

AI-Driven Smart Energy Scheduling for Telecom Microgrids using Demand Forecasting and Outage Prediction

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Abstract - Telecom towers require a continuous and reliable power supply to maintain uninterrupted communication services. However, existing energy management systems are largely reactive, leading to inefficient resource utilization and increased dependence on diesel generators during grid outages. This paper presents an AI-driven smart energy scheduling framework that integrates demand forecasting and outage prediction to improve operational efficiency. A Long Short-Term Memory (LSTM) model is employed to capture temporal patterns in energy consumption and predict short-term demand, while a Random Forest classifier estimates the probability of grid outages using temporal features such as hour and day of the week. These predictions are incorporated into a context-aware scheduling algorithm that considers battery state-of-charge (SOC) and operational constraints to dynamically allocate energy between grid, battery, and diesel sources. The scheduler also includes necessity-aware logic to prevent unnecessary charging and improve decision efficiency. Simulation results demonstrate that the proposed system achieves consistent reductions in operational cost and diesel usage compared to conventional reactive approaches, while maintaining reliability under uncertain conditions.

Keywords: Energy Scheduling, LSTM, Outage Prediction, Micro grid, Telecom Energy, Artificial Intelligence.

1. INTRODUCTION

Telecom infrastructure plays a critical role in modern communication systems, requiring a continuous and reliable power supply to ensure uninterrupted network availability. In many regions, especially those with unstable grid conditions, telecom towers frequently experience power outages, leading to increased dependence on backup energy sources such as batteries and diesel generators. This reliance not only raises operational costs but also results in inefficient energy utilization and higher environmental impact [4].

Traditional energy management approaches used in telecom systems are largely reactive, where decisions are made based on immediate conditions without considering future demand or potential outages. Such approaches fail to optimize resource usage and often lead to unnecessary diesel consumption or inefficient battery usage. With the growing demand for sustainable and cost-effective energy solutions, there is a need for more intelligent and predictive energy management strategies [4].

In this context, this work proposes an AI-driven smart energy scheduling system that integrates demand forecasting and outage prediction to enable proactive decision-making. A Long Short-Term Memory (LSTM) model is employed to predict short-term energy demand by capturing temporal patterns in consumption data [1], while a Random Forest classifier is used to estimate the probability of grid outages based on time-related features [2]. These predictive insights are incorporated into a context-aware scheduling mechanism that considers battery state-of-charge (SOC) and operational constraints to optimize energy allocation among grid, battery, and diesel sources.

The proposed system aims to improve energy efficiency, reduce operational costs, and minimize diesel usage while maintaining system reliability under uncertain conditions.

2. LITERATURE REVIEW

Recent advancements in energy management systems have focused on improving efficiency through predictive modeling and intelligent control strategies. Time-series forecasting techniques, particularly Long Short-Term Memory (LSTM) networks, have been widely adopted for energy demand prediction due to their ability to capture temporal dependencies and periodic patterns in consumption data [1]. Several studies have demonstrated that LSTM-based models outperform traditional statistical approaches such as ARIMA in handling non-linear and dynamic energy usage patterns [3].

In parallel, optimization-based energy scheduling methods have been explored to manage power distribution across multiple sources, including grid supply, battery storage, and backup generators. These approaches typically rely on predefined rules or mathematical optimization techniques to minimize operational costs. However, most existing scheduling systems operate in a reactive manner, making decisions based only on current system conditions without incorporating future demand variations or uncertainty in grid availability [4].

More recent works have attempted to introduce predictive elements into scheduling frameworks, but the integration of outage prediction remains limited. Grid reliability, especially in regions with frequent power interruptions, plays a crucial role in energy planning, yet it is often overlooked in conventional models. Additionally, many existing systems do not account for battery state-of-charge constraints or the need to avoid unnecessary charging, which can lead to inefficient energy usage.

To address these limitations, the proposed work combines demand forecasting and outage prediction within a unified framework. By integrating LSTM-based demand prediction with Random Forest-based outage estimation [2], the system enables more informed and adaptive scheduling decisions. This approach enhances the ability of the system to operate efficiently under uncertain conditions while maintaining reliability.

3. METHODOLOGY

The proposed AI-driven smart energy scheduling system is designed as a multi-stage framework that integrates demand forecasting, outage prediction, and intelligent decision-making. The overall workflow of the system is illustrated in **Fig. 1**, where historical data is first processed and fed into predictive models, whose outputs are then utilized by the scheduling module to determine optimal energy allocation. The architecture highlights the interaction between forecasting, outage estimation, and decision logic, enabling a coordinated and adaptive energy management process.

3.1 Data Pre-processing

The dataset used in this study is derived from the UCI Electricity Load dataset, which is resampled into hourly intervals to better represent telecom tower energy consumption patterns. Since the original dataset contains high-frequency measurements, resampling helps in reducing noise and aligning the data with practical operational intervals.

Missing values are handled through standard cleaning techniques, and the dataset is structured into a time-series format suitable for sequential modeling. Feature engineering is performed by extracting temporal attributes such as hour of the day and day of the week, which help capture periodic consumption trends. In addition, lag features are introduced to incorporate historical dependencies, enabling the model to learn how past consumption influences future demand.

3.2 Demand Forecasting using LSTM

A Long Short-Term Memory (LSTM) neural network is employed for short-term energy demand forecasting due to its effectiveness in modeling temporal sequences and capturing long-term dependencies in time-series data [1]. The model utilizes a sliding window approach with a window size of 24 hours, allowing it to capture daily consumption patterns and periodic variations.

The input data is normalized to improve training stability, and the model is trained to predict the next time-step demand based on previous observations. The LSTM architecture, with its memory cell structure, enables the model to retain relevant historical information while filtering out noise, making it suitable for energy demand prediction.

The performance of the model is illustrated in **Fig. 2**, where the predicted values closely follow the actual demand trend, demonstrating the model's ability to capture both peak and off-peak variations in energy consumption.

3.3 Outage Prediction using Random Forest

To enhance the adaptability of the system under uncertain grid conditions, an outage prediction module is incorporated using a Random Forest classifier. The model estimates the probability of grid failure based on temporal features such as hour of the day and day of the week.

Random Forest is selected due to its robustness and ability to handle non-linear relationships without extensive parameter tuning [2]. As an ensemble learning method, it combines multiple decision trees to improve prediction accuracy and reduce overfitting.

The predicted outage probability provides a measure of risk associated with grid availability and is used as a key input to the scheduling module. This enables the system to anticipate potential outages and make proactive energy allocation decisions.

3.4 Intelligent Scheduling Algorithm

The scheduling module is responsible for determining the optimal distribution of energy among grid power, battery storage, and diesel generators. As shown in **Fig. 1**, this module acts as the central decision-making unit, combining inputs from both the demand forecasting and outage prediction models along with system constraints.

Two scheduling approaches are implemented:

Reactive Scheduler

The reactive scheduler serves as a baseline method. It makes decisions based solely on current demand and grid availability, without considering future demand or outage risk. While simple to implement, this approach often leads to inefficient energy utilization and higher diesel consumption.

Predictive Scheduler

The predictive scheduler incorporates multiple factors to make informed decisions, including:

- Forecasted energy demand
- Outage probability
- Battery State of Charge (SOC)
- Cost parameters of grid and diesel

By analyzing future demand trends and outage likelihood, the scheduler determines whether to utilize grid power, discharge the battery, or rely on diesel generation.

A key feature of the proposed system is the incorporation of **necessity-aware logic**, which ensures that battery charging occurs only when required. Instead of continuously charging whenever grid power is available, the system evaluates whether the stored energy is sufficient to handle anticipated future demand and outages. This prevents overcharging, reduces unnecessary energy usage, and improves overall system efficiency.

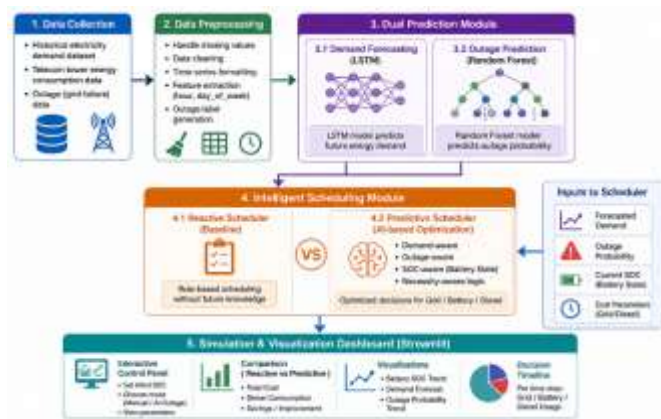


Fig. 1. Proposed AI-driven energy scheduling system architecture

4. RESULTS

The proposed predictive energy scheduling system was evaluated across multiple simulation scenarios with varying initial battery state-of-charge (SOC) levels and different outage patterns. This multi-scenario evaluation ensures that the system performance is not dependent on a single configuration but reflects realistic operating conditions.

The performance of the predictive scheduler is compared with a baseline reactive approach, and the results are summarized in **Table I**.

Method	Cost (₹)	Diesel Used (kWh)
Reactive	15651.00 ± 2930.27	521.80 ± 242.18
Predictive	15363.58 ± 2635.86	505.83 ± 232.58

Table I: Performance comparison (Mean ± Standard Deviation)

From Table I, it can be observed that the predictive scheduling approach achieves a reduction in both operational cost and diesel consumption when compared to the reactive baseline. On

average, the predictive model reduces cost by approximately **1.84%** and diesel usage by **3.06%**.

Although the improvement margins are moderate, they indicate that the system is capable of making more informed and forward-looking decisions by incorporating both demand forecasting and outage prediction. Unlike the reactive approach, which operates solely on current conditions, the predictive scheduler anticipates future demand and potential grid failures, allowing it to allocate energy resources more effectively.

The relatively small improvement can be attributed to the inherent uncertainty in outage prediction and the conservative nature of the scheduling constraints. The system is designed to prioritize reliability, ensuring that sufficient energy reserves are maintained to handle unexpected outages. As a result, the scheduler avoids overly aggressive optimization strategies that could compromise system stability.

LSTM Model Performance Analysis

The performance of the demand forecasting model is illustrated in **Fig. 2**, which shows the comparison between actual and predicted energy demand over a sequence of time steps.

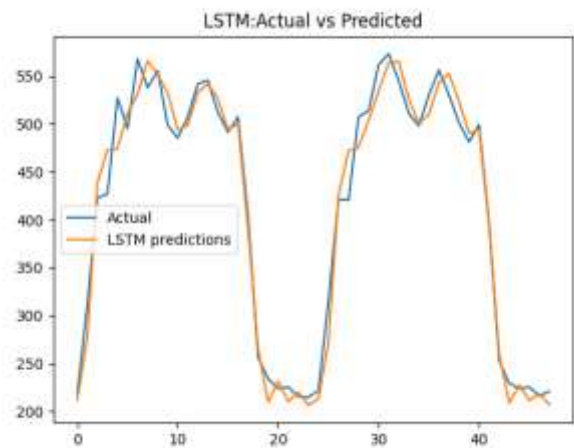


Fig. 2. LSTM model performance: Actual vs predicted energy demand

As observed in Fig. 2, the predicted values closely follow the actual demand curve, indicating that the LSTM model has effectively learned the underlying temporal patterns in energy consumption. The model successfully captures both peak and off-peak variations, which are essential for accurate scheduling decisions.

Minor deviations are visible during sharp transitions and sudden peaks in demand. These variations are expected due to the stochastic nature of real-world energy consumption and the limitations of short-term forecasting models. However, the overall trend alignment demonstrates that the model provides sufficiently accurate predictions for practical use.

The effectiveness of the LSTM model plays a crucial role in the performance of the scheduling system. Accurate demand forecasting enables the scheduler to anticipate future energy requirements and make proactive decisions, thereby improving overall system efficiency.

5. DISCUSSION

The integration of demand forecasting and outage prediction enables the proposed system to operate in a more adaptive and context-aware manner. By combining predictive insights with system constraints such as battery SOC and cost considerations, the scheduler achieves a balance between efficiency and reliability.

One key observation is that the predictive scheduler does not always produce significantly lower costs in every scenario. This is because the system adopts a cautious strategy when outage probability is high, often prioritizing energy availability over immediate cost savings. While this may lead to slightly higher cost in certain cases, it enhances the robustness of the system and reduces the risk of power interruptions.

Overall, the results demonstrate that even modest improvements in cost and diesel consumption can be meaningful in large-scale telecom deployments, where energy usage is continuous and cumulative. The proposed approach provides a scalable and intelligent solution for improving energy management in telecom microgrids.

6. CONCLUSION

This paper presented an AI-driven smart energy scheduling system for telecom microgrids by integrating demand forecasting and outage prediction into a unified decision-making framework. The proposed approach combines an LSTM-based model for short-term energy demand prediction with a Random Forest classifier for estimating outage probability, enabling the system to make proactive and context-aware scheduling decisions.

The results demonstrate that the predictive scheduler achieves consistent reductions in operational cost and diesel consumption compared to conventional reactive methods. Although the improvements are moderate, they highlight the effectiveness of incorporating predictive intelligence into energy management systems. The inclusion of necessity-aware logic further enhances system efficiency by avoiding unnecessary battery charging and ensuring optimal resource utilization.

Overall, the proposed system improves energy efficiency while maintaining reliability under uncertain conditions, making it a suitable approach for real-world telecom applications. Future work may focus on improving outage prediction accuracy, incorporating real-time data, and extending the system to multi-tower environments for large-scale deployment.

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