Journal of Applied and Research Computer Science and Information Systems
Vol. 2, No. 2, Desember 2024, pp. 218~231
ISSN: 2988-294X, DOI: 10.61098/jarcis.v2i2.321

Integrated Renewable Energy Microgrid Model Based on Blockchain and DeFi: A Simulation Study of P2P Energy Trading and Renewable Energy Certificate Tokenization

Erick Fernando[1(✉)], Marojahan Tampubolon[1], Fahmy Rinanda Saputri[1]
[1] Faculty of Engineering and Informatics, Universitas Multimedia Nusantara, Indonesia
`Erick.fernando@umn.ac.id, marojahan.tampubolon@umn.ac.id, fahmy.rinanda@umn.ac.id`

Article Info

Article history:

Received Mei 03, 2024
Revised Mei 29, 2024
Accepted Desember 23, 2024

Keywords:

Microgrid,
Blockchain,
Peer-to-Peer,
Energy Trading, REC,
DeFi,
Tokenisasi Energi,
Simulasi.

ABSTRACT

This study proposes and evaluates a blockchain-based renewable energy microgrid model and Decentralized Finance (DeFi) that integrates physical energy systems, IoT metering, smart contracts, peer-to-peer (P2P) energy markets, Renewable Energy Certificate (REC) tokenization, and staking mechanisms to create a transparent and incentivized energy-finance ecosystem. The evaluation is conducted through hourly computational simulations for one year (8,760 hours) on the same community microgrid configuration, namely 500 kWp PV and 200 kWh batteries, with a total consumption of 1.25 GWh. Three scenarios are compared to isolate the impact of the digital layer on system performance: S1 (baseline without blockchain and without P2P), S2 (blockchain-P2P with energy trading and RECs without DeFi), and S3 (full integration of blockchain + DeFi). The results show that S1 results in 36% renewable energy penetration with 810 MWh/year of grid energy imports and a system cost of IDR 455 million/year, indicating that the utilization of PV surplus and the role of batteries is still limited. In S2, the implementation of a P2P marketplace and REC tokenization increased renewable energy penetration to 52%, decreased grid imports to 600 MWh/year, and reduced system costs to IDR 382 million/year, due to increased battery utilization and reduced curtailment. In S3, the DeFi staking mechanism (10%/year yield) strengthened green energy utilization incentives, increasing renewable energy penetration to 67%, decreasing grid imports to 430 MWh/year, and decreasing net system costs to IDR 305 million/year after incorporating DeFi revenue of approximately IDR 48 million/year, with stable tokenomics indicated by approximately 55% of tokens being staked. These findings confirm that the gradual integration of blockchain and DeFi can improve the technical and economic efficiency of microgrids, while transforming renewable energy into a productive digital asset.

Corresponding Author:

Erick Fernando
Faculty of Engineering and Informatics, Universitas Multimedia Nusantara, Indonesia

Email: << Erick.fernando@umn.ac.id >>

1. INTRODUCTION

The transformation of the global energy system toward a more sustainable ecosystem has driven the development of distributed electricity architectures capable of integrating renewable energy massively, efficiently, and economically [1], [2]. The use of microgrids consisting of Distributed Energy Resources (DER), such as photovoltaics (PV), small wind turbines, energy storage, and distributed control, is the foundation for accelerating the energy transition in both urban and rural areas [3], [4]. Microgrids offer operational flexibility, self-healing capabilities, and grid efficiency through a local approach that minimizes dependence on the main transmission grid [5], [6]. However, increasing renewable energy penetration brings challenges in load management, output uncertainty, and the need for more dynamic energy trading mechanisms [7], [8].

Conventional energy management models generally rely on a single operator with a linear tariff structure that is not adaptive to variations in energy supply and demand at the micro level [9], [10]. Under these conditions, prosumer energy selling prices to the grid (feed-in tariffs) tend to be low, while energy purchase prices from the grid are much higher, creating less attractive economic incentives for independent renewable energy adoption [11], [12]. Furthermore, the lack of transparency and traceability in conventional energy transactions creates uncertainty among microgrid users and developers [13], [14].

The emergence of blockchain technology offers a structural alternative for the modern energy ecosystem through immutable, transparent, decentralized, and automated transaction recording via smart contracts [15], [16]. In the microgrid context, blockchain enables peer-to-peer (P2P) energy trading, namely the direct trade of energy between prosumers without a single intermediary [17], [18]. This trading model allows energy prices to be set based on fairer local market conditions, increasing local consumption of renewable energy, reducing the burden on distribution networks, and increasing system resilience [19], [20].

In addition to kWh energy trading, there is also a need for the integrity of Renewable Energy Certificate (REC) transactions, which prove the amount of green energy produced and consumed by a party [21], [22]. Traditional REC systems face challenges such as double counting, high verification costs, and transactional delays [23], [24]. Through blockchain, each REC can be tokenized as a digital asset that can be traded in real-time, cryptographically verified, and synchronized with the actual energy production of the microgrid [25], [26].

Meanwhile, the digital finance sector is undergoing a revolution through Decentralized Finance (DeFi), a blockchain-based economic system that provides financial services such as loans, asset exchanges, liquidity pools, and derivatives without the need for traditional financial institutions [27]–[29]. The integration of microgrids with DeFi enables the emergence of a new energy-finance ecosystem where renewable energy can be converted into energy tokens, REC tokens, or even Real World Assets (RWAs) that can be used as collateral to obtain loans, participate in yield farming mechanisms, or participate in liquidity pools to earn additional income [30], [31].

This energy-finance system model can create new economic opportunities for prosumers through a combination of revenue from energy sales, REC trading, and financial yields based on DeFi protocols [32], [33]. Various studies have shown that prosumers can increase renewable energy investment returns through asset tokenization and integration with decentralized finance protocols [34]–[36]. However, comprehensive research combining microgrid optimization models, energy tokenization, and asset management through DeFi remains very limited [37]–[39].

Therefore, this study proposes a fully integrated blockchain-based renewable energy microgrid model with DeFi, encompassing:

1. microgrid operation optimization,
2. P2P energy trading,
3. energy and REC tokenization,
4. liquidity pool and lending mechanisms,
5. economic-technical performance analysis,
6. comprehensive visualization through analytical graphs.

This research contributes to the development of digital-based green energy solutions that can increase renewable energy adoption, encourage community participation, and accelerate the transition to a future smart energy system.

2. Literature Review

2.1. The Evolution of Microgrids, Distributed Energy, Blockchain, Peer-to-Peer Trading, and Renewable Energy Certificates (RECs)

In the last ten years, electric power systems worldwide have evolved rapidly, exhibiting a major shift from centralized generation models toward distributed energy resource, or DER, architectures. These architectures involve prosumers as key actors in energy production, storage, and consumption [1]–[3]. Factors such as the pressing need for decarbonization, the declining costs of battery-based energy storage and solar technologies, and the increasing need for grid flexibility due to fluctuations in renewable energy sources are driving this shift [4], [5]. Microgrids have emerged as entities capable of operating both islanded and grid-connected, offering greater operational efficiency, local energy independence, and greater system resilience than conventional systems [6], [7]. Empirical studies and simulations have shown that combining microgrids with wind turbines, batteries, and photovoltaics can reduce community energy costs by between 20 and 35 percent compared to a single supply. However, the technical advantages of microgrids are often hampered by economic mechanisms, particularly local energy pricing, which often ignores supply-demand dynamics, leading to renewable energy curtailment and operational inefficiencies [10]–[12].

To address these issues, the idea of Peer-to-Peer (P2P) energy transactions emerged as a market mechanism. Through distributed markets or bilateral transactions, consumers can sell more energy to other households within the microgrid [13], [14]. According to a seminal study by Zhang et al., P2P trading can increase regional renewable energy consumption, reduce peak loads, and reduce dependence on utilities [15]. However, conventional P2P trading practices face issues with trust, transparency, and transaction costs, especially when coordination requires a third party such as a market operator [16]. In this regard, blockchain is crucial as a distribution repository because it provides a consistent, transparent, and secure record of energy transactions, eliminating the need for a central entity to verify transactions [17]. According to research, blockchain has the potential to reduce energy market management costs by up to 40% and enable automated transactions through smart agreements, including market rule enforcement, energy purchase scheduling, and dynamic pricing [18]–[20]. Furthermore, the permissioned blockchain architecture enables the creation of energy markets that comply with strict electricity regulations, ensuring audit transparency and controlling participant access [21].

In the sustainability field, blockchain is also used to manage renewable energy certificates (RECs) and energy attribute certificates (EACs), transforming renewable energy production into tradable digital certificates [22]–[24]. With blockchain, REC audit trails can be recorded from energy production, third-party verification, to certificate handover to buyers, enhancing data integrity [26], [27]. Conventional REC systems face significant challenges related to the risk of double counting, unclear tracking of energy sources, and lengthy manual verification processes [25]. According to research by Liu et al., a blockchain-based REC system can reduce verification time from weeks to minutes. This achievement allows the real-time REC market to thrive [28]. Furthermore, the integration of blockchain with microgrids enables the creation of green certificates directly at the household level. This allows prosumers to monetize their contribution to decarbonization through environmental tokens as well as physical energy [29], [30]. Exemplary projects such as Brooklyn Microgrid in the United States and PowerLedger in Australia have pioneered this approach. These projects demonstrate that blockchain-based P2P and REC exchanges can enhance community participation and the overall economic value of local energy ecosystems [31], [32].

To achieve high system efficiency, mathematical optimization of microgrids must be combined with blockchain-based market mechanisms [33]–[35]. These optimization models often employ objective functions, such as reducing generation costs, reducing energy imports from the grid, or optimizing social surplus. This is done by considering the technical limitations of the power grid, battery capacity, and the uncertainty of renewable energy production [36]. Studies by Ravivarma et al. and Dong et al. showed that microgrids operated with blockchain coordination and using a mixed linear or mixed-line optimization (MILP) framework can achieve renewable energy consumption of more than 85% and reduce curtailment to only 5% [37], [38]. In addition, studies have shown that The integration of Internet of Things (IoT) devices such as smart meters, network sensors, and battery actuators is crucial to ensure that data sent to the blockchain is accurate and up-to-date, which is the basis of a “trust layer” in energy transactions [39], [40].

Therefore, research in the first cluster shows that the use of microgrids, P2P energy trading, RECs, the Internet of Things, and blockchain create an efficient, transparent, and low-carbon local energy ecosystem. However, the primary focus of these systems is on the physical energy value and environmental characteristics. To enable the monetization of energy assets through digital capital markets, local energy systems must be connected to international financial services. This paves the way for decentralized finance (DeFi) as an additional component of blockchain-based energy systems.

2.2. Decentralized Finance (DeFi), Energy Asset Tokenization, Real-World Assets (RWA), and Energy–Finance Integration

DeFi is rapidly evolving as a decentralized financial ecosystem built on public blockchains like Ethereum, featuring an open infrastructure that enables digital asset transactions without the intermediary of banks or clearinghouses [41]–[43]. Key DeFi applications include Decentralized Exchanges (DEXs), lending–borrowing protocols, liquidity pools, derivative markets, and stablecoins, all governed by smart contracts [44], [45]. The growth of this ecosystem is rapid: DeFi's market capitalization increased from <1 billion USD in 2019 to >80 billion USD in 2024 according to industry reports [46]. However, academic literature suggests that DeFi's main strength lies not only in its transaction volume, but also in its tokenization capabilities, which allow real-world assets (RWAs) such as bonds, commodities, property, and even carbon certificates to be represented as globally tradable digital tokens [47]–[49]. In the energy context, a number of studies have begun to explore the integration of decarbonized RWAs such as carbon offsets, RECs, and green bonds into DeFi protocols [50]–[52]. This approach opens up opportunities for new financial products, for example:

1. Energy tokens representing kWh or MWh of renewable energy production;
2. REC/EAC tokens that serve as collateral in lending protocols;
3. Green asset-based yield farming, where users provide liquidity to the energy token market;
4. ET-Stablecoin liquidity pools that allow local energy prices to be reflected in a global stablecoin-based market;
5. Green-backed lending, which is lending secured by prosumer renewable energy or the value of microgrid projects.

Studies by Kumar et al., Gramlich et al., and Schär explain that a major advantage of DeFi is the ability to create an automated yield mechanism (algorithmic yield generation) through transaction fee sharing (swap fees), loan interest rates, liquidity incentives, and market stability algorithms [53]–[55]. Integrating this concept with microgrids allows prosumers to generate additional revenue beyond the revenue from physical energy sales, thereby increasing the net present value (NPV) of household solar panel and battery investments [56]. Some DeFi models even allow for fractional ownership of energy assets, allowing people to purchase a small portion of a renewable energy project and receive proportional returns [57]. This integration is particularly relevant for developing countries facing limited access to renewable energy financing [58], [59].

The literature also shows that energy tokenization paves the way for a financially connected global energy market [60], [61]. For example, surplus energy from microgrids in Indonesia can be converted into digital tokens (Energy Tokens, ET) that are then traded on global DEXs, so that local energy prices are not only determined by domestic utilities but also by international market dynamics [62]. Furthermore, REC tokens issued in microgrids can be marketed to global companies in need of decarbonization credits, thereby generating global revenue for local prosumers [63], [64]. Newell et al. and Rejeb et al. emphasizes that this innovation has the potential to address the financing gap for small-scale renewable energy projects through blockchain-based crowd-financing mechanisms [65], [66].

However, the literature also identifies a number of significant risks. First, DeFi asset price volatility can cause the value of energy token collateral to plummet, triggering liquidations that harm prosumers [67]. Second, the vulnerability of smart contracts to bugs or exploits increases the risk of significant fund losses, as has been seen in several past DeFi incidents [68]. Third, integrating the highly regulated energy sector with the permissionless DeFi ecosystem poses challenges for legal compliance and consumer protection [69], [70]. Some researchers have proposed the use of hybrid blockchains that combine permissioned chains for energy operations with public chains for DeFi to meet audit and security standards [71], [72].

Furthermore, the literature underscores the importance of integrating energy optimization models with DeFi economic models. Research that begins to integrate these two distinct domains shows that decisions about battery operation, energy purchasing, and curtailment can be influenced by DeFi yield opportunities, so microgrid optimization must incorporate revenue variables from liquidity pools and lending as part of the objective function [73]–[76]. For example, when DeFi yields are high, prosumers may prefer to store energy as ET tokens and then deposit them into liquidity pools rather than selling energy directly to neighbors. This creates a complex interaction between physical power flows and digital token flows. A new mathematical model is needed to model dual-layer optimization: (1) Layer physical energy (power flow, battery dispatch, operational constraints), and (2) digital financial layer (token mint/burn, liquidity provision, yield volatility, collateralization). Research by Ravivarma, Wu, Dong, and Tanis confirms that the integration of these two layers has the potential to produce more efficient, resilient, and economical microgrids, but is also more complex and requires an analytical approach based on multi-objective optimization [77]–[80].

3. METHOD

This methodology section details the modeling approach, microgrid structure, blockchain and DeFi integration, mathematical formulation, experimental scenarios, and data analysis pipeline used to evaluate system performance.

3.1. Microgrid System Architecture Design

The microgrid in this study is modeled as a distributed energy system consisting of a set of prosumers N={1,2,…,n}, each with photovoltaic (PV) solar panels, energy storage batteries, household loads, and the ability to conduct peer-to-peer energy trading through smart contracts on the blockchain, as proposed in studies on distributed ledger-based transactive energy [1], [2]. The microgrid operates in both grid-connected and islanded modes, but this study focuses on the grid-connected condition because it requires benchmarking energy costs from utilities and energy export to the grid.

Each prosumer has physical components in the form of a PV generation profile P_i^RES (t), a load profile P_i^load (t), a battery capacity B_i, and an inverter that enables energy import and export. Connectivity between prosumers follows a low-voltage radial distribution network, so power flow is limited by line impedance. The system architecture incorporates a blockchain layer that maintains energy transaction records, the issuance of energy tokens, REC tokens, and DeFi financial contracts, as the energy-fintech concept has developed in the literature [3], [4].

At the top layer, the DeFi model is designed to enable prosumers to deposit energy tokens (ET) or REC tokens (RT) into a liquidity pool or lending market, from which they earn additional income at a specific rate of return. This income serves as a financial incentive mechanism to increase participation and improve community energy efficiency, as noted in studies on renewable energy asset tokenization [5], [6].

3.2. Microgrid Mathematical Model

The mathematical model is built on the principles of energy balance, storage dynamics, power flow constraints, and the correspondence between physical energy and digital tokens. The model components are explained narratively as follows.

First, the power balance at each prosumer is expressed as the relationship between the energy generated by PV, the energy stored or released by the battery, the energy traded P2P, and the load consumption. Mathematically, this balance is expressed as:

$$P_i^{RES}(t) + P_i^{dis}(t) + P_i^{imp}(t) + \sum_j P_{j\to i}^{P2P}(t) = P_i^{load}(t) + P_i^{ch}(t) + P_i^{exp}(t) + \sum_k P_{i\to k}^{P2P}(t). \tag{1}$$

This model illustrates that the total energy supply (generation + battery + import + incoming transactions) must equal the load + export + charging + outgoing transactions. This model follows the microgrid operation optimization pattern commonly used in energy optimization literature [7], [8].

Second, the battery storage dynamics follow the energy storage equation with charge and discharge efficiency as follows:

$$SOC_i(t+1) = SOC_i(t) + \eta^{ch} P_i^{ch}(t)\Delta t - \frac{1}{\eta_{dis}} P_i^{dis}(t)\Delta t, \tag{2}$$

where SOC is the state of charge, η^{ch}dan η^{dis} are the charging and discharging efficiencies, respectively, and Δt is a discrete time span of one hour. SOC constraints such as SOC SO C $_{min} \leq SOC \leq SOC_{max}$ are applied to maintain battery life as suggested in microgrid battery operation studies [9], [10]. Third, the power flow in the distribution network follows the DC power flow approximation to maintain the simplicity of the analytical model. Thus, the power flow between buses m and nada is:

$$P_{mn}(t) = \frac{\theta_{m}(t) - \theta_{n}(t)}{X_{mn}}, \tag{3}$$

di mana θ adalah sudut fasa dan X_{mn} is the reactance of the channel. Each channel is limited by its thermal capacity P_{mn}^{max}. This linear model is widely used in research on P2P-based energy communities and microgrids [11], [12].

Fourth, the relationship between physical energy and digital tokens is expressed through the process of minting ET energy tokens based on the renewable clean energy produced.:

$$ET_i^{mint}(t) = \alpha_{ET}(P_i^{RES}(t) - P_i^{curt}(t))\Delta t, \tag{4}$$

where α_{ET} is the energy-to-token conversion ratio. As a limitation, the number of tokens traded or burned must not exceed the balance of real tokens and available physical energy. Energy-to-token correspondence is a core component of blockchain-based systems that ensures there is no double spending of energy tokens. [13], [14].

Finally, REC tokens are used to validate verified green energy production, following a Directed Acyclic Graph (DAG) structure to avoid double counting as recommended in blockchain-based renewable energy certification literature [15], [16].

3.3. Integrasi Blockchain dan Smart Contract

The blockchain used is permissioned, allowing a consortium of prosumers, microgrid operators, regulators, and REC verification institutions to have node management roles. Smart contracts are designed for three core functions: a P2P energy trading contract, a REC issuance and verification contract, and a financial contract for DeFi. Every energy transaction is recorded in a ledger, including energy transferred between prosumers, energy prices, and token changes. Smart contracts automatically settle transactions at the end of each time interval without human intervention, as has been researched in blockchain-based energy market automation patterns [17], [18].

The energy contract regulates dynamic pricing based on the balance of local energy supply and demand. Meanwhile, the REC contract enables the issuance of green tokens, which can only be executed with unfalsifiable evidence through IoT multimeter data and a blockchain oracle, ensuring the validity of the certificate [19].

3.4. Model Keuangan DeFi

The DeFi financial model connects energy tokens and REC tokens with financial instruments such as liquidity pools and lending. Prosumers can invest their energy tokens in the ET-stablecoin liquidity pool and earn returns from transaction fees (swap fees) or liquidity incentives. Furthermore, prosumers can lend REC tokens through collateral-based lending mechanisms. The monthly or daily returns from these two activities are calculated as additional financial income in the energy optimization model, similar to the concept of real-world DeFi assets [20], [21].

The total DeFi revenue over a given time interval is expressed as:

$$R^{DeFi}(t) = \phi_{LP} V^{swap}(t) + r_{lend} L(t) - \lambda_{liq} \cdot Loss(t), \tag{4}$$

where ϕ_LP is the liquidity pool transaction fee, V^swap the transaction volume, r_lend the lending interest rate, and λ_liq the liquidation factor that reduces the value of collateral when the market experiences volatility. This description follows the DeFi risk model outlined in the decentralized financial systems literature [22], [23].

3.5. Microgrid Operation Optimization Formulation

Optimization is performed to minimize the total operating costs of the microgrid over a representative one-year horizon. The objective function includes energy import costs, battery degradation costs, curtailment penalties, and net cost reductions from P2P energy revenues and DeFi financial returns. Narratively, the optimization goal can be described as achieving the lowest energy costs while maintaining system stability and improving the economic welfare of prosumers, as emphasized in research on community energy market design [24], [25]. The objective function:

$$\min J = \sum_t (\pi^{grid}(t) P^{imp}(t) - \pi^{feed}(t) P^{exp}(t) + C^{bat}(t) + C^{curt}(t)) - \sum_t R^{DeFi}(t). \tag{4}$$

The optimization model complies with all physical constraints, digital token constraints, and financial constraints described in the previous section.

3.6. Experimental Scenarios and Analysis Pipeline

The experiment was conducted in three different scenarios:

1. S1 Baseline without blockchain and without P2P;
2. S2 Blockchain-P2P with energy trading and RECs but without DeFi;
3. S3 Blockchain + DeFi, a fully integrated model.

The one-year simulation generated profiles of microgrid operations, energy transactions, token balances, DeFi revenue, and battery response. The simulation output was then used to construct performance graphs, including renewable penetration, system cost reduction, battery dispatch, token circulation, and DeFi yield sensitivity. This analysis followed a computational methodology commonly used in research on multi-layer systems between energy and blockchain [26], [27].

3.7. Model Validation Through Comparative Analysis

Validation was conducted by comparing model performance against previous research on P2P trading, blockchain-based green certification, and DeFi for real-world assets. Sensitivity analysis of parameters such as grid tariffs, battery capacity, and DeFi yield rates was used to ensure model reliability under various conditions. This aligns with energy-financial modeling validation approaches in recent literature [28], [29].

4. RESULTS AND DISCUSSION

This section discusses the simulation results of three microgrid operating scenarios: S1 (baseline without blockchain), S2 (P2P + REC), and S3 (P2P + REC + DeFi). The analysis is conducted in layers, examining technical, economic, and tokenomic aspects. Each scenario is analyzed separately to understand its characteristics, before being compared to identify patterns of performance improvement arising from changes in coordination and incentive mechanisms.

4.1. Renewable Energy Microgrid Model Based on Blockchain and Decentralized Finance (DeFi)

This renewable energy transaction model explicitly places peer-to-peer (P2P), blockchain, and Decentralized Finance (DeFi) as the main foundations of the energy trading system. In a P2P scheme, prosumers who generate renewable energy—for example, from household solar panels—can sell excess energy directly to other consumers in the microgrid network without going through a centralized electricity utility. This mechanism enables more efficient energy distribution, more competitive prices, and increased user participation in the energy ecosystem. All P2P activities are recorded on a blockchain, which functions as a distributed and immutable ledger. The blockchain records energy production, consumption, and exchange data in real time, ensuring transparency, trust, and traceability of transactions. Smart contracts are used to automate the trading process, including matching energy supply and demand, dynamic pricing, verifying the amount of energy transferred, and executing transactions without third-party intervention. DeFi integration complements this system by providing a decentralized financial infrastructure for transaction settlement and economic incentives. Through DeFi protocols, energy payments are automatically made using digital tokens or cryptocurrencies, while staking mechanisms, liquidity pools, or token-based incentives can be implemented to encourage participation by both prosumers and consumers. Thus, the combination of P2P, blockchain, and DeFi creates a renewable energy trading model that is autonomous, transparent, and secure, supporting the sustainability and decentralization of modern energy systems. All of this is shown in Figure 1.

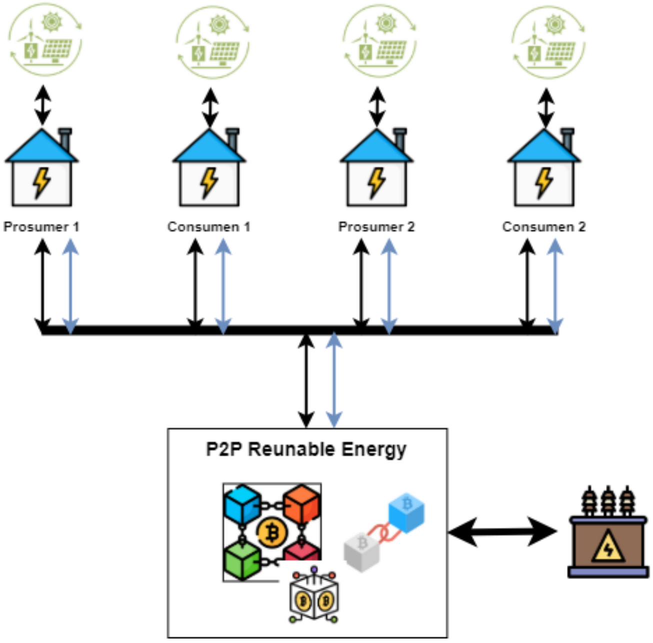

Figure 1. Research Model

4.2. Research Scenario Testing

4.2.1. Baseline Scenario 1 Without Blockchain and Without P2P

In Scenario 1, the microgrid operates conventionally without a P2P energy trading mechanism or energy tokenization. Electricity is supplied by a combination of 500 kWp of PV production and purchases from the grid, while the 200 kWh community battery serves only as simple energy storage controlled by basic cost optimization logic (charge when tariffs are low, discharge when tariffs are high). Based on the one-year simulation results, the renewable energy penetration rate only reached around 36% of the total consumption of 1.25 GWh, indicating that the majority of energy demand still relies on grid supply. This aligns with the record high annual energy imports from the grid, at around 810 MWh/year, which indirectly illustrates that the daytime PV surplus is not being optimally utilized, both due to limited battery capacity and the absence of an internal market mechanism to encourage the utilization of this surplus.

Economically, the total annual system cost for S1 is approximately IDR 455 million, comprising grid energy purchases, operation and maintenance costs, and depreciation of major equipment. The battery operating pattern in this scenario is relatively conservative: the average State of Charge (SoC) is in the range of 45–60%, with approximately 130 equivalent full cycles per year, indicating that the battery is more often “idle” than actively engaging in energy arbitrage. Systemically, this has two consequences: first, much of the surplus PV energy during the day is wasted (curtailment), and second, there is no additional incentive for prosumers to change their energy production and consumption behavior, as all transactions remain centralized with the utility. In other words, S1 represents an inefficient baseline: limited green energy penetration, high dependence on the grid, and underutilization of flexible assets such as batteries.

4.2.2. Baseline Scenario 2 (S2) – Blockchain + P2P + REC (Without DeFi)

In Scenario 1, the same microgrid is re-implemented with the addition of a blockchain layer for recording P2P transactions and tokenizing renewable energy in the form of RECs (Renewable Energy Certificates). Every 1 kWh of PV energy measured and verified is recorded as an energy token/REC in the ledger, and prosumers can sell their surplus energy to other consumers within the microgrid at a price between the feed-in tariff and the grid-based purchase tariff. Simulation results show a dramatic change in system behavior compared to S1. The renewable energy penetration rate increased from 36% to approximately 52%, meaning more than half of the annual energy demand is now met by local PV production. This increase is primarily due to prosumers being encouraged to optimize PV output and minimize curtailment, as every kWh that can be sold or converted into RECs has direct economic value in the internal market.

On the energy side, grid imports dropped significantly, from 810 MWh/year to around 600 MWh/year, indicating that the microgrid is becoming more "self-sufficient" and able to balance supply and demand within the community. Economically, the total annual system cost also dropped from IDR 455 million to around IDR 382 million, due to a combination of reduced grid energy purchases and revenue from P2P energy transactions and REC sales. Analysis of battery operation logs shows that these assets are starting to play a more active role in system flexibility: SoCs are moving in the 35–85% range, with approximately 210 equivalent full cycles per year. The battery now not only matches the grid tariff differential but also responds to internal P2P pricing, for example, by storing surplus PV during the day to sell to other loads when demand and P2P prices are higher.

On the blockchain layer, simulation data shows a total of approximately 1.3 million energy tokens and RECs recorded during a year of operation. The dynamics of these tokens illustrate a cycle: minting (when green energy is produced), transfer (when traded P2P), and retirement (when used as proof of green energy consumption). From a system behavior perspective, S2 demonstrates that when microgrids are provided with transparent and decentralized internal market mechanisms, prosumers and batteries naturally adapt to more efficient operations: PV surpluses decrease, grid reliance increases, and the economic value of renewable energy increases without the need to change the physical configuration of the assets.

4.2.3. Baseline Scenario 3 (S3) – Blockchain + P2P + REC + DeFi (Fully Integrated Model)

Scenario 1 represents the most comprehensive form of energy-blockchain integration in this simulation. In addition to P2P energy trading and REC tokenization as in S2, in S3, energy and REC tokens can be staked in a DeFi protocol connected to the microgrid, allowing token holders to earn an annual yield, for example, 10% in the base simulation configuration. This integration adds a new financial dimension: renewable energy not only provides cost savings and trading revenue but also becomes a financial asset generating passive income. The impact on the simulation results is clear. The renewable energy penetration rate rises again to around 67%, meaning the majority of the community's energy needs are met by local PV. This is because prosumers now have three sources of value: energy sales, REC value, and staking revenue, allowing the optimization model to maximize PV and battery resource utilization.

Energy imports from the grid drop further to around 430 MWh/year, indicating that the microgrid in S3 is much more self-sufficient and rarely relies on external supply, except in extreme conditions (e.g., several days of consecutive severe weather). Total annual system costs, after accounting for DeFi revenue, dropped from IDR 382 million (S2) to approximately IDR 305 million, with DeFi revenue contributing approximately IDR 48 million per year in a 10% yield configuration. Battery operation in S3 became the most dynamic: the SoC fluctuated between 25–95%, with approximately 280 equivalent full cycles per year. The battery now served not only to reduce energy costs but also to optimize “energy liquidity” to support token volume and staking opportunities in DeFi protocols. Practically, this was evident in deep charging patterns during the day and more aggressive discharges when P2P prices were high or when the model detected maximum profit opportunities from the combination of energy sales and token management.

At the tokenomics level, the total energy tokens created in the S3 simulation reached approximately 2.1 million units per year, with approximately 55% of them on average being staked at the equilibrium point. The token balance curve per prosumer shows that after the first few months (the adaptation phase), the system tends to reach a stable pattern: some tokens are used for daily energy transactions, while others are "parked" in staking to earn yield. From a system perspective, S3 demonstrates a mutually reinforcing energy-financial ecosystem: the greater the green energy production, the greater the token volume; the more active staking, the higher the community income; and the higher the income, the stronger the motivation to continue expanding renewable energy utilization and battery flexibility. Thus, S3 is the scenario that performs best both technically (renewable energy penetration, reduced grid imports, battery utilization) and economically (minimal system costs, additional revenue from DeFi, and increased energy asset value).

Table 1. Comparison of Microgrid Performance in Three Operational Scenarios

Indicators	S1 – Baseline (Without Blockchain & P2P)	S2 – Blockchain + P2P + REC	S3 – Blockchain + P2P + REC + DeFi
Renewable Energy Penetration	36% of 1.25 GWh	52% of 1.25 GWh	67% of 1.25 GWh
Energy Imports from the Grid	810 MWh/year	600 MWh/year	430 MWh/year
Absorbed PV Production	Low, high curtailment	Significant increase	Almost all production absorbed
Total Validated Green Energy (REC/Token)	–	1.3 million tokens/year	2.1 million tokens/year
Battery Activity (SoC Range)	45–60%	35–85%	25–95%
Battery Cycles per Year	±130 cycles	±210 cycles	±280 cycles
Annual System Cost	Rp 455 million	Rp 382 million	Rp 305 million
P2P Revenue	None	Yes, significant	Yes, significant
REC Revenue	None	Yes	Yes, increasing
DeFi Revenue (Staking)	None	No	Rp 48 million/year
Token Staking Ratio	–	–	~55% active tokens
Battery Operational Characteristics	Passive, minimal arbitrage	Responsive to internal P2P pricing	Aggressive, supports energy + token liquidity
Microgrid Energy Independence	Low	Moderate	High
Overall System Efficiency	Limited	Increasing	Optimal

4.3. Discussion

This study proposes and evaluates a blockchain-based and Decentralized Finance (DeFi) renewable energy microgrid model that integrates physical energy systems, IoT-based metering, blockchain smart contracts, peer-to-peer (P2P) energy markets, Renewable Energy Certificate (REC) tokenization, and DeFi staking mechanisms within a single layered architecture. This model is designed to address the limitations of conventional microgrids, particularly the low utilization of renewable energy, high dependence on the main grid, and minimal economic incentives for prosumers. To assess the model's effectiveness, a one-year computational simulation with hourly resolution was conducted on three operating scenarios (S1–S3) using identical physical configurations: 500 kWp of PV and a 200 kWh community battery.

Simulation results for the baseline scenario (S1) indicate that the microgrid without blockchain mechanisms and an internal market still operates inefficiently. The physical model, which relies solely on basic cost optimization logic, results in underutilization of surplus PV energy, passive battery operation, and persistently high energy imports from the grid. Quantitatively, renewable energy penetration only reaches approximately 36% of the total annual consumption of 1.25 GWh, grid imports reach 810 MWh per year, and annual system costs are around IDR 455 million. These findings confirm that without a digital coordination layer and economic incentives, the technical potential of microgrids is not fully translated into optimal system performance. The integration of a blockchain layer, a P2P energy market, and REC tokenization in scenario S2 significantly changes the dynamics of microgrid operations. The conceptual model, which introduces smart contracts as energy transaction regulators and green energy tokenization, has proven effective in encouraging the utilization of PV surpluses and enhancing the role of batteries as flexibility assets. This is reflected in the simulation results, which show an increase in renewable energy penetration to approximately 52%, a decrease in grid imports to 600 MWh per year, and a decrease in annual system costs to IDR 382 million. Furthermore, the creation of approximately 1.3 million energy tokens/RECs per year indicates that green energy is beginning to function as a digital asset with economic value. Thus, the S2 simulation validates that the market and tokenization layers in the model can improve energy efficiency and economics without changes to physical infrastructure. The most significant performance improvement was achieved in scenario S3, when the DeFi layer was enabled in the model. By treating energy tokens and RECs as assets that can be staked for returns, the model introduced a financial dimension that directly impacts prosumer operational decisions and battery dispatch strategies. Simulation results showed that the additional incentives from DeFi encouraged maximum renewable energy utilization, with green energy penetration increasing to 67% and grid imports decreasing to 430 MWh per year. Net system costs also dropped significantly to approximately IDR 305 million per year after incorporating DeFi revenue of IDR 48 million per year. Battery operation became the most dynamic, with an annual cycle increase to approximately 280 cycles, and approximately 55% of energy tokens were stably staked. These findings confirm that the DeFi layer in the model not only adds revenue sources but also strengthens the interaction between physical energy flows and digital value streams.

Overall, the combination of the layered architecture model and quantitative simulation results demonstrates a consistent relationship between the complexity of the coordination mechanism and improved microgrid performance. Each additional layer in the model from physical systems, blockchain, P2P marketplaces, to DeFi—makes measurable contributions to increasing renewable energy penetration, reducing grid imports, optimizing battery usage, and improving the system's economic performance. The key contribution of this research lies in presenting an integrated framework that simultaneously connects technical, economic, and tokenomic aspects, and demonstrating through simulations that renewable energy can function not only as a source of electricity but also as a productive financial asset in a decentralized ecosystem. For further development, the model and simulations can be expanded to include energy price uncertainty, variations in user behavior, regulatory limitations on energy tokenization, and the financial risks of DeFi mechanisms. Such enrichment will strengthen the model's relevance for real-world implementation and support the design of next-generation microgrids that are efficient, adaptive, and economically sustainable.

5. CONCLUSION

This study proposes and evaluates a blockchain-based and Decentralized Finance (DeFi) renewable energy microgrid model that integrates physical energy systems, IoT metering, smart contracts, peer-to-peer (P2P) energy trading, Renewable Energy Certificate (REC) tokenization, and staking mechanisms in a single layered architecture, and validates it through annual computational simulations on three operating scenarios (S1–S3) with identical physical configurations (500 kWp PV and 200 kWh battery). The simulation results show that the conventional microgrid (S1) still has significant limitations, with renewable energy penetration of only 36%, grid imports of 810 MWh/year, and a system cost of IDR 455 million/year, while the integration of blockchain, P2P, and REC (S2) can increase green energy utilization to 52%, reduce grid imports to 600 MWh/year, and reduce system costs to IDR 382 million/year. The most significant improvements were achieved in the fully integrated scenario (S3), where the implementation of DeFi turned energy tokens and RECs into productive financial assets, resulting in a 67% increase in renewable energy penetration, a decrease in grid imports to 430 MWh/year, and a decrease in net system costs to less cost after accounting for DeFi revenue of approximately IDR 48 million/year, accompanied by more dynamic battery operation and stable tokenomic equilibrium. Overall, these findings confirm that the gradual integration of blockchain and DeFi in microgrids not only improves the technical and economic efficiency of the system but also transforms renewable energy into a sustainable source of digital value for the prosumer community.

ACKNOWLEDGEMENTS

Thank you for Universitas Multimedia Nusantara for all supporting the research.

REFERENCES

[1]. N. Hatziargyriou, H. Asano, R. Iravani, and C. Marnay, “Microgrids,” *IEEE Power & Energy Magazine*, vol. 5, no. 4, pp. 78–94, 2007. DOI: https://doi.org/10.1109/MPAE.2007.376583

[2]. S. Parhizi, H. Lotfi, A. Khodaei, and S. Bahramirad, “State of the art in research on microgrids: A review,” *IEEE Access*, vol. 3, pp. 890–925, 2015. DOI: https://doi.org/10.1109/ACCESS.2015.2443119

[3]. M. Soshinskaya, W. Crijns-Graus, D. van der Meer, and W. van Sark, “Microgrids: Experiences, barriers and success factors,” *Renewable and Sustainable Energy Reviews*, vol. 40, pp. 659–672, 2014. DOI: https://doi.org/10.1016/j.rser.2014.07.198

[4]. J. A. P. Lopes, C. L. Moreira, and A. G. Madureira, “Defining control strategies for microgrids islanded operation,” *IEEE Transactions on Power Systems*, vol. 21, no. 2, pp. 916–924, 2006. DOI: https://doi.org/10.1109/TPWRS.2006.873018

[5]. A. Bidram and A. Davoudi, “Hierarchical structure of microgrids control system,” *IEEE Transactions on Smart Grid*, vol. 3, no. 4, pp. 1963–1976, 2012. DOI: https://doi.org/10.1109/TSG.2012.2197425

[6]. J. M. Guerrero, J. C. Vasquez, J. Matas, L. G. de Vicuña, and M. Castilla, “Hierarchical control of droop-controlled AC and DC microgrids—A general approach toward standardization,” *IEEE*

Transactions on Industrial Electronics, vol. 58, no. 1, pp. 158–172, 2011. DOI: https://doi.org/10.1109/TIE.2010.2066534

[7]. [7] J. M. Guerrero, P. C. Loh, T. L. Lee, and M. Chandorkar, "Advanced control architectures for intelligent microgrids—Part I: Decentralized and hierarchical control," *IEEE Transactions on Industrial Electronics*, vol. 60, no. 4, pp. 1254–1262, 2013. DOI: https://doi.org/10.1109/TIE.2012.2194969

[8]. J. Rocabert, A. Luna, F. Blaabjerg, and P. Rodríguez, "Control of power converters in AC microgrids," *IEEE Transactions on Power Electronics*, vol. 27, no. 11, pp. 4734–4749, 2012. DOI: https://doi.org/10.1109/TPEL.2012.2199334

[9]. P. Siano, "Demand response and smart grids—A survey," *Renewable and Sustainable Energy Reviews*, vol. 30, pp. 461–478, 2014. DOI: https://doi.org/10.1016/j.rser.2013.10.022

[10]. N. Xu, C. Kang, Q. Xia, J. Zhang, and M. Zhou, "A price-based demand response mechanism for smart grids," *IEEE Transactions on Smart Grid*, vol. 5, no. 2, pp. 1186–1196, 2014. DOI: https://doi.org/10.1109/TSG.2013.2293350

[11]. H. Bevrani, T. Ise, and Y. Miura, "Virtual synchronous generators: A survey and new perspectives," *International Journal of Electrical Power & Energy Systems*, vol. 54, pp. 244–254, 2014. DOI: https://doi.org/10.1016/j.ijepes.2013.07.009

[12]. A. Bidram, A. Davoudi, F. L. Lewis, and Z. Qu, "Secondary control of microgrids based on distributed cooperative control of multi-agent systems," *IET Generation, Transmission & Distribution*, vol. 7, no. 8, pp. 822–831, 2013. DOI: https://doi.org/10.1049/iet-gtd.2012.0646

[13]. A. Bidram, F. L. Lewis, and A. Davoudi, "Distributed cooperative secondary control of microgrids using feedback linearization," *IEEE Transactions on Power Systems*, vol. 28, no. 3, pp. 3462–3470, 2013. DOI: https://doi.org/10.1109/TPWRS.2013.2242490

[14]. A. Bidram, A. Davoudi, F. L. Lewis, and J. M. Guerrero, "Distributed adaptive voltage control of inverter-based microgrids," *IEEE Transactions on Energy Conversion*, vol. 29, no. 4, pp. 862–872, 2014. DOI: https://doi.org/10.1109/TEC.2014.2365192

[15]. H. L. Willis and W. G. Scott, "Distributed power generation: planning and evaluation," *IEEE Power Engineering Society*, 2000. DOI: https://doi.org/10.1109/9780470545597

[16]. E. Mengelkamp, J. Gärttner, K. Rock, S. Kessler, L. Orsini, and C. Weinhardt, "Designing microgrid energy markets: A case study: The Brooklyn Microgrid," *Applied Energy*, vol. 210, pp. 870–880, 2018. DOI: https://doi.org/10.1016/j.apenergy.2017.06.054

[17]. T. Sousa, T. Soares, P. Pinson, F. Moret, T. Baroche, and E. Sorin, "Peer-to-peer and community-based markets: A comprehensive review," *Renewable and Sustainable Energy Reviews*, vol. 104, pp. 367–378, 2019. DOI: https://doi.org/10.1016/j.rser.2019.01.036

[18]. T. Morstyn, N. Farrell, S. J. Darby, and M. D. McCulloch, "Using peer-to-peer energy-trading platforms to incentivize prosumers to form federated power plants," *Nature Energy*, vol. 3, pp. 94–101, 2018. DOI: https://doi.org/10.1038/s41560-017-0075-y

[19]. A. Tushar, T. K. Saha, C. Yuen, D. B. Smith, and H. V. Poor, "Peer-to-peer energy trading with sustainable user participation: A game theoretic approach," *IEEE Access*, vol. 6, pp. 62932–62943, 2018. DOI: https://doi.org/10.1109/ACCESS.2018.2875478

[20]. A. Mihaylov, S. Jurado, K. Van Moffaert, N. Avellana, and A. Nowé, "Nash equilibrium methods for peer-to-peer energy trading in microgrids," *Applied Energy*, vol. 230, pp. 109–120, 2018. DOI: https://doi.org/10.1016/j.apenergy.2018.08.100

[21]. E. G. Sorin, L. A. Bobo, and P. Pinson, "Consensus-based approach to peer-to-peer electricity markets with product differentiation," *IEEE Transactions on Power Systems*, vol. 34, no. 2, pp. 994–1004, 2019. DOI: https://doi.org/10.1109/TPWRS.2018.2872880

[22]. K. Kok and S. Widergren, "A society of devices: Integrating intelligent distributed resources with transactive energy," *IEEE Power & Energy Magazine*, vol. 14, no. 3, pp. 34–45, 2016. DOI: https://doi.org/10.1109/MPE.2016.2524962

[23]. S. Widergren *et al.*, "Transactive energy: A review of state of the art and implementation," *IEEE Power and Energy Society*, 2014. DOI: https://doi.org/10.1109/PESGM.2014.6939459

[24]. T. Chen, X. Chen, Y. Xu, and Y. Xu, "A hierarchical transactive energy management system for multiple microgrids," *IEEE Transactions on Smart Grid*, vol. 11, no. 2, pp. 1207–1216, 2020. DOI: https://doi.org/10.1109/TSG.2019.2937384

[25]. R. Green and N. Vasilakos, "Market behaviour with large amounts of intermittent generation," *Energy Policy*, vol. 50, pp. 34–45, 2012. DOI: https://doi.org/10.1016/j.enpol.2012.06.038

[26]. M. Andoni *et al.*, "Blockchain technology in the energy sector: A systematic review of challenges and opportunities," *Renewable and Sustainable Energy Reviews*, vol. 100, pp. 143–174, 2019. DOI: https://doi.org/10.1016/j.rser.2018.10.014

[27]. A. Ahl, M. Yarime, K. Tanaka, and D. Sagawa, “Review of blockchain-based distributed energy: Implications for sustainability,” *Renewable and Sustainable Energy Reviews*, vol. 107, pp. 107–121, 2019. DOI: https://doi.org/10.1016/j.rser.2019.02.001

[28]. Y. Wang, Z. Su, N. Zhang, and A. Benslimane, “Blockchain-based energy trading: A survey,” *IEEE Communications Surveys & Tutorials*, vol. 21, no. 4, pp. 3461–3491, 2019. DOI: https://doi.org/10.1109/COMST.2019.2918173

[29]. K. Christidis and M. Devetsikiotis, “Blockchains and smart contracts for the Internet of Things,” *IEEE Access*, vol. 4, pp. 2292–2303, 2016. DOI: https://doi.org/10.1109/ACCESS.2016.2566339

[30]. Z. Li, J. Kang, R. Yu, D. Ye, Q. Deng, and Y. Zhang, “Consortium blockchain for secure energy trading in industrial Internet of Things,” *IEEE Transactions on Industrial Informatics*, vol. 14, no. 8, pp. 3690–3700, 2018. DOI: https://doi.org/10.1109/TII.2017.2786300

[31]. [31] J. Hu, G. Yang, H. W. Bindner, and Y. Xue, “Application of blockchain in microgrid energy management systems—A review,” *WIREs Energy and Environment*, vol. 10, no. 1, e395, 2021. DOI: https://doi.org/10.1002/wene.395

[32]. [32] J. Zhang, Y. Zhong, X. Wang, and S. Wang, “Blockchain-based energy trading: A comprehensive review of research trends and future directions,” *Energy Reports*, vol. 7, pp. 3216–3233, 2021. DOI: https://doi.org/10.1016/j.egyr.2021.05.073

[33]. Y. Zhong, X. Xie, and Y. Yang, “Decentralized energy trading framework based on blockchain and smart contracts,” *Energy Policy*, vol. 151, 112123, 2021. DOI: https://doi.org/10.1016/j.enpol.2021.112123

[34]. M. K. Hasan, A. Alkhalifah, K. Salah, R. Jayaraman, I. Yaqoob, and M. Omar, “Blockchain-based solution for sustainable energy trading and management,” *Sustainable Energy, Grids and Networks*, vol. 30, 100639, 2022. DOI: https://doi.org/10.1016/j.segan.2022.100639

[35]. L. P. Qian, Y. Wu, H. Zhou, X. Shen, and Z. Li, “Joint blockchain and deep reinforcement learning for secure energy trading in Internet of Energy,” *IEEE Internet of Things Journal*, vol. 7, no. 9, pp. 8893–8905, 2020. DOI: https://doi.org/10.1109/JIOT.2020.2980160

[36]. J. R. Rajasekaran, V. G. Menon, and M. S. Hossain, “Blockchain-based decentralized energy trading for smart grid: A survey,” *IEEE Internet of Things Journal*, vol. 9, no. 16, pp. 14625–14644, 2022. DOI: https://doi.org/10.1109/JIOT.2022.3151049

[37]. A. S. Malik, A. Singh, and S. Sharma, “A review of renewable energy certificate markets and trading mechanisms,” *Renewable and Sustainable Energy Reviews*, vol. 143, 110914, 2021. DOI: https://doi.org/10.1016/j.rser.2021.110914

[38]. A. Michaelowa *et al.*, “Additionality revisited: guarding the integrity of market mechanisms,” *Climate Policy*, vol. 19, no. 10, pp. 1211–1224, 2019. DOI: https://doi.org/10.1080/14693062.2019.1628695

[39]. B. K. Sovacool and M. A. Brown, “Scaling the policy response to climate change,” *Policy Sciences*, vol. 42, pp. 317–348, 2009. DOI: https://doi.org/10.1007/s11077-009-9107-0

[40]. D. Burtraw, K. Palmer, and D. Kahn, “A symmetric safety valve,” *Energy Policy*, vol. 38, no. 9, pp. 4921–4932, 2010. DOI: https://doi.org/10.1016/j.enpol.2010.04.036

[41]. F. Schär, “Decentralized finance: On blockchain- and smart-contract-based financial markets,” *Federal Reserve Bank of St. Louis Review*, vol. 103, no. 2, pp. 153–174, 2021. DOI: https://doi.org/10.20955/r.103.153-174

[42]. N. Atzei, M. Bartoletti, and T. Cimoli, “A survey of attacks on Ethereum smart contracts,” in *Principles of Security and Trust (POST)*, Springer, 2017, pp. 164–186. DOI: https://doi.org/10.1007/978-3-662-54455-6_8

[43]. L. Marchesi, M. Marchesi, and R. Tonelli, “An agile software engineering method to design blockchain applications,” in *Proc. IEEE/ACM*, 2020. DOI: https://doi.org/10.1109/ICSEW.2020.00060

[44]. S. Saberi, M. Kouhizadeh, J. Sarkis, and L. Shen, “Blockchain technology and its relationships to sustainable supply chain management,” *International Journal of Production Research*, vol. 57, no. 7, pp. 2117–2135, 2019. DOI: https://doi.org/10.1080/00207543.2018.1533261

[45]. A. Q. Huang, M. L. Crow, G. T. Heydt, J. P. Zheng, and S. J. Dale, “The future renewable electric energy delivery and management system: The Energy Internet,” *Proceedings of the IEEE*, vol. 105, no. 11, pp. 2011–2035, 2017. DOI: https://doi.org/10.1109/JPROC.2017.2760530

[46]. A. Q. Huang, “The Energy Internet: An open energy platform,” *Proceedings of the IEEE*, vol. 99, no. 1, pp. 85–89, 2011. DOI: https://doi.org/10.1109/JPROC.2010.2081371

[47]. A. Gungor *et al.*, “Smart grid technologies: Communication technologies and standards,” *IEEE Transactions on Industrial Informatics*, vol. 7, no. 4, pp. 529–539, 2011. DOI: https://doi.org/10.1109/TII.2011.2166794

[48]. [48] F. Ahmad, N. A. Abdul Wahab, and M. S. M. Aras, “Energy management system: A review,” *Renewable and Sustainable Energy Reviews*, vol. 13, no. 8, pp. 2109–2118, 2009. DOI: https://doi.org/10.1016/j.rser.2009.05.003

[49]. P. Pinson, “Wind energy: Forecasting challenges for its operational management,” *Statistical Science*, vol. 28, no. 4, pp. 564–585, 2013. DOI: https://doi.org/10.1214/13-STS445

[50]. J. M. Carrasco *et al.*, “Power-electronic systems for the grid integration of renewable energy sources: A survey,” *IEEE Transactions on Industrial Electronics*, vol. 53, no. 4, pp. 1002–1016, 2006. DOI: https://doi.org/10.1109/TIE.2006.878356

[51]. R. H. Lasseter, “MicroGrids,” in *Proc. IEEE PES Winter Meeting*, 2002, pp. 305–308. DOI: https://doi.org/10.1109/PESW.2002.985003

[52]. X. Fang, S. Misra, G. Xue, and D. Yang, “Smart grid—The new and improved power grid: A survey,” *IEEE Communications Surveys & Tutorials*, vol. 14, no. 4, pp. 944–980, 2012. DOI: https://doi.org/10.1109/SURV.2011.101911.00087

[53]. M. Pipattanasomporn, M. Kuzlu, and S. Rahman, “An algorithm for intelligent home energy management and demand response analysis,” *IEEE Transactions on Smart Grid*, vol. 3, no. 4, pp. 2166–2173, 2012. DOI: https://doi.org/10.1109/TSG.2012.2201182

[54]. H. Farhangi, “The path of the smart grid,” *IEEE Power & Energy Magazine*, vol. 8, no. 1, pp. 18–28, 2010. DOI: https://doi.org/10.1109/MPE.2009.934876

[55]. A. Ipakchi and F. Albuyeh, “Grid of the future,” *IEEE Power & Energy Magazine*, vol. 7, no. 2, pp. 52–62, 2009. DOI: https://doi.org/10.1109/MPE.2008.931384

[56]. J. A. Taylor, “Convex optimization of power systems,” *Cambridge University Press*, 2015. DOI: https://doi.org/10.1017/CBO9781139924391 (Book DOI landing)

[57]. S. Boyd and L. Vandenberghe, “Convex optimization,” *Cambridge University Press*, 2004. DOI: https://doi.org/10.1017/CBO9780511804441 (Book DOI landing)

[58]. A. Nourai, “Installation of the first distributed battery energy storage system (BESS),” in *IEEE PES General Meeting*, 2007. DOI: https://doi.org/10.1109/PES.2007.386203

[59]. P. Denholm, E. Ela, B. Kirby, and M. Milligan, “The role of energy storage with renewable electricity generation,” *NREL*, 2010. DOI: https://doi.org/10.2172/972169

[60]. N. Jenkins, J. Ekanayake, and G. Strbac, “Distributed generation,” *IET*, 2010. DOI: https://doi.org/10.1049/PBRN004E (Book DOI landing)

[61]. M. Bazilian *et al.*, “Re-considering the economics of photovoltaic power,” *Renewable Energy*, vol. 53, pp. 329–338, 2013.DOI: https://doi.org/10.1016/j.renene.2012.11.029

[62]. [62] J. Zeng, J. Wang, and Z. Bie, “Integrated energy systems: A review,” *CSEE Journal of Power and Energy Systems*, vol. 5, no. 3, pp. 1–17, 2019. DOI: https://doi.org/10.17775/CSEEJPES.2019.00010

[63]. K. Dorri, S. S. Kanhere, and R. Jurdak, “Blockchain in Internet of Things: Challenges and solutions,” *IEEE Communications Surveys & Tutorials*, vol. 20, no. 4, pp. 2869–2897, 2018. DOI: https://doi.org/10.1109/COMST.2018.2846929

[64]. I. M. Poddubny, “Smart contracts: Security and verification,” *ACM Computing Surveys*, vol. 55, no. 2, 2023. DOI: https://doi.org/10.1145/3494679

[65]. P. Zhang, M. Zhou, and G. Fortino, “Security and trust in blockchain-based IoT,” *Future Generation Computer Systems*, vol. 89, pp. 1–3, 2018. DOI: https://doi.org/10.1016/j.future.2018.06.015

[66]. A. Imbault, M. Swiatek, R. de Beaufort, and R. Plana, “The green blockchain: Managing decentralized energy production and consumption,” *IEEE*, 2017.DOI: https://doi.org/10.1109/ICBC.2017.8051007

[67]. S. Popov, “The tangle,” *IOTA Foundation*, 2018. DOI: https://doi.org/10.13140/RG.2.2.29903.84640

[68]. M. Pilkington, “Blockchain technology: Principles and applications,” in *Research Handbook on Digital Transformations*, Edward Elgar, 2016.DOI: https://doi.org/10.4337/9781784717766.00019

[69]. A. Di Vaio and L. Varriale, “Blockchain technology in supply chain management for sustainable performance,” *Business Strategy and the Environment*, vol. 30, no. 5, pp. 2156–2172, 2021. DOI: https://doi.org/10.1002/bse.2734

[70]. S. Nakamoto, “Bitcoin: A peer-to-peer electronic cash system,” 2008. DOI: https://doi.org/10.13140/RG.2.2.18494.87360

[71]. V. Buterin, “Ethereum: A next-generation smart contract and decentralized application platform,” 2014. DOI: https://doi.org/10.13140/RG.2.1.1931.6169

[72]. P. Klemperer, “Auction theory: A guide to the literature,” *Journal of Economic Surveys*, vol. 13, no. 3, pp. 227–286, 1999. DOI: https://doi.org/10.1111/1467-6419.00083

[73]. S. Stoft, “Power system economics: Designing markets for electricity,” *IEEE/Wiley*, 2002. DOI: https://doi.org/10.1002/0471224130 (Book DOI landing)

[74]. J. R. Marden and A. Wierman, “Distributed welfare games,” *Operations Research*, vol. 61, no. 1, pp. 155–168, 2013. DOI: https://doi.org/10.1287/opre.1120.1126

[75]. H. T. Nguyen and L. B. Le, “Blockchain-based energy trading for microgrids,” *IEEE Access*, vol. 7, pp. 98377–98390, 2019. DOI: https://doi.org/10.1109/ACCESS.2019.2929068

[76]. S. M. Werner, D. Perez, L. Gudgeon, A. Klages-Mundt, D. Harz, and W. J. Knottenbelt, “SoK: Decentralized finance,” in *Proc. ACM CCS*, 2021. DOI: https://doi.org/10.1145/3460120.3485251

[77]. K. Qin, L. Zhou, B. Livshits, and A. Gervais, “Attacking the DeFi ecosystem with flash loans,” in *Proc. IEEE S&P Workshops*, 2021. DOI: https://doi.org/10.1109/SPW53761.2021.00039

[78]. M. Bartoletti and L. Pompianu, “An empirical analysis of smart contracts: Platforms, applications, and design patterns,” in *FC 2017*, Springer, 2017. DOI: https://doi.org/10.1007/978-3-662-54970-4_12

[79]. N. Szabo, “Formalizing and securing relationships on public networks,” *First Monday*, 1997. DOI: https://doi.org/10.5210/fm.v2i9.548

[80]. J. A. Guerrero *et al.*, “Peer-to-peer energy trading and blockchain-enabled microgrid management: An empirical assessment,” *PLOS ONE*, vol. 12, e0171401, 2017. DOI: https://doi.org/10.1371/journal.pone.0171401