blockchain-based GIS models have been proposed. One such model is the Distributed Ledger Technology (DLT) GIS, which uses a decentralized database to store and manage spatial data. This model offers improved data quality, as the data is continuously updated and verified by multiple nodes in the network. It also provides enhanced security, as the data is distributed across the network, making it difficult for hackers to manipulate.

However, DLT GIS models have their own set of limitations. The use of consensus algorithms to validate and add data to the blockchain can be time-consuming and resource intensive. This can result in slower transaction speeds and higher costs, making it less feasible for real-time applications. Moreover, DLT GIS models still lack transparency, as the data is controlled by a limited number of nodes, making it difficult for users to verify the data. To address these limitations, we propose an ABM GIS and blockchain-based approach. ABM is a modeling technique that simulates the actions and interactions of individual agents to understand the behavior of a system. In this approach, each agent represents a unique data point, and the interactions between agents result in the emergence of complex patterns and behaviors. By combining ABM with blockchain technology, we can create a decentralized and self-organizing system, where agents can interact and exchange data in a peer-to-peer manner. One of the main advantages of our proposed model is improved data quality. As the data is continuously updated and validated by multiple agents, the accuracy and completeness of the data are greatly enhanced. Moreover, the use of ABM reduces the need for costly and time-consuming consensus algorithms, resulting in faster transaction speeds and lower costs. Additionally, the decentralized nature of the model ensures better data security, as there is no single point of failure. Furthermore, our proposed model also offers improved transparency. As the data is controlled by multiple agents, users can easily verify the authenticity of the data. This is particularly useful in applications such as disaster management, where real-time and accurate data is crucial for decision making.

This study proposes a novel and distinct use of GIS layers in the simulation methodology to demonstrate decentralized energy trading in a residential community facilitated by blockchain technology. Section III describes the used technique for incorporating geographic vector information into the agent-based modeling (ABM) system. The capabilities of the validated modeling solutions are highlighted in Section IV.

III. PROPOSED METHODOLOGY: DATA&MODELS

A. DEVELOPED GIS MODEL

The proposed model for the application of a blockchain-based transactive energy (TE) framework in the ECCH microgrid utilizing distributed energy resources (DER) is described in Fig. 8. In the model, each ECCH household is represented as an independent agent. The probability that an agent will either "buy" or "sell" excess energy produced by residential energy systems in the neighborhood is determined by a convergence of factors including energy demand, availability and pricing at the time of transaction. Every agent in the community is associated with a variety of assets, including electric loads, such as domestic appliances, and power generating resources, such as solar PV, wind turbines, electric storage. Some electric loads are flexible, i.e. they can be shifted from times of peak usage to off-peak time to restore grid balance. Additionally, the system's electricity production and consumption are tracked by means of sensor devices.

This study's model examines the peer-to-peer trading of photovoltaic (PV) energy among household agents within ECCH. The ECCH Energy Blockchain Community Ecosystem (EBCE), depicted in Fig. 7, enables consumers to buy energy from local or main grid sources through the energy blockchain application. Trading scenarios are influenced by market conditions, including population density, consumer and prosumer counts. Agents interact with neighboring agents, adapting their behavior based on trade history, user parameters, energy prices, and updates from nearby households (Fig. 8).

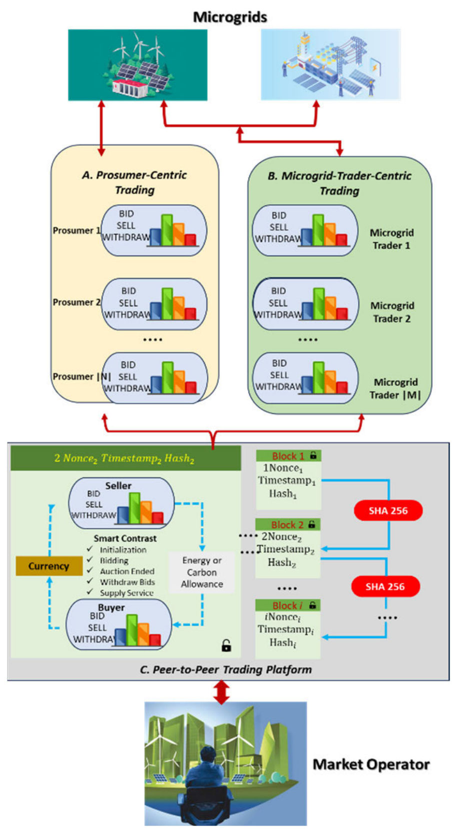


FIGURE 8. Proposed framework and transactions logs stored on blockchain.

B. DATA

Power transmission, building types, roof photovoltaic (RPV) efficiency, and hourly power request profiles well defined for the ECCH complex are integrated with the ABM utilized in this study. In microgrid scenarios, smart meters, which are installed in all ECCH units and provide detailed consumption data, are used to maximize resource utilization and storage size. PV capability is estimated through a solar-based cadastre application created in a joint effort coordinated by Qatar Environment and Energy Research Institute with Mapdwell Inc. and Qatar's Ministry of Municipality. The ECCH electrical network's voltage stability, PV capacity, and real-time fault detection are all modelled using data from cutting-edge sensors, such as phasor measurement units (PMUs) and machine learning methods. A 5 kW PV system with a 20 kW Li-ion battery installed in one of the homes in ECCH is used as the reference nano grid. The potential for reverse power flow and its application are evaluated using power supply data from the PV system, battery, and main grid.

1) PV GENERATION DATA

All villa accommodations (townhouses) in the model have a rooftop photovoltaic (RPV) system with 5-kW capacity similar to the one installed in ECCH. The RPV system either uses its own power internally or sends it to the grid. Qatar has an average of 5.8 peak sun hours per month, resulting in an estimated 811 kWh of power generation. With an average electricity rate of 4.50375/kWh, a typical two-bedroom villa can save \$36.48 per month, which equates to a total savings of \$437.76 per year. The equivalences below specify how these calculations were obtained.

- Monthly power generation based on the installed RPV system and peak sun hours:

Monthly Power Generation = Installed RPV System * Peak Sun hours.

- Monthly savings for a typical 2-bedroom villa:

Monthly Savings = Monthly Power Generation * Electricity Tariff.

- Cumulative yearly savings for a typical 2-bedroom villa:

Yearly Cumulative Savings = Monthly Savings *12.

2) PV DEMAND DATA

At present, we have demand profile data solely for the 2-bedroom villa with the installed reference RPV in ECCH. This data allows us to examine the hourly demand-to-generation ratio for individual homes. Smart meters have been installed in the ECCH homes and once operational are operational, we will have access to demand data for each home. Hourly demand-to-generation ratio (to be developed once smart meters are operational) is determined as follows:

- Demand-to-Generation Ratio = Hourly Demand / Hourly Generation.

C. GIS MODEL

Three parts make up the model used in this study: an API sublayer, blockchain sub-layers, and GIS data-integrated ABM simulation environment. The primary objective of the ABM simulation experiments is to investigate trading patterns among consumer agents. A population of 623 households/agents (i.e., the number of homes in ECCH) was created for the reference energy market. Based on daily energy use, homes are classified as ''high-energy-consumption'' or ''low-energy-consumption'' to make educated guesses about energy needs [3]. Energy can be bought from peers in the neighborhood or the grid considering the best available price.

Our developed ABM Platform [3] includes power transmission, network topology, rooftop PV capacity, and hourly power demand profiles. OpenStreetMap[6] was used to model the geospatial layout of the ECCH compound [3]. Considering various home configurations and types, the model focuses on simulating energy trading among neighborhood households [3]. The proposed GIS model (Fig. 9 (a&b)) includes various kinds of agents: prosumers, consumers, and utilities. Prosumers provide electricity at a fixed price per kWh, while consumers represent household seeking to ''buy'' or ''sell'' power.

D. AGENT'S BEHAVIORAL MODEL

The development of a behavioral model to optimize peer-to-peer transactions for energy consumers and prosumers is a crucial step towards minimizing energy costs for households. By analyzing consumer behavior and integrating it with the peer-to-peer energy trading process, this model aims to ensure that households meet their energy demands while also maximizing the utilization of available resources. To achieve this goal, several constraints govern the trading process. These constraints include prioritizing the fulfillment of each household's energy demand before engaging in trading and maintaining a positive difference between energy production and consumption. Through the integration of behavioral rules in the Agent-Based Model, a comprehensive understanding of consumer behavior and decision-making processes can be achieved. This understanding will enable the optimization of energy transactions by considering factors such as energy demand, availability, and pricing.

1) DEVELOPMENT OF THE BEHAVIORAL MODEL

The behavioral model described in Algorithm 1 in the Appendix, is designed to optimize peer-to-peer transactions for energy consumers and prosumers. The primary goal is to minimize the energy cost for all households, including prosumers and consumers. The energy cost for each household is determined by the price and amount of energy obtained from the grid. The model is designed to ensure that each household meets its energy demand before engaging in trading, while also maintaining a positive difference between energy production and consumption. Additionally, the prosumer's trading energy price cannot surpass the grid energy price.

Developing agent behavioral models for energy trading involves several important steps.

- *Collecting Data:* The first step in developing an agent behavioral model for energy trading is to collect relevant data. This data includes information on energy demand and production, as well as any other factors that may influence energy trading decisions.

[6]OpenStreetMap.

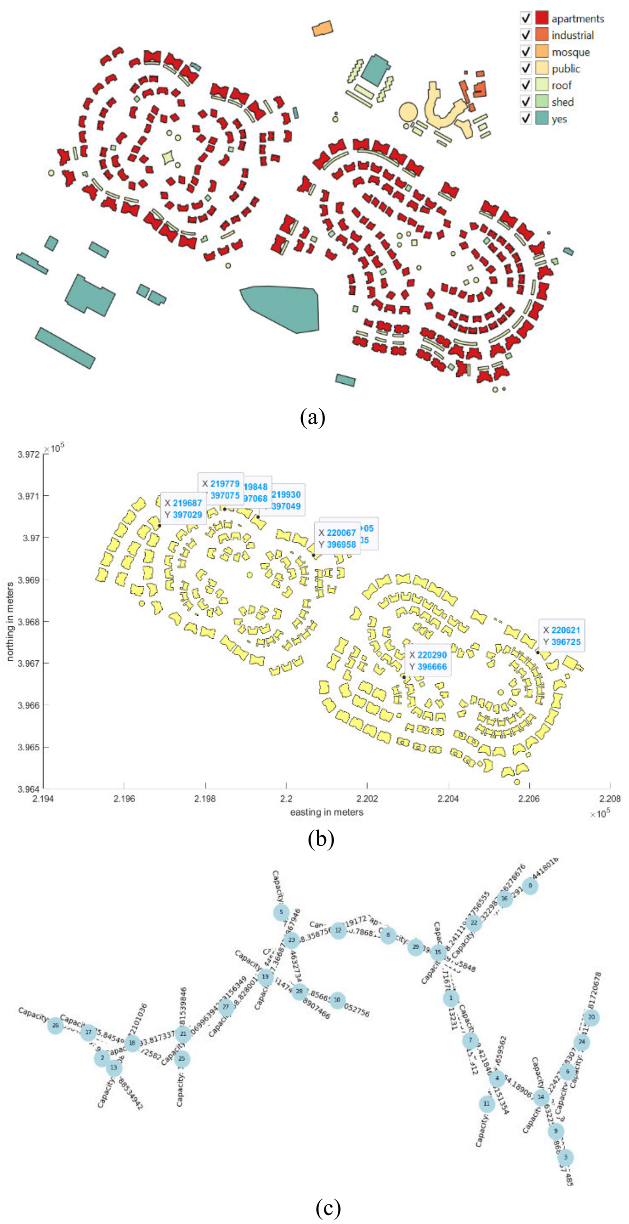


FIGURE 9. **(a) Representation of ECCH lots #1 and #2 from node shapefiles. Each building is associated with geographic coordinates as shown in (b). (c) Electrical scheme of the ECCH grid.**

- *Data Analysis:* Once the data is collected, it needs to be analyzed to identify patterns and trends. This data analysis step involves using various statistical and machine learning techniques to extract meaningful insights from the data.
- *Creating a Behavioral Model:* Based on the insights gathered from data analysis, a behavioral model needs to be developed that can simulate the decision-making process of energy consumers and prosumers during energy trading transactions. This model should consider factors such as energy demand, production, and cost, as well as any constraints or regulations that govern the trading process.
- *Model Validation*: Once developed, the behavioral model needs to be validated to ensure its accuracy and reliability. This involves comparing the model's predictions with real-world data or conducting simulations to test its performance in different scenarios.
- *Optimization and Performance Evaluation*: Once the behavioral model is validated, it can be used to optimize peer-to-peer transactions for energy consumers and prosumers to minimize energy costs for all households.

2) CONSTRAINTS OF THE TRADING PROCESS

The trading process described in Algorithm. 1 is governed by several constraints (as shown in Fig. 10):

- Each household must meet its energy demand before engaging in trading. This ensures that the households are not trading energy that is needed in situ.
- The prosumer's trading energy price cannot surpass the grid energy price. This prevents the prosumer from selling energy to other households at an unfairly high price.
- There must be a positive difference between energy production and consumption. This ensures that the prosumer's energy needs are satisfied before the prosumer engages in energy selling activities.

The energy marketplace involves different actors that work together to facilitate the exchange of energy. These actors include energy market participants, an authentication system, a trade process model, and a business management module. Energy market participants play a crucial role in the energy marketplace as they are the key actors involved in buying and selling energy. Market participants operate under known energy market identities and are authenticated using a certificate-based authentication method before they can participate in the trade process model. The authentication system plays a crucial role in ensuring the security and legitimacy of the participants [1]. By using a certificate-based authentication method, the system verifies the identities of energy market participants before they can take part in the trading process. This authentication process helps to establish trust between parties and ensures that only authorized participants can engage in energy trading.

Once the energy market participants are authenticated, they can then engage in the trade process model. This trade process model involves the decision-making of participants, who have specific interests and objectives. After a smart contract has been deployed, the Network Administrator (NA) notifies blockchain network participants of the market's availability. Customers then bid on energy services available from prosumers and owners of renewable energy sources. Consumers examine various offers from sellers before finally settling on one. Once the market is closed by the NA, the appropriate supplier is then able to provide electricity.

Smart contracts also enable the Network Administrator (NA) to automate the bidding process for energy services. The NA creates a market, and buyers and sellers can post bids and offers for energy services. With smart contracts, all transactions are transparent and auditable, and all communications are securely recorded on the blockchain. This facilitates the monitoring of bids and offers, eliminates any discrepancies between the two parties, and ensures that the right amount of energy is supplied to the customer. Additionally, smart contracts reduce the time and costs associated with the transaction, allowing the NA to close the market faster and more efficiently. The implementation of smart contracts has enabled the NA to facilitate a more efficient and secure market for energy services.

The immutable and transparent nature of blockchain technology enables the NA to easily monitor and audit all transactions. The use of smart contracts also helps reduce the time and cost associated with energy services. This, in turn, allows customers to get the energy they need faster and more efficiently. As technology continues to evolve, it is expected that smart contracts will become even more efficient and secure, enabling the NA to further improve the energy services market.

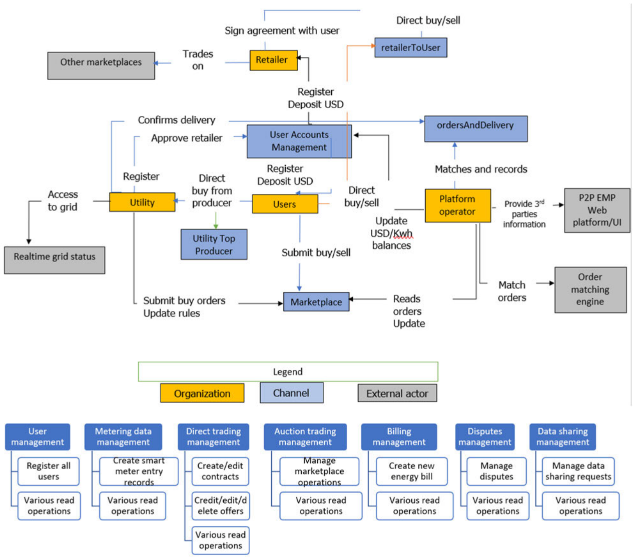


FIGURE 10. Proposed trading process and data flow among the marketplace's actors.

3) INTEGRATING THE BEHAVIORAL MODEL WITH THE ABM

The behavioral model is integrated with the ABM to allow for more efficient energy trading amongst households. By integrating the two models, it is possible to determine the optimal energy trading strategies for the of household agents in the model. Additionally, the integration of the two models allows for the simulation of more complex energy trading scenarios, such as those involving renewable energy sources.

E. FINANCIAL MODEL

1) THE MID-MARKET RATE METHOD

P2P investing prices, represented by the ATOMp2p equation below, are determined using the Mid-Market Rate (MRR) approach (Fig. 11). This approach takes into consideration the utility grid electricity purchase price and the utility grid energy sale price and calculates a value that falls in the middle, hence the term "Mid-Market Rate." This pricing approach is applied to both parties involved in the microgrid, ensuring fairness and transparency in P2P energy trading. Building on the results of the forecasted energy, the bedrock of the P2P energy trading market is an efficient auction and pricing mechanism [21].

The MRR approach takes the value in the middle between the utility grid electricity purchase price (ATOMubuy) and the utility grid energy sale price (ATOMusell). It applies to both parties in the microgrid. Based on the formula in equation (1), the MMR technique estimates that the investing energy swapping cost is the average of these two values. Within a dynamic pricing of electricity such as Time-of-Use, the daily fluctuations in supply and demand in each area determine the purchasing and selling prices. However, dynamic pricing has its limitations. In a microgrid where the load-generation balance needs to be maintained, the dynamic pricing approach can be a significant drawback. This is because when the local demand and generation are unequal, the excess electricity is sold to or drawn from the utility grid. The microgrid must therefore be able to both generate and store energy.

$$ATOMp2p = \frac{ATOMubuy + ATOMusell}{2} \tag{1}$$

2) USING THE SDR AND PRICE ELASTICITY MODEL

Before deciding on a set price for energy, the Price Elasticity and Supply Demand Ratio (SDR) technique consider three fundamental economic principles [10]:

a. Internal pricing should be capped between rewards rates for prosumers (net metering or net/gross billing) and power costs from the utility grid.
b. A fundamental premise of economics is that the price and the SDR are inversely related.
c. For microgrid energy sharing, there must always be a monetary equilibrium.

In microgrids, consumers buy power when it is less expensive from local prosumers than from the grid, while prosumers with a surplus may profitably offload their excess power. So, the P2P selling price should be somewhere in the middle between the purchasing and selling prices on the grid. Everyone stands to gain from P2P pricing systems. The actual cost of power is calculated by comparing local production to total demand.

The SDR is defined in terms of the net load and production profiles of prosumers and the microgrid [21].

Net Load Profile of the Prosumers,

$$NhL, p = \sum Pp = 1\,(lhp{-}ghp)\,,\ when\ NhL, p > 0$$
$$When\ NhL, p > 0 = 0,\ when\ NhL, p \leqslant 0 \tag{2}$$

Net Load Profile of the Microgrid,

$$NhL = \sum Mm = 1lhm + NhL, p \tag{3}$$

Moreover, at the hth hour, the microgrid's net generation profile is provided by:

Net Production Profile of the Prosumers,

$$Nhg,p = \sum Pp = 1\,(ghp{-}lhp)\,,$$
$$when\ Nhg,p > 0 = 0,$$
$$when\ Nhg,p \leqslant 0 \tag{4}$$

Net Production Profile of the Microgrid,

$$NhG = \sum Rr = 1ghr + Nhg,p \tag{5}$$

The net load profile, Nh L, and the net production profile, Nh G, at the h^{th} hour can be used to characterize the relationship between stock and request in a community microgrid. This leads to the following formulation for the microgrid's SDR at instant 'h':

$$SDRh = \frac{NhG}{NhL} \tag{6}$$

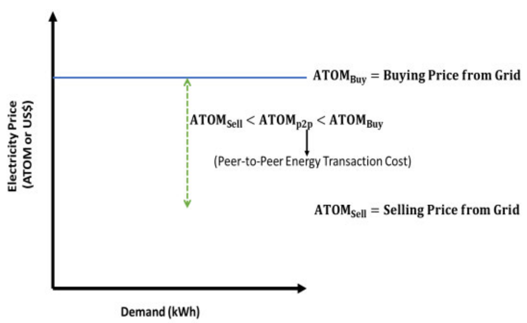


FIGURE 11. Pricing of energy in intra-day trading between peers. (adapted from [20]).

3) MOTIVE-BASED PRICING MODELS FOR PRICE-SENSITIVE LOADS

Modelling the effect of P2P price fluctuations on load is another objective of this study. The price-sensitive load responds to any price changes. Here, we will try to estimate how much of a drop in load occurs when prices on the peer-to-peer market rise sharply at peak times. Consumers and prosumers will respond to cost hikes by reducing their usage.

The concept of elasticity describes one's responsiveness or sensitivity to changes in another variable. Since there are numerous consumer loads in a microgrid, the elasticity factor measures how sensitive consumers are to changes in price. The elasticity factor (EF) is calculated as in (7),

$$EF = \frac{\frac{\Delta d}{d0}}{\frac{\Delta d}{p0}} \tag{7}$$

Only by switching on and off specific loads can prices be adjusted. Self-elasticity (εxx) is defined as a positive number when changes in load occur at the same time as changes in price, as in (8),

$$\varepsilon xx = \frac{\frac{\Delta dx}{dx}}{\frac{\Delta px}{px}} \tag{8}$$

Power consumption at the x-th period (represented by dox) is believed to have been adjusted to dx due to fluctuating electricity rates. This causes the shift in demand to be determined by equation (9),

$$\Delta dx = dxdox \tag{9}$$

Assume that in the x^{th} period, clients are offered an incentive of "I" US$/kWh to cut their usage. As a result, customers will be more likely to take part in incentive-based demand response programs as in (10).

$$I * (\Delta dx) = Ix * (dx - dox) \tag{10}$$

The equation below determines the adjusted selling and purchasing prices for peer-to-peer transactions at the busiest times.

$$SDRhm = N^hG, m/N^hL, m \tag{11}$$

4) DYNAMIC PRICING

The introduction of dynamic pricing in the electricity grid has been a major game changer in the energy industry. It has allowed for greater flexibility in the pricing of electricity, allowing for a more efficient and cost-effective system. This is especially true in the case of peer-to-peer (P2P) energy trading, where prosumers can "buy" and "sell" energy to each other. Typically, electricity prices are higher during periods of peak consumption, and lower when there is an excess of energy either due to lower consumption or/and higher electricity production [12].

5) NONDYNAMIC PRICING

Nondynamic pricing is a pricing model used in power grids to facilitate energy exchange between consumers and suppliers. In this model, the retail price of the grid and the feed-in price remain fixed regardless of the amount of energy exchanged in real-time. This makes it easier to compare experiments and evaluate data [12]. In our experiment, we used the utility grid's price information as input and employed the trading strategy described in Algorithm 1 to generate prices and conduct trading.

IV. CASE STUDY: RESULTS AND DISCUSSION

For ease of exposition, results are reported in three parts. The first part looks at the decentralized marketplace demonstrator, the second part examines the error metrics for all datasets described in section III, and the third part presents the results of the statistical tests. These tests measure the significance of the results, and provide an indication of the reliability of the model. The training strategy and algorithm were implemented in Python 3.7.3 and run on an Intel(R) Core (TM) i7-8565U CPU @ 1.80GHz 1.99 GHz computer with 16 GB RAM. We employed residential use data from real solar energy prosumers to validate the efficacy of the strategy presented in Fig. 12. Each prosumer agent in the model was equipped with a rooftop PV system integrating an energy storage device, and the model was composed of

TABLE 2. Units/symbols for the financial model.

Symbol	Quantity
$ATOMp2p$	P2P investing prices
$ATOMubuy$	Utility grid electricity purchase price
$ATOMusell$	Utility grid energy sale price
$Nh\ L,p$	Net load profile of the prosumer at h^th hour
$Nh\ L$	Net load profile of the microgrid
$Nh\ g,p$	Net generation profile of the prosumer
$Nh\ G$	Net generation profile of the microgrid
g	grid
p	prosumer
P	Prosumers
G	Microgrids
	moment
$\frac{\Delta dx}{dx}$	Change in load
$\frac{\Delta px}{px}$	Change in price
εxx	Elasticity factor
Δpx	Supply Demand Ratio

623 residential consumer agents. The Power System Network for Education City Community Housing Compounds (ECCH) served as a testbed to evaluate the potential of the proposed strategy and its impact on the power grid.

A. PROPOSED FRAMEWORK/DESIGN

The proposed model is based on a decentralized web platform that allows energy producers and consumers to transact energy directly, without a mediator. The platform is powered by blockchain and smart contract technology. The model takes advantage of Internet of Things (IoT) and Internet of Energy (IoE) technology. IoT allows energy producers and consumers to communicate and exchange data, and IoE enables them to trade energy in a secure and efficient manner.

The proposed model using blockchain, smart contract and web.3py[7] is reported in Fig. 12. The model is composed of three parts: the front-end, middleware and back-end. The front-end is a web page that provides information about the project (shown in Fig. 13 (d)); it uses HTML5 to display different kinds of data on the screen. The middleware is an integrated system that allows users to interact with each other in an open market; it uses Python 3 as its programming language. The back end is a database that stores all kinds of information about users, products, and transactions; it uses MySQL as its database management system (DBMS). The front-end application reported in Fig. 13 (d) includes user registration, participant approval or rejection, optimum power flow (OPF) simulation to set system limits, transaction request broadcasting to the P2P network, and consensus method validation. HF simulator[8] are used to compile and deploy smart contracts [11].

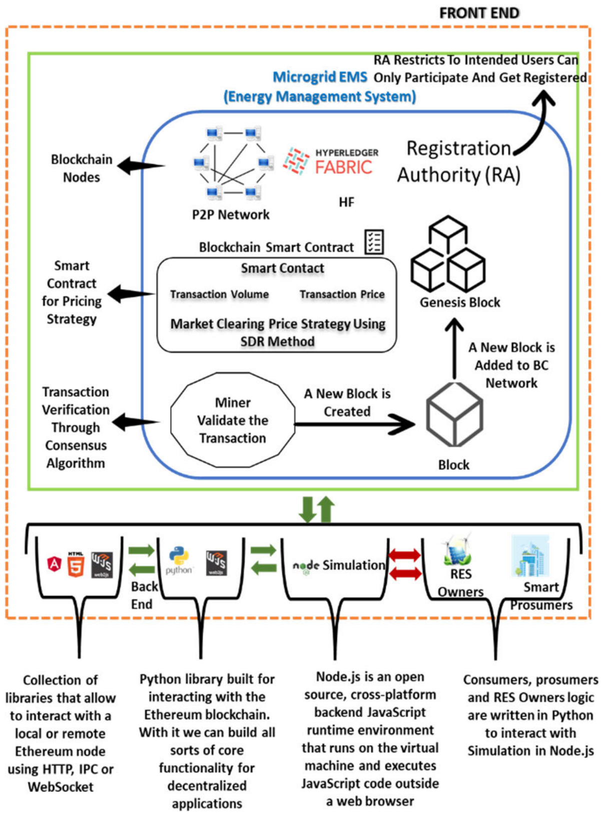


FIGURE 12. Simplified architecture of the proposed decentralized marketplace blockchain-enabled platform.

1) PEER TO PEER DEVELOPED BLOCKCHAIN-BASED DEMONSTRATOR/APP

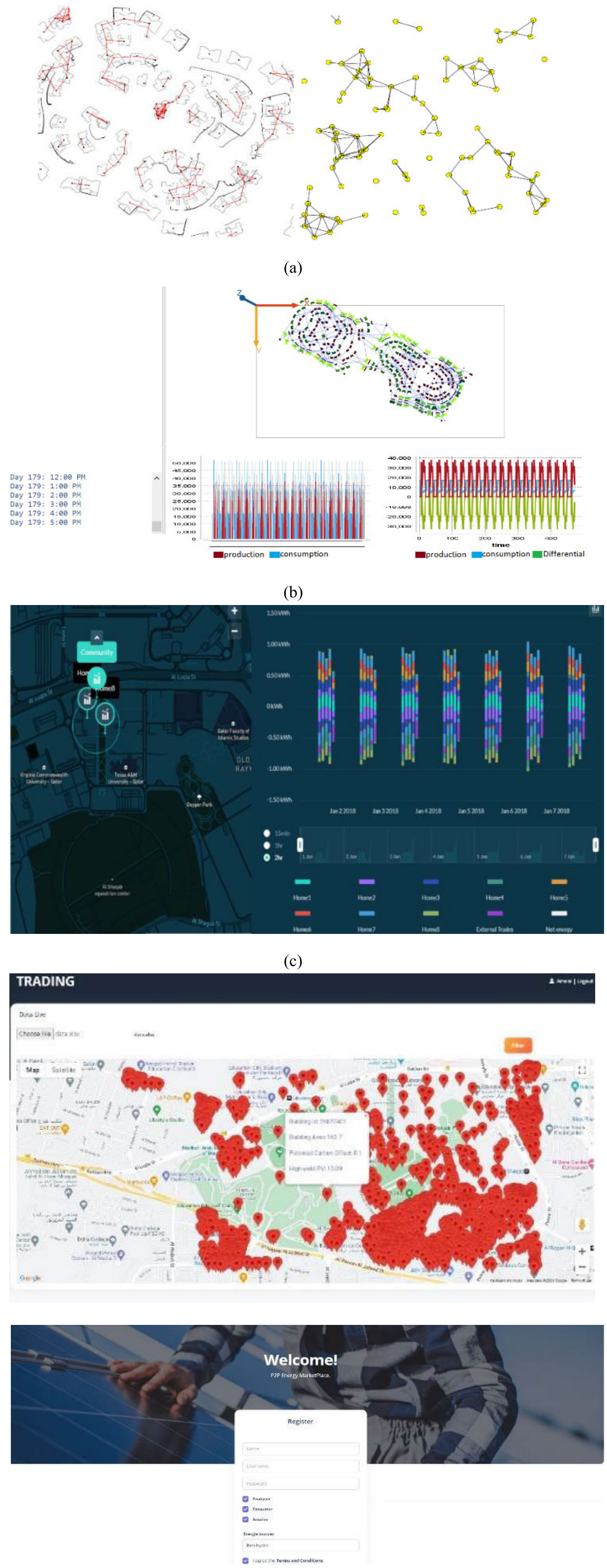
The trading platform, available as web application, showcases a simulation of the trading behavior of 623 potential transacting households in ECCH lots #1 and #2 (Fig. 13). Leveraging the Hyperledger Fabric blockchain, the platform tokenizes energy into assets, facilitating energy asset trade between prosumers and consumers. In addition to reducing transaction costs through peer-to-peer trade and automated contracts, the platform also ensures the involvement of utilities as grid infrastructure providers, energy sellers, and buyers. With its analysis, prediction, and optimization capabilities, the platform addresses the present and future energy market needs.

Controlled by a single organization (KAHRAMAA[9] in Qatar), the private blockchain allows consumers to purchase energy locally generated by peers or from the main grid. Smart meters provide local demand and supply data, and trade information is relayed to the utility company for billing reconciliation. This approach fosters an equitable energy trading framework for all participants, including utilities, prosumers, and consumers. The ensuing environment enables the following P2P energy trading functions: (1) verification of trading

[7] web.3py is a Python library for interacting with Ethereum, see https://web3py.readthedocs.io

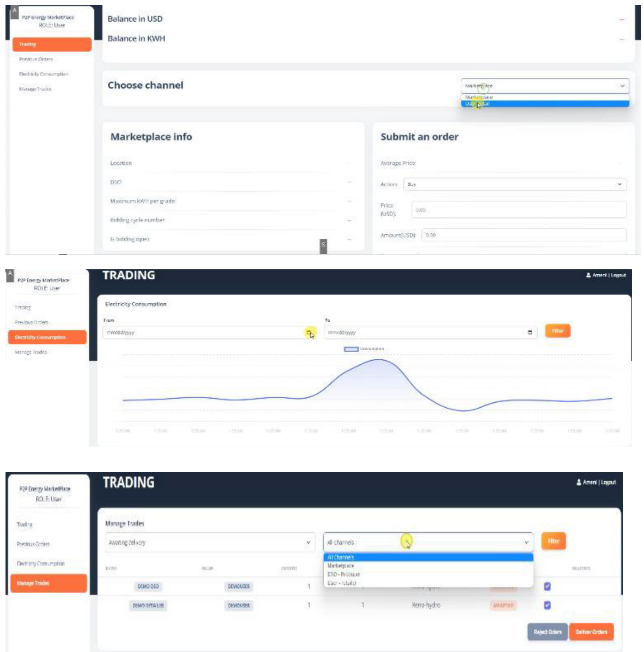
[8] https://trufflesuite.com/ganache

[9] Qatar General Electricity & Water Corporation: the local utility company in Qatar.



(a) (b) (c)

FIGURE 13. (a) Developed GIS Model: representation of ECCH lots #1 and #2 from node shapefiles. Each building is associated with GIS coordinates, (b) Virtual Trading ABM developed platform, (c) GIS-ABM Energy Marketplace front-end application.



(d)

FIGURE 13. *(Continued.)* (d) Web-based front-end Marketplace APP.

between different stakeholders; (2) traceability of prosumer energy, increasing transparency, and (3) information about price credit and energy cost, which provide demand response and energy management incentives. The developed platform incorporates a blockchain system with a social simulation platform for energy exchange, which will shortly be enhanced with a carbon trading component.

The experimental setup involves the use of trading agents, represented by yellow circles in Fig. 13 (a), which simulate the actions of "buyers" and "sellers" in the electricity market by making "offers" and "bids" for electricity. These trading agents play a pivotal role in the simulations as they enable the representation of real-world market dynamics. The power flow between the trading agents is depicted by the connecting lines in Fig. 13 (b). The power flow in ECCH simulations illustrates the exchange of electricity between market participants. This power flow information is crucial in understanding how electricity is being distributed and utilized within the market. By analyzing the power flow in ECCH simulations, market participants can gain insights into the efficiency and effectiveness of electricity distribution. Furthermore, the power flow information can also highlight any imbalances or bottlenecks within the electricity market.

The platform user interface shown in Fig. 13 (c&d) integrates a GIS component based on real-world data to enable precise modeling of medium-to large-scale trading markets. This allows for the efficient evaluation of energy prices, geographical proximity, and other market factors that influence PV trading. The platform is also designed to ensure the security of the energy trading process. It uses blockchain technology to store all data related to energy transactions in an immutable and secure ledger. This ledger is maintained by a decentralized network of computers, making it virtually impossible for malicious actors to tamper with the data.

Furthermore, the platform also uses smart contracts to provide transparency and trust in the trading process. It incorporates power transmission, network topology, rooftop PV capacity, and hourly power demand profiles across multiple layers. OpenStreetMap[10] was used to supply geographic information, deriving the layout of the for the ECCH compound from shapefiles.

2) ANALYZING MARKETPLACE DYNAMICS: A BLOCKCHAIN PERSPECTIVES

In the context of decentralized trading systems, analyzing hourly demand and generation capacity is crucial for effective market operations. Accurately modeling and forecasting electricity demand is a very important task to support decision-making in deregulated electricity markets. For the efficient management of day-to-day operations of a power system, short-term forecasts are very important. Short-term forecasts allow market participants to effectively plan and allocate their resources to meet the anticipated demand. By utilizing historical demand recordings and other relevant data, load forecasting provides valuable insights into energy consumption patterns. This information plays a key role in the development of modern electricity networks and ensures the reliable supply of electricity to consumers.

The Hyperledger Fabric (HF) was used to model a microgrid consisting of 10 individual customer profiles reported in Fig. 14. The energy consumption and surplus of prosumers were tallied using data from ECCH lot#2 houses. The network was chosen because it is representative of the larger community of 623 homes. The 10 households were chosen based on their geographic location, demographic information, and energy usage patterns. The 10 households in the network were monitored for one year. Data was collected on energy consumption, building characteristics, and occupant behavior. This data was used to generate a forecasting model for energy consumption in the larger community of 623 homes. Accounts with excess energy made "bids", while those with energy deficit made "requests". The dynamic grid price was used to derive the fixed marketing clearing price using the SDR method (grid selling and buying prices, as in equation. (6)).

The central grid satisfies unaccepted bids at the government-mandated price. After 48 hours, the simulation data was exported to a CSV file and plotted. Each simulation day is divided into three 8-hour periods, during which offers are collected and utilized based on their ranking, starting with the lowest offer (as described in Algorithm 1). The cycles of the simulations, each lasting approximately 15 minutes, analyze the errors between demand and supply. This helps to identify any discrepancies that may exist between the two. Based on the findings, adjustments to the offers can be made to ensure that the most cost-effective and reliable options are used. The graphs presented in Fig. 15 demonstrate the average intensity of traders' behaviors over time. Based on this information, the market agent calculates the market clearing price and determines which bids are accepted and rejected.

The hourly demand, the hourly demand served, and the available generating capacity are shown graphically in Fig. 16. The agent's status as "buying," "selling," or "energy-shared" is updated by the green curves that show the difference between production and consumption. In this specific model, all heaps are fulfilled, bringing about an ideal match among request and supply. The market is effectively stabilized because of the introduction of the "Pay-as-Bid" mechanism, which significantly reduces price volatility. Each energy generating residence tries to sell the most excess energy at the highest price for a given hour. The purchase price rises as buyer households compete. Energy demand is first satisfied by self-generation, wherein prosumers use the energy they produce at the lowest cost—the cost of solar energy. To prevent customers from buying their energy straight from the market, households generating excess energy may sell on the market at a price that is somewhat higher than the cost of solar energy but still below the market price. Prosumers may store surplus energy stored in lithium-ion batteries to take advantage of the 10% variable demand which the model anticipates.

The proposed model utilizes GIS data to determine the geographical distribution of trading activities, while the multi-level characterization allows for the inclusion of a variety of factors that influence the market. These factors can include economic, political, and social variables that are used to identify the potential impacts of market changes. By incorporating GIS data and multi-level characterization, the proposed model is able to accurately depict the current state of the market and predict how it will evolve over time. Fig. 17 shows returns from energy sales at different times under dynamic and nondynamic pricing conditions for the ten prosumers profiles described in Fig. 14 (assuming no energy storage equipment).

We analyze the spending and revenue of prosumers in both Peer To Grid (P2G) and Peer To Peer (P2P) trading situations. As there is a shortage of energy storage and limited production ability, a significant surplus of energy generated during the day is typically sold to the grid at a discounted rate. From 7:00 PM to 7:00 AM, all power is purchased from the grid, as expected. P2P energy trading takes place between 8:00–18:00. During times of weak sunlight, selling prices are higher due to lower solar energy production, and the purchased energy is sourced from the prosumers and the grid. Conversely, when the sun is strong, purchasers have an advantage over sellers, and the prosumers sell energy to both the buyers and the grid.

3) QUANTITAVE ASSESSMENT OF THE BLOCKCHAIN

The analysis presented in this section aims to model the number of energy transactions and associated costs within the developed blockchain framework, and to explore cost savings that the proposed solution offers. Data for the modelling of

[10]https://www.openstreetmap.org

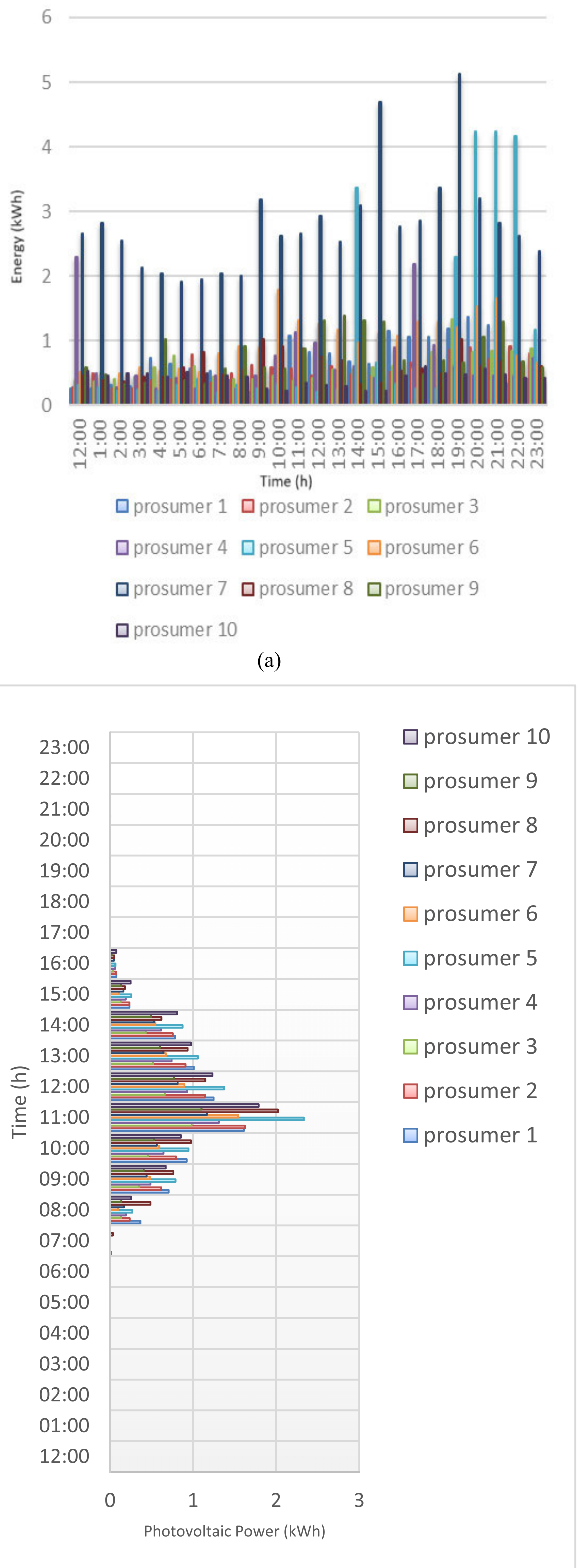


FIGURE 14. (a) Initial demands of prosumers, (b) Predicted PV Energy.

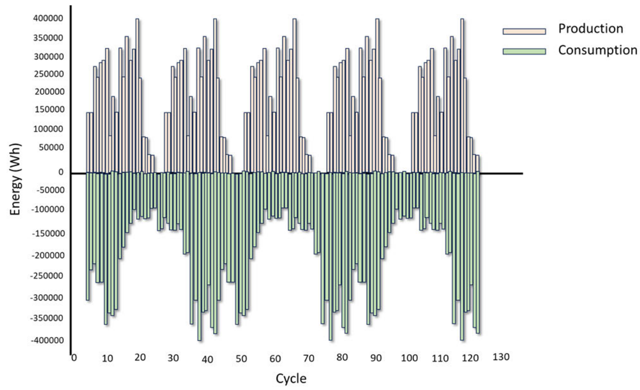


FIGURE 15. Average intensity of traders' behaviours over time: Average Intensity = (1/Number of Cycles) * Sum (Discrepancies).

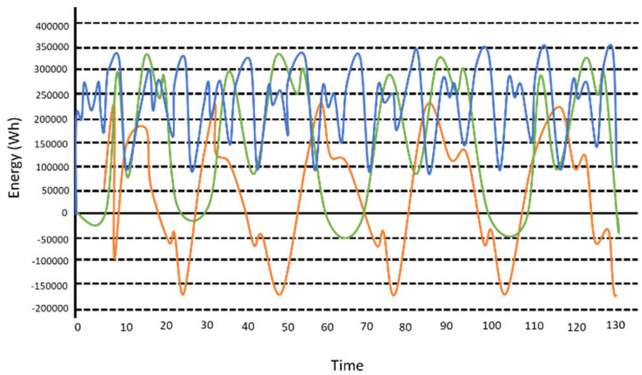


FIGURE 16. Energy simulation results: Hourly demand is represented in blue, available generation capacity in orange, and the difference in green.

FIGURE 17. A comparison of profits and expenses between sellers and buyers in the Peer-to-Grid (P2G) and Peer-to-Peer (P2P) scenarios. In this case study, the prosumers are composed of the ten prosumers profiles reported in Fig. 14 (assuming that the prosumers do not have energy storage equipment).

the transaction cost was sourced from the ECCH households. To calculate the number of transactions, the energy balance between prosumers and consumers must first be determined. When the purchased energy is higher than the sold energy demand is higher than supply.

To calculate the number of transactions, the energy balance between prosumers and consumers needs to be determined. This balance is determined by comparing the amount of energy purchased by the prosumer and the amount of energy sold by the consumer. If the purchased energy is higher than the sold energy, then the demand is higher than the supply. In this case, energy demand must be ranked and matched with energy supply in ascending order to yield the maximum number of transactions. This means that the highest energy demand will be matched with the highest energy supply until all the energy is used up. This will give the maximum number of transactions. On the other hand, if the demand is lower than the supply, then the energy supply must be ranked and matched with the energy demand in descending order to yield the minimum number of transactions. This means that the lowest energy demand will be matched with the lowest energy supply until all the energy is used up. This will give the minimum number of transactions. The minimum and maximum number of transactions (No. TRX) over the simulated period can be determined using Eq. 12 and Eq. 13, respectively, where R_t represents the possible number of transactions, t represents time slots in a day, and i represent number of day (in our simulation i =179 days).

$$minNb.TRX = \Sigma i = 1 : 179 minR \tag{12}$$

$$maxNb.TRX = \Sigma i = 1 : 179 maxR \tag{13}$$

The probability that a given cell in the agent-based model geospatial layout will have a higher or lower number of households is determined by the population density ($\wp$), which is a crucial model parameter. Households that actively participate as energy sellers in the examined use case scenarios are designated as "prosumers". Other important parameters that impact peer-to-peer energy trading include the number of transactions, consumers, and prosumers.

The results reported in Fig. 18 indicate that the number of transactions rises in tandem with population density ($\wp$). The number of transactions tends to be higher in larger "buyer/seller" networks. On the other hand, when looking at the proportion of verified transactions, smaller networks have a higher proportion. The longer transaction-validation time found in larger networks is the cause of this phenomenon.

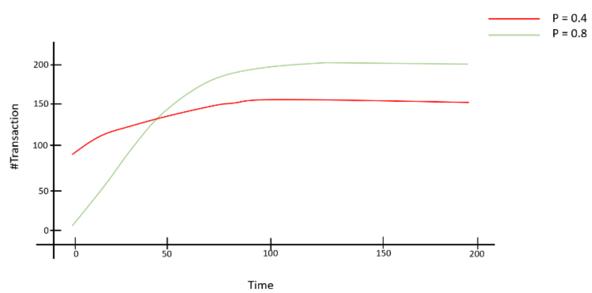


FIGURE 18. Impact of population density f ($\wp$) on the number of transactions No. TRX.

Fig. 19 shows the verification process in greater detail over 500 seconds, with system updates occurring every 10 seconds. According to the graph, scenarios with a lower population density ($\wp = 0.4$) have more verified transactions than those with a higher population density ($\wp = 0.8$). These results emphasize the dynamic nature of population density's influence on electricity transactions, flows, and market participation.

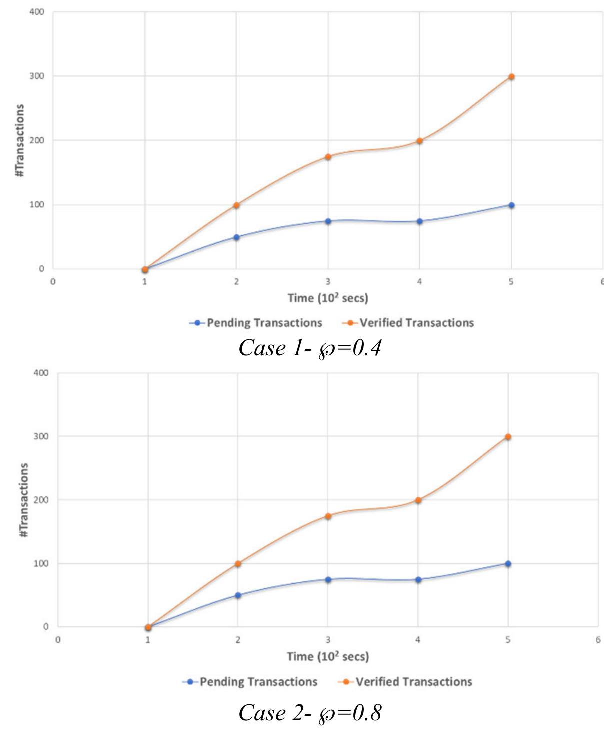


FIGURE 19. Verification process during a period (Fig. 9): Number of Verified Transactions = f ($\wp$, Time).

We ran a simulation of an energy blockchain network with 623 peers and 50 blockchain miners. The results, displayed in Fig. 20, validate that the network's size grows in correlation with the increase in both the number and density of peers, or households.

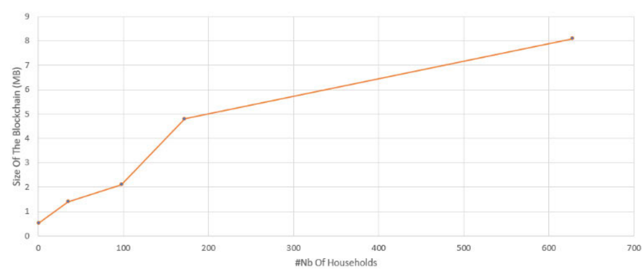


FIGURE 20. Impact of population density on the blockchain size (Fig. 10): Blockchain Size = f ($\wp$).

4) MULTI CRITERIA ANALYSIS OF MARKETPLACE DYNAMICS

The objective of multi-criteria analysis of marketplace dynamics is to provide a comprehensive overview of the forces driving competition in a given market. This type of analysis is important for businesses to understand the competitive landscape and identify areas of potential growth. It can be used to make strategic decisions and develop competitive strategies. The ECCH lot#1 lot#2 compounds' residents are referred to in the model as agents H_i, where $11 < i < 0$, and the model's objective is to evaluate household-level PV trading under different regulatory and financial scenarios based on market energy prices, local standards, and grid conditions. According to the present study, the cost price of PV in the electricity sector now in Qatar significantly promotes residential PV trading. This trading may be further facilitated by taking into account the homes' geolocation in "bid/ask" transactions. Consumers first use the energy they produce. If their output exceeds their requirements, they will try to sell the extra energy to other prosumers first by offering a lower price than the retail price (E("sell")) and send remaining energy to the grid to be rewarded according to the local regulatory framework, e.g. net metering, or net/gross billing. Prosumers will use all the energy they create if they cannot meet their demands, then they will try to purchase more from nearby prosumers, and final purchase from the grid to satisfy their remaining demand.

TABLE 3. Energy trading in neighborhoods: Input parameters for the j scenarios (0<j<6).

Symbol	S1	S2	S3
Electricity price (¢/kWh)	4.65	4.65	4.65
PV price (¢/kWh)	2.94	2.94	2.94
Carbon tax	0	0	0
Subsidy reduction	-	-	-
PV potential (kW)	10	20	10
Storage (kW)	0	0	15

- S1: Baseline scenario considered as the reference point of the simulation framework, fit with a 2.94 ¢/kWh of solar energy, a 10-kW rooftop PV installation and where we remove the storage component.
- S2: Fit with a 10-kW rooftop PV system and 2.98 PV pricing.
- S3: Scenario 2 + 15 kWh lithium-ion battery for energy storage.

- S1: Baseline scenario considered as the reference point of the simulation framework, fit with a 2.94 ¢/kWh of solar energy, a 10-kW rooftop PV installation and where we remove the storage component.
- S2: Fit with a 10-kW rooftop PV system and 2.98 PV pricing.
- S3: Scenario 2 + 15 kWh lithium-ion battery for energy storage.

We describe the results of the market simulations for three distinct scenarios (Table. 3), with the "business as usual" scenario (S_1) acting as the reference point for the baseline against which the other scenarios are measured. In the second scenario, S_2, no energy was sold to the grid, but the amount sold to other prosumers surpassed the amount sold under the first baseline scenario, S1. This points to the significance of adding batteries in market models to store surplus energy for potential future sales. The use of batteries in energy market models allows prosumers to store their excess energy for future sales. This has the potential to increase the value of energy sold to other prosumers, as it provides them with an additional source of clean, renewable energy. Furthermore, it can also help to reduce the strain on the electricity grid, as prosumers can use their stored energy when demand on the grid is high.

As reported in Fig. 21, the capacity of the PV system was raised to 10 kW for scenario S_3, which increased the amount of energy that could be traded. As the PV potential was enhanced, more home demand was met, resulting in more energy being sold to the grid than in S_1 and S_2 and less energy being bought from the grid, respectively. Battery storage made even more energy accessible for trade-in S_3, which led to increased energy sold to prosumers and the grid. Because of purchasing more energy from other prosumers, there was an increase in revenue from trading. Compared to S_3, the amount of energy available to be traded did not rise in S_2, but the utility's increased price per unit of energy resulted in increased revenues from trading.

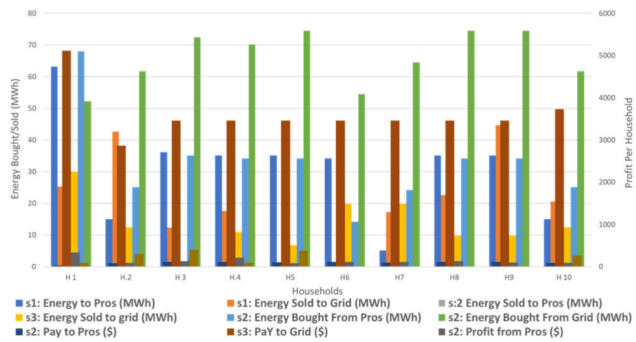


FIGURE 21. Energy "Bought" and "Sold" per Household Hi (0<i<9), Profit per Household Hi (0<i<9) for 3 scenarios Sj (1<j<4).

V. CONCLUSION

The study paper presents an experimental energy trading ABM model that is based on a real-world data that include geographic vector data from an integrated GIS component. The model provides a testing and validation environment for an energy blockchain application operating in the ECCH local power system in Doha, Qatar, which includes 623 household units. The model's simulation results show that the ABM model enriched with the GIS component provides a realistic characterization of market processes and evolution for medium to large energy trading frameworks. It offers a decision-making platform that helps stakeholders observe a transactive energy blockchain in action to plan the design of decentralized energy trading systems and test their outcomes.

This work champions *Community Solar* energy ecosystems that integrate a transactive energy blockchain to foster a culture of smart, secure, and sustainable exchange of distributed solar energy in Qatar. By fostering the trade of distributed solar energy in Qatar, the project contributes to

Algorithm 1 Decision-Making Process of Energy Consumers and Prosumers During Energy Trading Transactions Algorithm

Require: for each entry {1, ..., n} of settlement period (i.e. 5 mins and 30 mins) do
Read ENERGY-IN and ENERGY-OUT for all 623 ECCH households in that settlement period For each time slot
for each time slot do
Determine the energy demand and supply by comparing ENERGY-In and ENERGY-OUT
if Total Energy demand $\geq$ Total Energy Supply
MaxOrder$\Leftarrow$Ranking$-$Smallest$-$To$-$Largest(Energy Demand) MinOrder$\Leftarrow$Ranking$-$Largest$-$To$-$Smallest (Energy Demand)
Initial r to 1
end if
end for
for all energy demand at each time slot do
if cumulated MaxOrder[1:r] $\geq$ Total Energy Supply then minR=r; rt=t;
break; end if

- Reducing the nation's dependence on hydrocarbons to produce energy with ensuing savings of natural resources, decrease of the national carbon footprint, and air quality improvements.
- Curtailing power grid infrastructure investments by supporting demand response measures that reduce electricity consumption at peak times without lowering customer satisfaction.
- Increasing the security of the national power system by promoting system modularity to support resiliency in power outage emergencies.
- Fostering the integration of energy storage technologies to enable demand response and grid-to-vehicle and vehicle-to-grid technologies.

In its final form, the full virtual implementation of the ECCH BCS ecosystem will enable the testing and validation of the energy blockchain application in its intended context of application. The extensions planned to achieve the final version of the energy blockchain simulation platform include the integration of emulated version of the 623 ECCH household units as nano-grids with real-time averages of electricity consumption data from smart meters, and estimations of the available PV energy for trade. These estimations will use as reference a PV system capacity of about 10 kW per household, based on a sizing estimate obtained with the PV rooftop estimation platform shown in Fig. 6, and PV production forecasts for the 10 kW PV systems obtained through the PV productivity estimation platform such as PV syst (https://www.pvsyst.com/) with grounds solar radiation measurements for Education City.

Once the energy blockchain platform is fully tested in its emulation environment, it will be opened to ECCH households through a subscription campaign aimed to achieve maximum household enrollment and realistic engagement through a reward system to promote true to life trading behavior. Any needed additional adjustments to the energy blockchain platform will be made to ensure correct application in its real-world ECCH context. The participation of real household users will provide the ultimate test of the energy blockchain platform before its implementation with actual PV systems and a digital currency.

APPENDIX

See Algorithm 1.

ACKNOWLEDGMENT

Some of the material discussed in this paper is the result of work previously described in [1] and [7]. Permission to reuse material in these papers has already been obtained.

REFERENCES

[1] A. Boumaiza and A. Sanfilippo, "Peer to peer solar energy trading demonstrator blockchain-enabled," in *Proc. 11th Int. Conf. Smart Grid (icSmartGrid)*, Paris, France, Jun. 2023, pp. 1–7, doi: 10.1109/icSmartGrid58556.2023.10171013.

[2] Z. Ren, W. Wang, B. Chen, X. Li, Y. Zhang, Y. Hu, and H. Li, "A power trading mode based on blockchain for prosumers," vol. 237, R. F. C. Weerasinghe, Ed. Zhangjiajie, China: EDP Sciences, 2021.

[3] A. Boumaiza and A. Sanfilippo, "Blockchain-based electricity marketplace," in *Proc. 3rd Int. Conf. Electr., Comput., Commun. Mechatronics Eng. (ICECCME)*, Canary Islands, Spain, Jul. 2023, pp. 1–5, doi: 10.1109/iceccme57830.2023.10252228.

[4] R. Thakur, A. Angriawan, and J. H. Summey, "Technological opinion leadership: The role of personal innovativeness, gadget love, and technological innovativeness," *J. Bus. Res.*, vol. 69, no. 8, pp. 2764–2773, Aug. 2016, doi: 10.1016/j.jbusres.2015.11.012.

[5] A. M. Alizadeh, Z. Heydari, M. Rahimi, B. Bazgir, H. Shirvani, S. Alipour, Y. Heidarian, S. Khalighfard, and A. Isanejad, "Oxytocin mediates the beneficial effects of the exercise training on breast cancer," *Experim. Physiol.*, vol. 103, no. 2, pp. 222–235, Feb. 2018, doi: 10.1113/ep086463.

[6] F. S. Ali, O. Bouachir, O. Ozkasap, and M. Aloqaily, "SynergyChain: Blockchain-assisted adaptive cyber-physical P2P energy trading," *IEEE Trans. Ind. Informat.*, vol. 17, no. 8, pp. 5769–5778, Aug. 2021.

[7] R. R. Shrivastwa, A. Hably, K. Melizi, and S. Bacha, "Understanding microgrids and their future trends," in *Proc. IEEE Int. Conf. Ind. Technol. (ICIT)*, Melbourne, VIC, Australia, Feb. 2019, pp. 1723–1728, doi: 10.1109/ICIT.2019.8754952.

[8] L. Xue, Y. Teng, Z. Zhang, J. Li, K. Wang, and Q. Huang, "Blockchain technology for electricity market in microgrid," in *Proc. 2nd Int. Conf. Power Renew. Energy (ICPRE)*, Chengdu, China, Sep. 2017, pp. 704–708, doi: 10.1109/ICPRE.2017.8390625.

[9] P. Tasatanattakool and C. Techapanupreeda, "Blockchain: Challenges and applications," in *Proc. Int. Conf. Inf. Netw. (ICOIN)*, Chiang Mai, Thailand, Jan. 2018, pp. 473–475, doi: 10.1109/ICOIN.2018.8343163.

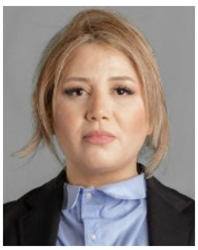
[10] N. A. Heriyanti, G. P. Cesna, N. A. Santoso, and Y. P. A. Sanjaya, "Blockchain technology evolution trends bibliometrics analysis on scopus database using VOSviewer," in *Proc. IEEE Creative Commun. Innov. Technol. (ICCIT)*, Tangerang, Indonesia, Nov. 2022, pp. 1–6, doi: 10.1109/ICCIT55355.2022.10118963.

[11] Q. Wang and M. Su, "Integrating blockchain technology into the energy sector—From theory of blockchain to research and application of energy blockchain," *Comput. Sci. Rev.*, vol. 37, Aug. 2020, Art. no. 100275, doi: 10.1016/j.cosrev.2020.100275.

[12] P. K. Karthik and R. Anand, "Energy trading in microgrids using BlockChain technology," in *Proc. 4th Int. Conf. Intell. Comput. Control Syst. (ICICCS)*, Madurai, India, May 2020, pp. 884–888, doi: 10.1109/ICICCS48265.2020.9121050.

[13] A. Poullikkas, "A comparative assessment of net metering and feed in tariff schemes for residential PV systems," *Sustain. Energy Technol. Assessments*, vol. 3, pp. 1–8, Sep. 2013, doi: 10.1016/j.seta.2013.04.001.

[14] S. M. S. Hussain, S. M. Farooq, and T. S. Ustun, ''Implementation of blockchain technology for energy trading with smart meters,'' in *Proc. Innov. Power Adv. Comput. Technol. (i-PACT)*, vol. 1, Vellore, India, Mar. 2019, pp. 1–5, doi: 10.1109/i-PACT44901.2019.8960243.
[15] A. Swain, K. P. Swain, S. R. Samal, S. K. Pattnaik, A. Mishra, J. K. Das, G. Palai, and S. Bandopadhaya, ''Blockchain powered energy monitoring system,'' in *Proc. 19th OITS Int. Conf. Inf. Technol. (OCIT)*, Bhubaneswar, India, Dec. 2021, pp. 144–148, doi: 10.1109/OCIT53463.2021.00038.
[16] J. McLaren, ''Community shared solar: Policy and regulatory considerations,'' in *Proc. Sol. Conf.*, vol. 1, Jan. 2014, pp. 996–1001.
[17] K. Brehm, T. K. Blank, and L. Mosier, ''Progress and potential for community-scale solar,'' in *How Rural Electric Cooperatives Can Use Low-Cost, Distributed Energy to Save Money, Serve Customers, and Unlock Billions in Infrastructure Spending*, 2018. [Online]. Available: https://rmi.org/wp-content/ uploads/2018/04/Progress-and-Potential-for-Commu nity-Scale-Solar.pdf
[18] RMI. (2016). *Community-Scale Solar*. Insight Brief. [Online]. Available: https://rmi.org/wp-content/uploads/2017/03/Shine-Report-CommunityScaleSolarMarketPotential-2016.pdf
[19] H. Guo, Y. Su, Y. Li, C. Zhao, Y. Wang, and H. Tian, ''Research on blockchain technology based energy trading architecture model,'' in *Proc. 7th Int. Conf. Electron. Technol. Inf. Sci. (ICETIS)*, Harbin, China, Jan. 2022, pp. 1–5.
[20] T. Chitra, M. Quaintance, S. Haber, and W. Martino, ''Agent-based simulations of blockchain protocols illustrated via Kadena's chainweb,'' in *Proc. IEEE Eur. Symp. Secur. Privacy Workshops (EuroS&PW)*, Jun. 2019, pp. 386–395.
[21] J. Dong, C. Song, S. Liu, H. Yin, H. Zheng, and Y. Li, ''Decentralized peer-to-peer energy trading strategy in energy blockchain environment: A game-theoretic approach,'' *Appl. Energy*, vol. 325, Nov. 2022, Art. no. 119852, doi: 10.1016/j.apenergy.2022.119852.
[22] A. Umar, D. Kumar, and T. Ghose, ''Blockchain-based decentralized energy intra-trading with battery storage flexibility in a community microgrid system,'' *Appl. Energy*, vol. 322, Sep. 2022, Art. no. 119544, doi: 10.1016/j.apenergy.2022.119544.



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