IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received 18 January 2024, accepted 29 January 2024, date of publication 31 January 2024, date of current version 8 February 2024.

*Digital Object Identifier 10.1109/ACCESS.2024.3360696*

RESEARCH ARTICLE

# Optimizing Microgrid Resilience: Integrating IoT, Blockchain, and Smart Contracts for Power Outage Management

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This work was supported in part by Amrita Vishwa Vidyapeetham, and in part by the Google Cloud Research Credits Programme under Award GCP19980904.

**ABSTRACT** Power outages can severely affect individuals, businesses, and communities, leading to disruptions, economic losses, and safety risks. The existing power recovery strategies often fail to adequately address the challenges associated with such outages. These challenges encompass a range of complexities, including resource allocation disparities, efficient prosumer integration, energy demand variability, and isolated generators. This paper presents a microgrid-centric power recovery strategy that leverages IoT, blockchain, smart contracts, and optimisation techniques for peer-to-peer energy sharing within the microgrid. The proposed strategy comprehensively addresses the challenges associated with the existing power recovery strategies. The paper outlines the system architecture for IoT and blockchain-enabled microgrids, discusses the mathematical modelling for energy sharing, and explores cost-optimal power restoration strategies. An incentive mechanism motivates prosumers to support restoration strategies during outages. Furthermore, the paper describes a blockchain smart contract facilitating peer-to-peer energy exchange in regions affected by power outages. This approach can mitigate the disruptive impact of power outages by providing reliable and community-centric power recovery solutions. Through validation with real-world data from our university's distribution grid test bed, Mean Time To Recover (MTTR) analysis and performance evaluations using the Hyperledger Caliper benchmark tool, this paper demonstrates its feasibility and effectiveness, paving the way for enhanced power recovery strategies and increased resilience in the face of energy disruptions.

**INDEX TERMS** Blockchain technology, Internet of Things, microgrid-centric approach, peer-to-peer energy exchange, smart contracts, power outage restoration.

## I. INTRODUCTION

Power outages can cause significant disruptions in electricity supply and affect various aspects of society, such as banking, communication, traffic, and safety. Such outages also have economic consequences, leading to reduced business operations, financial losses and the need to invest in backup systems. According to the World Bank, power outages cause annual losses of 4.4 billion dollars [1]. Frequent power outages in the United States have been reported to result in significant financial losses of approximately 1 million dollars per hour in one in four companies [2]. The existing power recovery strategies often fail to effectively address the challenges inherent in such outages. These challenges encompass a range of complexities, including Resource Allocation Disparities, Prosumer Integration, Energy Demand Variability, Microgrid Stability, Incentive Mechanisms and Isolated DERs. Mean Time to Recovery (MTTR) is one of the key metrics used in assessing the resilience of microgrid systems during power outages [3]. Table 1 shows the MTTR for power outages in different categories of cities in India during 2022-23.

The associate editor coordinating the review of this manuscript and approving it for publication was Ahmed M. Elmisery.


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**TABLE 1.** MTTR for power outages in different cities in india.

| S.No | Location | MTTR |
|---|---|---|
| 1 | All India average | 5 hours 28 minutes |
| 2 | Metro Cities | 26 minutes to 1 hour |
| 3 | Tier II Cities | 1 hour 15 minutes to 3 hours |
| 4 | Tier III Cities | 2 hours to 3 hours |
| 5 | Rural | upto 18 hours |

The table shows that the average MTTR for a power outage in India is 5 hours and 28 minutes. Metro cities exhibit the shortest MTTR, with power restoration typically occurring within 26 minutes to 1 hour. In contrast, rural areas face substantially longer recovery times, with MTTR extending up to 18 hours. Although advanced machine learning algorithms and data analysis enable the prediction and detection of power outages in large area distribution networks [4], [5], there is a critical need for a sustainable system that can support energy demands within outage areas. Peer-to-peer energy exchange can be a viable solution, provided fragmented lines are isolated and no faults exist in the remaining lines. This paper proposes a resilient outage restoration approach to quickly restore power to critical loads quickly. We leverage blockchain technology, smart contracts, optimisation techniques, and the Internet of Things (IoT) to achieve this.

Blockchain technology, originally introduced as part of the Bitcoin proposal in 2008 [6], provides an open, distributed, and decentralised ledger for secure transaction storage [7]. Nodes within the blockchain network participate in or validate transactions, while miners receive rewards for validation. Transactions are data transfers between entities, recorded in the blockchain ledger after successful validation [8].

The ledger, accessible to all network nodes, stores cryptographically encoded data linked to previous records, ensuring immutability. Consensus algorithms such as Proof of Work and Proof of Authority validate transactions. Smart contracts define transaction processing protocols, while cryptocurrencies are digital assets within the blockchain platform. We leverage the Ethereum platform, known for its performance and support for smart contracts and the Ether cryptocurrency [9], as demonstrated in our previous work [10], [11], [12], [13].

Integrating blockchain technology into the smart grid offers numerous advantages. It facilitates the seamless integration of renewable energy sources into the grid, enhancing energy efficiency and sustainability. Additionally, blockchain enables peer-to-peer energy trading, eliminating intermediaries and enabling new business models and market structures. When combined with IoT, blockchain improves grid security and reliability by allowing transparent and secure monitoring of electrical flow, helping to detect and prevent potential threats [14]. Blockchain IoT and smart contracts can automate energy supply management, ensuring reliable and secure grid operation [15].

We propose using IoT to collect real-time data from the smart meters installed at the consumer, prosumer, and DERs. The IoT system will collect and record the smart meter data to the blockchain ledger, thus ensuring immutable record keeping. The IoT system will also provide application programming interfaces (API) using which the prosumers, consumers and DERs can exchange information such as energy generation, usage and stored energy.

The microgrid is a self-sufficient hyperlocal community that generates and consumes electricity locally, primarily from renewable sources such as wind and solar [16], [17]. However, these microgrids often face power imbalance during generation shortfalls or low-demand periods. This paper proposes a peer-to-peer energy exchange system within a microgrid during a power outage. The system facilitates energy transfers by assuming uninterrupted distribution lines within the microgrid and leveraging existing grid infrastructure, such as distribution lines and controllers. The focus is on scenarios with higher consumer energy demand, particularly during critical load outages. We aim to utilise optimisation techniques to improve the power shared by prosumers, effectively supporting power demand during outages.

### A. KEY CONTRIBUTIONS OF THE PAPER

Our paper significantly addresses the challenges and gaps in microgrid management with resilience to outages, peer-to-peer energy exchange, and sustainable energy distribution. The key contributions of our work are as follows:

- We introduce a microgrid architecture, integrating IoT and blockchain, enabling peer-to-peer energy exchange during power outages.
- We develop microgrid-centric optimisation strategies to ensure reliable operations and efficient energy utilisation.
- We propose an incentive mechanism encouraging prosumers to actively support power restoration during outages without causing any burden on the microgrid.

### B. PAPER OUTLINE

The remainder of this paper is organised as follows. Section II delves into research similar to our proposed methods. Section III discusses the mathematical modelling of microgrids and introduces key entities involved in peer-to-peer energy exchange. Section IV outlines the problem we are solving in this paper. Section V describes the proposed system architecture. Section VI summarises the microgrid-centric strategies we have developed to restore power. Section VII explains the development and implementation of smart contracts on the Ethereum blockchain platform. Section VIII presents the numerical analysis of optimisation strategies and discusses the evaluation of smart contract performance. The paper is concluded in Section IX, which briefly discusses the limitations of the paper and its future scope.

## II. LITERATURE REVIEW

This section provides a comprehensive overview of previous research and relevant studies on the proposed system. This section also systematically reviews the literature on fault localisation, identification, restoration techniques, and blockchain technology in smart grids, highlighting the key findings and research gaps.

Fault location identification algorithms developed by Aly and El-Sayed [18] for smart grids in wind farms address system tripping caused by high power injection. The fault location algorithms based on wind power generation yield showed higher accuracy by comparing voltage and current signals at both ends of the power line. The simulation results demonstrated the effectiveness of the algorithms. However, their application to smart grids with multiple renewable and non-renewable sources remains untested.

An approach for black-out detection and response within smart grids was presented by Shahinzadeh et al. [19] through the integration of IoT and fog computing. The resilience of smart grids was improved by introducing an agile black-out detection and response paradigm by leveraging IoT-oriented initiatives, such as sensors and data collection devices, and integrating fog computing, which involves processing data closer to the data source. This combination enhances the efficiency and resiliency of black-out detection and response, ensuring minimal disruptions in power supply.

A microgrid architecture developed by Devidas and Ramesh [20] identifies and localises power theft incidents using smart meter data. The architecture includes renewable energy systems, distribution lines, transformers, and consumer loads, with smart devices deployed at common coupling points to transmit data to a central server. However, the proposed algorithm faces challenges, including increased communication cost, energy consumption, and latency with more smart devices. However, the system's effectiveness is compromised when a single point of failure occurs, suggesting the need for a decentralised architecture for improved functionality.

The fault localisation method in interconnected power transmission grids was proposed by Neethu et al. [21] using the discrete wavelet transform (DWT) and artificial neural networks (ANN). Combining DWT and ANN ensures an adaptive and accurate fault-locating scheme. The algorithms were deployed and tested on an IEEE nine-bus system using MATLAB/Simulink. The decision-making strategy devised by Xu et al. [22] restores the power grid in two steps with photovoltaic sources. The fault network is first isolated, and the renewable sources power the affected area in islanded mode. Then, power is restored by using the grid's additional power after fixing the faults.

An intelligent transmission line protection system Raj and Chandran [23] developed can detect faults, classify them, and identify their location using Artificial Neural Networks (ANN). The fault data set was generated through simulation by changing the fault parameters. A real-time model was developed for transmission line protection, which detects faults and turns off the circuit breaker to protect the system. The approach provides insights into predicting line outages and detecting multiple line failures in smart grids, highlighting the need to improve outage anticipation, power planning, and fault identification. However, a research gap remains in exploring fault location algorithms for smart grids with multiple renewable sources and developing decentralised architectures for improved functionality. Additionally, using artificial neural networks shows promise in fault localisation. At the same time, decision-making strategies for efficient power restoration and intelligent transmission line protection systems present innovative approaches to ensure grid reliability and stability. The fault location algorithms proposed in [18], [20], [21], and [24] can be combined with blockchain technology to improve fault identification and localisation. The blockchain can securely store and share fault data among relevant stakeholders, enabling real-time collaboration and faster resolution.

Blockchain technology is pivotal in reshaping the landscape of smart grids by revolutionising energy trading, enhancing grid security, and combating data tampering. Blockchain and cooperative game theory for peer-to-peer energy trading in smart grids, proposed by Moniruzzaman et al. [25], aims to maximise users' profit. Their proposed approach allows users to store renewable energy credits as an asset in the blockchain network and establish energy sharing with other users on the grid. Similarly, our proposed approach utilises blockchain technology but primarily concentrates on power restoration and outage resilience with minimal burden on the microgrid rather than profit maximisation. While the authors emphasise improving the proof of energy generation consensus algorithms and mining rewards, our work addresses the critical aspect of equitable resource allocation during power outages, which isn't directly tackled in their study.

The integration of emerging technologies such as Big Data Analytics, the Internet of Things (IoT), Artificial Intelligence (AI), and Blockchain in the context of transactive energy markets was discussed by Shahinzadeh et al. [26]. This paper's primary focus is to explore these technologies' potential in optimising energy trading and management, thereby contributing to more efficient and sustainable energy markets. The concepts presented in this paper align with the technological components of our proposed idea for optimising energy management within microgrids. The paper deals with large-scale energy markets, where numerous participants engage in energy trading, and the emphasis is on optimising these markets at a macro level. Our proposed idea is focused on a smaller scale, addressing microgrids' unique challenges and opportunities. It emphasises localised energy management and resilience during grid outages.

The application of blockchain technology and smart contracts to enhance the security of the Internet of Things

(IoT) was explored by Zanjani et al. [27]. Security challenges in IoT systems were also discussed, including data privacy, device authentication, and secure communication. Blockchain technology is proposed to enhance IoT security because it provides tamper-proof and transparent record-keeping. The paper and our proposed approach recognise the value of blockchain technology and smart contracts for IoT data sharing. The paper applies them to enhance IoT security. Our approach utilises blockchain and smart contracts for peer-to-peer energy exchange, leveraging IoT data and microgrid management during outages.

Near-real-time bilateral energy trading was proposed by Wang et al. [28] within a smart community. The proposed approach manages the supply and demand of the community without intermediaries using peer-to-peer energy trading. Smart contracts were developed for various processes such as grid initialisation, user registration, user negotiations, energy trading, power balancing, and settlements in peer-to-peer energy trading. A benchmark was conducted using the hyperledger caliper tool to understand the performance of the proposed approach in real-world scenarios. Our work optimises energy sharing during power outages within microgrids by emphasising the power restoration process during outages, aiming to minimise disruptions and ensure fair energy allocation.

Ethereum-based peer-to-peer bidirectional electric vehicle charging algorithms demonstrated by Kapoor et al. [10] use Ethereum virtual machines and smart contracts with fuzzy logic to manage energy balance in the power grid by harnessing the energy stored in electric vehicles.

Similarly, the Hyperledger blockchain platform performance was evaluated on a Raspberry Pi single-board computer by Mahesh et al. [29]. A cluster was set up using 6 Raspberry Pis, and the Hyperledger network was deployed using community-developed docker images. Our proposed system utilises the foundation laid by these studies but applies it uniquely to address power restoration and outage resilience.

A prosumer-centric framework proposed by Tushar et al. [30] for peer-to-peer energy trading using coalition formation games enable prosumers to form alliances and sell energy to the grid. Our work shares similarities in considering microgrid-centric trading but primarily emphasises outage resilience. Prosumers were classified according to the availability of energy storage. A case study conducted considering market size and energy demand demonstrates the effectiveness of their approach, revealing improved efficiency and cost savings compared to traditional trading methods. Our work extends beyond trading strategies to address power restoration during outages, which is not explicitly explored in the cited study.

The implementation and evaluation of a blockchain-based local energy market (LEM) in Walenstadt, Switzerland, demonstrated by Meeuw et al. [31], where 37 households trade energy using smart meters that run a private blockchain. The feasibility and scalability of a Byzantine fault-tolerant blockchain system under different bandwidth and validator settings were tested using a real-world microgrid setup. Communication networks with a bandwidth lower than 1000 kbit/s were unsuitable for operating a blockchain-managed microgrid and increasing the number of validators significantly reduces the throughput. The paper also provides guidelines and recommendations for utilities or grid operators interested in implementing LEMs based on blockchain technology.

A blockchain consensus model discussed by Hu et al. [32] for real-time distributed energy trading propose a consensus resource-slicing model that aims to improve the efficiency of energy trading by dividing the nodes into different domains. Blockchain-based decentralised virtual power plants for small prosumers were proposed by Cioara et al. [33] use smart contracts for registering a new prosumer, prosumer offering the energy to the grid, energy settlement, delivery tracking and financial settlement. The Ethereum platform was used to implement and validate the proposed system. Our work focuses on power restoration and outage resilience within microgrids, offering solutions for mitigating disruptions during grid disturbances. The research gaps identified from the literature are summarised below.

- Traditional approaches struggle to ensure appropriate allocation of energy resources during outages, potentially favouring specific microgrid segments [34], [35].
- Integrating prosumers into the grid poses unique challenges, as existing strategies may not effectively utilise their distributed energy resources [36], [37].
- Managing the fluctuating energy demand within a microgrid during outages is a challenge, as failures to predict and accommodate variations can lead to shortages or overloads [38].
- Designing incentive mechanisms to motivate prosumers without creating imbalances is intricate, balancing operational burden and prosumer participation [39], [40].
- Energy optimisations between buyers and sellers are primarily conducted off-chain, neglecting the potential benefits of utilising blockchain technology for contract validation and execution [30], [31].

To the best of our knowledge, our approach addresses a significant research gap that has not been explored extensively in the literature. Our paper focuses on a specific use case: peer-to-peer energy exchange within a microgrid during a power outage. We present microgrid-centric optimisation strategies that effectively balance power availability and consumption in outage situations. Our approach leverages the Internet of Things (IoT) to identify energy producers and consumers within the microgrid, monitor the generation and consumption, and use smart contracts to enable localised energy trading. This ensures that energy resources are efficiently allocated and used within the microgrid. We employ blockchain technology to facilitate secure and transparent peer-to-peer transactions, enhancing the overall reliability and trustworthiness of the proposed energy-balancing strategies.

## III. MATHEMATICAL MODELING OF THE MICROGRID

In this section, we introduce the key entities in the microgrid and discuss the mathematical modelling.

### A. MICROGRID ENTITIES

The proposed microgrid comprises entities such as Distributed Energy Resources (DER), Prosumers and Consumers. Each microgrid may contain a different combination of entities.

DER comprises solar photovoltaic systems and wind generators. The solar photovoltaic system works from 8 am to 6 pm with peak efficiency from 12 pm to 2 pm. The wind generator works throughout the day, and its efficiency depends on the wind conditions.

Prosumers produce their energy through rooftop solar photovoltaic systems and import energy from the microgrid if generation is insufficient. They also export excess energy to the microgrid. The efficiency of the energy produced by the prosumers depends on the weather conditions.

Consumers rely on microgrids, prosumers, or supporting services to meet their power needs. The microgrid provides electricity to consumers who do not generate electricity. Ancillary services support consumers, such as energy storage and load management.

### B. LEVERAGING IOT FOR REAL-TIME DATA COLLECTION AND CONTROL

The microgrid is equipped with IoT technology, enabling real-time data collection of energy statistics from all its entities and controlling the power flow. Illustrated in figure 1, our IoT middleware architecture, known as the Real-Time Data Collection and Control Unit (RTDCCU), orchestrates this data collection and power flow control seamlessly.

This architecture features a smart energy meter that captures parameters, including energy generation, consumption, and storage from all the entities in the microgrid. The data generated from the smart meter is first securely stored in a local database and subsequently committed to the Ethereum blockchain node, ensuring data integrity and transparency. The RTDCCU features a Power Flow Controller, which is crucial in rerouting power based on our optimisation strategy. The RTDCCU offers Application Programming Interfaces (APIs), allowing other entities to monitor power availability, consumption, storage, and generation status in real-time.

These APIs use a common data format called JavaScript Object Notation (JSON) to share information between different technologies. This format is widely accepted and works well with various systems [41]. The APIs are secured using Transport Layer Security (TLS) by implementing a public-private key combination [42]. TLS ensures a secure data transaction between different entities and technologies, protecting against data theft attempts, hijacking, and tampering [43]. This encryption protocol establishes a secure communication channel, encrypting data in transit and safeguarding the confidentiality and integrity of the exchanged information.

Two Decentralised Applications (DApps) run atop the Ethereum blockchain node within this framework. One DApp serves entity owners, providing them with a clear view of their energy parameters, while the other DApp is tailored for the grid operator, facilitating data visualisation and analysis. All entities function as edge nodes within this decentralised network, fostering seamless information sharing and collaboration.

### C. ENERGY BALANCE CONSENSUS IN THE MICROGRID

This paper introduces the Energy Balance Consensus, a consensus algorithm designed to validate the energy balance within a microgrid. By solving a mathematical equation, this algorithm ensures trust and agreement among the nodes in the blockchain network, verifying that power generation, consumption, and storage are in equilibrium, thus contributing to a stable and resilient microgrid.

Consider a microgrid ‘M’ consisting of ‘n’ consumers denoted as $C = c_1, c_2, \ldots, c_n$ and ‘n’ prosumers denoted as $P = p_1, p_2, \ldots, p_n$. The microgrid includes battery banks for auxiliary services denoted as $B = B_1, B_2, \ldots, B_n$. All entities within the microgrid are interconnected through distribution lines denoted $L = l_1, l_2, l_3, \ldots, l_n$. The DER generates power from solar and wind sources. Batteries store excess energy and discharge it during peak demand. The total power requirement of consumers in the microgrid is denoted as $P_c = P_{c1} + P_{c2} + \ldots + P_{cn}$. The power exported by all prosumers in the microgrid is denoted as $P_{pe} = P_{pe1} + P_{pe2} + \ldots + P_{pen}$. The power generated by the DER is represented as $P_{DER}$. The energy stored in the battery banks is indicated as $P_{BBi} = P_{BBi1} + P_{BBi2} + \ldots + P_{BBin}$, and the energy discharged from the battery banks is represented as $P_{BBd} = P_{BBd1} + P_{BBd2} + \ldots + P_{BBdn}$. Equation 1 illustrates the Energy Balance Consensus within the microgrid.

$$\Sigma[P_c + P_{BBi} - P_{pe} - P_{DER} - P_{BBd}] \tag{1}$$

The microgrid is balanced when the power generation is equal to the power consumption [44]. Equation 1 minimises the absolute value of the difference between the energy produced by prosumers, DERs, the energy consumed by consumers, and the energy stored and discharged from batteries. This distributed validation process involves the active participation of microgrid entities, accessing smart meter data through an Application Programming Interface [29]. Leveraging an IoT network and APIs enables efficient data collection, facilitating prompt consensus validation [45]. The algorithm 1 shows the steps in the energy balance consensus.

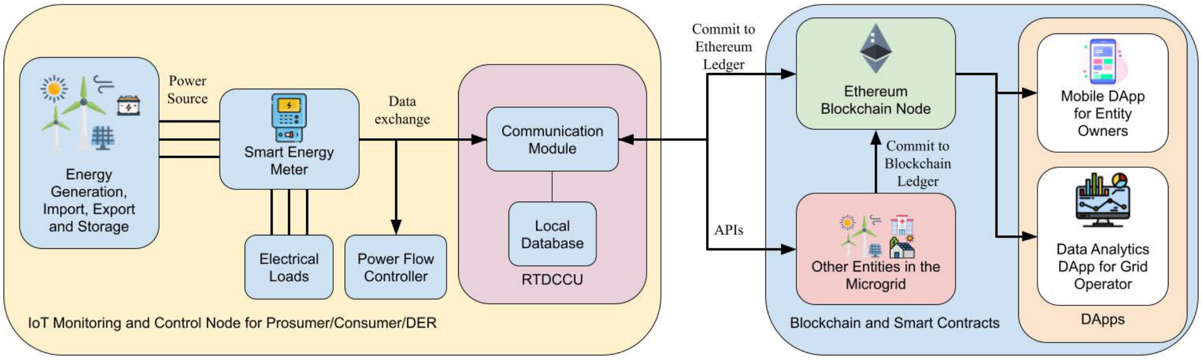


**FIGURE 1.** IoT for real time data collection and control unit.

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**Algorithm 1** Smart Contract to identify the number of entities in the microgrid and their power status

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**Inputs:** nP, nC, nDER, nBB
**Output:** $P_{Bal}$
**function** GET data from Smart Meter and Compute Export, Consumption, Generation and Storage(nP, nC, nDER, nBB)
  $P_e = P_{e1} + P_{e2} + \cdots + P_{en}$
  $P_c = P_{c1} + P_{c2} + \cdots + P_{cn}$
  $P_{DER}$
  $P_{BBi} = P_{BBi1}, +P_{BBi2}, \ldots, P_{BBin}$
  $P_{BBd} = P_{BBd1}, +P_{BBd2}, \ldots, P_{BBdn}$
  **return** $P_e, P_c, P_{DER}, P_{BBi}, P_{BBd}$
**function** Check Power Balance($P_c$,$P_{BBi}$,$P_{pe}$,$P_{DER}$,$P_{BBd}$)
  Compute: $P_{bal} = \Sigma[P_c + P_{BBi} - P_{pe} - P_{DER} - P_{BBd}]$
  **if** $P_{bal} == 0$ **then**
    Condition: Balanced
    **return** $P_{bal}$
  **else if** $P_{bal} < 0$ **then**
    Condition: Unbalanced; (Generation > Consumption)
    **return** $P_{bal}$
  **else if** $P_{bal} > 0$ **then**
    Condition: Unbalanced; ( Consumption > Generation)
    **return** $P_{bal}$

---

The *GET data from Smart Meter and Compute Export, Consumption, Generation, and Storage* function utilises the smart meter API to retrieve essential data, including energy consumption, energy generation, storage, and export from each entity within the microgrid. Subsequently, the function calculates the total energy generation, export, storage, and consumption, aggregating the data for comprehensive analysis and evaluation.

The *Check Power Balance* function accepts inputs including $P_c$ (consumer power), $P_{BBi}$ (battery charge power), $P_{pe}$ (prosumer power), $P_{DER}$ (distributed energy resource power) and $P_{BBd}$ (battery discharge power), and evaluates the power balance condition. The function outputs the variable $P_{bal}$ representing the power balance. The consensus algorithm is executed automatically whenever new readings are generated by the smart meters, typically within a 15-minute interval, ensuring real-time validation of the power balance.

#### 1) SAMPLE ENERGY BALANCE CONSENSUS VALIDATION WITHIN THE MICROGRID

Table 2 provides a consensus sample validation within the IoT-enabled microgrid. Condition 1 demonstrates a balanced system where generation matches consumption. However, in the other scenarios, a discrepancy between generation and consumption results in an unbalanced system, often encountered during microgrid outages. Our proposed system focuses on resolving the condition where generation is less than consumption (Condition 2), providing effective peer-to-peer power exchanges to optimise energy distribution. Addressing condition 3, where generation exceeds consumption, is considered for future work.

### D. TARIFF CALCULATIONS FOR PEER-TO-PEER ENERGY EXCHANGE BETWEEN PROSUMERS AND CONSUMERS IN THE MICROGRID

Traditionally, in power grids, consumer and prosumer tariffs are computed at the substation level over a designated period, typically 30 or 60 days, according to state policies [46]. Smart energy meters or net meters with SIM cards are commonly deployed for transmitting consumption and export data. Tariff calculations are automated, and the generated tariffs are sent to consumers and prosumers.

#### 1) TARIFF CALCULATIONS FOR PROSUMERS

The tariff for prosumers ($T_i$) in the microgrid is calculated using Equation 2. The prosumer tariff is based on the energy they export to the microgrid in kWh at time $t$ represented as $P_{ei}$, multiplied by the base tariff represented as $BT_p$. The base tariff for prosumers is Rs. 3 per unit of energy exported.

$$T_i = P_{ei} \times BT_p \quad (at \quad time \quad t) \tag{2}$$

**TABLE 2.** Sample energy balance consensus validation.

| S. No. | $P_c$ (kWh) | $P_{pe}$ (kWh) | $P_{DER}$ (kWh) | $P_{BBi}$ (kWh) | $P_{BBd}$ (kWh) | Total Generation (kWh) | Total Consumption (kWh) | Condition |
|---|---|---|---|---|---|---|---|---|
| 1 | 60 | 20 | 30 | 40 | 50 | 100 | 100 | Balanced |
| 2 | 20 | 30 | 10 | 20 | 30 | 70 | 40 | Unbalanced (Generation > Consumption) |
| 3 | 80 | 40 | 20 | 10 | 20 | 80 | 90 | Unbalanced (Consumption > Generation) |

#### 2) TARIFF CALCULATIONS FOR CONSUMERS

Our proposed consumer tariff is based on a slab system established by the Kerala State Electricity Board Limited in India ([47]). Consumer tariff ($T_j$) is determined by the amount of energy a consumer uses at a given time $t$ ($P_{cj}$), multiplied by the corresponding slab rate ($BT_c$). The consumer tariff equation is shown in Equation 3, and the tariff slabs are presented in Table 3.

$$T_j = P_{cj} \times BT_c \;\; (at \;\; time \;\; t) \tag{3}$$

**TABLE 3.** Tariff slabs considered for consumers([47]).

| Slabs (kWh) From | To | Base Tariff (INR) |
|---|---|---|
| 0 | 50 | 3.15 |
| 51 | 100 | 3.95 |
| 101 | 150 | 5.00 |
| 151 | 200 | 6.80 |
| 201 | 251 | 8.00 |
| 0 | 300 | 6.20 |
| 0 | 350 | 7.00 |
| 0 | 400 | 7.35 |
| 0 | 500 | 7.60 |
| | > 500 | 8.50 |

The tariff is structured in slabs, encouraging consumers to use electricity more efficiently while ensuring profitability for the microgrid.

## IV. PROBLEM DEFINITION

In a power outage, the microgrid 'M' becomes isolated from the main grid and may require additional energy or auxiliary energy contribution '$\delta$' to sustain itself without the main grid. Efficient distribution of this additional energy requirement among prosumers based on availability, cost, and restoration time is critical to ensure optimal power restoration. Thus, the problem can be defined as follows:

*To determine the optimal power restoration strategy that efficiently distributes the additional energy requirement among prosumers while minimising the cost burden on the microgrid.*

### A. RESEARCH OBJECTIVES

1) **Optimal Power Restoration Strategy:** Develop an optimal strategy for power restoration in a microgrid that efficiently distributes the additional energy available with the prosumers to consumers who require it during an outage situation.
2) **Cost Minimisation:** Develop a strategy to minimise the cost burden on the microgrid while ensuring efficient power restoration.

### B. RESEARCH QUESTIONS

The following research questions are designed to address the challenges and issues faced in maintaining energy balance in a microgrid during a power outage and finding efficient solutions to power outages.

1) How can the additional energy requirement be efficiently distributed among consumers within the isolated microgrid to optimise power restoration?
2) How can the prosumers be incentivised and the cost burden for the microgrid be minimised while maintaining energy balance?
3) How do microgrids communicate with consumers and prosumers to power outages and restoration scenarios?

### C. ASSUMPTIONS

Some of the assumptions for the proposed approach are as follows:

- Our proposed approach is designed primarily for post-outage scenarios, assuming a blackout detection system similar to the one discussed in [19] or another suitable system to support our approach.
- We assume that prosumers within the microgrid possess sufficient generation and storage capacity to meet their power requirements and can export surplus power to the grid.
- The microgrid's network topology, including the arrangement of prosumers, consumers, and distribution lines, is considered fixed after a power outage event.
- For our research, we assume that at least one prosumer is available within the microgrid during an outage situation.
- Our analysis operates under the assumption that power losses, such as transmission and distribution losses, can be considered negligible for the scope of our study.

These assumptions provide a simplified yet practical scenario for our optimisation problem and allow for a more streamlined solution. They also enable a comprehensive evaluation of system performance. Our proposed power restoration strategy involves reorganising isolated sections of the primary microgrid into microgrids comprising a small number of consumers and prosumers. In these microgrids, prosumers distribute surplus energy to consumers, enabling peer-to-peer energy sharing and utilisation.

## V. IOT AND BLOCKCHAIN-ENABLED PEER-TO-PEER ENERGY SHARING ARCHITECTURE

The architecture of the blockchain-enabled peer-to-peer energy-sharing system in a microgrid, as shown in Figure 2, uses smart contracts and optimisation strategies to maintain power balance during regular grid operation and power outage situations. This system comprises microgrid entities, IoT-enabled metering and monitoring devices (RTDCCU), blockchain ledger, cryptocurrency, and smart contracts.

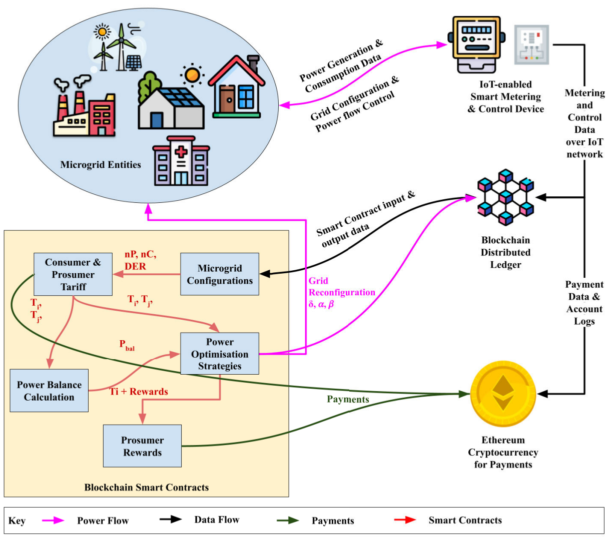



**FIGURE 2.** System architecture for blockchain-based P2P energy sharing in microgrid.

IoT-enabled smart energy meters with power flow controllers (RTDCCU) capture data such as power generated by prosumers, DER, consumer consumption, and energy storage generated from microgrid entities. The data collected by the IoT-enabled smart meters is recorded in the blockchain distributed ledger and broadcast to all entities in the microgrid. The smart meter can also control the power flow using contractors and relays.

This will enable routing power during peer-to-peer energy sharing. At each time interval $t$, a smart contract for the microgrid configuration calculates the number of prosumers ($nP$), consumers ($nC$), DERs, storage connections, power flow and tariffs for each entity. This paper considers a 15-minute calculation slot to simplify computation and optimise computing resources.

The system operates in two modes: power outage and regular grid operation. During the outage mode, the smart contract is invoked to compute the power balance. The smart contract checks all entities' generation and consumption. An optimisation strategy computes the additional power requirements and the reward for prosumers contributing to the power balance condition. Once the power transfer is completed, prosumers are rewarded using cryptocurrency. During the regular grid mode, the system computes and optimises the power balance. The system also calculates and collects tariffs from all entities in the microgrid. This architecture enables efficient and secure P2P energy sharing in microgrids, contributing to a sustainable and decentralised energy ecosystem.

## VI. POWER RESTORATION STRATEGIES: MICROGRID CENTRIC OPTIMIZATION MODEL FOR ENERGY BALANCE DURING OUTAGES

Outages are inherent in power grids, as they can occur unexpectedly at any time. While prosumers and distributed energy resources (DER) may be available to support during such outages, the key challenge lies in ensuring fair power allocation to consumers without imposing an excessive burden on the microgrid. The proposed microgrid-centric optimisation model addresses the fair distribution of power during outages, considering the availability of prosumers and DERs while maintaining the stability and reliability of the microgrid system.

During a power outage, the primary microgrid is divided into small microgrids, as shown in figure 3. Each microgrid may operate in island mode using the energy generated within the microgrids. The islanded microgrid may have one or more prosumers, consumers, and DERs. This ensures that power is still available to consumers.

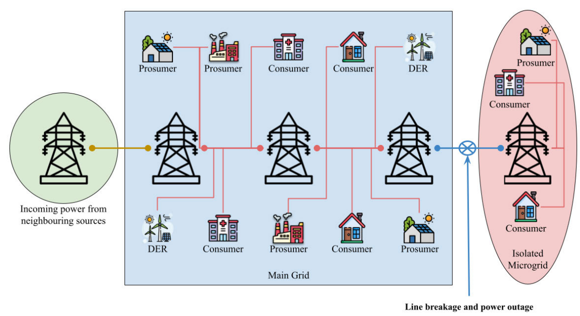



**FIGURE 3.** Primary microgrid split into small microgrids during outage scenario.

Consumption within the microgrid is assumed to remain constant, allowing the microgrid to focus on generating the required energy to meet demand. The microgrid considers the available energy from prosumers, consumer demand, and tariffs to optimise power generation and balance. This section discusses the energy balance strategies within a microgrid based on the limited energy availability, consumer demand, and tariff.

### A. CASE 1: PROSUMERS SHARE EXCESS ENERGY WITH CONSUMERS

In this case, we assume that all prosumers share the excess energy available with consumers. The optimisation function to calculate the energy balance is given in equation 4.

$$Min \sum_{i=1}^{n}[P_{ei} \times BT_p + \delta_i \times BT_p + \frac{\delta_i \times BT_p}{\sum_{i=1}^{n}(P_{ei}+\delta_i)} + \alpha_i \times \delta \times (BT_p)^2] \tag{4}$$

The non-linear optimisation equation minimises the total cost of electricity while ensuring that the energy demand of consumers is met without exceeding the available energy limit. In the equation, $P_{ei}$ represents the energy exported by the $i^{th}$ prosumer at time $t-1$, $BT_p$ is the base tariff for the prosumers, $\delta_i$ is the auxiliary energy contribution required by the $i^{th}$ prosumer at time $t$ to meet the demand under power outage conditions, $\alpha_i$ is the energy reduced from the consumption of the $i^{th}$ prosumer at time $t$ to meet the demand under energy outage conditions and $P_{ci}$ represents the energy consumed by the $i^{th}$ prosumer at time $(t-1)$.

The optimisation function is subject to the conditions mentioned in Equation 5 to Equation 13. In Equation 5, the term $\sum_{i=1}^{n} NT_i$ represents the total tariff paid by the microgrid to prosumers, while $\sum_{j=1}^{n} NT_j$ is the total tariff collected from consumers in the microgrid. The inequality constraint states that the total tariff paid to prosumers should be less than or equal that collected from consumers.

$$\sum_{i=1}^{n} NT_i \leq \sum_{j=1}^{m} NT_j \tag{5}$$

Equation 6 shows that the energy shared by all the prosumers ($\sum_{i=1}^{n} P_{ei}$) in the microgrid at time $t$ is greater than or equal to 0. Furthermore, the energy the prosumers share after an outage at time $t$ is greater than before the outage at time $(t-1)$.

$$\sum_{i=1}^{n} P_{ei} \geq 0 \quad and \quad \sum_{i=1}^{n} P_{ei} \;\; (at \;\; t) \; > \sum_{i=1}^{n} P_{ei} \;\; at \;\; (t-1) \tag{6}$$

Equation 7 shows that the energy required by all consumers ($\sum_{j=1}^{m} P_{cj}$) in the microgrid at time $t$ is greater than or equal to 0. Similarly, consumption during the outage at time $t$ equals before the outage at time $(t-1)$.

$$\sum_{j=1}^{m} P_{cj} \geq 0 \;\; and \quad \sum_{j=1}^{m} P_{cj} \;\; (at \;\; t) \;\; = \sum_{j=1}^{m} P_{cj} \;\; (at \;\; (t-1)) \tag{7}$$

Equation 8 represents an inequality constraint that ensures that the energy shared by the prosumers and the additional energy from the prosumers is greater than or equal to the total energy demand in the microgrid. In the equation, $\sum_{i=1}^{n}(P_i + \delta_i)$ is the additional energy shared by prosumers, while $\sum_{j=1}^{n} C_j$ is the total energy demand in the microgrid. With this condition, the microgrid can guarantee sufficient energy to meet the needs of all consumers.

$$\sum_{i=1}^{n}(P_i+\delta_i) \geq \sum_{j=1}^{m} C_j \tag{8}$$

Equation 9 represents an equality constraint that ensures that the energy generated by prosumers is equal to the energy exported, consumed and stored in their battery bank, with negligible losses. In the equation, $P_{Gi}$ represents the energy generated from renewable sources by the $i^{th}$ prosumer, $P_{ei}$ is the energy exported to the microgrid, $P_{ci}$ is the energy consumed by the prosumer, and $P_{Bi}$ is the energy stored in the battery.

$$P_{Gi} = P_{ei} + P_{ci} - P_{Bi} \tag{9}$$

Equation 10 is an equality constraint that shows how a prosumer can reduce their consumption ($P_{ci}$) in time $t$ by a factor of $\alpha$ times their consumption $t-1$, to generate the additional energy required for export ($\delta_{pci}$). $\alpha$ is a constant from 0 to 1, and the prosumer decides the value.

$$\delta_{pci} = \alpha \times P_{ci} \;\; where: \;\; 0 \leq \alpha \leq 1 \tag{10}$$

Equation 11 is an equality constraint that shows how the energy stored in a prosumer's battery ($P_{Bi}$) can be used to export to the grid. In the equation, $\delta_{pbi}$ represents the amount of energy the prosumer shares from their battery, and $\beta$ is the fraction of the stored energy used from the battery for exporting to the microgrid. By reducing their energy consumption and sharing the energy from battery storage, prosumers can contribute more energy to the microgrid and receive incentives.

$$\delta_{pbi} = \beta \times P_{Bi} \;\; where: \;\; 0 \leq \alpha \leq 1 \tag{11}$$

Equation 12 is an equality constraint that shows how the additional energy shared by prosumers ($\delta_i$) is equal to the sum of energy reduced from their consumption ($\delta_{pci}$) and the energy shared from their battery ($\delta_{pbi}$). The values for $\delta_i$, $\delta_{pci}$ and $\delta_{pbi}$ are greater than or equal to 0 for all prosumers, indicating that any energy reduction or share by the prosumer should not exceed their available energy capacity.

$$\delta_i = \delta_{pci} + \delta_{pbi}, \;\; where: \;\; \delta_i \geq 0, \; \delta_{pci} \geq 0 \;\; and \;\; \delta_{pbi} \geq 0 \;\; \forall \, i \tag{12}$$

Equation 13 represents an equality constraint that shows how the energy generated by the $i^(th)$ prosumer at time $t$ is equal to the sum of the additional energy shared by the prosumer at time $t$ ($P_{ei} + \delta_i$), the energy reduction at time $t$ ($P_{ci} - \alpha \times P_{ci}$), and the energy shared from their battery at time $t$ ($P_{Bi} - (1-\alpha) \times P_{Bi}$).

$$P_{Gi} \geq (P_{ei}+\delta_i) + (P_{ci} - \alpha_i \times \delta_i) - (P_{Bi} - \beta_i \times \delta_i) \tag{13}$$

### B. CASE 2: FEW PROSUMERS DO NOT HAVE SUFFICIENT POWER FOR SHARING

Once all prosumers' shares of the auxiliary units ($\delta$) have been determined and allocated fairly, the issue of prosumers backing off their initial commitments becomes significant. This case examines the strategies and mechanisms implemented to handle such instances, ensuring uninterrupted microgrid operation effectively. When certain prosumers cannot provide sufficient power due to poor generation or load requirements, the microgrid adjusts accordingly by excluding those prosumers and recalculating the power balance equation (4). Assuming P2 and P4 cannot share $\delta$, the objective function can be represented as shown in Equation 14.

$$Min \sum_{i=1,3,5} [P_{ei} \times BT_p + \delta_i \times BT_p + \frac{\delta_i \times BT_p}{\sum_{i=1}^{n}(P_{ei} + \delta_i)} + \alpha_i \times \delta \times (BT_p)^2] \tag{14}$$

By solving equation 14, we can obtain the precise value of the auxiliary units ($\delta$) that need to be obtained from other prosumers within the microgrid. This equation considers various factors discussed in the previous case to determine the auxiliary units from the prosumers. Both the models depicted in 4 and 14 exhibit high sensitivity to initial conditions, boundary conditions, and parameters $\alpha$ and $\beta$.

Our incentive mechanism is designed to encourage prosumers within the microgrid to contribute their energy resources during power outages actively. We have integrated a system of rewards into the optimisation strategy to motivate prosumers. Prosumers are offered fair compensation for the energy they provide during outages. This also depends on the energy source, such as power generated from DER and energy stored in batteries. The compensation is based on an equitable calculation as shown in 4 and 14, ensuring that prosumers are adequately rewarded for their contributions.

## VII. INTEGRATING MICROGRID-CENTRIC OPTIMIZATION STRATEGIES WITH SMART CONTRACTS ON ETHEREUM BLOCKCHAIN PLATFORM

This section discusses integrating the microgrid-centric optimisation strategies presented in the previous sections with smart contracts on blockchain. This integration enables the secure execution of peer-to-peer energy exchange, ensuring reliable and sustainable operation within the microgrid ecosystem.

Smart contracts are algorithms in the Ethereum platform that define the transaction execution process. The implementation of these smart contracts is achieved using the Solidity programming language.

### A. GRID INITIALISATION: SMART CONTRACT TO CLASSIFY ENTITIES IN THE MICROGRID

Grid Initialisation Smart Contract focuses on classifying entities within the microgrid as prosumers, consumers, or distributed energy resources (DER). This smart contract leverages the Internet of Things (IoT) technology to gather energy data from smart meters, allowing the assessment of total generation and consumption. The algorithm 2 shows the pseudo-code of the smart contract.

**Algorithm 2** Smart Contract to identify the number of entities in the microgrid and their power status

**Inputs:** nP, nC, nDER
**Output:** network configuration, Entity Power Data
**for** every t **do**
  **function** FindEntities(Input 1)
    NWConfig = arrange(nP,nC,nDER)
    **return** NWConfig
  **function**PowerData($NWConfig, P_{e_t}, P_{c_t}, P_{nBB_t}, P_{DER_t}$)
    $P_p = P_{e1_t} + P_{e2_t} \cdots + P_{en_t}$
    $P_c = P_{c1_t} + P_{c2_t} \cdots + P_{cn_t}$
    $P_{DER} = P_1DER_t + P_2DER_t \cdots + P_nDER_t$
    **return** $(P_p, P_c, P_{DER})$
  **function** TotalGeneration($P_p, , P_{DER}$)
    $P_{gen} = \sum_{j=1}^{n}[P_{DER} + P_{pj}]$
    **return** $P_{gen}$
  **function** TotalConsumption($P_c$)
    $P_{con} = \sum_{j=1}^{n}[P_{cj}]$
    **return** $P_{con}$
**Exit**

The primary input to the smart contract is the number of entities. The function *FindEntities* identifies the entities such as prosumers, consumers, and DERs in the microgrid and maps the network configuration. This function returns the network configuration (NWConfig variable), which we can use during other calls. The function *PowerData* computes the net power generation or consumption of each category of entities. The input to this function is the power consumption or generation of data from individual entities collected using IoT-enabled smart energy metres. The function returns the total power consumption and generation data variables ($P_p$, $P_c$, $P_{BBi}$, $P_{BBd}$, $P_{DER}$) of all entities categories. We can use the output variables in other function calls.

The function *TotalGeneration* compute the total power generation in the microgrid. The inputs to this function are the power data from entities such as DER and Prosumers. The function returns the total power generation variable ($P_{gen}$), which we can use in other calls. The function *TotalConsumption* computes the total power consumed by all consumers and returns the variable total power consumed ($P_{con}$).

### B. TARIFF COMPUTATION: SMART CONTRACT TO COMPUTE THE TARIFF FOR PROSUMERS AND CONSUMERS

Tariff Computation Smart Contract is designed to compute the tariffs for prosumers and consumers within the microgrid. The algorithm outlined in Algorithm 3 presents the pseudocode that drives the tariff computation process within the smart contract.

**Algorithm 3** Smart Contract to compute tariff for prosumers and consumers

**Input 1:** $P_i, P_{ei_t}$
**Input 2:** $C_j, P_{cj_t}$
**Output 1:** $T_i$
**Output 2:** $T_j$
**for** every t **do**
  **function** ProsumerTariff(Input 1)
    $T_i = P_{ei_t} \times BT_p$
    **return** $T_i$
  **function** ConsumerTariff(Input 2)
    $T_j = P_{cj_t} \times BT_c$
    **return** $T_j$
**Exit**

This smart contract has two functions, two inputs and two outputs. The function *ProsumerTariff* computes the tariff for the prosumers. The input to this function is the number of prosumers $(P_1, \ldots, P_n)$ and the power they export to the microgrid $(P_1 exp_t, \ldots, P_n exp_t)$. The output of this function is the tariff $(T_i)$.

The function *ConsumerTariff* computes the consumer tariff, and the inputs for this function are the number of consumers $(C_1, \ldots, C_n)$ and their power consumption $(P_1 imp_t, \ldots, P_n imp_t)$. The output of this function is the tariff $(T_j)$.

### C. OPTIMISATION HANDLER: SMART CONTRACT FOR THE MICROGRID-CENTRIC OPTIMISATION MODEL

The Optimisation Handler smart contract consists of two main functions. These smart contracts interact with the off-chain optimisation model and record the auxiliary energy unit values obtained after solving the blockchain. Algorithm 4 shows the pseudocode for the Smart Contract of the Optimisation Handler.

The smart contract has one input and four outputs. The algorithm initiates Step 1, where the optimisation function is defined. In Step 2, the constraints are set up. Step 3 solves the optimisation equation by employing the Python Scipy library's optimisation function with the Sequential least squares programming (SLSQP) option. Step 4 obtains the optimal auxiliary units $\delta, \alpha \& \beta$, the tariff, and the rewards. Finally, in Step 5, the algorithm returns the obtained results to the optimisation handler.

**Algorithm 4** Optimisation Strategies to minimise the total cost of energy obtained from prosumers to balance the power required by consumers in the microgrid

**Input:** $P_{ei}, P_{ci}, P_{cj}, BT_{Tp}$
**Output:** $\alpha, \delta, \beta, R_\delta + R_{extra}$
**function** OptimisationExecution(Input)
  **Step 1:** Define the optimisation function as follows:
  $Min \sum_{i=1}^{n}[P_{ei} \times BT_p + \delta_i \times BT_p + \frac{\delta_i \times BT_p}{\sum_{i=1}^{n}(P_{ei}+\delta_i)} + \alpha_i \times \delta \times (BT_p)^2]$
  **Step 2:** Set the following constraints:
  $\sum_{i=1}^{n} NT_i \leq \sum_{j=1}^{m} NT_j$
  $\sum_{i=1}^{n} P_{ei} \geq 0$ *and* $\sum_{i=1}^{n} P_{ei}$ $(at \;\; t) > \sum_{i=1}^{n} P_{ei}$ $at \;\; (t-1)$
  $\sum_{j=1}^{m} P_{cj} \geq 0$ *and* $\sum_{j=1}^{m} P_{cj}$ $(at \;\; t) = \sum_{j=1}^{m} P_{cj}$ $(at \;\; (t-1))$
  $\sum_{i=1}^{n}(P_i + \delta_i) \geq \sum_{j=1}^{m} C_j$
  $P_{Gi} = P_{ei} + P_{ci} - P_{Bi}$
  $\delta_{pci} = \alpha \times P_{ci}$
  $\delta_{pbi} = (1-\alpha) \times P_{Bi}$
  $\delta_i = \delta_{pci} + \delta_{pbi}$
  $P_{Gi} \geq (P_{ei} + \delta_i) + (P_{ci} - \alpha_i \times \delta_i) - (P_{Bi} - \beta_i \times \delta_i)$
  **Step 3:** Solve the optimisation problem using the Python Scipy Optimise Library using the Sequential Least Squares Programming (SLSQP) algorithm.
**Step 4:** Obtain the optimal auxiliary units $\delta$, $\alpha$ and $\beta$ to be shared by the prosumers and the rewards, $R_{pe_{t-1}}$ and $R_\delta + R_{extra}$.
**Step 5:** Return $\delta, \alpha, \beta, R_{pe_{t-1}}$ and $R_\delta + R_{extra}$ as output.

**function** OptimisationHandler(Output)
  Transact $\delta, \alpha, \beta, R_\delta + R_{extra}$ to ledger

### D. INTEGRATING OPTIMISATION STRATEGIES WITH SMART CONTRACTS

Ethereum smart contracts have limitations and do not support complex optimisation algorithms. To implement these algorithms alongside smart contracts, we must deploy them off-chain, i.e. outside the blockchain network. Web3 is a Python library to interact with Ethereum blockchain networks [48]. It provides a secure interface to deploy smart contracts on the Ethereum blockchain and interact with off-chain algorithms.

We developed a smart contract to gather and store data from the optimisation algorithm discussed in Algorithm 4 on the Ethereum blockchain. This smart contract integrates the off-chain optimisation strategy with the Ethereum blockchain platform. Using the Web3 Python library, we integrated the optimisation algorithms discussed in section VI with the smart contract. This enables us to achieve desirable results for power restoration in the microgrid using the energy from the prosumers. We illustrate the integration of optimisation algorithms with smart contracts in Ethereum using the Python Web3 library in Figure 4.

Figure 4 demonstrates how optimisation strategies can be integrated with Ethereum smart contracts using the Python Web3 library. We used the truffle suite to set up a local Ethereum test network, which provided ten Ethereum addresses and test tokens representing the entities in the microgrid. We deployed the smart contracts within this test network, and once deployed, Truffle provided the contract address and Application Binary Interface (ABI).

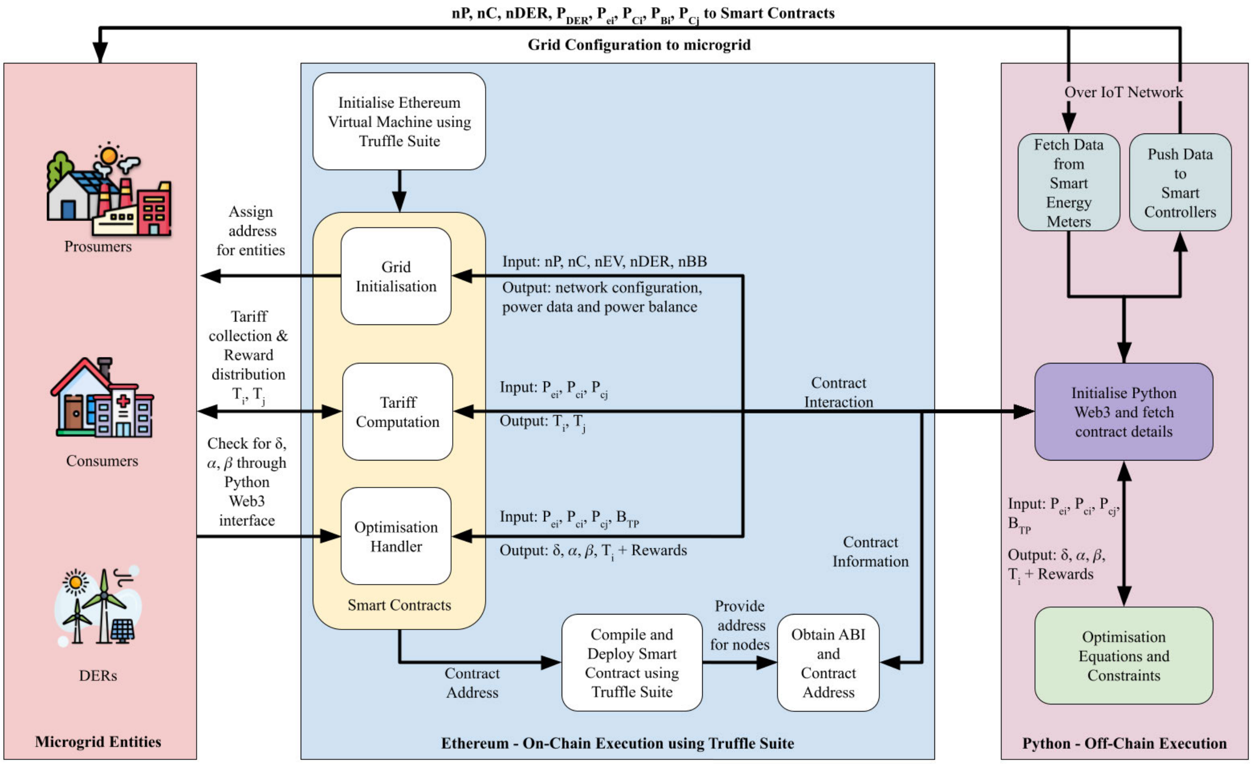



**FIGURE 4.** Integrating optimisation strategies with ethereum platform.

Using the deployed address and ABI, the Web3 library interacted with the smart contract to check the power balance using the data from the smart energy meter through the IoT network. If there was an imbalance in power, optimisation strategies were invoked with the necessary inputs, such as $P_{ei}$, $P_{ci}$, $P_{cj}$, and $B_{Tp}$. The optimisation algorithm optimised the energy balance and provided $\delta$, $\alpha$, and $\beta$. These auxiliary unit contributions were required for energy balance in the microgrid and passed back to the smart contract. After the energy exchange, the smart contract validated the energy balance and distributed the reward to the prosumers.

The UML sequence diagram, depicted in Figure 5, illustrates the interaction and message flow between key entities, including prosumers, consumers, smart contracts, the Ethereum blockchain, and off-chain optimisation. This diagram represents the system's communication and data exchange processes, highlighting the seamless integration of off-chain optimisation with blockchain-based smart contracts. The UML sequence diagram has three stages: Initialisation, Tariff Computation, and Optimisation Handler.

### 1) INITIALISATION

During the initialisation stage, the Ethereum blockchain platform assigns unique addresses to all entities participating in the microgrid. The smart contract, designed for energy transactions (as shown in algorithm 2), is deployed on the blockchain platform. As the system operates, energy data from consumers and prosumers is transmitted through the IoT network and recorded on the blockchain. The smart contract facilitates peer-to-peer (P2P) energy transfers between prosumers and consumers, ensuring direct exchanges within the microgrid. The smart contract actively monitors the power balance in the microgrid. It checks whether total energy production matches demand, ensuring a balanced and stable energy distribution within the network.

### 2) TARIFF COMPUTATION

The Tariff Computation stage calculates tariffs for the energy consumed by consumers and the energy exported by prosumers. Once the tariffs are calculated, the system collects consumer payments based on the units consumed. Simultaneously, payments are made to prosumers based on the units of energy they export. This process ensures a fair and transparent exchange of energy, where consumers are accurately billed for their consumption and prosumers are appropriately compensated for their contribution to the grid.

### 3) OPTIMISATION HANDLER

Optimisation Handler demonstrates the interaction between the Ethereum platform and an off-chain optimisation algorithm. The optimisation algorithm estimates the contribution of the prosumer's auxiliary energy unit to the microgrid, which supports the demand during a power outage. During this process, prosumers securely share their power data with the off-chain optimisation algorithm. The algorithm then

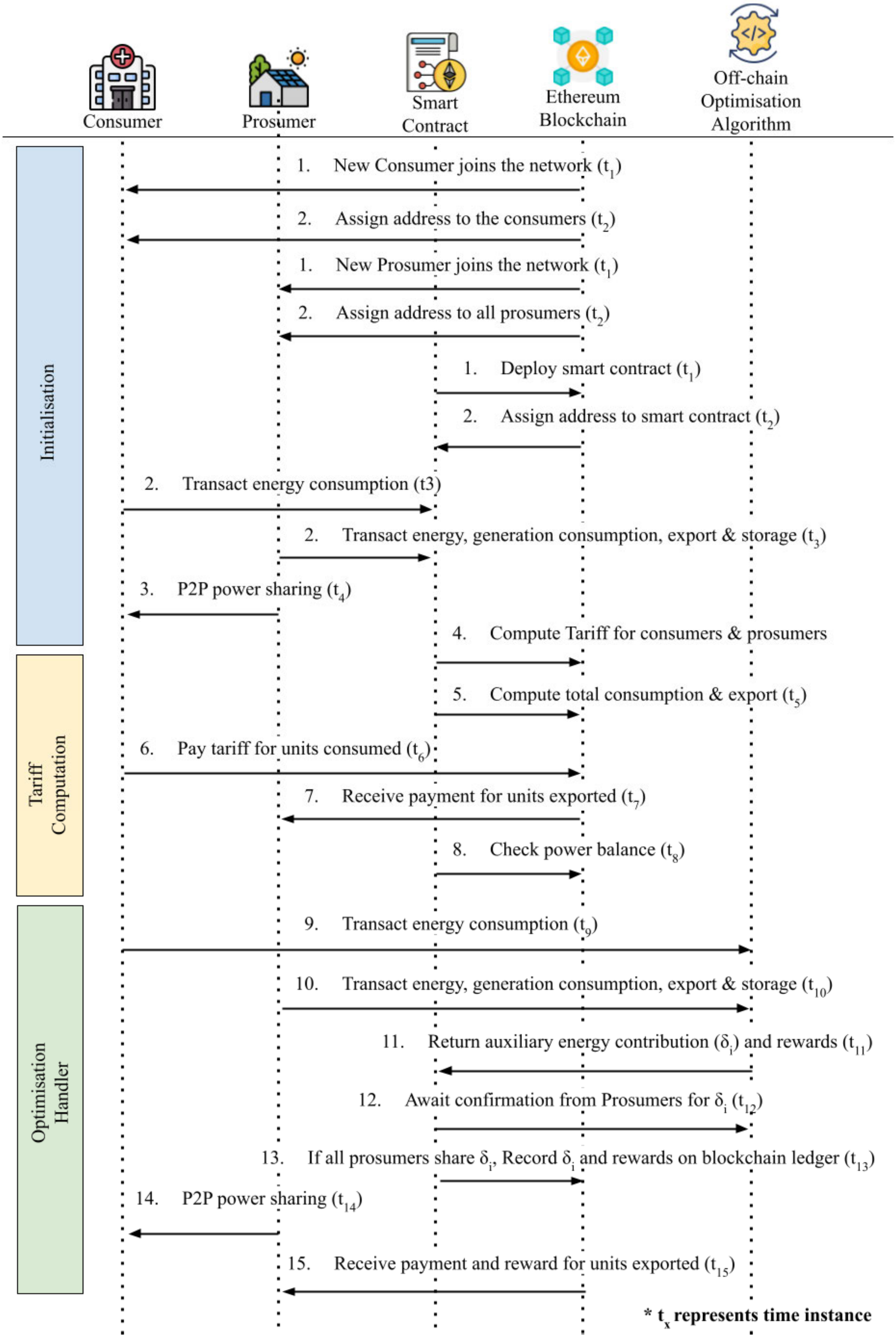



**FIGURE 5.** UML sequence diagram for blockchain based P2P power exchange in the microgrid.

computes the auxiliary energy contribution for each prosumer and communicates this information to the smart contract. The smart contract monitors peer-to-peer energy exchange and power balance and handles reward and tariff payments.

(a) Rooftop solar panel in Hostel block


(b) Mess Hall


(c) Sewage Treatment Plant

**FIGURE 6. Entities in the university's distribution grid testbed.**

## VIII. RESULTS AND DISCUSSIONS

In this section, we discuss the simulation results of the optimisation algorithm during outage conditions. We also analyse the performance of our Ethereum smart contract. We evaluated the effectiveness of our optimisation algorithms in achieving power balance in the microgrid and investigated the system's efficiency.

### A. SIMULATION RESULTS OF THE MICROGRID-CENTRIC OPTIMISATION MODEL DURING POWER OUTAGE CONDITIONS

In this section, we present the simulation of the optimisation model defined in the equations 4 to 13 and the simulation of the algorithm described in Section VII-D. The optimisation model simulation is performed with the data from the microgrid setup within the campus-level smart distribution network on the university campus [49] as shown in figure 7.

We built the simulation environment on our university campus smart distribution network testbed. The testbed encompasses a 13-node system that incorporates various key components, including the power source from the Kerala State Electricity Board (KSEB), university hostel buildings with rooftop solar panels, a sewage treatment plant, water pumps, solar-based Distributed Energy Resources (DER), and the mess hall. Within this system, the university hostel buildings play the role of prosumers, equipped with rooftop solar panels capable of generating electricity, which can be supplied to the microgrid. Meanwhile, other energy-consuming entities, such as water pumps, sewage treatment plants, and the mess hall, are consumers. Figure 6 shows some of the entities in the smart distribution grid testbed.

The connection topology of these entities is visually represented in Figure 7. Each entity has a Real-Time Data Collection and Control Unit (RTDCCU) responsible for collecting and disseminating real-time data, including information on energy generation, consumption, storage, and power routing control. In our simulation, we intentionally introduce faults, specifically between Node 3 and Node 4, as well as between Node 6 and Node 7. These simulated faults, depicted as red cross marks in Figure 7, effectively isolate the incoming power supply from KSEB and the Solar DER, creating an outage scenario.

Consequently, this fault simulation transforms the system into a microgrid configuration, with Node 7, Node 8, Node 9, Node 10, and Node 11 operating as prosumers, actively contributing energy resources, while Node 4, Node 12, and Node 13 continue to serve as consumers. Table 4 illustrates the mapping of microgrid entities within the simulation environment.

**TABLE 4. Mapping entities in the microgrid with simulation setup.**

| Simulation Environment | Entities |
|---|---|
| Node 7 | Prosumer 1 |
| Node 8 | Prosumer 2 |
| Node 9 | Prosumer 3 |
| Node 10 | Prosumer 4 |
| Node 11 | Prosumer 5 |
| Node 4 | Consumer 1 |
| Node 12 | Consumer 2 |
| Node 13 | Consumer 3 |

The primary objective of simulating this model is to ascertain each prosumer's optimal tariff and auxiliary energy contributions during power outage conditions. This insight is invaluable for designing efficient and resilient microgrid strategies, ensuring continued power supply despite disruptions.

In our simulation, we consider five prosumers and three consumers, each characterised by varying power export, power consumption, power generation, battery backup, and

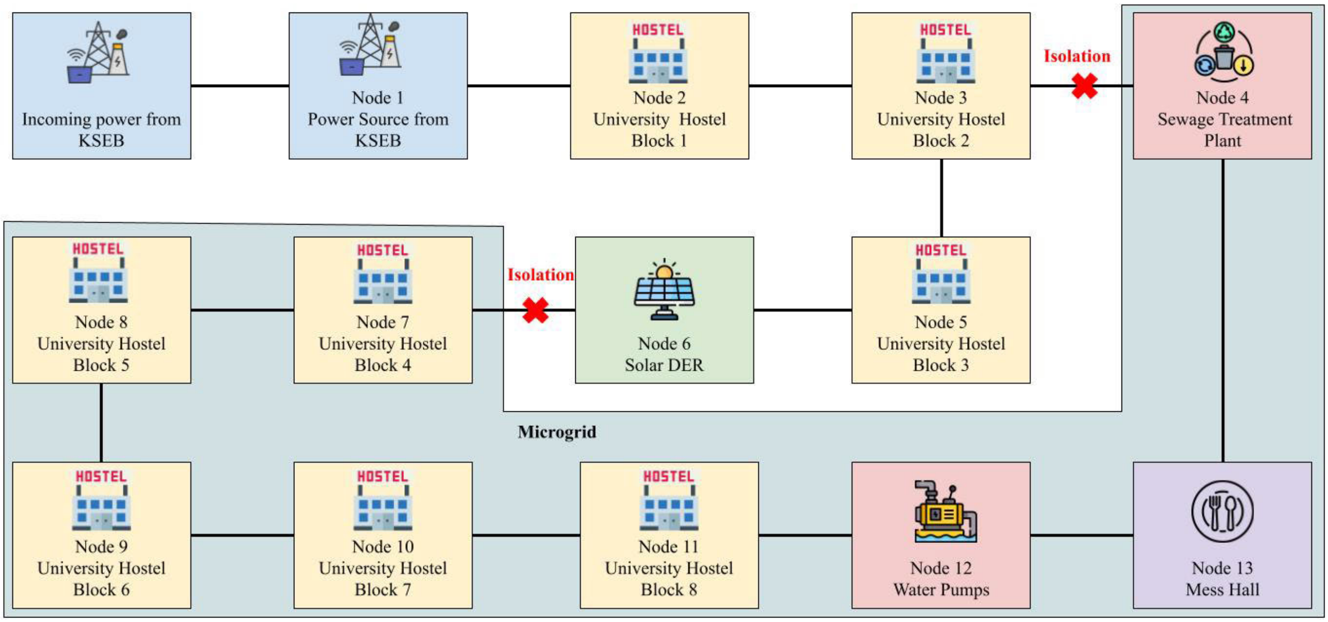



**FIGURE 7.** Simulation setup within the campus-level smart distribution network.

**TABLE 5.** Simulation parameters for microgrid-centric optimisation model for acquiring auxiliary energy contribution.

| Entities | Unit Exported (kWh) at (t-1) | Generation Units of Prosumers (kWh) | Stored Energy in Batteries of Prosumers (kWh) | Expected Energy Consumption at t (kWh) | Tariff/Rewards at (t-1) (INR) |
|---|---|---|---|---|---|
| Prosumer1 | 500 | 862 | 468 | 616 | 1500 |
| Prosumer2 | 200 | 883 | 485 | 928 | 600 |
| Prosumer3 | 300 | 648 | 513 | 533 | 900 |
| Prosumer4 | 150 | 1000 | 191 | 955 | 450 |
| Prosumer5 | 600 | 650 | 706 | 492 | 1800 |
| Consumer1 | Nil | Nil | Nil | 368 | 2706 |
| Consumer2 | Nil | Nil | Nil | 800 | 4550 |
| Consumer3 | Nil | Nil | Nil | 839 | 7132 |

tariff or reward structures. The values of all these parameters considered for the simulation are given in table 5. The reward optimisation model gives the auxiliary units $\delta$, expected from each prosumer based on the power outage condition, and also gives the auxiliary unit contribution from the remaining battery units and each prosumer's energy consumption reduction, $\beta$ and $\alpha$ respectively.

The results in figure 8 show the units of energy exported ($Pe_{t-1}$) in $t-1$ before the power outage and the distribution of the export of the auxiliary units among the prosumers after the power outage. The plot shows that the distribution of exported auxiliary units to meet demand is almost uniform, except for Prosumer 1 ($P1$) and Prosumer 2 ($P2$). There is a 14-unit reduction in the value of prosumer1 's $\delta$ and a 13-unit increase in the value of prosumer4 's $\delta$ compared to exporting all other auxiliary units of prosumers. The $Pe_{t-1}$ of $P1$ is comparatively high and its energy consumption is close to the average of all other prosumers. In the case of $P4$, $Pe_{t-1}$ is the lowest compared to all other prosumers, and the energy consumption is the highest. At the same time, the remaining battery units are the lowest compared to all other prosumers. The $\delta$ value for all other prosumers is uniform.

The simulation result shown in figure 9 shows the rewards provided to the prosumers for exporting energy units at $t-1$ before the power outage and the rewards provided for exporting auxiliary energy units after the power outage condition. $R_{extra}$ is the extra reward the prosumers are gaining other than $R_{t-1}$ and $R_\delta$ for the export of energy units after power outage. The table 6 shows the values of $\alpha$, $\beta$, $R_\delta$ and $R_{extra}$ for each prosumers. The export of auxiliary energy units is mainly from the remaining battery units. The gain $R_{extra}$ is predominantly based on $\alpha$. Since the $\alpha$ for prosumer4

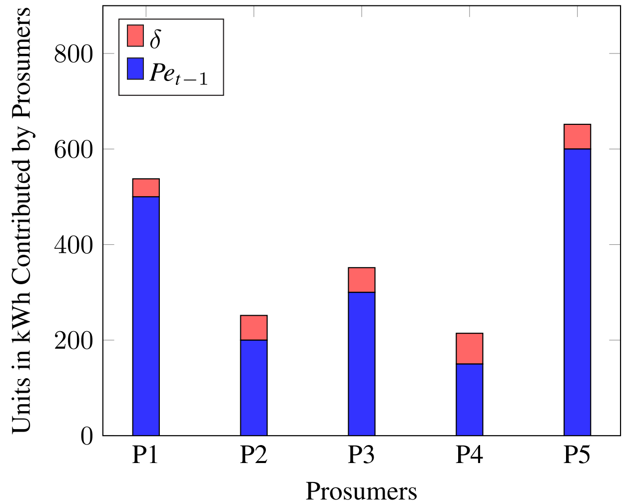



**FIGURE 8.** Energy export at (t-1) and expected auxiliary energy contribution after power outage.

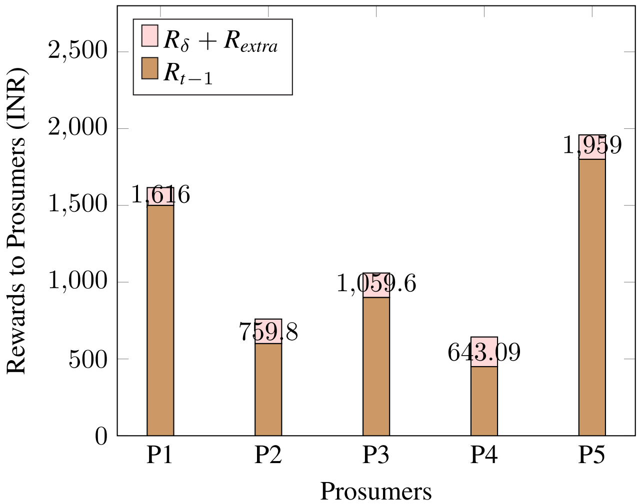



**FIGURE 9.** Rewards at (t-1) and rewards for the auxiliary energy units contribution after power outage.

is zero, the $R_{extra}$ of prosumer 4 becomes 0.0962 INR. For the other prosumers, 1% of their power consumption is reduced and contributes to $\delta$. So the extra rewards are higher for the other prosumers except for the prosumer 4. The total rewards for all prosumers are within the limit of the total consumer tariffs. Therefore, the simulation results shown in figure 9 and table 6, show that the optimisation model fairly allocates the expected auxiliary energy unit exports among the prosumers without burdening the microgrid.

For new consumers and prosumers joining the microgrid during or after a power outage, validating the optimisation model's results is crucial. To evaluate this, we introduced two additional consumers with consumption values of 780 and 480 units while keeping all other parameters consistent with the previous simulation case.

Figure 10 presents the results, showing the exported energy units ($Pe_{t-1}$) before the power outage and the distribution

**TABLE 6.** Rewards to prosumers and energy units contribution from battery and consumption to auxiliary energy units to meet the demand after power outage.

| Entities | $\alpha$ | $\beta$ | $R_\delta$ in INR | $R_{extra}$ in INR |
|---|---|---|---|---|
| Prosumer1 | 0.01 | 0.067 | 112.792 | 3.439 |
| Prosumer2 | 0.01 | 0.087 | 155.069 | 4.729 |
| Prosumer3 | 0.01 | 0.090 | 155.071 | 4.729 |
| Prosumer4 | 0 | 0.337 | 192.995 | 0.0962 |
| Prosumer5 | 0.01 | 0.066 | 155.071 | 4.729 |

of auxiliary units among prosumers after the power outage with the inclusion of new consumers. The plot indicates that the distribution of auxiliary units to meet the demand is not uniform. Prosumer2 ($P2$) and prosumer1 ($P1$) contribute the highest $\delta$ values, while prosumer4 ($P4$) contributes the lowest $\delta$ value contribution. Prosumer3 ($P3$) and prosumer5 ($P5$) exhibit similar contributions of value $\delta$.

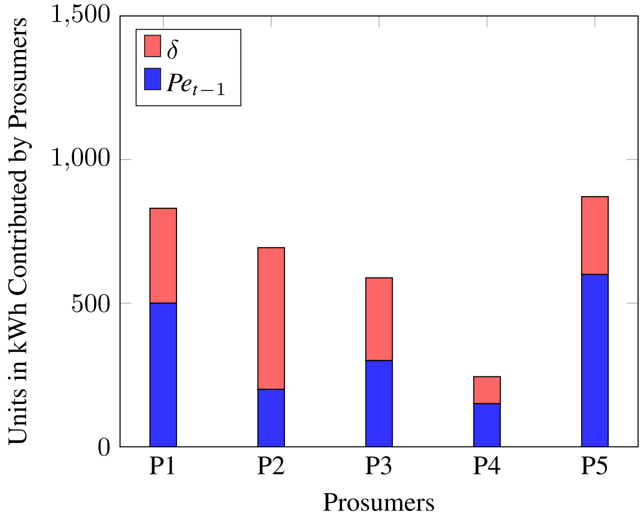



**FIGURE 10.** Energy export at (t-1) and expected auxiliary energy contribution after power outage with new consumers.

Figure 11 displays the simulation results, showing the rewards offered to prosumers for exporting energy units before and after the power outage. Prosumer2 received the highest reward, while prosumer4 received the lowest based on their contributions to the demand of the microgrid during outages. Table 7 presents the values of $\alpha$, $\beta$, $R_\delta$, and $R_{extra}$ for each prosumer after the addition of new consumers. The allocation of auxiliary energy unit exports and corresponding rewards demonstrates the effectiveness of the optimisation model. Prosumers 1 and 2 reduce consumption, increasing $R_{extra}$. Prosumers 3 and 5 distribute exports between consumption reduction and remaining battery, resulting in similar $R_{extra}$. The simulation confirms that the optimisation model efficiently allocates auxiliary energy units without burdening the microgrid, maintaining the total export from prosumers in line with consumer demand of 3227 units after the power outage condition.

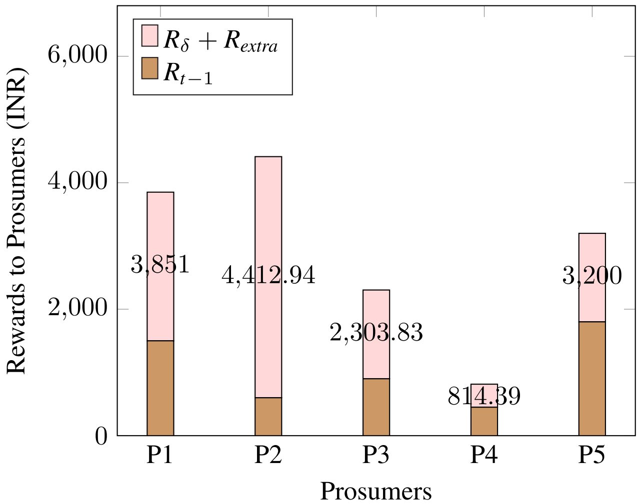



**FIGURE 11.** Rewards at (t-1) and rewards for the auxiliary energy units contribution after power outage with new consumers.

**TABLE 7.** Rewards to prosumers and energy units contribution from battery and consumption to auxiliary energy units to meet the demand after a power outage with new consumers.

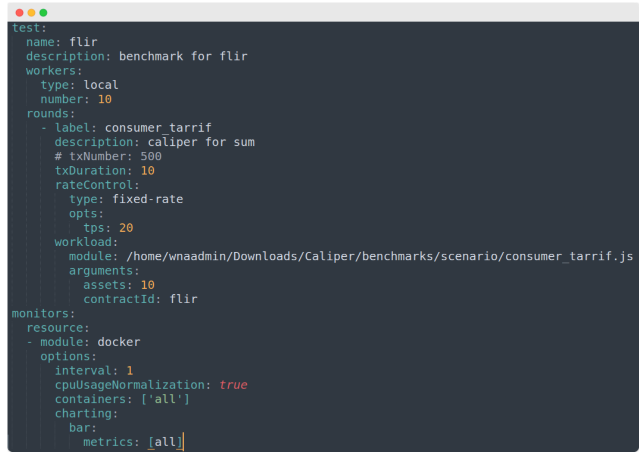
| Entities | $\alpha$ | $\beta$ | $R_\delta$ in INR | $R_{extra}$ in INR |
|---|---|---|---|---|
| Prosumer1 | 0.46 | 0.105 | 991.463 | 1359.759 |
| Prosumer2 | 0.53 | 0.012 | 1479.931 | 2333.011 |
| Prosumer3 | 0.21 | 0.35 | 864.59 | 539.233 |
| Prosumer4 | 0.09 | 0.01 | 282.457 | 81.934 |
| Prosumer5 | 0.24 | 0.22 | 812.553 | 587.711 |

### B. SMART CONTRACT BENCHMARK USING HYPERLEDGER CALIPER

Hyperledger Caliper (HC) is a benchmarking tool to evaluate the performance of blockchain platforms such as Hyperledger Fabric, Ethereum, Hyperledger Besu, and FISCO BCOS. HC benchmarks a smart contract based on the parameters such as transaction throughput, latency, and CPU utilisation and RAM usage. We used HC to evaluate the performance of the smart contract deployed on the Ethereum test network. The performance test help us evaluate the reliability and robustness of the smart contracts under different test conditions.

To initiate the benchmark test, it is necessary to configure the benchmark configuration files and the benchmark scenarios. Figure 12 provides an overview of the configuration utilised for the smart contract performance test, showcasing the settings and parameters chosen for the benchmarking.

The configuration file consists of three main modules. The first module, labelled "test" in the figure, includes essential details such as the name and description of the benchmark. The second module, "worker", defines the type and number of working nodes employed in the benchmark. By default, the worker type is set to "local", indicating that a local node operates within the test environment. The worker



```yaml
test:
  name: flir
  description: benchmark for flir
  workers:
    type: local
    number: 10
  rounds:
    - label: consumer_tarrif
      description: caliper for sum
      # txNumber: 500
      txDuration: 10
      rateControl:
        type: fixed-rate
        opts:
          tps: 20
      workload:
        module: /home/wnaadmin/Downloads/Caliper/benchmarks/scenario/consumer_tarrif.js
        arguments:
          assets: 10
          contractId: flir
monitors:
  resource:
  - module: docker
    options:
      interval: 1
      cpuUsageNormalization: true
      containers: ['all']
      charting:
        bar:
          metrics: [all]
```

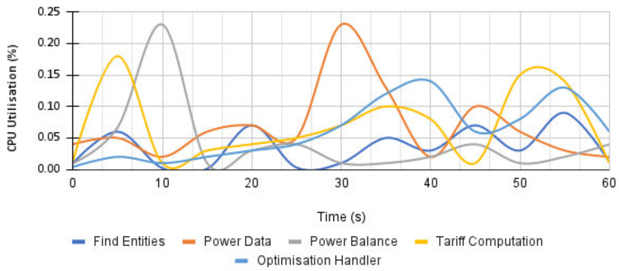
**FIGURE 12.** Benchmark configuration file for hyperledger caliper.

number signifies the total number of workers processing the benchmark.

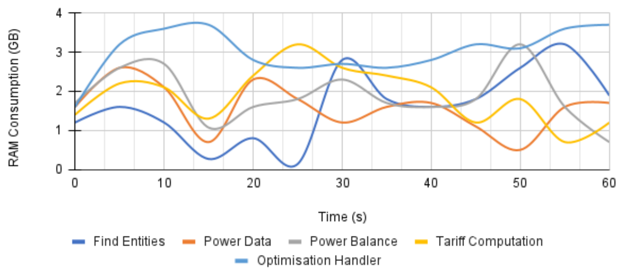
The subsequent module, titled "rounds", is an array that encompasses various parameters essential for benchmarking. These parameters include the label and description, which serve as brief identifiers and workload descriptions. The "txNumber" denotes the total number of transactions submitted during each round, while "txDuration" represents the duration, in seconds, for each transaction. The "rateControl" parameter, also an array, specifies the rate at which transactions are entered into the blockchain network. In this particular benchmark, a fixed-rate control strategy is employed with a rate of 20 transactions per second (TPS). The "workload" module, an array within the "rounds" module, contains specific information on the smart contract and the corresponding test inputs.

Additionally, the "monitor" module captures crucial resource utilisation parameters, such as CPU utilisation (in percentage) and RAM usage (in GB). These parameters enable monitoring of resource consumption during the benchmark, providing insights into the smart contract's performance characteristics and resource requirements. Our benchmark test consists of five functions. Figure 13 shows the benchmark results by showcasing a graph of performance metrics obtained from Hyperledger Caliper. The figure shows four key parameters: CPU, RAM, latency, and throughput. The benchmark was conducted over 60 seconds, capturing the performance metrics at regular intervals of 5 seconds.

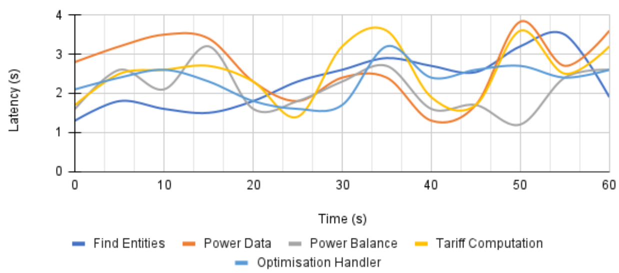
The first parameter, CPU, represents the CPU utilisation expressed as a percentage, which indicates the amount of computational resources consumed during the benchmark. We can understand how efficiently the smart contract utilises the available processing power by monitoring CPU utilisation. The second parameter, RAM, denotes the usage of Random Access Memory (RAM) measured in gigabytes (GB). RAM usage reflects the memory consumption of the smart contract during the benchmark. The third parameter, latency, represents the response time or the time taken for



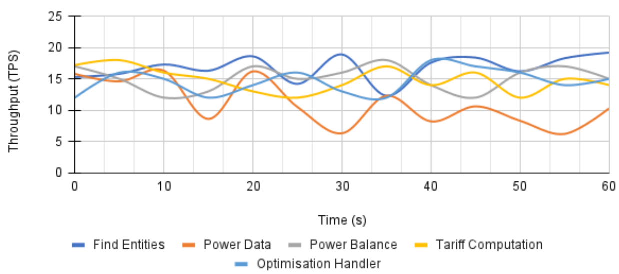

(a) CPU Utilisation (%)




(b) RAM Consumption (GB)




(c) Latency (s)




(d) Throughput (TPS)

**FIGURE 13. Performance metrics from hyperledger caliper.**

a transaction to be processed by the smart contract. It measures the delay or lag experienced by transactions during execution. Lower latency values indicate faster transaction processing.

The fourth parameter, throughput, signifies the number of transactions processed per unit of time, expressed as transactions per second (TPS). Throughput measures the smart contract's processing capacity, indicating how many transactions it can handle within a given timeframe. Higher throughput values indicate greater transaction processing capabilities. Table 8 summarises the benchmark results under various test conditions. It presents the average values for CPU utilisation, RAM usage, latency, and throughput.

The results of the benchmarking tests indicate that our smart contract is highly robust, with minimal resource usage in terms of CPU, memory, and data. The total average CPU utilisation is 0.05% and RAM usage is 2.03 GB. Additionally, the Hyperledger Caliper tool rigorously assessed the reliability and robustness of the smart contract by subjecting it to rigorous stress tests, significantly increasing the load through dynamic variations in input parameters and a diverse range of worker scenarios. Despite the increased load, the latency and throughput of the smart contract were found to be minimal, indicating that it can handle a large number of transactions in a short period. The total average latency is 2.38 seconds, and throughput is 14.52 TPS. These findings suggest that our smart contract is well-suited for power restoration and P2P energy sharing applications, where reliable and secure transactions are essential.

### *C. MEAN TIME TO RECOVERY (MTTR) ANALYSIS FOR THE PROPOSED MICROGRID-CENTRIC POWER RESTORATION SYSTEM*

Ensuring the resilience and reliability of the power distribution systems depends on effectively restoring power. The Mean Time to Recovery (MTTR) is a crucial measure for evaluating the effectiveness of power restoration procedures [50]. This section analyses the MTTR for our proposed power restoration system. The MTTR evaluation offers insights into the system's responsiveness and capacity to minimise downtime during power outages. The MTTR analysis was conducted using the campus-level smart distribution network data.

- **Pre-Outage (t-2):** In this phase, the microgrid is in the normal operation. It includes system monitoring, load forecasting, tariff and optimisation processes. The optimisation algorithm operates every 5-minute time window in this phase to optimise power allocation, distribution and energy balance.
- **Outage (t-1):** The outage phase indicates the presence of a power interruption. During this phase, the system undergoes an induced power supply outage. The main power grid is disconnected. The outage duration is recorded as it directly impacts the overall MTTR. In our approach, the RTDCCU system can detect the outage in under 5 seconds.
- **Recovery (t):** The recovery phase focuses on restoring power supply to consumers affected by the outage, utilising the energy available from prosumers within the isolated area. Our approach employs the microgrid-centric optimisation strategy to analyse the energy requirement in the microgrid. The optimisation algorithm requires less than 1 second to process the energy requirements from the consumers ($\sum_{j=1}^{n} P_{cj}$), energy that a prosumer can share ($\delta$) and the incentives for the additional power the prosumer shares ($R_\delta$). However in different test scenarios with large scale power grid,

**TABLE 8.** Performance metrics and resource utilisation for smart contracts benchmarked using hyperledger caliper.

| Function | Total Transactions | CPU (%) | RAM (GB) | Latency (s) | Throughput (TPS) |
|---|---|---|---|---|---|
| FindEntities | 1640 | 0.033 | 1.6 | 2.28 | 16.80 |
| PowerData | 1590 | 0.067 | 1.57 | 2.68 | 11.09 |
| PowerBalance | 1400 | 0.041 | 1.87 | 2.10 | 15.15 |
| TariffComputation | 2100 | 0.068 | 1.89 | 2.53 | 14.86 |
| OptimisationHandler | 1280 | 0.060 | 3.05 | 2.33 | 14.61 |
| Total | 8010 | 0.05 | 2.03 | 2.38 | 14.52 |

the optimisation algorithm may take maximum of 2 seconds to estimate the parameters. The smart contract and P2P energy-sharing mechanisms handle the tariff management and energy distribution during this phase to expedite power restoration. The smart contract takes 3 seconds, and P2P energy-sharing mechanisms take 60 seconds to control the power flow and restore the power supply to affected consumers.

MTTR is calculated from the time of outage to full recovery. Equation 15 [51] shows the formula to calculate the MTTR for the proposed system, where N is the number of outages.

$$MTTR = \frac{\sum_{i=1}^{N} \left[Outage_{(t-1)_i} + Recovery_{(t)_i}\right]}{N} \tag{15}$$

The calculated MTTR value for our proposed microgrid-centric power restoration strategy in the simulated environment is determined based on the individual time components mentioned above. This analysis yields an understanding of our system's resilience in power outages. By solving equation 15 for one outage instance, the proposed power restoration system, with an MTTR of 19 seconds, exhibits remarkable responsiveness in addressing the resiliency of power outages. However, real-world MTTR may vary due to the complexities inherent in operational power grids. Factors such as system complexity, the number of prosumers and consumers, geographical considerations, and external contingencies can introduce variability in outage response times.

### D. CHALLENGES AND LIMITATIONS

Despite the potential benefits, the proposed strategy has challenges and limitations. One of the main challenges is the scalability of blockchain technology. The Ethereum blockchain platform used in this paper can only handle a limited number of transactions per second. This could be a problem for a large-scale microgrid with more prosumers and consumers with high electricity demand [52]. The Ethereum platform also has limitations for data storage. Implementing the proposed approach on a large scale would require addressing scalability concerns. This could involve exploring alternative blockchain platforms or layer-2 scaling solutions like sidechains or state channels that can handle a higher throughput of transactions [53]. The feasibility of such solutions depends on the available infrastructure and the willingness of stakeholders to adopt them. Interplanetary File System (IPFS) is a distributed ledger technology that can be integrated with the blockchain platform for better data storage [54]. IPFS-based databases such as Orbitdb can be used for real-time data from various entities [55]. Integrating IPFS or IPFS-based databases like Orbitdb can be technically feasible for the proposed system. If data storage and accessibility are critical for monitoring and managing the microgrid effectively, then IPFS integration could be a practical solution. Similarly, P2P data exchange has some limitations regarding the type and size of the data. When a node needs to exchange large chunks of data, it can be used using the IPFS Pubsub protocol [56]. The IPFS Pubsub protocol provides a decentralised and efficient way to distribute data across a network, making it a suitable solution for overcoming data type and size limitations. Enhancing P2P data exchange with IPFS Pubsub could be practical and beneficial if the microgrid regularly deals with large datasets. This integration leads to better real-time monitoring and decision-making within the microgrid.

### E. PRACTICALITY OF IMPLEMENTING THE PROPOSED APPROACH IN REAL-WORLD SCENARIOS

While our research outlines a theoretical approach to address a specific problem, we recognise that real-world implementation often involves additional complexities and considerations. Here are some key points to consider regarding the feasibility and practicality of our proposed approach:

1) Our research presents a foundational framework that offers adaptability and customisation capabilities. When implementing our proposed approach in real-world scenarios, it is essential to tailor the methodology to align with the targeted microgrid or energy system's specific requirements, infrastructure, and regulatory frameworks. This customisation ensures that the approach effectively addresses each context's unique challenges and objectives.
2) Implementing advanced technologies, such as IoT, blockchain, and smart meters, may require significant investments in infrastructure and technology. The readiness of these technologies in a given region or context would impact feasibility.

3) Successful implementation of our proposed method often necessitates collaboration and engagement with diverse stakeholders, including energy providers, regulatory bodies, prosumers, and consumers. The active involvement of these stakeholders is vital to address their concerns, align interests, and ensure the seamless integration of our approach into existing energy systems.
4) Although the MTTR for the proposed system is 19 seconds in the simulated environment, it could be slightly more in the real-world system due to the complex nature of the power grid. The distribution line losses and power system synchronisations must be counted during energy exchange between multiple consumers and prosumers in the isolated area.

## IX. CONCLUSION

The microgrid-centric power restoration strategy proposed in this paper utilises the Internet of Things (IoT), blockchain, smart contracts, and optimisation strategies for peer-to-peer energy exchange during power outages. The paper presents the mathematical modelling of the microgrid, discussing optimisation strategies to manage energy balance during outages. The proposed microgrid-centric power restoration strategy provides a robust solution to address the challenges commonly faced in an isolated microgrid, such as resource allocation disparities, prosumer integration, and demand management. The proposed strategy ensures continuous operation even during grid disruptions by using locally available power sources to manage energy demands. This enhanced resilience minimises the inconvenience and losses experienced during power outages. Restoration strategies employ a microgrid-centric cost-optimal model, ensuring fair allocation of auxiliary units from prosumers without burdening the microgrid. This approach prevents disproportionate energy burdens on individual prosumers and ensures equitable distribution, fostering a sense of community and cooperation.

Blockchain-based smart contracts for peer-to-peer energy exchange include an incentive mechanism. Prosumers are motivated to contribute their energy resources during outages, knowing they will receive fair compensation. These incentives encourage active participation and help maintain energy balance. The proposed approach addresses the technical aspects of power outage management and introduces a promising business model for prosumers within the microgrid. Prosumers, previously passive electricity consumers, can now become active participants in the energy marketplace. They can contribute excess energy during outages, turning their surplus electricity into a valuable asset. During power outages, they can offer excess energy to the grid, earning compensation through blockchain-based smart contracts. This opens a new revenue stream for individuals, small businesses, and even larger communities.

Evaluation using the hyperledger caliper benchmark tool validates the efficiency of the approach in peer-to-peer energy exchange during outages. The smart contract consumes minimal resources and has better latency and transactions per second. The average CPU utilisation is 0.05%, and RAM usage is 2.03GB. The latency and transaction per second are 2.38s and 14.52 TPS. Our Mean Time To Recovery (MTTR) analysis indicates that in a simulated environment, the proposed approach could restore power to consumers within 19 seconds following an induced outage. These results reinforce the system's efficiency in minimising downtime and enhancing resilience in power restoration.

### A. FUTURE SCOPE

Our ongoing work focuses on developing a user interface with real-time visualisation and integrating a Non-Fungible token-based reward mechanism. These enhancements aim to enhance user engagement and incentivise sustainable energy practices. In future, we plan to extend our system to include other utilities and category-wise energy exchange allocation, fostering a more comprehensive and sustainable microgrid ecosystem. We are actively exploring load optimisation algorithms that dynamically adjust load allocations based on real-time demand patterns. This approach aims to reduce conservativeness while maintaining the required reliability levels. We are also investigating resource efficiency measures that can help maximise the utilisation of available resources without compromising system stability. These measures aim to strike a balance between conservativeness and efficiency.

## ACKNOWLEDGMENT

The authors would like to thank the university's chancellor, the staff, and the faculty members for supporting them in preparing this article.

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