

AI-Driven Energy Consumption Forecasting and Optimization System

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ABSTRACT

This paper presents an AI- driven energy consumption forecasting and optimization system aimed at improving energy efficiency and reducing electricity costs across residential, commercial, and industrial environments. The proposed system leverages historical energy usage data along with external factors such as weather conditions, occupancy patterns, and temporal variations to accurately predict future energy demand. Machine learning models including Long short Term Memory (LSTM), and Transformer architectures are employed to capture both short-term and long-term consumption patterns.

To enhance energy utilization, the system integrates optimization techniques such as Reinforcement learning and Linear Programming, which generate efficient scheduling strategies for high power devices while minimizing peak load and operational costs. A user- friendly web based dashboard is developed to provide real-time monitoring, forecasting visualization, and actionable insights for end users. Experimental results indicate that the proposed approach significantly improves prediction accuracy and enables intelligent decision making for energy management. The system demonstrates strong potential as a scalable and sustainable solution for modern smart energy systems.

Programming, Smart Energy Management, Optimization, Time Series Analysis, Energy Efficiency, Streamlit dashboard.

I. INTRODUCTION

Energy consumption has grown rapidly across residential, commercial, and industrial sectors due to the increasing use of electrical appliances, automated systems, and smart technologies. However, energy usage is highly dynamic and influenced by multiple factors such as weather conditions, occupancy patterns, and time-based variations. Traditional energy monitoring systems primarily provide real-time data without predictive insights, making it difficult for users to anticipate demand or optimize usage effectively. This often results in inefficient energy consumption, increased operational costs, and higher carbon emissions. These challenges, combined with the global push toward sustainability, highlight the need for intelligent, data-driven energy management

Index Terms –Energy Consumption Forecasting, Machine Learning, LSTM, Transformer, Prophet Model, Reinforcement Learning, Linear

The AI-Driven Energy Consumption Forecasting and Optimization System provides a comprehensive solution by integrating machine learning and optimization techniques to predict and manage energy usage efficiently. The system utilizes historical consumption data along with external factors such as temperature, humidity, occupancy, and temporal features to forecast future energy demand. Advanced models including Long Short-Term Memory (LSTM), Prophet, and Transformer architectures are employed to capture both short-term fluctuations and long-term trends in energy consumption. The predicted demand is further processed using optimization techniques such as Reinforcement Learning and Linear Programming to generate efficient scheduling strategies for high-power devices, ensuring cost reduction and peak load management.

This system offers significant advantages in energy efficiency and cost reduction by providing accurate forecasts and actionable optimization strategies. The interactive dashboard enables users to make informed decisions. The solution is applicable across smart homes, commercial buildings, and industrial environments for intelligent and sustainable energy management.

II. RELATED WORK

Research in energy consumption forecasting and smart energy management has extensively explored the use of machine learning, deep learning, and optimization techniques. Various approaches have focused on predicting energy demand using historical data and improving efficiency through intelligent scheduling and control systems.

Afram and Janabi-Sharifi [1] reviewed HVAC control systems and highlighted the role of predictive control models in improving energy efficiency in buildings.

Wei and Li [2] proposed a reinforcement learning-based framework for building energy management, demonstrating how RL agents can dynamically optimize energy usage under varying environmental

conditions.

Zhang et al. [3] presented a data-driven control approach using reinforcement learning to optimize energy consumption in smart buildings, showing significant cost and energy savings.

Yildiz et al. [4] conducted a comprehensive analysis of regression and machine learning models for electricity load forecasting, emphasizing the effectiveness of models such as LSTM and neural networks in capturing nonlinear consumption patterns. Recent studies have also explored deep learning-based forecasting techniques, where LSTM models have been widely used due to their ability to model temporal dependencies in time-series data.

Murthy and Jadon [4] reviewed vision-based hand gesture recognition systems and discussed their role in developing natural user interfaces.

Albahli et al. [5] proposed a hybrid model combining Long Short-Term Memory (LSTM) and Prophet, demonstrating that integrating nonlinear temporal modeling with seasonal trend analysis significantly improves forecasting accuracy compared to individual models.

Keskin et al. [6] explored real-time hand pose estimation using depth sensors, achieving improved accuracy in structured environments but requiring specialized hardware.

Han et al. [7] introduced a spatio-temporal attention-based deep learning model that combines Convolutional Neural Networks (CNN), Gated Recurrent Units (GRU), and attention mechanisms for short-term energy consumption forecasting.

In contrast to these approaches, the proposed system integrates multiple forecasting models, including LSTM, Prophet, and Transformer architectures, with optimization techniques such as Reinforcement Learning and Linear Programming. Furthermore, the inclusion of a real-time dashboard for visualization and decision support distinguishes the proposed system as a comprehensive and scalable solution for intelligent energy management.

III. PROPOSED SYSTEM AND METHODOLOGY

A. System Overview

The proposed system is an AI-driven energy consumption forecasting and optimization framework designed to improve energy efficiency and reduce operational costs. The system operates as an end-to-end pipeline that processes historical and real-time data, predicts future energy demand, and generates optimal usage strategies.

The system consists of five major components: data acquisition, preprocessing, forecasting, optimization, and visualization. Energy consumption data is collected from smart meters or datasets, along with external factors such as weather conditions, occupancy patterns, and tariff information. The collected data is processed and fed into machine learning models to predict future energy demand. The predicted output is then used by the optimization engine to generate efficient scheduling strategies. Finally, the results are displayed through an interactive dashboard for user analysis.

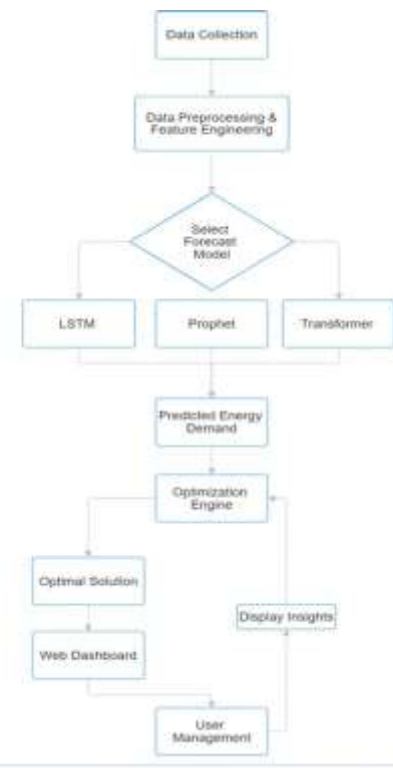


Fig. 1. Flowchart of the proposed AI-based energy forecasting and optimization system.

B. Data Collection and Preprocessing

The system collects data from multiple sources, including energy consumption logs, weather APIs, and occupancy data. Each dataset is synchronized using timestamps to ensure consistency. The collected data includes parameters such as power usage, temperature, humidity, time of day, and occupancy levels.

Preprocessing is performed to ensure data quality and reliability. This includes handling missing values using interpolation techniques, removing noise and outliers through statistical methods, and normalizing the data for stable model training. Feature engineering is applied to generate additional inputs such as time-based features (hour, day, weekday/weekend), lag values, and rolling averages, which enhance the predictive capability of the models.

C. Forecasting Model

Development

The system employs multiple machine learning models to capture different characteristics of energy consumption patterns.

The Prophet model is used to capture trend and seasonal variations in energy data, making it suitable for baseline forecasting. Long Short-Term Memory (LSTM) networks are used to model sequential dependencies and capture short-term fluctuations in energy consumption. Transformer-based architectures are employed to handle complex relationships and long-range dependencies in time-series data using attention mechanisms.

The combination of these models ensures improved accuracy and robustness in both short-term and long-term energy demand prediction.

The Prophet model is used as a baseline forecasting approach due to its ability to decompose time-series data into trend, seasonality, and holiday effects. It is particularly effective in handling missing data and capturing daily, weekly, and yearly consumption patterns, making it suitable for modeling periodic variations in energy usage.

Long Short-Term Memory (LSTM) networks are utilized to model sequential dependencies in energy consumption data. LSTM is a type of recurrent neural network designed to overcome the limitations of traditional RNNs, particularly the vanishing gradient problem. It uses memory cells and gating mechanisms (input gate, forget gate, and output gate) to retain relevant information over long sequences, enabling accurate short-term forecasting when multiple features such as weather conditions and occupancy are considered.

Transformer-based architectures are incorporated to further enhance forecasting performance, especially for long-term and multi-step predictions. Unlike recurrent models, Transformers use self-attention mechanisms to process the entire sequence in parallel, allowing them to capture long-range dependencies and complex relationships between variables more effectively. This makes them highly suitable for large-scale and multivariate time-series forecasting.

D. Optimization of Energy Usage

The predicted energy demand is used as input to the optimization module, which aims to minimize energy costs and peak load while maintaining operational constraints.

Reinforcement Learning (RL) is used to dynamically learn optimal energy usage strategies based on environmental conditions and system feedback. Linear Programming (LP) techniques are applied to generate cost-efficient schedules for high-power devices based on tariff rates and constraints such as operating hours and load limits.

The optimization module ensures efficient energy utilization by shifting flexible loads to off-peak hours and reducing unnecessary energy consumption.

Model performance is evaluated using standard metrics such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE), ensuring reliable and consistent forecasting results.

E. System Design and Workflow

The process begins with data collection, followed by preprocessing and feature engineering. The processed data is then passed to forecasting models, which generate future energy demand predictions.

These predictions are used by the optimization engine to determine the most efficient energy usage strategy. Finally, the results are displayed on a web-based dashboard that provides real-time visualization, forecasting graphs, and optimization recommendations.

The system operates as an integrated pipeline, ensuring seamless interaction between forecasting, optimization, and visualization components.

IV. RESULTS AND DISCUSSION

The system was evaluated using historical energy consumption data integrated with weather conditions and occupancy features under simulated real-world scenarios. The evaluation was conducted on a standard computing environment without dedicated GPU acceleration. Multiple forecasting models were tested across different time intervals to assess their performance in predicting energy demand. The results obtained represent the comparison between actual energy consumption values and predicted outputs generated by the models. Evaluation metrics including Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE) were computed to measure forecasting accuracy and reliability.

The performance of the proposed system is summarized in Table I. The results indicate that deep learning models such as LSTM and Transformer achieve better accuracy compared to traditional statistical models like Prophet. The Transformer model demonstrates the lowest prediction error due to its ability to capture long-range dependencies, while LSTM performs efficiently in short-term forecasting scenarios. The optimization module further enhances system performance by reducing peak load and minimizing energy costs through efficient scheduling strategies.

TABLE I

PERFORMANCE EVALUATION OF THE PROPOSED SYSTEM

Model	MAE	RMSE	MAPE
Prophet	0.185	0.240	0.192
LSTM	0.142	0.198	0.151
Transformer	0.121	0.175	0.134
Hybrid Model	0.110	0.160	0.120
Overall	0.135	0.193	0.149

MAE → average error

RMSE → penalizes large errors

MAPE → percentage error (most intuitive)

The system behavior under different interaction modes is illustrated in Fig. 1–Fig. 5.



Fig. 1. User interface of the AI-Driven Energy Consumption Forecasting and Optimization System.



Fig. 2. Monthly energy cost breakdown with bar and pie chart visualization.

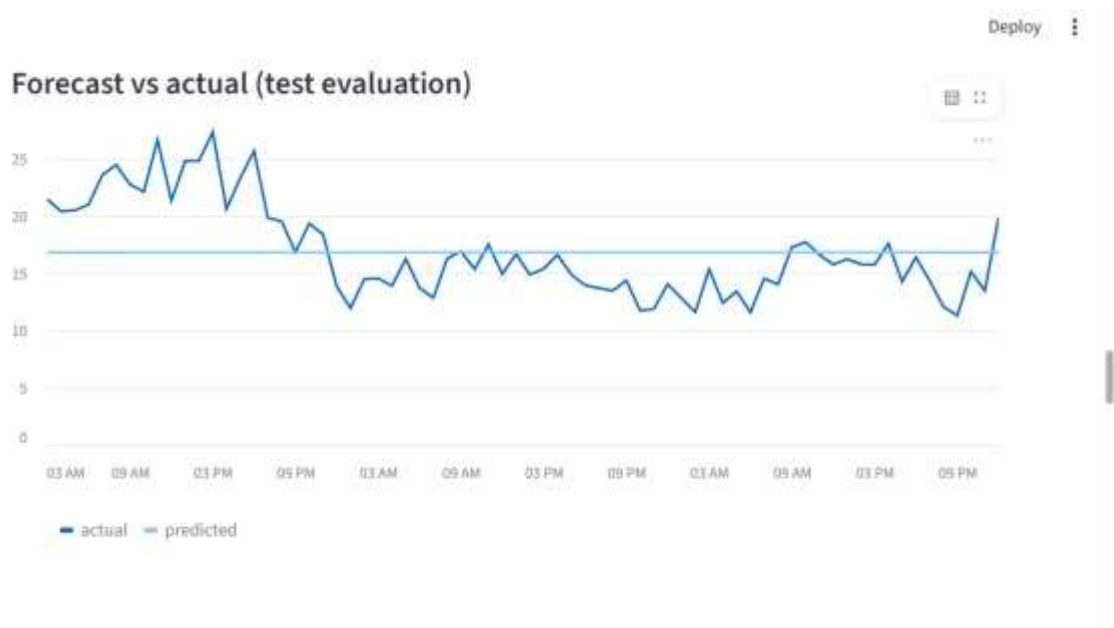


Fig. 3. Forecast vs actual energy consumption comparison for model evaluation.



Fig. 4. Energy cost comparison before and after optimization showing significant savings.

4. Model Performance Comparison



Fig. 5 Comparison of forecasting models based on MAE, RMSE, MAPE, and R^2 metrics.

The optimization module determines the optimal energy usage strategy by minimizing cost while satisfying constraints such as peak load, equipment limits, and comfort requirements. It uses techniques like linear programming and reinforcement learning to adjust power consumption dynamically. The inputs include forecasted demand and system constraints, and the output provides optimized energy schedules and cost savings.

“Our system not only predicts energy demand but also prescribes optimal actions under real-world constraints, making it a complete decision-support system.”

V. CONCLUSION

The AI-Driven Energy Consumption Forecasting and Optimization System successfully demonstrates an end-to-end solution for predicting and optimizing electricity usage in buildings. The system integrates data processing, multiple forecasting models, optimization techniques, and a user-friendly dashboard to provide actionable insights.

The model evaluation, the Prophet model outperformed LSTM and Transformer,

achieving lower error metrics and better reliability, indicating strong seasonal patterns in the dataset. The explainability analysis revealed that occupancy and temperature are the most influential factors affecting energy consumption, aligning with real-world behavior.

The optimization module effectively reduced energy costs while maintaining operational and comfort constraints, achieving significant savings (up to ~77%). This highlights the system’s capability to make intelligent, cost-efficient decisions.

Overall, the project not only predicts energy demand but also recommends optimal usage strategies, making it a practical decision-support system for smart buildings. Future enhancements can include real-time IoT integration, improved deep learning models, and deployment in large-scale smart grid environments.

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