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A Data-Driven Autonomous Energy Management Framework Using Machine Learning for Microgrid Systems

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Abstract: Intelligent, scalable, and self-sufficient energy management is needed when localised energy systems incorporate solar and wind energy. Most classic microgrid control methods rely on reactive, static optimisation and human intervention, rendering them vulnerable to changes in renewable energy generation, load variations, and information uncertainty. Some current solutions rely on hardware- or cloud-based architectures, which are inflexible, increase latency, and lack reliability due to communication constraints. This paper proposes an intelligent energy management system, AetherGrid. This software-based technology operates autonomously in high-dynamic, uncertain renewable energy conditions. AetherGrid values post-data-capture intelligent processing, including feature extraction, prediction, and optimisation, utilising hybrid machine learning models. This system continuously analyses energy data to forecast demand, renewable energy output, and system state, enabling intelligent decision-making. This system adapts to new consumption trends and environmental conditions without affecting performance or stability, regardless of whether it uses hardware-dependent regulatory mechanisms or cloud services. The layers that handle and analyse information in AetherGrid become intelligent, making it a future smart energy solution. Home energy management systems, campus-scale systems, and other applications benefit from the technology. This research shows that energy management systems can become intelligent through software-based artificial intelligence.

Keywords: Renewable Energy; Energy Management; Artificial Intelligence; Machine learning; Demand Prediction; Smart Grids; Edge Computing; Time-Series Prediction; Feature Extraction.

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1. Introduction

The rapid integration of renewable energy sources such as solar and wind power into modern energy networks has brought about significant changes in the configuration and operation of localised power grids. Distributed energy systems exhibit fluctuating energy production and changing consumption patterns, leading to high uncertainty in managing energy distribution

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[11]. Consequently, achieving stability, efficiency, and reliability has become more difficult. Conventional energy management systems use rule-based controllers and static optimisation as their primary design techniques. Such techniques are reactive, meaning their operation depends on detecting changes after they occur [12]. This means that such systems cannot effectively manage the random fluctuations associated with renewable power sources and varying load demands. In addition, most energy management systems currently available rely on hardware and cloud-based systems, which may be disadvantageous when resources are limited [13]. Advances in artificial intelligence and modelling techniques have paved the way for intelligent, self-governing energy management systems. The use of machine learning algorithms, especially time-series analysis, to forecast future energy needs has led to the evolution of systems that can predict future behaviour rather than only react to it. Nevertheless, many studies today approach energy prediction and optimisation in isolation [14]. To address such problems, this paper proposes a software-oriented solution that provides an all-in-one platform for autonomous energy management [15].

The system suggested here relies on post-data-collection intelligence by incorporating feature extraction, modelling, and optimisation into a single cycle [16]. It enables proactive decision-making and optimal energy use via hybrid machine learning algorithms and optimisation. The growth in the volume of energy datasets is also driving the emergence of various data-driven solutions to optimise the performance of energy management systems [17]. It becomes possible to employ historical consumption data alongside real-time data to detect correlations and trends that would be difficult to notice using conventional rules [18]. This way, it becomes possible to predict the amount of energy required and utilise available resources more efficiently. Moreover, by applying methods such as feature engineering, it becomes feasible to transform raw sensor data to improve model performance and results. Overall, these data-related approaches not only improve prediction but also make systems more robust and adaptable to changing conditions. Since intelligent software is less dependent on specific infrastructure than conventional hardware, the solution's scalability is higher, which calls for designing systems that consider both analytical and implementation aspects. The remaining sections of this paper focus on the design and implementation of the model, with special attention to its ability to upgrade existing energy management systems into intelligent, autonomous systems that meet the needs of future smart grids [19].

2. Related Work

Despite these contributions, most prior works focus on isolated approaches such as prediction, optimisation, or data gathering. Although ensemble and deep learning methods achieve strong predictive performance, they are generally unable to integrate with decision-support frameworks. Also, many existing optimisation models are highly computationally intensive and cannot be incorporated into lightweight simulations. Another problem with the current hybrid solutions is their inability to adopt any useful feature engineering methods that would improve predictions. Moreover, there is a shortage of frameworks that combine feature extraction, hybrid prediction models, and optimisation into a single loop. To overcome these drawbacks, an intelligent simulation-based framework is proposed that utilises feature engineering, hybrid prediction models, and optimisation methods to achieve better results in autonomous microgrid control (Table 1).

Table 1: Comparative analysis of recent intelligent energy management systems for microgrids and smart grids

No.	Authors	Methodology	Key Contribution	Limitations
1	Ioannou et al. [1]	Reinforcement Learning (DQN)	Near-optimal autonomous energy management	Limited real-world use; no feature-model integration
2	Xue et al. [2]	Decentralized ADP	Fully distributed energy management	High complexity; poor scalability
3	Bilal et al. [3]	Computational Intelligence (ML, RL)	Improved adaptability under uncertainty	Cloud-dependent; not lightweight
4	Zia et al. [4]	Optimisation (LP, GA, PSO, MPC)	Efficient scheduling and dispatch	Computationally heavy; prediction-sensitive
5	Pasandideh et al. [5]	ML-based Energy Trading	Scalable data-driven energy management	Weak prediction/optimisation integration
6	Nguyen and Ahn [6]	Edge AI, Data-driven Models	Reduced latency; better local decisions	No closed-loop simulation
7	Yu et al. [7]	Edge Computing + Power Control	Delay minimisation in smart grids	Communication-focused only
8	Zhang et al. [8]	Explainable Deep RL	Improved interpretability	No hybrid prediction-optimisation focus
9	Chakraborty et al. [9]	Hybrid EMS (ML + Rule-based)	Better voltage stability and optimization	Limited feature engineering/ensemble use

10	Morello et al. [10]	Smart Sensing Systems	Accurate data acquisition	No prediction or optimisation

2.1. Problem Statement and Research Gap

Energy systems today rely heavily on data extracted from renewable energy production, distributed generators, and dynamic loads. Yet, due to the intermittent nature of renewable energy production, variable energy demand, and limited storage data availability, optimising energy flows is highly computationally intensive. Complicating matters further is the necessity to handle vast amounts of time-series data and provide real-time recommendations. Current methodologies of energy management tend to be based on fixed rules, predictive modelling, and/or optimisation. Such methods are mostly implemented as stand-alone algorithms, resulting in a disjointed system architecture with no interaction between its components. Furthermore, many data-oriented approaches are prone to prediction errors and do not adapt well to different settings. The development of new technologies in artificial intelligence, including machine learning and reinforcement learning, shows increased proficiency in dealing with uncertainties and nonlinear dynamics. Still, most of them rely on single-level decision-making processes, depend heavily on cloud computing, or are validated through isolated simulations. Such simplifications prevent applications from being used in situations where real-time responses, distributed processing, and scalability are essential requirements. Moreover, there are no software frameworks that provide unified tools for feature extraction, prediction, and optimisation.

Currently, many algorithms treat each aspect of the decision-making process as an independent module, whereas it should be viewed as a single, consistent procedure. In addition, scalable approaches that are light enough to support small energy systems, such as residential, university, or other distributed energy systems, are seldom considered. Current solutions are characterised by high resource requirements or complex system setups, making them difficult to use for broader applications. Decision-making based on prediction and adaptation techniques in energy management is an approach yet to be implemented in software solutions. There is a need for a universal, software-based intelligent framework that would combine all aspects mentioned above into a coherent, closed loop. The software framework should not impose resource limitations and be able to make intelligent decisions in real time. This approach will eliminate the dependency on specialised hardware and cloud-based solutions. The proposed solution will provide a software energy management pipeline powered by artificial intelligence. In this regard, the main objective of the work presented is to overcome the limitations by developing an all-inclusive intelligent energy management framework based on software technology. In essence, such a framework employs machine learning algorithms to analyse actual energy consumption data and provide accurate forecasts for adaptive energy control. It should be noted that the proposed approach is based on a lightweight, scalable design, making it suitable for use in small-scale environments.

2.2. System Objectives

The main goal of the proposed project is to develop a model for an intelligent, software-driven, autonomous system to manage energy information. This system will efficiently analyse and optimise energy information. The system will be hardware- and cloud-infrastructure-independent. The specific goals of the proposed system include the following:

- The creation of an efficient data processing module that can deal with live and historic energy data to extract vital information related to the behaviour of voltage levels, current, and energy consumption from various energy sources.
- The creation of short-term prediction models based on time-series data using artificial intelligence techniques to forecast energy consumption patterns and the availability of renewable energy sources.
- The development of an autonomous decision-making process that uses the predicted data and live data to optimise energy distribution, priorities, and allocations.
- The development of a closed-loop computational process that adjusts decisions within the system based on live input data, providing a real-time, adaptive system with minimal human intervention.
- Testing the proposed system through simulation to evaluate the effectiveness of the suggested solution.

3. Proposed System Architecture

3.1. System Overview

The proposed approach is to implement a pure software solution for an intelligent energy management scheme that operates directly on energy data streams in distributed energy systems. In contrast to existing hardware-based techniques, our solution relies on post-acquisition intelligence, enabling efficient processing, prediction, and optimisation of energy data. Moreover, the system architecture is not tied to any hardware platform and can be deployed outside the cloud. The block diagram of the system's general architecture is shown in Figure 1. It illustrates the structure of the energy data processing pipeline, enabling independent operation of the energy management system. Specifically, the pipeline allows continuous conversion of raw energy data into practical control decisions using various datasets. The proposed architecture will run based on the functions of three key layers. These include the Data Processing Layer, the Predictive Intelligence Layer, and the Optimisation and Decision Layer. The Data Processing Layer is charged with gathering and processing raw data from energy use sources. The Predictive Intelligence Layer will implement machine learning models to provide insights into future energy demand and renewable energy sources. The Optimisation and Decision Layer will provide the decisions on optimal methods for utilising energy. The system will employ a feedback loop that continuously feeds new inputs into the process to enhance adaptability and efficiency. In this way, the system evolves from being reactive to energy use situations to become proactive in its energy management function.

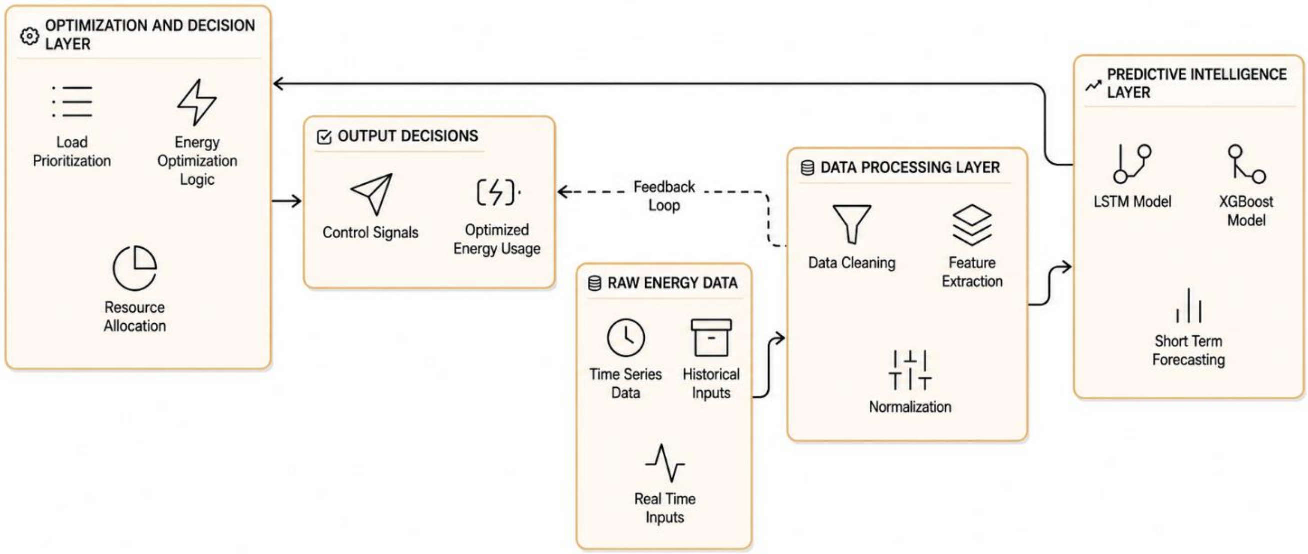

Figure 1: Overall architecture of the proposed edge-enabled autonomous microgrid energy management system

This proposed architecture of the intelligent system can be regarded as a data-centric intelligent system with three main layers: Data Acquisition Layer, Edge Intelligence Layer, and Decision and Control Layer. The Data Acquisition Layer gathers energy consumption and generation data from various datasets containing values for voltage, current, power, demand load, battery state of charge, and renewable energy production. This layer provides a real-time simulation of the system using historical and time-series data. The Edge Intelligence Layer involves data processing, feature extraction, and the prediction of the system's future states. Preprocessing of acquired data converts them into useful feature vectors such as moving averages, demand trends, and energy imbalance. Artificial intelligence techniques are employed to process these features to predict near-future energy consumption/demand and renewable energy production in the system. This layer uses the predicted output values to optimise and create the necessary controls. Actions such as charging or discharging batteries or selecting a priority load can be determined by predefined goals that include optimising the use of renewable energy sources, minimising energy waste, and maintaining system stability. This process is conducted in a simulation setting that reflects practical control system cases. In total, the system operates in a closed loop, with predictions and controls constantly fed back into it.

3.2. Layered Architecture

The intended architecture provides features such as modularity, scalability, and real-time intelligence through a well-defined layered approach, as shown in Figure 2. In general, there are three principal layers: the Data Processing Layer, the Predictive Intelligence Layer, and the Optimisation and Decision Layer. Real-time communication between all these layers supports autonomy and adaptability. At the core of the entire system, the Data Processing Layer processes raw input data from energy datasets. Feature extraction, cleaning, normalisation, and transformations are performed in this layer to create inputs for the predictive algorithm. It is at this layer that important features such as temporal features and energy generation are extracted. The Predictive Intelligence Layer predicts future states of the system using a hybrid machine-learning model. This layer receives historical and real-time data to estimate short-term energy generation demand and supply. By combining time-series analysis tools, such as long short-term memory (LSTM), with ensemble techniques, such as extreme gradient boosting (XGBoost), the system enhances its predictive efficiency and reliability across different scenarios. Predictions are then transmitted to the next layer for optimisation. The Optimisation and Decision Layer serves as the system's intelligence core. Based on predictions, real-time data, and other information, it makes decisions on how to optimise the energy management process. The decision-making process aims to achieve specific goals, such as increasing renewable energy generation capacity, reducing energy losses, and ensuring system reliability. The Predictive Intelligence Layer predicts future states of the system using a hybrid machine learning model.

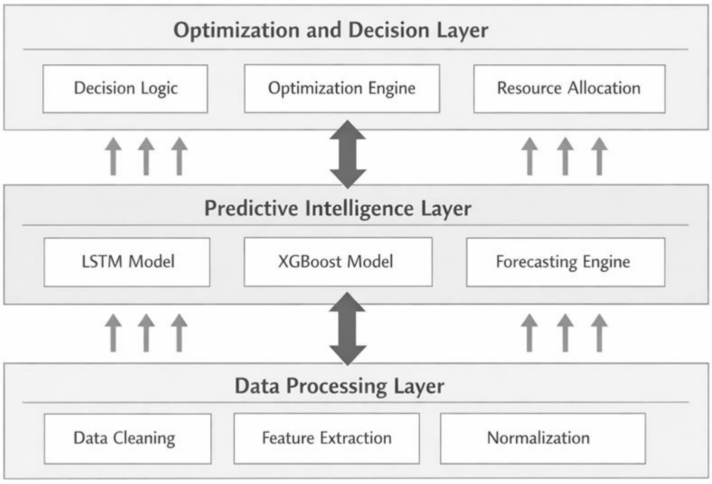

Figure 2: Architecture diagram

This layer receives historical and real-time data to estimate short-term energy generation demand and supply. By combining time-series analysis tools, such as long short-term memory (LSTM), with ensemble techniques, such as extreme gradient boosting (XGBoost), the system enhances its predictive efficiency and reliability across different scenarios. Predictions are then transmitted to the next layer for optimisation. The Optimisation and Decision Layer serves as the system's intelligence core. Based on predictions, real-time data, and other information, it makes decisions on how to optimise the energy management process. The decision-making process aims to achieve specific goals, such as increasing renewable energy generation capacity, reducing energy losses, and ensuring system reliability. The feedback cycle tracks the output generated at the decision level and sends it back to the data processing level for further improvement. The entire process is made possible by the feedback cycle and operates as a completely independent system, without depending on any other structure.

3.3. Closed-Loop Operational Principle

The system's design employs a closed-loop computational approach, in which constant data processing, state prediction, and decision-making optimisation are carried out in real time. The process involved in the operation is represented in Figure 3 below.

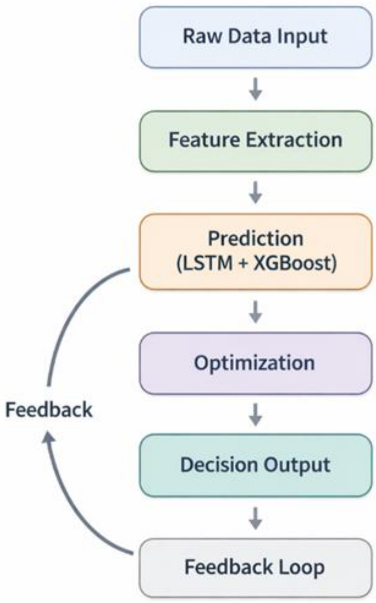

Figure 3: Closed-loop intelligent decision-making system architecture

First, initial information is gathered as raw energy data. Next, the data is analysed to identify features that the predictive module can use to estimate energy demand and generation over the coming period. These decisions become the new input into the system for further analysis and predictions in future rounds. With this loop, the system can adapt to changes in data patterns. This way, all processes of feature extraction, prediction, and optimisation are performed by the system within a single workflow, without the fragmentation that exists in conventional systems.

3.4. System Operational Workflow

3.4.1. Data Acquisition Phase

The system operation process begins with data collection, which involves gathering energy datasets from available sources. The datasets gathered include past and present values of energy consumption and production parameters, along with their temporal variability. The datasets obtained reflect the system's operational status and serve as input to subsequent stages of the process.

3.4.2. Feature Extraction Phase

The process of feature extraction involves using raw data to derive features that enable effective predictive modelling. Some of these processes include data cleansing, normalisation, transformation, and the extraction of important features such as moving averages, load variations, and temporal features. Transforming raw data into useful features increases the precision of prediction models.

3.4.3. Prediction Phase

During the prediction phase, the feature vectors generated during feature engineering serve as inputs to machine learning and deep learning models, which predict future energy consumption and behaviour. The model used to capture temporal data dependencies is an LSTM, while the XGBoost model is used to learn the non-linear relationship between features. The trained models help predict future trends by analysing historical and current data. These predictions give an idea of what to expect in terms of energy consumption in the coming period. The predicted information is further sent to the optimisation and decision-making module.

3.4.4. Decision-Making Phase

The decision-making stage assesses the estimated outcomes alongside existing information about the system and established optimisation criteria. The system then decides on the best methods for distributing energy resources, managing loads, and using them. Constraints such as variations in demand and efficiency requirements help the decision-making process achieve optimal energy management.

3.4.5. Optimisation and Execution Phase

In this stage, the chosen decisions are fed into an optimisation model to fine-tune control methods and achieve specific goals. These optimised results are decision statements, such as reorganising energy distribution or reallocating resources. Unlike the hardware-driven implementation stage, this stage focuses on formulating optimised control signals.

3.4.6. Feedback Loop

After execution, the system proceeds to the feedback process, where the input data, informed by the effects of past decisions, is fed back into the system for further processing. The constant flow of feedback enables the system to continuously adjust based on changing data patterns.

3.5. Software Implementation

The proposed system is implemented as a data-driven simulation framework that models microgrid energy behaviour using machine learning, feature engineering, and optimisation techniques. The implementation focuses on transforming raw energy data into intelligent control decisions without reliance on physical hardware.

Table 2: Software components and functional roles

Component	Function	Layer
Dataset	Energy data input (voltage, current, load, generation)	Data Layer
Preprocessing Module	Data cleaning and normalisation	Data Processing Layer
Feature Engineering Module	Feature extraction and vector formation	Feature Layer
Prediction Model	Energy forecasting (LSTM, XGBoost, Random Forest)	Intelligence Layer
Optimization Module	Decision-making and control logic	Optimization Layer

3.5.1. Data Processing Module

The data processing module acts as the initial stage of the system, where raw energy datasets are imported and prepared for further analysis. This module performs preprocessing operations such as handling missing values, normalisation, and noise removal to ensure data consistency. The processed data serves as the foundation for feature extraction and model training. This module replaces physical sensing by simulating real-time energy data using datasets. The data set utilised for this research is the Household Power Consumption Data Set, collected from the UCI Machine Learning Repository via Kaggle. This data set comprises time-series data on electrical variables, including voltage, current (global intensity), energy usage, and metering variables. These readings have been collected periodically and represent the true energy consumption pattern. This data set has been further processed and enriched with additional variables, including moving-average and energy-balance variables.

3.5.2. Feature Engineering Module

The feature engineering module transforms raw input data into meaningful feature vectors, thereby improving model performance. Derived features such as moving averages of power, load variation rates, energy surplus or deficit, and time-based attributes are generated. These features capture hidden patterns in energy consumption and generation, enabling the system to learn complex relationships. The feature vectors produced by this module serve as inputs to predictive modelling.

3.5.3. Prediction Model

The prediction module utilises machine learning and deep learning models to forecast future energy demand and renewable generation. Long Short-Term Memory (LSTM) networks are used to capture temporal dependencies in time-series data. In contrast, ensemble learning models such as Random Forest and Extreme Gradient Boosting (XGBoost) are used for efficient prediction. A hybrid approach combining LSTM and XGBoost is adopted to improve prediction accuracy by leveraging both sequential and non-linear feature learning capabilities. The models are trained on historical data and validated using cross-validation.

3.5.4. Optimisation and Decision Module

The optimisation module is responsible for generating intelligent control decisions based on predicted outputs. It applies rule-based and threshold-based optimisation strategies to determine actions such as battery charging and discharging, as well as load prioritisation. The decision-making process considers multiple objectives, including maximising renewable energy utilisation, minimising energy wastage, and maintaining system stability. This module replaces the physical control and actuation layer by simulating decision execution.

3.5.5. Simulation and Visualisation Platform

The simulation platform executes the generated control actions in a virtual environment to mimic real-world system behaviour. All computations, predictions, and decision-making processes are carried out using a Python-based software stack, including NumPy, Pandas, Scikit-learn, TensorFlow/Keras, and XGBoost. Visualisation tools such as Matplotlib and Seaborn are used to analyse system performance and display results as graphs and charts. The entire system is developed in environments such as Jupyter Notebook or Google Colab, ensuring flexibility and reproducibility.

4. Results and Discussion

The evaluation of the proposed energy management system has been carried out using machine learning and deep learning. The analysis has been performed using the Household Power Consumption dataset to simulate real-world microgrid conditions, with additional engineered features added to reflect microgrid settings. The XGBoost model showed better results, with a Mean Absolute Error (MAE) of 0.024 and Root Mean Square Error (RMSE) of 0.035. Small error values suggest accurate predictions and efficient learning of complex parameter-energy interactions. On the other hand, the Long Short-Term Memory (LSTM) model achieved an MAE of 0.091 and an RMSE of 0.232. It is worth mentioning that the LSTM algorithm is designed for time-series predictions, but its results are not as good due to insufficient training and hyperparameter tuning. Results of the analysis and performance comparisons are illustrated in Table 2. As shown, the XGBoost model performs much better than the LSTM model, suggesting that feature-based ensemble learning can outperform neural networks when appropriate feature engineering is applied (Table 3).

Table 3: Model performance comparison

Model	MAE	RMSE
XGBoost	0.024	0.035
LSTM	0.091	0.232

For further analysis, the actual and predicted energies were compared, and the results are presented in Figure 4. The predicted energy consumption follows the pattern of the actual energy consumption, indicating the model's generalisation capability. There are some discrepancies during periods of energy consumption variation due to sudden changes in energy requirements.

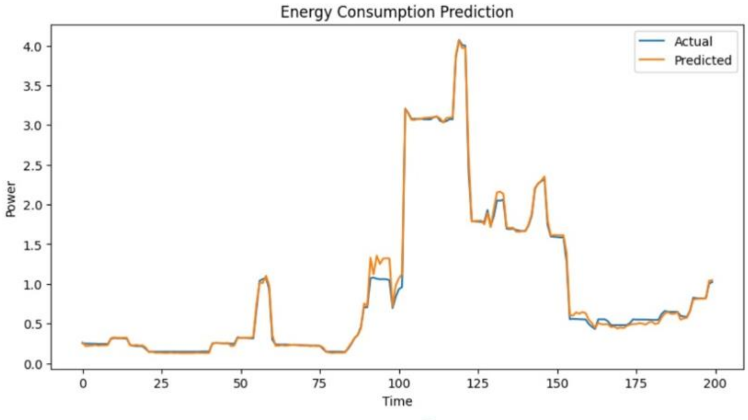

Figure 4: Prediction vs actual graph

Regarding the feature importance analysis results for the proposed model, Figure 5 shows that Global Intensity is the most important feature for prediction, followed by the power consumption moving average and voltage-based features. State-of-charge features contributed less to prediction than other electrical features due to real-time changes in energy consumption.

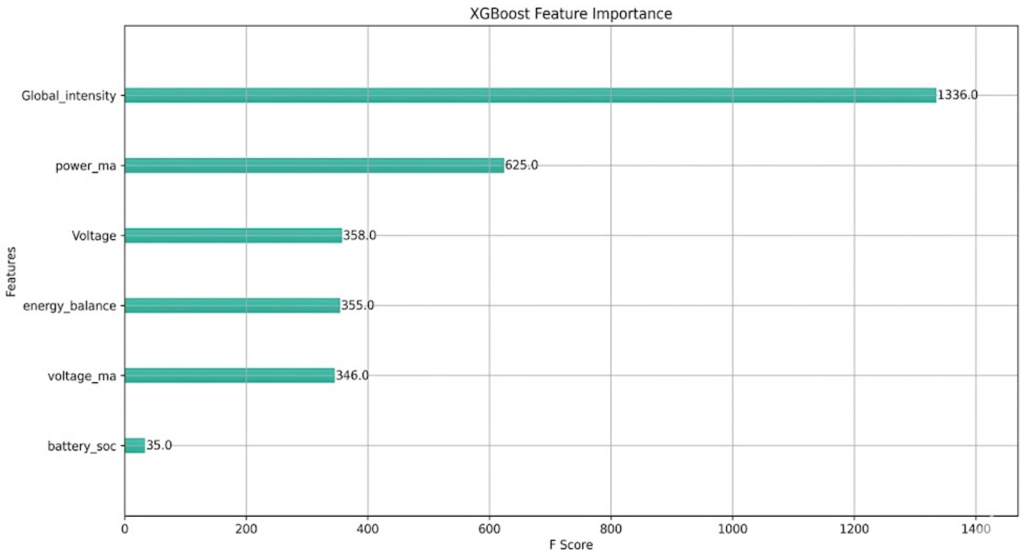

Figure 5: Feature importance analysis

In addition to analysing the model's performance, a web-based interface was designed to demonstrate the feasibility of the proposed approach. As illustrated in Figure 6, the interface enables the user to enter electricity parameters and receive instant predictions, along with intelligent decision-making support for energy management. By categorising energy consumption at various levels, the system suggests options such as energy storage and load management, thereby facilitating user engagement and decision-making.

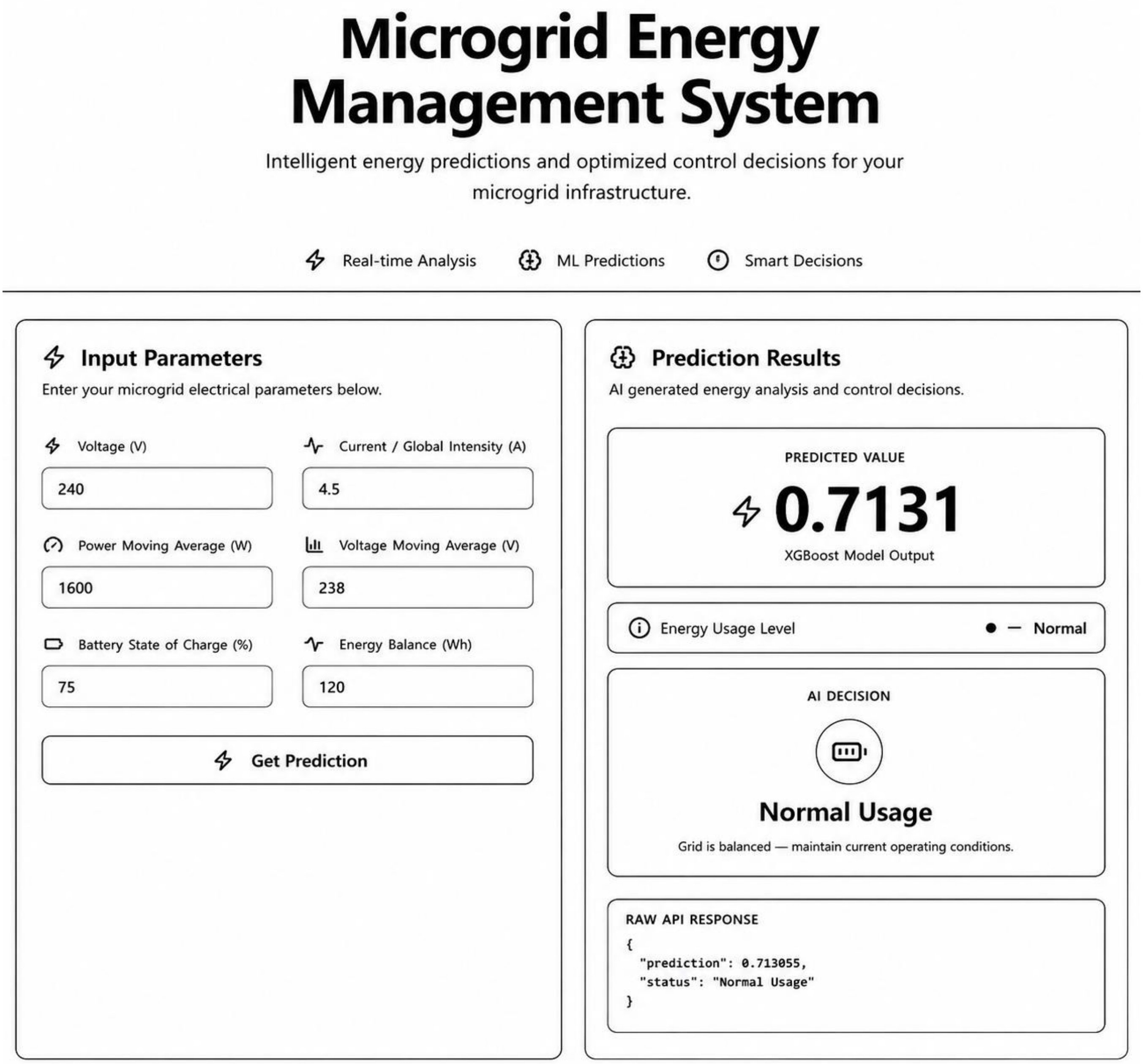

Figure 6: UI screenshot

In summary, the findings show that the suggested framework can efficiently utilise ML and intelligent decision-making to generate accurate energy predictions and recommendations. The application of feature engineering and ensemble modelling is crucial to the system's performance.

5. Conclusion and Future Work

An autonomous energy management framework leveraging edge computing is presented as an efficient, viable approach to microgrid management, grounded in a data-driven strategy. Through feature engineering, machine learning, and real-time decision logic, it is possible to predict energy usage patterns and develop relevant strategies to control consumption. The application of the XGBoost algorithm yielded highly accurate predictions and outperformed LSTM due to its ability to leverage engineered features. In this case, the developed system operates in a closed loop, enabling monitoring, prediction, and decision-making without requiring cloud infrastructure. In addition, using a web interface makes the solution easier to implement, as users can interact with the model and receive immediate feedback. These findings demonstrate that the proposed solution can effectively optimise energy use and eliminate waste. Generally, this study demonstrates the effectiveness of feature engineering and ensemble machine learning models for energy management.

Despite the system's good performance, there is still room for improvement in future studies. For example, one may consider incorporating actual hardware elements connected via the Internet of Things and replacing artificial input data with real data. Another area to explore is incorporating additional renewable energy sources into the analysis, including solar and wind datasets. In terms of modelling algorithms, future research can focus on developing hybrid approaches that combine deep learning and ensemble methods to optimise prediction. In addition, the inclusion of adaptive learning features in the model can facilitate more effective model updates in response to changes in energy consumption. Concerning the system itself, its implementation on cloud or edge computing can provide additional opportunities for scalability and availability. Moreover, an improved user interface design, coupled with analytical tools, can also be considered. Finally, it might be useful to incorporate energy-pricing models and demand response mechanisms into the system architecture.

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Conflicts of Interest Statement: All authors declare that they have no competing financial, professional, or personal interests that could have influenced the design, conduct, analysis, or publication of this research. All sources of information have been properly acknowledged and cited.

Ethics and Consent Statement: The authors affirm that the study was carried out in accordance with recognised ethical principles and research standards. Informed consent was obtained from all participants before their involvement, and appropriate measures were implemented to ensure confidentiality, privacy protection, and the responsible handling of research data.

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