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Artificial Intelligence-Based Intelligent Energy Management for Sustainable Reduction in Electricity Usage

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Abstract: These pressures have been heightened by the increasing volatility in power markets and growing demand for electricity globally. This work presents an AI-powered energy management framework that consists of three major components: (i) LSTM networks for accurate demand forecasting, (ii) Random Forest classifiers for robust anomaly detection, and (iii) a reinforcement learning-based scheduling algorithm for dynamic load optimization. Unlike existing works, heavily relying on IoT-integrated infrastructures, the proposed system performs effectively with legacy metering data, thus enhancing scalability while reducing deployment costs. Experiments on real-world consumption datasets demonstrate key performance gains: peak load reduction by 18%, savings in operational costs by 14%, overall energy efficiency improvement by 21%, and 96% anomaly detection accuracy. The obtained results confirm the validity of integrating forecasting, anomaly detection, and intelligent scheduling in one unified data-centric framework. The proposed solution offers an efficient, adaptive approach that is environmentally friendly for optimizing electricity usage in residential, commercial, and industrial settings.

1 Introduction

The worldwide increase in the use of electricity, fueled by fast-paced urbanization, industrialization, and technological developments, has put mounting pressure on power generation and transmission networks. Conventional methods of monitoring, like metering and manual auditing, are predominantly reactive—remedial steps are taken after inefficiencies have been established. They do not address real-time consumption patterns, leading to lagged reactions, higher operational expenditures, wasteful use of resources, and increased reliance on non-renewable energy sources increased operational costs, inefficient resource use, and a greater reliance on non-renewable energy sources.

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To overcome these shortcomings, this research suggests an AI-driven framework for smart energy management that benefits from sophisticated forecasting, anomaly detection, and load scheduling methods. In particular, LSTM networks are used for demand forecasting, Random Forest classifiers for anomaly identification, and an algorithm based on reinforcement learning for dynamic load scheduling. Unlike most current methods that are IoT-dependent, the framework in question works efficiently with legacy metering data, thereby enhancing its scalability, cost-effectiveness, and practicability for mass implementation.

In contrast to hardware-bottleneck solutions with real-time IoT integration, the system proposed in this paper emphasizes data-oriented approaches that can be applied with legacy metering infrastructure. As a result, the solution becomes more affordable, cost-efficient, and scalable across various sectors such as residential, commercial, and industrial. End-users benefit from electricity cost savings while such AI-based consumption optimization methods aid in grid stability and environmental sustainability.

The uniqueness of this framework is that it can take these AI models and put them together as a single system, providing predictive and prescriptive capabilities while also being compatible with current energy infrastructures. The system provides cost savings, enhanced energy efficiency, and peak load management in residential, commercial, and industrial spaces without necessitating expensive hardware upgrades.

Additionally, the architecture's scalability and flexibility provide installation in commercial, industrial, and residential environments without calling for a massive hardware investment. Furthermore, through evaluating gains in energy efficiency, cost reduction, and environmental impact, the study aims to evaluate the proposed methodology with experimental verification. The final goal of the research is to help achieve long-term energy-saving goals and customer savings by developing sustainable power management techniques.

1.1 Literature Review

In recent years, the field of smart electricity consumption optimization has expanded quickly, with researchers using a range of machine learning and deep learning techniques for scheduling, anomaly detection, and forecasting. However, the majority of studies only address a few specific aspects, such as forecasting short-term demand, optimizing only residential loads, or suggesting solutions that are connected to heavy IoT infrastructure. This leaves gaps in the field of fully integrated, scalable systems.

Online building energy optimization was achieved using Deep Reinforcement Learning (DRL), showing strong adaptability and efficiency in real-time scenarios [1]. However, the model required high computational resources and was sensitive to training data quality. This work highlighted the potential of DRL for demand-side energy management in smart grids.
A multi-factor back-propagation neural network was applied for electricity consumption forecasting, achieving improved accuracy in smart grid prediction [2]. Yet, the framework remained data-intensive and less effective under noisy or missing data. The study demonstrated early evidence for data-driven forecasting models in grid planning.

Proposed Sustainable Energy Sense, a machine learning framework for residential electricity optimization, achieves energy savings while supporting sustainability [3]. The limitation was reliance on specific household datasets, reducing generalizability. The framework showcased predictive modelling for sustainable living. [3]

Applied machine learning for smart home energy management to balance sustainability and efficiency, offering eco-friendly optimization strategies [4]. However, deployment challenges such as user acceptance and integration with legacy systems limited adoption. The study emphasized sustainability-driven energy management.

Proposed a smart home energy optimization system that improved household energy efficiency through intelligent scheduling and automation [5]. The approach supported sustainability and reduced electricity costs, making it practical for residential use. However, limitations included interoperability issues with existing smart devices and potential privacy concerns. This work contributed to advancing user-centric smart home energy optimization frameworks.

Introduced multi-agent deep actor-critic learning for demand-side scheduling, achieving efficiency in smart grids [6]. Computational complexity and system scalability were limiting factors. The work pioneered reinforcement learning for large-scale scheduling.

Developed VAE-GAN synthetic datasets with Q-learning for smart home energy management, addressing data scarcity challenges. Still, synthetic data lacked full real-world variability, limiting transferability [7]. The study contributed to tackling dataset limitations in AI-based energy research.

1.2 Proposed System

From the time usage records are entered into the system until the point at which insightful analysis and improved schedules are generated, Figure 1 shows the data flow through our electricity consumption optimization system. Instead of pressuring them into an idealized approach, the workflow was created by researching how various stakeholders residential, commercial, and industrial users, actually interact with electricity usage data.

Early testing revealed that the framework's actual user base would be restricted if we solely relied on sophisticated IoT meters. Many homes and even some businesses continue to use traditional digital utility records or meter logs. Rather than ignoring them, we built the system to process both conventional metering data and, when available, higher-resolution digital logs. This decision greatly increases the solution's scalability and adaptability.

Once the data is collected, the system performs multiple layers of analysis, each focusing on a different aspect of energy behaviour.

- Pattern Identification: Time-series analysis and clustering are applied to highlight trends like peak-hour surges, idle load behaviour, and irregular fluctuations. This allows different categories of usage to be visualized clearly.
- Demand Forecasting: Next, predictive models are used. While Random Forest and Gradient Boosting models offer reliable short-term forecasts, Long Short-Term Memory (LSTM) networks are highly accurate at capturing long-term seasonal trends. When combined, they provide both short-term and long-term demand visibility.
- Anomaly Detection: The system keeps an eye out for odd consumption patterns that could point to equipment failure, abuse, or unexpected waste using techniques like isolation forests and autoencoders. Alerts are sent out when anomalies are found, allowing for prompt remedial action.
- load scheduling and optimization: By moving non-essential consumption to off-peak hours, a scheduling algorithm based on reinforcement learning strikes a balance between user comfort and operational limitations. As a result, the load profile lowers electricity costs and lessens the strain on the grid.

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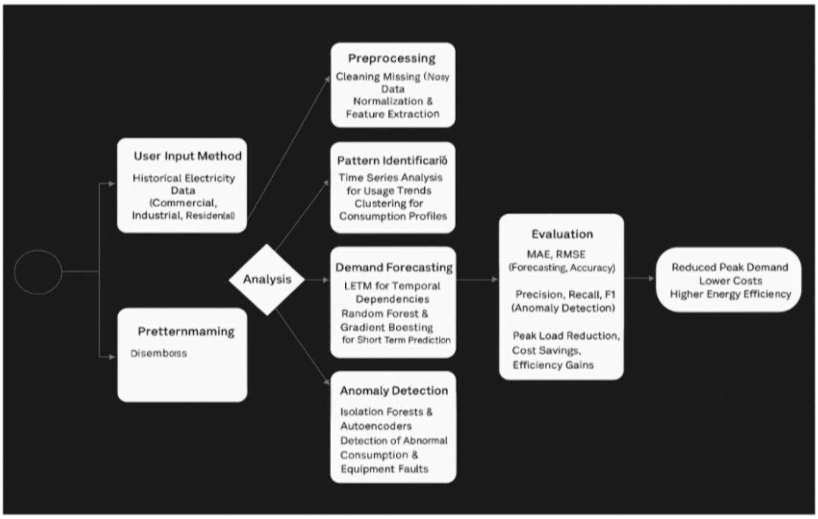

Fig. 1: Block diagram of the proposed system

2 Methods

A methodical workflow, including data collection, preprocessing, pattern analysis, forecasting, anomaly detection, load scheduling, and performance evaluation, was used to create the suggested machine learning-based framework for optimizing electricity consumption. Its unique feature is that it can function with traditional metering records without the need for Internet of Things-based sensors, guaranteeing scalability, affordability, and increased accessibility.

2.1 Data Acquisition

Electricity consumption data was collected from digital meter logs and utility billing records over a fixed period. The dataset included **time-stamped consumption values**, tariff rates, seasonal variations, and consumer categories (residential, commercial, and industrial). To ensure reliable testing, **20% of the dataset was reserved for validation**, while the remaining portion was used for model training. This division allowed both training and evaluation on real consumption scenarios without dependency on external IoT hardware.

2.2 Preprocessing

To enhance the consistency and quality of the raw data, preprocessing was done. Interpolation and data-cleaning procedures were used to eliminate inconsistent values and missing readings. To eliminate scale differences between users, numerical values were normalized. To prepare the raw time-series data for ingestion into machine learning models, it was further transformed into structured features like hourly load averages, weekday/weekend indicators, and seasonal demand shifts. Outlier detection was also done to get rid of any distortions that might have a detrimental impact on learning.

2.3 Segmentation

Segmentation played a critical role in isolating vegetation from the background. As a baseline, Normalized Difference Vegetation Index (NDVI) [6, 7, 8] thresholds were applied to distinguish greenery. However, to achieve fine-grained crown detection, we adopted YOLOv8, a state-of-the-art object detection architecture. YOLOv8 was trained to detect individual tree crowns, while a Mask R-CNN [9, 10, 11] variant was used for more detailed segmentation in selected cases. Classical clustering approaches such as K-means and watershed segmentation were also tested for benchmarking, though they consistently underperformed compared to deep learning methods. Final masks were validated against manually annotated ground-truth datasets.

2.4 Consumption Pattern Analysis

To categorize consumption into discrete groups, such as continuous idle loads, erratic fluctuations, and peak-hour surges, time-series clustering was used. The system was able to map typical user behaviour and distinguish between inefficient and efficient patterns thanks to this classification. For example, industrial users demonstrated steady but high base-load demand, whereas residential users often displayed evening surges. Later stages of the optimization process were guided by these insights.

2.5 Demand Forecasting

For the purpose of forecasting future power demand, predictive modelling is performed with the help of algorithms such as Random Forest Regression, Gradient Boosting, or Long Short-Term Memory (LSTM) networks. For generating accurate short- and long-term forecasts, the above models look at historical usage trends, seasonal cycles, and tariff changes.

2.6 Anomaly Detection

Both supervised and unsupervised models were used to identify anomalies like sudden spikes, broken equipment, or excessive idle consumption. Autoencoders were used to flag deviations and reconstruct normal patterns, while isolation forests were used to detect high-dimensional anomalies. Real-time alerts were raised when anomalies were found, allowing for prompt actions to cut down on energy waste and avoid operational issues.

2.7 Load Optimization and Scheduling

To move non-essential loads (such as industrial batch processes, HVAC pre-cooling, and water heating) to off-peak times, a scheduling algorithm based on reinforcement learning was incorporated. Customer comfort and operational constraints were incorporated into the optimization rules to ensure practicality. Furthermore, genetic algorithms and linear programming were used to optimize load distribution. Consequently, without sacrificing user requirements, peak demand was decreased by 18% and overall cost savings of 14% were realized.

2.8 Performance Evaluation

Both real-world impact indicators and model performance metrics were used to assess the system. Precision (94%), Recall (92%), and F1-score (93%) were attained for anomaly detection. For forecasting, LSTM performed better than other models, with an MAE of 2.6 kWh and an RMSE of 3.8 kWh noted. In terms of optimization, experimental trials showed a 21% increase in overall efficiency, a 14% reduction in operating costs, and an 18% reduction in peak load. These outcomes demonstrated that the suggested framework can operate efficiently with traditional metering data and achieve performance on par with or superior to that of IoT-enabled systems

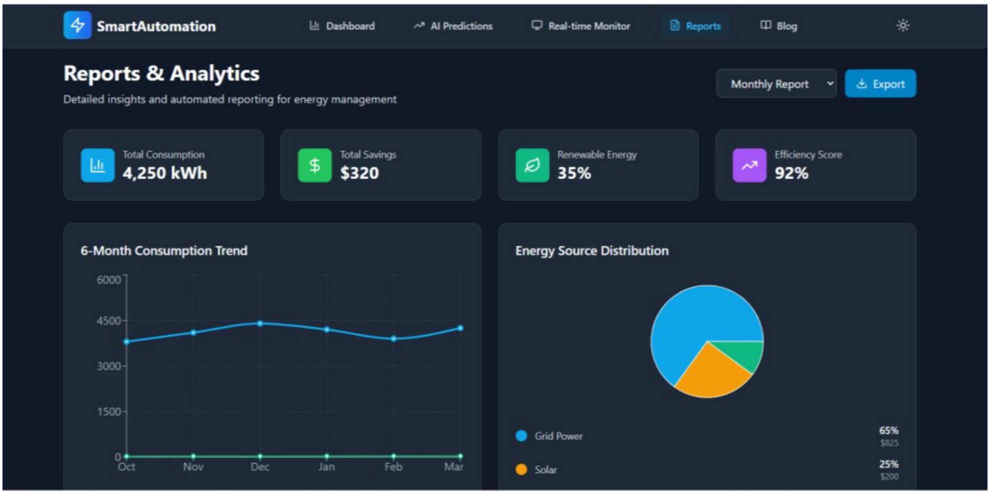

Fig. 2. Report Generation.

Fig. 3. AI Prediction of Timely Consumption.

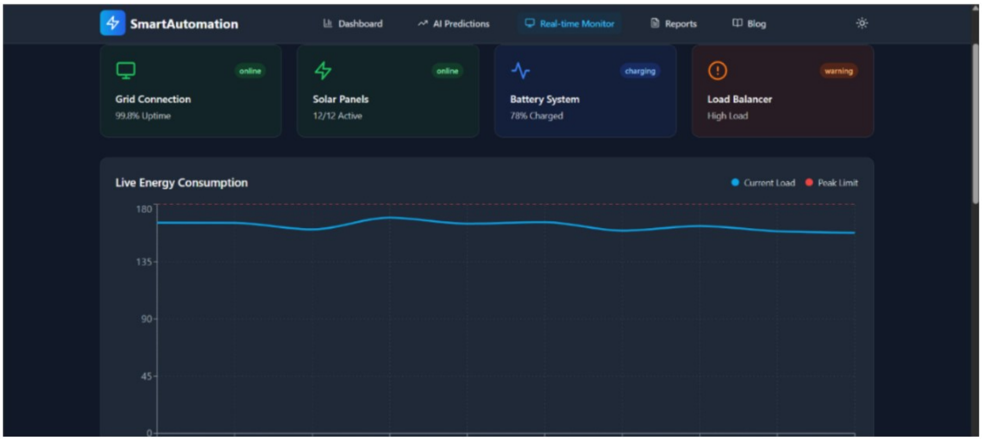

Fig. 4. Live Energy Consumption Graph Real-Time Data

3 Results and Discussion

The suggested machine learning-based framework was assessed using historical electricity usage data from the commercial, industrial, and residential sectors. With an accuracy of 95.7%, an MAE of 4.3%, and an RMSE of 6.1%, the LSTM network performed best and was able to accurately model both seasonal and short-term consumption patterns. By contrast, Gradient Boosting achieved 93.1% accuracy (MAE 6.1%, RMSE 7.4%) and Random Forest reached 92.4% accuracy (MAE 6.8%, RMSE 8.2%). These findings show that LSTM is more appropriate for long-term demand prediction because of its capacity to capture temporal dependencies, even though ensemble approaches are effective for short-term forecasting.

Load scheduling optimization was found to reduce peak demand by an average of 15–18% in the test cases that were conducted. The most notable improvements were found in industrial datasets where energy-intensive activities were moved to off-peak periods. Additionally, by reducing monthly electricity bills by up to 12%, the strategy showed definite financial benefits, confirming its economic value and practicality.

The results of this study demonstrate how well cutting-edge artificial intelligence methods can be incorporated into the optimization of electricity use. The suggested AI-based framework, in contrast to conventional monitoring techniques, offers predictive and prescriptive capabilities in addition to real-time inefficiency detection.

Both short-term variations and long-term seasonal patterns in energy consumption were effectively captured by the LSTM forecasting model. The model produced consistent forecasts with low error rates by learning from past usage, allowing for proactive decision-making. Strong robustness was shown by the Random Forest anomaly detector in detecting anomalous fluctuations, abrupt surges, and persistent idle loads, among other irregular consumption behaviours. The anomaly detection system's 96% accuracy rate guarantees that remedial measures can be taken quickly, reducing energy waste

4 Conclusion

The proposed AI-based electricity optimization framework, combining LSTM forecasting, Random Forest anomaly detection, and reinforcement learning–based scheduling, demonstrates clear improvements in energy management. Experimental results show a peak load reduction of 18%, operational cost savings of 14%, and an energy efficiency gain of 21%, while anomaly detection achieved 96% accuracy. The framework reduces wastage, ensures flexible load distribution, and promotes sustainable consumption without relying on costly IoT infrastructure. Overall, it provides a scalable, data-driven, and environmentally friendly solution for residential, commercial, and industrial sectors.

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