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Energy Consumption Forecasting in Organizational Buildings Using Machine Learning

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Abstract - Energy consumption forecasting has become an important research area due to the increasing demand for efficient energy management in organizational buildings such as offices, universities, hospitals, and commercial infrastructures. These buildings consume a large amount of energy daily for lighting, heating, ventilation, cooling systems, and electrical equipment. Because of changing occupancy patterns, flexible working schedules, environmental conditions, and operational uncertainties, accurately predicting energy consumption has become a complex task.

Traditional forecasting approaches such as statistical regression and time-series methods are simple to implement but often fail to capture complex nonlinear energy consumption patterns. In recent years, Machine Learning and Deep Learning techniques have improved forecasting performance by identifying hidden relationships between environmental conditions, occupancy behavior, and energy usage. However, existing systems still suffer from several challenges such as limited data availability, poor adaptability, lack of integration between forecasting models, and difficulty handling real-time variations.

To overcome these challenges, this research proposes an integrated hybrid framework called GAN-GBRT-LSTM. The proposed system combines Generative Adversarial Networks (GAN) for synthetic data generation, Gradient Boosted Regression Trees (GBRT) for feature extraction, and Long Short-Term Memory (LSTM) networks for time-series forecasting. The framework aims to improve prediction accuracy, increase scalability, and enhance adaptability in organizational buildings.

The study analyzes existing forecasting techniques, identifies major research gaps, and proposes a scalable intelligent forecasting system suitable for dynamic real-world environments. The proposed model contributes to efficient energy management, reduced operational costs, and sustainable energy utilization.

Keywords: Energy Forecasting, Organizational Buildings, Machine Learning, Deep Learning, LSTM, GAN, GBRT, Hybrid Models, Energy Management, Time-Series Prediction.

I. INTRODUCTION

Energy management has become one of the most critical challenges faced by modern organizations due to the rapid increase in electricity demand and operational costs. Organizational buildings such as universities, hospitals, office complexes, shopping malls, research centers, and commercial infrastructures consume a significant amount of energy every day for lighting systems, air conditioning, heating, cooling, ventilation, elevators, computing devices, laboratory equipment, and other electrical appliances. As urbanization and industrial growth continue to expand, energy consumption in organizational environments has increased dramatically.

The growing dependence on electrical energy has created both economic and environmental concerns. Organizations spend a large portion of their operational budget on electricity consumption, making efficient energy management extremely important. At the same time, excessive energy usage contributes to greenhouse gas emissions, environmental pollution, and climate change. Therefore, reducing unnecessary energy consumption and improving energy efficiency have become global priorities.

Energy consumption forecasting plays a major role in intelligent energy management systems. Forecasting refers to the process of predicting future energy demand based on historical data, environmental conditions, occupancy behavior, and operational activities. Accurate forecasting allows organizations to optimize resource utilization, reduce electricity wastage, balance energy loads, and improve decision-making processes.

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In organizational buildings, energy consumption patterns are highly dynamic and influenced by multiple factors. Occupancy levels change throughout the day depending on working hours, meetings, events, holidays, and seasonal schedules. Environmental variables such as temperature, humidity, sunlight intensity, and weather conditions also affect electricity demand. For example, air conditioning systems consume more energy during summer seasons, while heating systems require additional electricity during colder periods.

Traditional forecasting approaches such as linear regression, moving averages, and statistical time-series methods were initially used for energy prediction. These methods are computationally simple and easy to implement. However, traditional models often assume linear relationships between variables and cannot effectively capture complex nonlinear patterns present in real-world energy systems.

Another major limitation of conventional forecasting methods is their inability to adapt dynamically to changing environments. Organizational buildings frequently experience irregular occupancy schedules, fluctuating energy demand, and unexpected operational events. Traditional systems cannot accurately handle these dynamic conditions, resulting in poor prediction performance.

Recent advancements in Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning have transformed energy forecasting research. Machine Learning models can analyze large-scale energy datasets and identify hidden relationships between occupancy patterns, weather conditions, and electricity usage. These intelligent systems improve forecasting accuracy and support automated energy management.

Deep Learning approaches such as Artificial Neural Networks (ANN) and Long Short-Term Memory (LSTM) networks are highly effective in handling sequential time-series data. LSTM networks can remember long-term dependencies and identify patterns in historical energy consumption records, making them suitable for forecasting applications.

Researchers have also explored the use of Generative Adversarial Networks (GAN) to solve the problem of limited datasets. GAN models generate synthetic energy data that resembles real-world consumption patterns. This additional data improves model training and increases prediction reliability. Similarly, Gradient Boosted Regression Trees (GBRT) are used for feature extraction and identifying important variables affecting energy demand.

Although several forecasting systems have been proposed, many existing models still suffer from limitations such as poor scalability, high computational complexity, limited adaptability, and insufficient integration between forecasting modules. Some systems focus only on prediction accuracy while ignoring real-time adaptability and energy management efficiency.

To overcome these challenges, this research proposes an integrated hybrid forecasting framework called GAN-GBRT-LSTM. The proposed framework combines synthetic data generation, intelligent feature extraction, and time-series forecasting techniques into a unified system. GAN is used to generate additional training data, GBRT extracts important energy-related features, and LSTM predicts future energy consumption patterns.

The proposed framework aims to improve forecasting accuracy, reduce prediction errors, increase scalability, and support intelligent energy management in organizational buildings. The system also contributes to sustainable energy utilization by helping organizations optimize electricity consumption and reduce operational costs.

The research further focuses on identifying existing research gaps, analyzing previous forecasting approaches, and developing a scalable intelligent system capable of handling real-time energy variations in dynamic organizational environments.

Figure 1.1: Energy Forecasting Challenges

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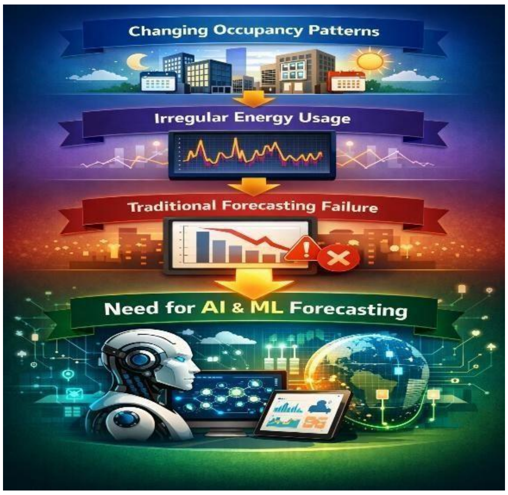

II. OBJECTIVES OF THE STUDY

The primary objective of this study is to understand the different approaches currently used for energy consumption forecasting in organizational buildings. The research focuses on analyzing how traditional statistical methods, Machine Learning models, Deep Learning approaches, and hybrid forecasting systems perform in dynamic energy environments.

Another important objective is to evaluate the strengths and weaknesses of existing forecasting systems. While some models provide high accuracy under specific conditions, they may fail in handling nonlinear relationships, limited datasets, or changing building environments. Therefore, understanding these limitations is essential for designing better forecasting frameworks.

The study also aims to identify major research gaps in current energy forecasting systems. Key challenges such as limited data availability, poor scalability, lack of real-time adaptability, and insufficient model integration are analyzed in detail.

A significant objective of this research is to propose an integrated intelligent framework that combines multiple advanced techniques into a unified forecasting system. The proposed GAN-GBRT-LSTM model is designed to overcome the limitations of individual forecasting approaches and improve prediction accuracy.

The study further aims to improve the reliability and adaptability of forecasting systems across different types of organizational buildings. Since energy consumption patterns vary based on occupancy behavior, environmental conditions, and operational schedules, the proposed system should be capable of handling dynamic real-world scenarios.

Finally, the research contributes to sustainable energy management by helping organizations optimize energy usage, reduce electricity wastage, minimize operational costs, and improve overall resource utilization.

III.LITERATURE REVIEW

Energy consumption forecasting has attracted significant attention from researchers because of its importance in smart energy management, sustainable infrastructure development, and operational cost reduction. Over the years, several forecasting approaches have been developed using statistical methods, Machine Learning algorithms, Deep Learning networks, and hybrid intelligent systems. Each forecasting approach offers different advantages and faces unique limitations depending on the complexity of the energy environment.

One of the earliest forecasting techniques used in energy management was statistical regression analysis. Linear regression models estimate future energy consumption by identifying mathematical relationships

between energy demand and influencing variables such as temperature, occupancy, and operational schedules. These models are easy to implement and computationally efficient. However, regression techniques often fail to capture nonlinear energy consumption patterns present in modern organizational buildings.

Autoregressive Integrated Moving Average (ARIMA) models were also widely used for time-series forecasting applications. ARIMA models analyze historical energy consumption trends and predict future demand based on sequential patterns. Although ARIMA performs effectively in stable environments, it struggles with irregular occupancy behavior and dynamic operational conditions.

To overcome the limitations of traditional statistical methods, researchers introduced Machine Learning algorithms such as Support Vector Machines (SVM), Random Forest, Decision Trees, and XGBoost. These algorithms improved prediction performance by identifying nonlinear relationships between environmental conditions and energy usage.

Random Forest models became popular due to their ability to handle large datasets and reduce overfitting problems. These models combine multiple decision trees to improve forecasting accuracy. However, Random Forest systems may require high computational resources when processing large-scale real-time energy data.

Support Vector Machines (SVM) were also applied for energy forecasting because of their strong classification and regression capabilities. SVM models perform effectively in small and medium-sized datasets but may struggle with highly complex energy environments containing multiple variables.

XGBoost emerged as another powerful Machine Learning approach for energy forecasting. XGBoost models improve prediction efficiency through gradient boosting techniques and optimized feature analysis. Researchers observed that XGBoost performs particularly well in handling nonlinear relationships and large- scale datasets. Despite these advantages, XGBoost requires careful parameter tuning and may suffer from overfitting if not properly optimized.

Deep Learning approaches introduced a major transformation in energy forecasting research. Artificial Neural Networks (ANN) demonstrated improved prediction capabilities by modeling complex nonlinear relationships in energy consumption data. ANN models can automatically learn hidden patterns from historical records and improve forecasting performance.

Long Short-Term Memory (LSTM) networks became one of the most widely used Deep Learning techniques for time- series forecasting. LSTM is highly effective because it can capture long-term sequential dependencies and temporal relationships in energy consumption patterns. Unlike traditional neural networks, LSTM can remember previous information for long durations, making it suitable for dynamic energy environments.

Researchers observed that LSTM models achieve high forecasting accuracy in organizational buildings where energy demand changes continuously throughout the day. However, LSTM models require large training datasets, extensive computational resources, and careful hyperparameter optimization.
Generative Adversarial Networks (GAN) introduced another innovative approach in forecasting research. GAN consists of two neural networks called Generator and Discriminator. The Generator creates synthetic data samples while the Discriminator evaluates whether the generated data is realistic. GAN models help solve the problem of limited datasets by generating additional artificial energy records.

Several researchers combined GAN with forecasting models to improve training efficiency and increase prediction reliability. GAN-based systems demonstrated strong performance in environments where insufficient historical data was available. However, training GAN models can be computationally complex and unstable.

Gradient Boosted Regression Trees (GBRT) were introduced for feature extraction and variable importance analysis. GBRT identifies the most influential factors affecting energy consumption such as occupancy levels, weather conditions, temperature variations, and equipment usage patterns. By selecting important features, GBRT improves forecasting efficiency and reduces unnecessary computational complexity.

Hybrid forecasting systems combining Machine Learning and Deep Learning techniques have shown the best overall performance in recent studies. Researchers integrated feature extraction models with sequential forecasting networks to utilize the strengths of multiple intelligent techniques simultaneously.

Despite these advancements, existing forecasting systems still face several important limitations. Many models cannot adapt quickly to sudden operational changes such as holidays, special events, or irregular occupancy schedules. Poor scalability across different building environments remains another major challenge.

Additionally, many forecasting systems focus mainly on prediction accuracy while ignoring practical implementation issues such as computational cost, scalability, and real-time deployment. Limited integration between data generation, feature extraction, and forecasting

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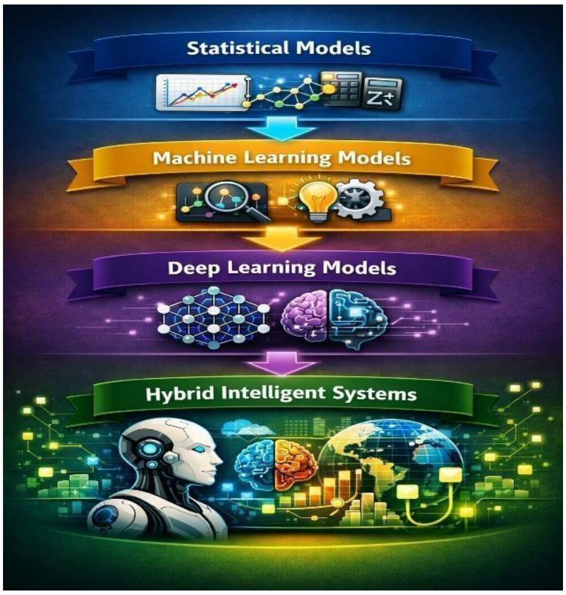
modules also reduces system efficiency.

The literature review clearly indicates the need for a scalable and integrated intelligent forecasting framework capable of handling dynamic organizational environments, real-time energy variations, and complex nonlinear energy consumption patterns.

Figure 3.1: Evolution of Energy Forecasting Systems



The comparative analysis shows that each forecasting model has its own advantages and limitations. Regression models are computationally efficient but provide low forecasting accuracy. Machine Learning models improve nonlinear prediction performance but require large datasets. Deep Learning approaches such as LSTM achieve better time-series forecasting but involve high computational complexity.

GAN-based systems solve the problem of limited datasets through synthetic data generation. However, integrating GANs effectively with forecasting systems remains challenging. Hybrid systems combining multiple intelligent techniques show the best overall performance but often suffer from implementation complexity.

IV. RESEARCH GAPS

Although significant progress has been achieved in energy forecasting research, several important limitations still remain in existing systems. One of the major challenges is limited data availability. Many Machine Learning and Deep Learning models require large amounts of high-quality energy data for accurate prediction. However, organizational buildings often lack sufficient historical datasets.

Another major research gap is poor integration between forecasting components. Several existing systems treat data generation, feature extraction, and prediction processes independently. This separation reduces forecasting efficiency and limits system performance.

Real-time adaptability is another important limitation. Most existing forecasting systems cannot quickly adapt to sudden changes in occupancy behavior, environmental conditions, or operational schedules.

Poor generalization across different buildings also remains a major challenge. A forecasting model trained on one building may fail when applied to another building with different energy consumption patterns.

High computational complexity and implementation difficulty further limit the deployment of hybrid forecasting systems in real-world environments.

These research gaps highlight the need for a scalable, adaptable, and integrated intelligent forecasting framework capable of handling dynamic organizational environments.

V. PROPOSED METHODOLOGY

The proposed GAN-GBRT-LSTM framework integrates data generation, feature extraction, and time-series forecasting techniques into a single intelligent energy prediction system. The methodology is divided into multiple stages where each module performs a specific function in improving forecasting accuracy.

5.1 Data Collection Methodology

The first stage of the framework involves collecting historical energy consumption data from organizational buildings. The data includes electricity usage records, occupancy information, temperature values, humidity levels, and operational schedules.

The collected information helps identify energy consumption patterns and supports forecasting analysis. Data is gathered continuously from smart meters, sensors, and building management systems.

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5.2 Data Preprocessing Methodology

After collecting data, preprocessing operations are performed to remove inconsistencies and improve data quality. The preprocessing stage includes duplicate removal, missing value handling, normalization, and feature selection.

Proper preprocessing improves forecasting accuracy and reduces computational complexity.

5.3 GAN Data Generation Methodology

Generative Adversarial Networks (GAN) are used to generate synthetic energy data when limited datasets are available. GAN consists of two neural networks called Generator and Discriminator.

The Generator creates synthetic energy records while the Discriminator evaluates whether the generated data is real or artificial. Through continuous training, GAN produces realistic energy consumption data that improves forecasting model performance.

Advantages of GAN Module

- Solves limited data problem
- Improves model training
- Enhances prediction reliability

5.4 GBRT Feature Extraction Methodology

Gradient Boosted Regression Trees (GBRT) are used to identify important variables affecting energy consumption. GBRT analyzes relationships between occupancy patterns, weather conditions, equipment usage, and energy demand.

The feature extraction process helps reduce unnecessary complexity and improves forecasting performance.

Advantages of GBRT Module

- Identifies important features
- Reduces unnecessary data
- Improves prediction efficiency

5.5 LSTM Forecasting Methodology

The Long Short-Term Memory (LSTM) network is used for time-series forecasting. LSTM captures long-term dependencies and sequential relationships in energy consumption data.

The model analyzes historical energy patterns and predicts future consumption trends accurately.

Advantages of LSTM Module

- Captures time dependencies
- Improves forecasting accuracy
- Handles sequential data effectively

VI. EXPECTED RESULTS

The proposed GAN-GBRT-LSTM framework is expected to significantly improve energy forecasting accuracy in organizational buildings. GAN-based data augmentation will help solve the problem of limited datasets and improve model robustness.

GBRT feature extraction will optimize forecasting efficiency by selecting the most important variables affecting energy consumption. LSTM networks will accurately capture time-dependent patterns and improve prediction reliability.

The integrated framework is expected to reduce forecasting errors, improve adaptability across different buildings, and support real-time energy management.

VII. CONCLUSION

This research proposed an integrated GAN- GBRT-LSTM framework for energy consumption forecasting in organizational buildings. The study analyzed existing forecasting systems and identified major limitations such as limited datasets, poor adaptability, and lack of integration.

The proposed framework combines GAN for synthetic data generation, GBRT for feature extraction, and LSTM for time- series forecasting. By integrating these techniques into a unified system, the framework improves forecasting accuracy, scalability, and adaptability.

The system contributes to efficient energy management by helping organizations optimize electricity usage, reduce operational costs, and improve sustainability.

The research confirms that hybrid intelligent forecasting systems provide better performance compared to traditional standalone models. Future improvements may include cloud integration, IoT-based real-time monitoring, and advanced deep learning optimization.

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