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Energy Management and Edge-Driven Trading in Fractal-Structured Microgrids: A Machine Learning Approach

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Abstract: The integration of renewable energy into residential microgrids presents significant challenges due to solar generation intermittency and variability in household electricity demand. Traditional forecasting methods, reliant on historical data, fail to adapt effectively in dynamic scenarios, leading to inefficient energy management. This paper introduces a novel adaptive energy management framework that integrates streaming machine learning (SML) with a hierarchical fractal microgrid architecture to deliver precise real-time electricity demand forecasts for a residential community. Leveraging incremental learning capabilities, the proposed model continuously updates, achieving robust predictive performance with mean absolute errors (MAE) across individual households and the community of less than 10% of typical hourly consumption values. Three battery-sizing scenarios are analytically evaluated: centralised battery, uniformly distributed batteries, and a hybrid model of uniformly distributed batteries plus an optimised central battery. Predictive adaptive management significantly reduced cumulative grid usage compared to traditional methods, with a 20% reduction in energy deficit events, and optimised battery cycling frequency extending battery lifecycle. Furthermore, the adaptive framework conceptually aligns with digital twin methodologies, facilitating real-time operational adjustments. The findings provide critical insights into sustainable, decentralised microgrid management, emphasising improved operational efficiency, enhanced battery longevity, reduced grid dependence, and robust renewable energy utilisation.

Keywords: streaming machine learning (SML); Hoeffding trees; renewable energy; microgrid; battery size optimization; adaptive energy management; battery lifecycle; digital twin; grid dependence; real-time forecasting

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1. Introduction

Efficient energy management in modern power systems is crucial for maintaining grid stability, enhancing renewable energy utilisation, and minimising environmental impact. However, the increasing integration of renewable energy sources, particularly solar power, introduces significant challenges due to their inherent variability and intermittency. These fluctuations result in concept drift, a phenomenon in machine learning where the statistical properties of energy generation and consumption patterns evolve unpredictably over time [1]. Traditional static machine learning models struggle to maintain accuracy in such dynamic environments because they are trained on historical data and are not equipped to adapt to ongoing changes. To address these challenges, this research explores the application of streaming machine learning (SML) algorithms to optimise energy management in microgrids. Unlike conventional models, SML continuously updates its predictive models as new data becomes available, ensuring that forecasts remain accurate and relevant in rapidly changing scenarios [2,3].

Previous research has applied SML to microgrid forecasting and control tasks; however, these studies typically focus on centralised configurations or static learning approaches. The novelty of this research lies in its specific exploration of incremental real-time learning algorithms—particularly Hoeffding Trees—in decentralised residential microgrids, explicitly addressing dynamic consumption and generation patterns at the household scale.

The incremental learning capability of SML is particularly advantageous in energy systems characterised by fluctuating supply and demand. By updating models incrementally rather than retraining them from scratch, streaming algorithms adapt to changes efficiently, maintaining high predictive accuracy even as other external factors influence consumption and generation patterns. This adaptability is essential for ensuring appropriate real-time decision-making, enabling energy management systems to respond promptly to sudden shifts in demand and supply [4]. Additionally, streaming models are designed to be computationally lightweight, requiring less memory and processing power compared to traditional batch learning methods. This efficiency makes them ideal for deployment in decentralised environments such as microgrids, where computing resources may be limited but real-time decision-making is critical [5].

By integrating streaming analytics into existing energy management frameworks, this research introduces a novel approach to real-time optimisation, enabling intelligent control of power generation, storage, and consumption. This integration allows for dynamic adjustments based on immediate energy availability and demand, enhancing the efficiency of battery storage management and reducing dependency on central grid power. Furthermore, the capability to process continuous data streams supports grid-edge trading, which involves dynamically redistributing or storing surplus solar power for later use. This not only maximises renewable energy utilisation but also minimises the need for grid imports, thereby promoting energy independence and reduction in grid losses [6].

As suggested earlier, the dynamic nature of SML makes it particularly suitable for environments where energy consumption and generation are highly variable, such as residential microgrids dependent on solar power. These systems must continuously adapt to changes in weather conditions, user behaviour, and other external influences impacting energy availability and demand. By enabling real-time forecasting and adaptive control mechanisms, SML enhances the responsiveness of localised energy systems. In residential settings, where consumption typically comprises both base loads (essential demand) and discretionary loads (flexible or deferable demand such as heating, cooling, or electric vehicle charging), this adaptability provides significant opportunities for load shifting and demand-side management. Such capabilities significantly improve load balancing and grid reliability, ensuring a stable and efficient power supply even under fluctuating conditions. In this context, Hoeffding Trees [7] and ensemble methods are particularly effective, as they support fast, incremental learning and robust decision-making. These methods have demonstrated high accuracy in predicting short-term fluctuations in solar power generation and electricity usage, thereby minimising reliance on external power sources for residential microgrids [8].

In addition to enhancing forecasting accuracy, SML also facilitates the automation of energy management processes. By continuously learning from new data, the models can automatically adjust control strategies to optimise energy flows in real time. This includes making intelligent decisions about when to store surplus energy in batteries, when to discharge stored energy to meet demand, and when to engage in grid-edge trading to maximise economic benefits. The ability to autonomously manage power generation, consumption, and storage supports the development of decentralised, self-sustaining energy networks. These networks operate independently of traditional grid infrastructures, making them ideal for isolated or remote communities that rely on renewable energy sources. By reducing dependency on centralised power grids, such systems contribute to greater energy security and resilience, especially in regions prone to grid outages or supply disruptions [4,8,9].

As energy systems become more complex and interconnected, the need for adaptive, real-time solutions becomes increasingly critical. This research provides a scalable and flexible framework that can be adapted to various energy management scenarios, demonstrating the transformative impact of machine learning on modern power systems.

In Section 2, the key challenges related to temporal energy imbalances within microgrids are identified, traditional static energy management methodologies are critiqued, and SML as a viable real-time adaptive solution is introduced. Section 3 then describes the proposed fractal architecture framework for intelligent energy management, detailing its hierarchical structure, the integration of SML for forecasting and adaptive control, and the implementation of three scenario-based battery sizing strategies: centralised, decentralised (distributed), and a hybrid approach. Following this, Section 4 provides a comprehensive comparative evaluation of energy management and forecasting strategies, highlighting the predictive accuracy of the SML model, the effectiveness of adaptive control mechanisms, the reduction in grid dependency, and improvements in battery lifecycle management. Section 5 summarises the findings, emphasising practical implications, contributions toward sustainable and resilient microgrid operations, and future research opportunities.

2. Adaptive Energy Management in Smart Microgrids

While the introduction highlighted the strategic value of SML for managing the dynamic nature of renewable-powered microgrids, this section explores the complexities of temporal energy imbalances, critiques the limitations of conventional energy management approaches, and proposes SML as a viable solution for real-time adaptive energy management in smart microgrids.

2.1. Challenges of Temporal Energy Imbalances

Microgrids, characterised by their decentralised nature and integration of renewable energy sources, face inherent fluctuations in both energy production and consumption. Renewable sources such as solar and wind are inherently variable, leading to periods of surplus and deficit within short time frames. Traditional Net-Zero Energy models, which focus on achieving an annual balance between energy production and consumption, fail to address these short-term discrepancies [10]. As a result, microgrids may experience frequent transitions between importing energy from the main grid and exporting excess energy back to it, leading to operational inefficiencies and increased dependency on the central grid.

The main challenge lies in the temporal mismatch between energy generation and consumption. For instance, peak solar generation occurs during the day, which may not align with peak consumption periods in residential areas. This misalignment necessitates the need for effective energy storage solutions and real-time management strategies to ensure a continuous and reliable energy supply. Moreover, frequent charging and discharging cycles of battery storage systems, prompted by these imbalances, can lead to accelerated wear and reduced lifespan of the storage infrastructure [11].

2.2. Limitations of Conventional Energy Management

Conventional energy management systems (EMS) in microgrids predominantly utilise static models that rely heavily on historical data to forecast energy demand and generation.

These models are built on predefined rules and statistical patterns observed over extended periods, assuming that future energy behaviours will closely mirror past trends. While this approach provides a foundational understanding of consumption and generation patterns, it is fundamentally limited in its ability to respond to real-time fluctuations and unforeseen changes in energy dynamics. This limitation becomes particularly pronounced in fractal microgrids, which comprise a hierarchical network of self-similar nodes which operate autonomously, and local variations in energy flow can significantly impact overall system stability [12].

In fractal microgrids, energy generation and consumption are highly localised and vary across different hierarchical nodes. This decentralised structure enables localised decision-making and promotes energy exchange between nodes. However, it also introduces significant variability in energy flows due to differences in solar exposure, local load demands, and storage capacities at each node. Static prediction models, which are generally built on aggregated historical data, fail to capture these localised variations, leading to inaccurate forecasts and suboptimal energy management decisions [13].

Moreover, in a fractal architecture, energy flows between nodes are highly dynamic, with nodes exchanging surplus energy or drawing power based on real-time conditions. Static models lack the adaptability needed to account for these inter-node dependencies, resulting in inaccurate load balancing and inefficient resource allocation. For instance, if one node experiences excess solar generation while a neighbouring node faces a deficit, static models may fail to identify this imbalance in real time, leading to unnecessary grid imports or wasted renewable energy [14].

A critical challenge that further undermines the effectiveness of static models is concept drift, where the statistical properties of energy consumption and generation change over time [15]. In the context of fractal microgrids, concept drift can occur due to seasonal variations, changes in user behaviour, and the intermittent nature of renewable energy sources. These dynamic patterns introduce non-stationarity into energy flows, making it challenging for static models to maintain accurate predictions. In fractal microgrids, where local nodes experience unique patterns of generation and consumption, concept drift is even more pronounced. Static models, which rely on the assumption that patterns in the data remain constant over time, are ill-equipped to handle these changes, leading to degraded performance and reduced prediction accuracy over time [16].

Figure 1 summarises the sequential limitations inherent to static energy management systems within fractal microgrids. Starting from suboptimal resource allocation, these deficiencies cascade into inaccurate load balancing and reliance on outdated historical data, ultimately resulting in significant prediction inaccuracies due to unaddressed local variations and concept drift. This cyclical illustration emphasises the necessity of transitioning from static methodologies toward adaptive machine learning models for effective energy management.

Given these challenges, there is a growing consensus on the need for adaptive energy management systems capable of learning from evolving data streams and adjusting to real-time changes. In fractal microgrids, where energy flows are decentralised and highly variable, SML emerges as a promising solution. These algorithms are designed to handle data in motion, continuously updating their parameters to reflect the most recent patterns.

This capability is particularly beneficial for fractal architectures, where energy flows are asynchronous, and local nodes operate autonomously. SML offers several key advantages over static models, such as updating models continuously as new data arrives and also maintaining accurate predictions even under dynamic conditions [17].

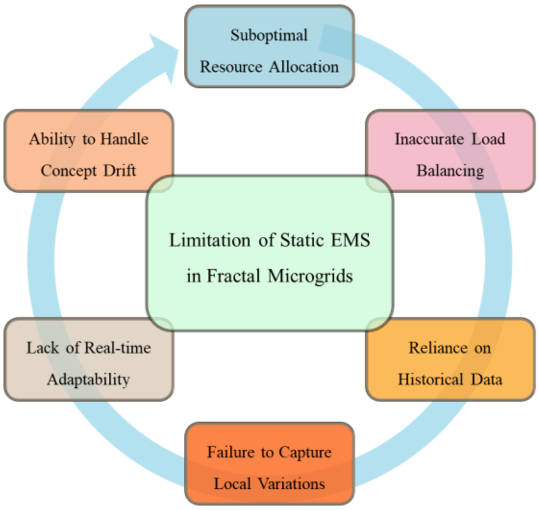


Figure 1. Limitations of static energy management systems in fractal microgrids.

2.3. Streaming Machine Learning for Real-Time Adaptation

Given the challenges of temporal energy imbalances and the limitations of traditional energy management systems discussed earlier, SML presents a viable adaptive solution, offering the flexibility and scalability essential for managing dynamic conditions in decentralised renewable energy systems. Unlike batch learning models that rely heavily on historical datasets, SML algorithms incrementally process incoming data, continuously updating their models. This incremental learning capability allows them to maintain high predictive accuracy in rapidly changing environments typical of microgrids powered by renewable energy sources such as solar and wind.

One of the core strengths of SML is its ability to handle concept drift—changes in the statistical properties of data over time—common in microgrids due to seasonal variations, changes in user behaviour, weather conditions, and integration of new renewable sources [17,18]. For instance, residential microgrid energy consumption patterns may shift due to household routines, appliance upgrades, or unforeseen events, reducing the effectiveness of static prediction models. Algorithms like Hoeffding Trees and Adaptive Random Forests, central to SML, are specifically designed to detect and respond to these dynamic shifts by updating predictions incrementally [18]. This ensures sustained accuracy even as energy generation and consumption patterns evolve [1].

By integrating SML into microgrids, operators can perform real-time decision-making to optimise adaptive energy management strategies. Accurate, real-time forecasting of energy production and consumption guides critical operational decisions, including timing for battery storage charging or discharging and engaging in grid-edge trading [19]. For example, microgrids utilising solar power generation can predict short-term solar availability using SML, enabling proactive storage of surplus energy or intelligent interaction with the main grid. This approach optimises both energy utilisation and economic benefits, ensuring continuous power availability while minimising reliance on external power sources.

Moreover, real-time adaptability via streaming algorithms directly contributes to optimising battery storage efficiency. Traditional battery management approaches often suffer inefficiencies due to temporal mismatches in energy generation and consumption cycles. SML-driven forecasts allow microgrids to better synchronise battery operations with actual real-time demands, significantly reducing battery wear and extending storage system lifespans [20]. Additionally, the lightweight and computationally efficient nature of streaming models supports effective deployment even in resource-constrained microgrid environments.

Finally, integrating SML into microgrid systems enhances the capability for efficient grid-edge trading, facilitating dynamic interaction with the central grid. Microgrids can optimise trading decisions based on continuous real-time data streams, ensuring energy exchanges occur at the most beneficial times, thus improving economic returns and overall energy efficiency [21]. Ultimately, SML represents a transformative approach, significantly enhancing the resilience, sustainability, and autonomy of microgrids, promoting smarter and more adaptable energy infrastructures.

3. Fractal Architecture for Intelligent Energy Management

This research introduces a fractal architecture framework that employs SML to achieve dynamic and intelligent control, marking a significant evolution from traditional fractal modelling techniques. By integrating self-similar structures, this framework enables scalable and decentralised management across various operational levels, from individual households to extensive community networks. Each node within this hierarchical system can autonomously perform local energy exchanges and engage in grid-edge trading, enhancing distributed and adaptive control through localised decision-making.

The integration of SML into the fractal architecture significantly enhances its capabilities by enabling real-time predictive analytics and adaptive control mechanisms across the energy management system. Local nodes use these capabilities for immediate responses to fluctuations in energy demand and supply, ensuring efficient operations at the micro-level. Concurrently, higher-level nodes aggregate insights from the grassroots to orchestrate comprehensive energy management strategies across the grid. This establishes a robust multi-level learning hierarchy that enhances decision-making efficacy and system resilience.

The concept of temporal energy balance is central to maintaining stability within the fractal architecture. By utilising SML, the system dynamically adjusts power generation, storage, and consumption to maintain a continuous balance, optimising energy flows and minimising grid dependency. These adaptive control mechanisms are crucial for enhancing the grid's performance, enabling it to swiftly and effectively respond to changes, thus promoting sustainability and efficiency within the energy network.

3.1. Multi-Level Node Interconnection and Hierarchical Tree Structure

Building on insights from Apperley et al. [22], this research employs a uniform node architecture interconnected through a local grid. Unlike traditional hierarchical architectures, where each node often has distinctly different roles, this fractal framework uses identical structural nodes at every level—household, neighbourhood, and community. Each node independently functions as a microgrid, managing its own energy generation, consumption, and storage dynamically. The local grid connectivity ensures efficient and simplified interactions between nodes, facilitating seamless local energy exchanges and grid-edge trading.

In this design, each node within the microgrid network autonomously manages its energy state, balancing local generation with consumption and storage. When surplus energy generation occurs at a household node, the surplus is efficiently distributed to neighbouring nodes experiencing a deficit via a local grid. This localised redistribution of energy substantially enhances the microgrid's overall efficiency and reduces dependence on external central grid infrastructure, significantly improving local energy balance [23].

The local grid interconnection also simplifies communication between nodes, employing concise, standardised pricing signals. These signals facilitate effective local energy transactions and enable nodes to make rapid economic decisions regarding energy buying, selling, or storage actions based on real-time predictive data provided by SML algorithms. This streamlined communication approach aligns well with principles from smart communication protocols, which emphasise simplicity, minimal data overhead, and robust reliability [24].

The hierarchical fractal architecture of the network, featuring uniform nodes interconnected via a local grid, is shown in Figure 2. The diagram emphasises the uniformity and simplicity of each node, highlighting their capabilities for local energy generation, storage management, and consumption balancing. In the proposed framework, each node operates in one of three clearly defined states, as characterised by Apperley et al. [22]:

- Deficit state: Local consumption exceeds local generation and available storage, necessitating energy import from adjacent nodes or higher-level grids.
- Balanced state: The node can precisely match local generation and consumption, optimising local energy use without surplus or deficit.
- Surplus state: Local energy generation exceeds consumption and storage capacity, prompting the node to export excess energy to neighbouring nodes or higher hierarchical levels.

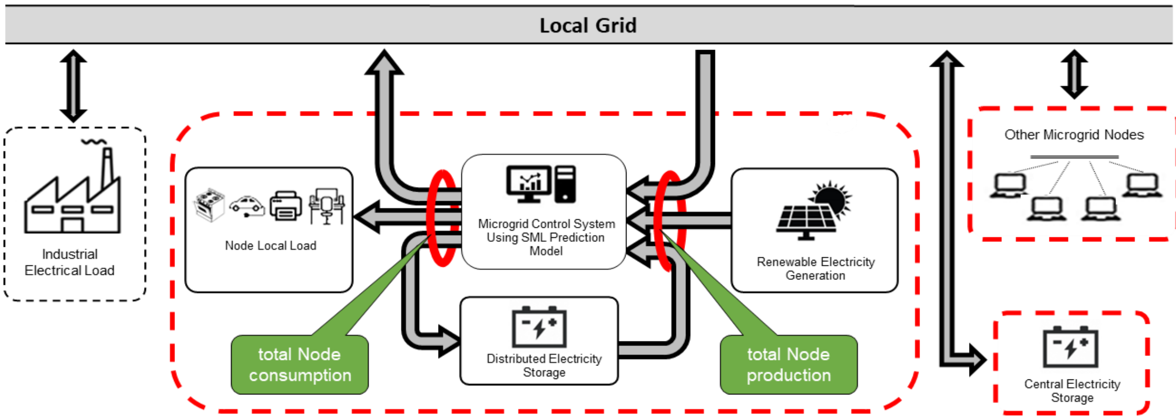


Figure 2. Hierarchical fractal architecture with uniform nodes interconnected via a local grid.

Through real-time predictive analytics enabled by SML, each node continuously forecasts its future state based on real-time data streams such as weather forecasts, energy usage trends, and storage status. These predictions inform adaptive control decisions, enabling nodes to proactively transition between states. This dynamic state management enhances local energy utilisation efficiency, reduces unnecessary reliance on external grids, and significantly improves grid stability and operational resilience.

Thus, the hierarchical tree structure, interconnected by a local grid complemented by intelligent SML-driven forecasting, establishes a powerful, scalable solution for achieving optimal energy management across multiple levels of a fractal-structured microgrid.

3.2. Integration of Streaming Machine Learning into Fractal Structures

The integration of SML into fractal microgrid architectures significantly advances autonomous energy management, enabling real-time adaptive control and optimised decision-making at individual node levels. In this research, Hoeffding Trees, a prominent incremental learning algorithm, were employed due to their efficiency in processing continuous data streams and rapidly adapting to changes in consumption patterns [25]. Unlike traditional machine learning methods that require periodic retraining with historical data, Hoeffding Trees incrementally update their predictive models with each incoming data point. This incremental learning capability ensures sustained accuracy and responsiveness, crucial for handling the concept drift inherent in renewable energy generation and consumption dynamics [24].

The dataset used in this study consists of hourly energy consumption data recorded over a full calendar year from multiple residential households situated in an isolated community environment at a similar latitude to Great Barrier Island, New Zealand. Given that the selected community is not connected to a centralised grid, the data profiles were developed from carefully chosen households on the New Zealand mainland with similar characteristics, including occupancy patterns, seasonal variations, and appliance utilisation. The dataset captured significant variability among households, with additional stochastic elements included to represent localised events such as community gatherings (hui), thereby ensuring the models closely reflect realistic and diverse operational scenarios.

Preprocessing of this high-resolution dataset included several critical steps to enhance predictive accuracy. Lag variables were incorporated to capture immediate temporal dependencies, providing the model with contextual information regarding recent energy consumption. Data normalisation was applied to ensure consistency and comparability across diverse household profiles, which was essential for the SML model to accurately respond to the high variability present in the real-time data.

A predictive model utilising Hoeffding Trees was developed and validated, leveraging ensemble learning through Bagging Regressors [26] to enhance robustness and accuracy. The Hoeffding Tree Regressor used a default MSE loss function, with a grace period of 20 samples and a maximum tree depth of 10, while the ensemble comprised 20 base models. The model continuously updated its predictions as new hourly data became available, implicitly managing concept drift through ongoing incremental learning. Predictive effectiveness was quantitatively assessed using Mean Absolute Error (MAE), demonstrating reliable forecasting performance across individual nodes. Sensitivity analysis of the grace period and tree depth parameters confirmed stable model performance across variations, supporting the chosen defaults.

The following pseudocode (Algorithm 1) outlines the real-time implementation logic of the proposed model. After initialising a Hoeffding Tree ensemble with parameters such as maximum depth and grace period, the model receives hourly consumption data in streaming format. Each new data point is pre-processed to generate lag features and normalised for consistency across household profiles. Forecasted energy demand is computed and immediately used to inform energy balancing decisions at the household level. If a surplus is predicted, available excess energy is stored in local batteries within defined operational constraints; if a deficit is anticipated, discharge is triggered provided the battery's state-of-charge exceeds a preset threshold. Grid interaction is dynamically adjusted to either export or import energy depending on the real-time net demand. This process is repeated continuously, allowing the system to adapt incrementally to evolving consumption and generation patterns. The summarised pseudocode reflects this workflow.

While more sophisticated ensemble-based streaming models such as Adaptive Random Forests (ARF) may offer improvements in predictive accuracy under certain conditions, they also introduce significantly higher computational overhead, memory consumption, and complexity compared to Hoeffding Trees, making them less suited for lightweight, real-time applications in decentralised microgrid settings. Similarly, adaptive variations such as Adaptive Hoeffding Trees and explicit drift detection methods (e.g., DDM, ADWIN) were not explored in this study, as the primary focus was on evaluating the effectiveness of lightweight incremental learners in practical energy management scenarios. Nevertheless, to support our selection of Hoeffding Trees, a comparative evaluation was conducted with the Adaptive Hoeffding Tree model on the same dataset, demonstrating lower MAE and confirming the effectiveness of our chosen approach. Future studies could further enhance real-time adaptability and robustness by exploring these advanced techniques [27].

Algorithm 1 Adaptive Streaming Energy Management using Hoeffding Trees

Input: Streaming data of energy consumption $\{x_0, x_1, \ldots, x_n\}$, system parameters θ, battery state $B(t)$ at time t
Output: Forecasted energy demand $\hat{y}(t)$, battery management actions $A(t)$
1: Initialise Hoeffding Tree Regressor with predefined depth and grace period
2: For each incoming data point x_t in the stream, do
3: Extract feature vector f_t = preprocess(x_t, lag features, normalization)
4: Predict energy demand $\hat{y}_t$ using the current Hoeffding Tree model
5: Update the model incrementally with (f_t, x_t) if feedback is available
6: Compute energy surplus/deficit: $\Delta_t = \text{generation}_t - \hat{y}_t$
7: If $\Delta_t > 0$, then
8: Charge battery $B(t)$ within operational constraints
9: Else if $\Delta_t < 0$, then
10: Discharge battery $B(t)$ if state-of-charge > threshold
11: Else, maintain the current battery state
12: Adjust grid interaction accordingly (export/import power)
13: End for
14: Output updated $\hat{y}(t)$ series and battery control actions $A(t)$

Accurate forecasting of energy demand directly enables efficient grid-edge trading by clearly identifying periods of surplus or deficit. Nodes within the fractal microgrid can proactively manage local energy exchanges, enhancing energy autonomy, economic efficiency, and resilience against centralised grid disruptions. This strategic, predictive-based energy management framework significantly reduces dependency on external infrastructure, improving both local and system-wide stability.

Moreover, contemporary studies underline the critical importance of reliable forecasting methods for effective microgrid management. Hosseini et al. [28] introduced a similar pattern algorithm for monthly electricity consumption prediction, emphasising the value of historical pattern recognition in forecasting accuracy. Similarly, research on fractal smart grids highlights how adaptive ML algorithms effectively respond to real-time fluctuations in renewable energy sources, thereby improving overall grid performance and reliability [28]. These insights further validate the approach adopted in this study, reinforcing the suitability of Hoeffding Trees for addressing the inherent variability and concept drift encountered in decentralised renewable energy systems.

Recent literature also supports the combined use of predictive analytics with emerging digital technologies, such as digital twins, to optimise energy consumption and storage strategies dynamically. Digital twins, as high-fidelity virtual models reflecting physical energy systems, leverage real-time predictive analytics to enhance operational efficiency and responsiveness, paralleling the SML methods applied here [29]. In this context, integrating streaming machine learning into digital twin models involves using real-time predictions to continuously update the virtual representation of the physical system. This allows for the timely simulation of future scenarios, supports proactive decision-making, and improves the system's responsiveness to evolving conditions. Such an approach enhances the predictive and adaptive capabilities of digital twins, particularly in managing decentralised and dynamic energy environments.

3.3. Adaptive Control Mechanisms and Dynamic Energy Flow Management

Adaptive control mechanisms within the fractal microgrid structure play a pivotal role in optimising energy utilisation and balancing real-time electricity demand and renewable generation. The implemented decision-making logic dynamically controls battery charging and discharging by integrating real-time load predictions from SML and solar generation forecasts. This ensures effective energy management, significantly reducing dependence on external grid resources [29].

The energy management strategy continuously assesses forecasted household consumption relative to expected solar generation. When predicted solar generation exceeds demand, surplus energy is preferentially stored in batteries, considering maximum storage capacity constraints. Conversely, if forecasted consumption exceeds generation, the system evaluates the battery state-of-charge, which should never fall below the critical threshold of 20% of total battery capacity and supplies the necessary power from battery storage accordingly. Only when battery storage drops below this threshold does the system draw electricity from the external grid, ensuring reliability without compromising battery health through excessive deep discharges.

Reducing grid dependency through this adaptive policy also positively impacts the operational lifetime and efficiency of battery storage. Frequent charge–discharge cycles and deep discharging significantly accelerate battery degradation, leading to capacity loss over time. The developed control logic explicitly mitigates these risks by limiting unnecessary cycling and avoiding frequent deep discharges, thus extending battery lifespan and maintaining high operational efficiency. Such practices align well with recent recommendations on maximising the operational efficiency and lifespan of lithium-ion battery systems, which exhibit high efficiency (85–95%) but require carefully controlled charging and discharging to minimise degradation [30].

Evaluations conducted with real-world consumption profiles and solar data validate the effectiveness of the adaptive management approach. The results demonstrated substantial reductions in grid energy consumption, fewer battery charge–discharge cycles, and enhanced temporal energy balance. This outcome not only improves energy efficiency but also optimises long-term battery health and reduces maintenance and operational costs [31].

By leveraging predictive analytics and adaptive control mechanisms, the developed framework ensures optimal utilisation of renewable energy resources, extends battery system lifespan, and significantly reduces grid reliance, providing a robust and efficient solution for decentralised energy management in modern microgrids.

3.4. Scenario-Based Battery Size Optimisation

Battery sizing significantly influences the economic viability and operational efficiency of microgrid systems. To thoroughly evaluate battery size optimisation, this research explores three distinct scenarios employing detailed analytical methodologies and predictive insights derived from SML. Each scenario applies unique logic, providing a comparative view of the centralised, distributed, and hybrid approaches.

- Scenario 1: Centralised Battery

In the centralised scenario, a single large-scale battery system is optimised to serve the aggregated energy demands of the entire microgrid community. The optimisation approach employs a constrained minimisation method, explicitly defining the battery capacity required to meet the community's highest observed peak demand. This optimisation uses a well-defined objective function that seeks the minimal battery capacity sufficient to handle the most extreme consumption scenario, ensuring uninterrupted power supply throughout varying load conditions.

This centralised battery strategy has inherent advantages, primarily through the economy of scale, allowing for potentially lower unit costs and simplified centralised management. However, centralised systems inherently demand robust distribution infrastructures to manage energy flows across diverse households, which may also lead to increased transmission distances, greater cable losses, or the need for higher-specification cabling to reduce those losses. Additionally, reliability hinges on accurate prediction of peak loads, highlighting the importance of real-time analytics provided by SML methods [28]. The optimised central battery size thus represents a carefully balanced decision between capacity, cost, and reliability, acknowledging the critical importance of precise forecasting.

- Scenario 2: Uniformly distributed Batteries

Conversely, the second scenario examines a decentralised approach, allocating identical distributed batteries to each household. The sizing logic assesses individual peak demands across various households. It employs three distinct sizing metrics: the maximum peak, the 95th percentile of peak demands, and the average peak demand. Among these, the 95th percentile metric was selected due to its optimal balance between over- and under-capacity provisioning. Unlike the absolute maximum, the 95th percentile offers significant resilience without excessive investment, thereby balancing cost-effectiveness and reliability across the community [32].

Adopting a uniformly distributed battery size simplifies battery management and maintenance but may lead to underutilisation in households with lower demands or occasional shortfalls in homes with notably higher peaks. Nonetheless, this uniform strategy significantly reduces operational complexity and provides households autonomy over energy usage, effectively enhancing localised resilience and empowering individual nodes within the fractal architecture [33].

- Scenario 3: Hybrid (Central and Distributed Batteries)

Recognising the distinct strengths and limitations of centralised and decentralised systems, the hybrid scenario integrates both a central community-level battery and distributed household batteries. Simulations underpinning this scenario reveal a complementary strategy where distributed batteries primarily manage regular household-level fluctuations, while the central battery provides additional backup capacity, strategically sized at a fraction of the combined distributed battery capacities.

This dual-layer optimisation logic dynamically assesses both solar generation and predicted consumption patterns. In periods of widespread generation surplus, the central battery absorbs excess energy, which distributed batteries may not individually accommodate. Conversely, during widespread deficits, particularly under adverse weather conditions or high-demand events, the central battery supplements distributed storage, preventing deep discharge cycles and extending the operational lifespan of the household batteries [34].

The simulations demonstrate reduced grid usage, optimised battery cycling, and improved energy allocation between the central and distributed batteries. Consequently, the central battery substantially enhances system robustness by managing broader community-wide fluctuations, while the distributed batteries efficiently address localised, daily energy variations. The combination markedly enhances grid resilience, minimises total battery cycle frequency [35], and reduces long-term maintenance and operational costs [36].

These scenario-based analyses collectively offer critical insights into optimal battery sizing approaches within fractal-structured microgrids. By leveraging predictive analytics through SML, each scenario is precisely tailored to the microgrid's consumption profiles, ensuring cost-effective, reliable, and efficient energy storage and management solutions.

4. Comparative Evaluation of Energy Management and Forecasting Strategies

Accurate forecasting and adaptive energy management strategies are central to enhancing the operational efficiency and reliability of renewable energy-based microgrids. In this context, the developed SML model, leveraging Hoeffding Trees, offers a robust solution to predict real-time electricity consumption for ten residential households and a *marae* with high precision. A *marae* is a traditional *Māori* gathering place typically consisting of a ceremonial area *marae ātea*, a meeting house *wharenui*, and a kitchen or dining area *wharekai*. It hosts smaller meetings *hui* as well as larger tribal *iwi* events lasting multiple days, with overnight stays usually in the wharenui [24]. The effectiveness of this predictive framework, characterised by notably low MSE, forms the foundation for evaluating subsequent energy management policies aimed at minimising grid dependency and optimising local energy utilisation.

To validate and illustrate the model's predictive accuracy, Figure 3 presents a detailed comparison between actual electricity consumption and predicted values for representative households and the *marae*. Although there are minor discrepancies in magnitude between predicted and actual values, the model effectively captures the overall trends and fluctuations in electricity demand. Leveraging incremental learning capabilities, the proposed model continuously updates, achieving robust predictive performance with MAE ranging from 54.69 kWh to 320.71 kWh, representing less than 10% of typical hourly consumption values. The close alignment between actual and forecasted values demonstrates the model's capability to consistently deliver reliable predictions, thus enabling proactive and informed decision-making within the energy management framework. To quantitatively assess the model's resilience to concept drift during dynamic operating conditions, an augmented Dickey–Fuller (ADF) test was performed on the prediction error series. The results (ADF statistic: -17.06, p-value: 7.99×10^{-30}) confirmed the stationarity of the error series, reinforcing the model's robustness to evolving data patterns.

Leveraging this predictive capability, adaptive management algorithms are implemented to dynamically regulate local energy resources, effectively minimising the community's dependence on an external electricity grid. Critical insights into the effectiveness of this strategy are presented through cumulative grid usage metrics, as depicted in Figure 4. Here, the performance of the predictive management approach (green line) is compared with traditional management relying solely on historical consumption data without predictive capabilities (red line). As demonstrated, predictive management substantially reduces cumulative grid usage over the evaluated period. This reduction not only underscores improved efficiency in energy allocation but also represents a meaningful step toward greater energy independence and sustainability within the microgrid community.

Further assessment of system resilience is conducted by examining occurrences of energy deficit events, defined as periods when local generation and available battery storage fail to satisfy the community's immediate energy requirements. Figure 5 provides a comparative visualisation of these deficit events, clearly indicating fewer occurrences under the predictive energy management strategy. The graph illustrates that deficit events predominantly occur during winter months (June–August), aligning with decreased solar generation and increased energy demand. Notably, the predictive strategy, when compared to a baseline scenario using the same energy storage infrastructure but operating without real-time forecasting, significantly delays and reduces reliance on grid-supplied energy. By the year's end, the predictive approach results in approximately a 24% reduction in cumulative grid energy use. This reduction in energy shortfalls directly translates into improved reliability and optimised utilisation of available energy resources, reinforcing the practical benefits of integrating predictive analytics into real-time adaptive management processes.

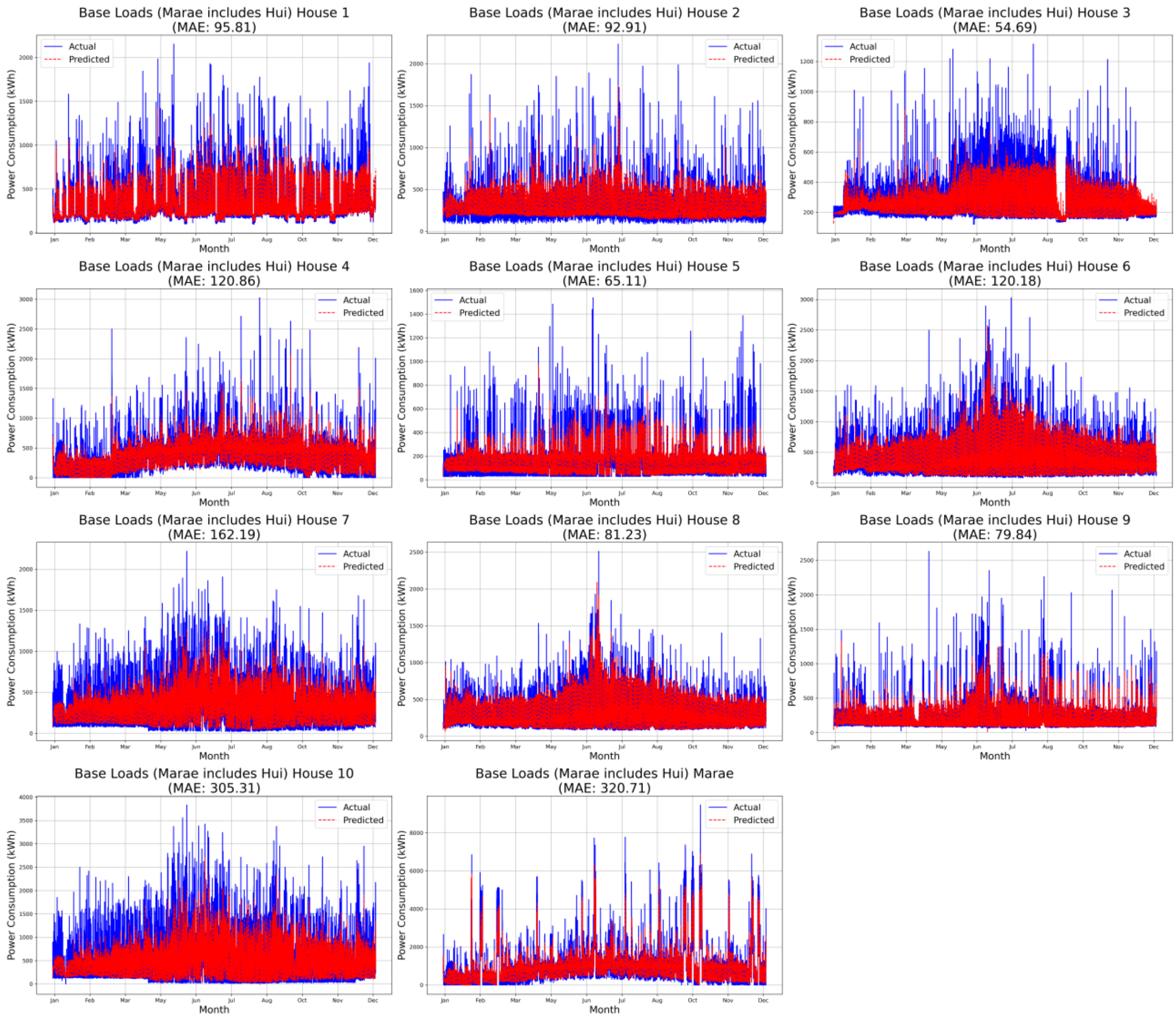


Figure 3. Actual versus predicted electricity consumption for each of the ten houses and *marae*.

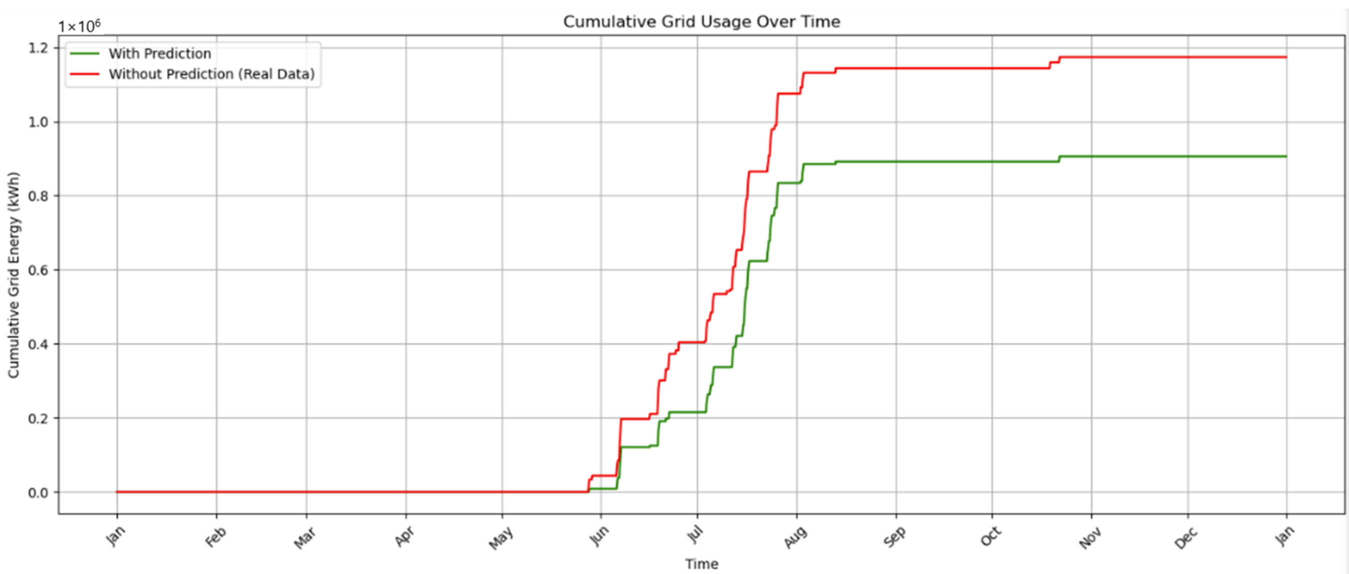


Figure 4. Cumulative grid usage over time (forecast-based vs. actual management).

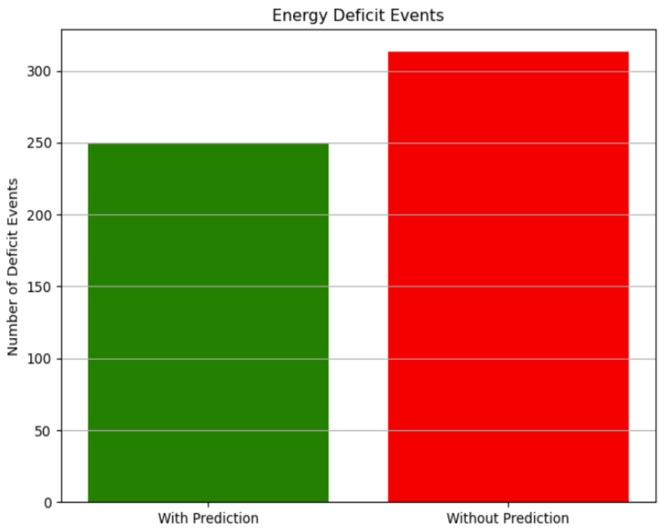


Figure 5. Comparison of energy deficit events (forecast-based vs. actual management).

Complementary to reliability improvements, the evaluation includes a detailed analysis of the broader benefits derived from predictive energy management strategies, particularly regarding reducing grid dependence and optimised battery utilisation. As depicted in Figure 6, predictive energy management results in a 24% reduction in grid dependency and a 2.5% reduction in battery cycling. Lower battery cycling frequency directly enhances battery longevity, reducing maintenance requirements and operational expenditures over the microgrid's lifespan.

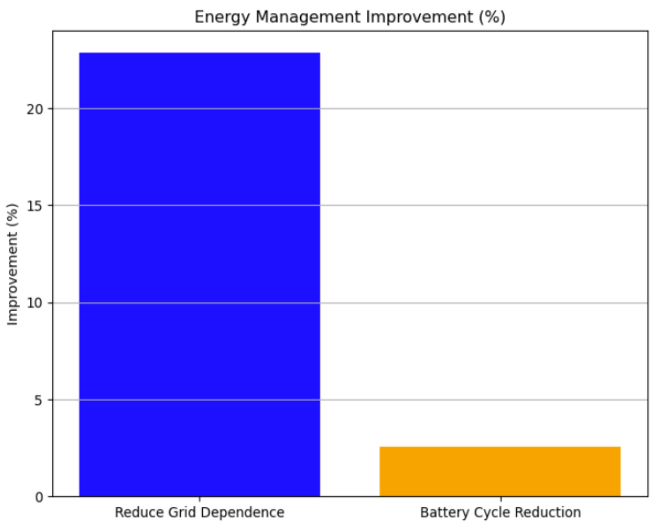
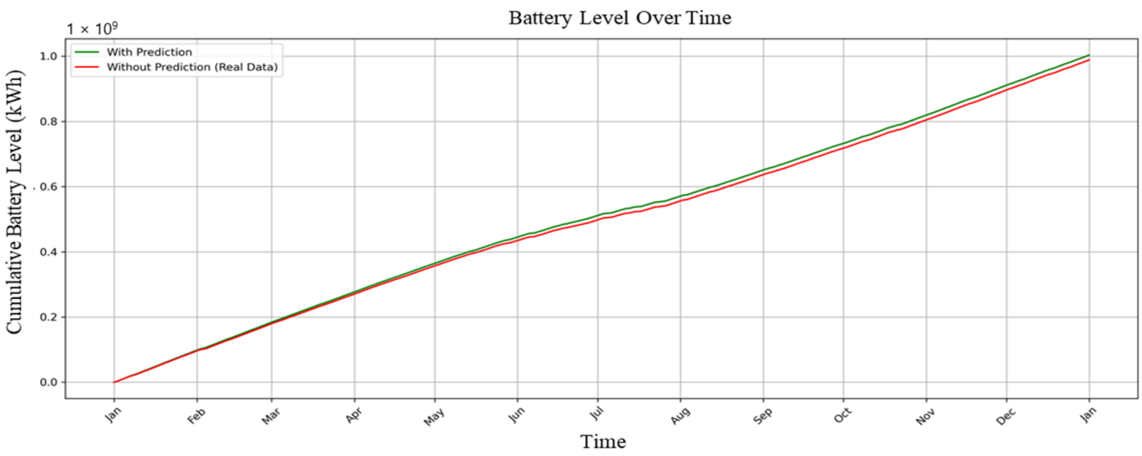
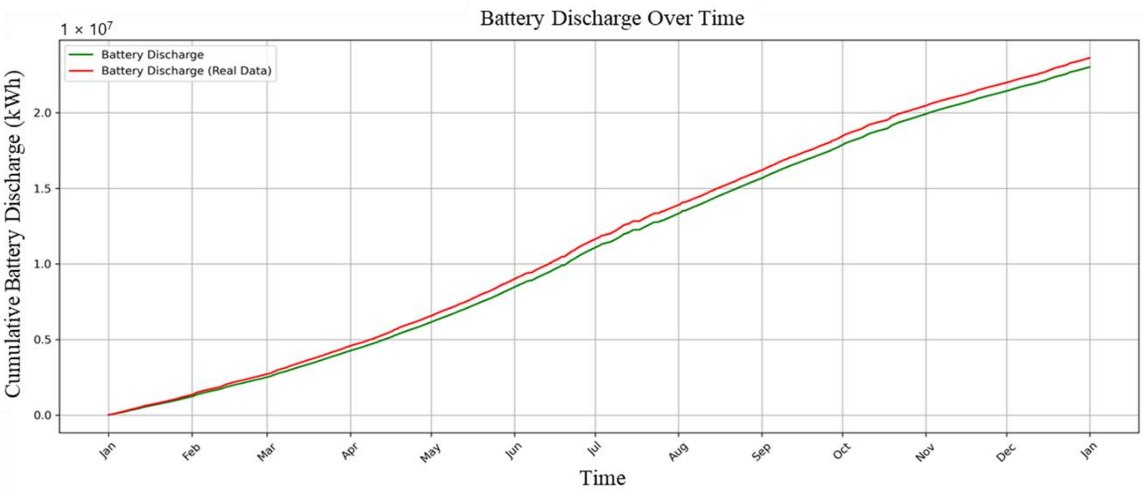


Figure 6. Energy Management Improvement, Grid Dependence and Battery Cycle Reduction.

To provide deeper insights into battery usage dynamics, cumulative analyses of battery charging and discharging patterns are presented in Figure 7, further demonstrating improved battery management efficiency under predictive conditions. Although visually subtle, the cumulative curves exhibit a gradually increasing divergence over the year, particularly noticeable during high solar generation periods. This divergence indicates fewer unnecessary battery cycles under predictive conditions, resulting in approximately a 2–3% reduction in total charged and discharged energy, or roughly a dozen fewer full battery cycles annually. Such modest improvements substantially contribute to battery longevity by slowing capacity fade, reducing energy losses, and minimising the frequency of battery replacements, thereby significantly enhancing operational sustainability.



(**a**)



(**b**)

Figure 7. Battery performance analysis: (**a**) cumulative battery level vs. time, (**b**) cumulative battery discharge vs. time.

Additionally, Table 1 summarises the comparative performance of three distinct battery-sizing scenarios: a centralised battery (Scenario 1), uniformly distributed batteries (Scenario 2), and a hybrid approach combining both centralised and distributed storage (Scenario 3). Scenario 1 employs a large, centralised battery (150,000 kWh), resulting in moderate total grid usage (~1,173,815.85 kWh) and relatively low battery cycling (315.43 cycles), indicating efficient centralised management but at the expense of significant infrastructure and distribution costs.

Table 1. Limitations of Static Energy Management Systems in Fractal Microgrids.

Scenario #	Distributed Battery Size (kWh)	Central Battery Size (kWh)	Total Grid Usage (kWh)	Total Battery Cycles
1	-	150,000	1,173,815.85	315.43
2	6649.09	-	378,527.89	511.45
3	6649.09	666.17 (optimised)	2,101,719.61	2943.95

Scenario 2, using uniformly distributed batteries sized according to individual household peak demands (6649.09 kWh each), significantly reduces grid dependency

(378,527.89 kWh), reflecting enhanced local resilience. However, this scenario experiences increased cumulative battery cycling (511.45 cycles), potentially accelerating battery degradation and increasing maintenance costs due to more frequent charge–discharge activities.

Scenario 3 adopts the same uniformly distributed battery sizes as Scenario 2 but integrates an optimised central battery (666.17 kWh) to handle communal fluctuations. Although the total grid usage increases notably (2,101,719.61 kWh)—partially due to the smaller centralised backup—this hybrid scenario effectively manages community-level energy variability by providing enhanced flexibility and improved robustness against widespread deficits or surpluses. The trade-off observed in Scenario 3, while resulting in higher grid dependence and battery cycling, is particularly justified in operating contexts where ensuring broader system stability, community-level energy balancing, and resilience during abnormal events or critical conditions is prioritised over strict minimisation of grid imports or battery usage frequency. In such scenarios, the hybrid approach offers a pragmatic balance between autonomy and centralised support, which can better accommodate unpredictable generation and demand patterns. Nevertheless, it also records a substantial increase in battery cycling events (2943.95 cycles), highlighting a clear trade-off between system flexibility and battery longevity.

Overall, the analysis emphasises that each scenario offers distinct advantages and limitations, underscoring the importance of aligning battery sizing strategies with specific community priorities such as cost, reliability, resilience, and operational complexity.

5. Conclusions and Perspectives

This study presented an adaptive energy management strategy for fractal-structured residential microgrids, leveraging SML to address the complexities introduced by renewable energy integration and dynamic electricity demand. Employing Hoeffding Trees within a Bagging Regressor ensemble, the proposed method demonstrated robust predictive performance, maintaining real-time accuracy under continuously evolving load and generation conditions. Results highlighted significant operational enhancements, notably reducing cumulative grid dependence by approximately 22.84%, decreasing energy deficit events by 20%, and optimising battery cycling frequency to extend the lifecycle of storage systems.

Three battery sizing scenarios—centralised storage, distributed batteries, and a hybrid approach—were evaluated, each illustrating distinct benefits and trade-offs. Centralised storage provided effective load management with fewer battery cycles but introduced challenges related to infrastructure requirements and resilience. Conversely, distributed battery storage improved local autonomy and reduced reliance on centralised systems, but led to increased cycling events. The hybrid approach balanced these extremes, demonstrating flexibility and robustness by combining distributed storage for everyday demand fluctuations with a modestly sized central battery optimised for broader community-level variability.

This research underscores the practicality of integrating advanced streaming analytics into existing microgrid management infrastructures, promoting sustainable energy utilisation, resilience, and operational efficiency. The application of real-time forecasting facilitated intelligent decision-making, enabling proactive grid-edge trading and adaptive battery management. Furthermore, the integration of SML aligns closely with digital twin methodologies, providing a scalable and replicable framework that can dynamically respond to evolving conditions within diverse microgrid configurations. Importantly, by introducing a lightweight yet scalable learning model, this work establishes a computationally efficient baseline for real-time microgrid management.

However, the effectiveness of the proposed framework may be influenced by certain limitations inherent in the applied methods and data conditions. Forecast accuracy could be sensitive to the representativeness and variability of the historical data, particularly under unusual or extreme operational scenarios. Moreover, while Hoeffding Trees offer advantages in computational efficiency, their relatively simple structure might restrict their capability to fully capture complex nonlinear relationships compared to more sophisticated machine learning architectures.

Future studies can build on this foundation by conducting comparative evaluations with other streaming algorithms, such as Adaptive Random Forests, and by implementing more comprehensive hyperparameter tuning and drift adaptation techniques (e.g., ADWIN and DDM) to further improve adaptability and forecasting accuracy under non-stationary conditions. Additional research could also investigate economic optimisation strategies, integrating pricing signals and market dynamics to enhance grid-edge trading. Expanding this framework to accommodate diverse renewable resources and various geographic contexts would further demonstrate the broader applicability and transformative potential of SML in decentralised energy systems.

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