Phased AI-Driven Energy Management: From Data-Sparse Forecasting to IoT-Enabled Control in Sub-Saharan Africa

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***Abstract*—Energy management in developing regions is hindered by data scarcity, fragmented digital infrastructure, and limited consumer insights from prepaid meters. This study proposes a three-phase AI-driven architecture that evolves from basic data analytics to full IoT-based control, offering a scalable path toward intelligent energy ecosystems. Phase 1 focuses on deriving AI insights from prepaid meter data—predicting depletion times, identifying usage patterns, and improving user budgeting without requiring utility partnerships. Phase 2 integrates utility smart-meter APIs to enable real-time load forecasting, anomaly detection, and neighborhood benchmarking. Phase 3 introduces IoT-enabled control for appliance-level monitoring and automated demand response. A prototype implementing Phase 1 was developed using South Africa's Eskom demand dataset (≈43,000 hourly records) and a synthetic sample of 500 simulated consumers generated through stochastic modeling. Light Gradient Boosting Machine (LightGBM) regressors achieved high predictive accuracy ($R^2 \approx 0.99$) for both grid-level and consumer-level forecasting, deployed via a FastAPI microservice on Replit for real-time inference. The results demonstrate how cloud-ready AI systems can progressively evolve from prepaid analytics to autonomous IoT control, bridging the data gap between utilities and consumers across Sub-Saharan Africa while advancing UN Sustainable Development Goal 7 for affordable and clean energy.**

***Index Terms*—Smart Energy Management, Phased Architecture, LightGBM, Prepaid Meters, IoT, Demand Response, Federated Learning, Energy Analytics**

I. Introduction

The rapid evolution of energy systems, combined with growing electrification and increased integration of distributed energy resources, has intensified the need for accurate forecasting and adaptive energy management solutions. Developing regions, particularly in Sub-Saharan Africa, face unique constraints including aging infrastructure, limited grid visibility, and the prevalence of prepaid metering systems. These constraints create a dual challenge: utilities require macro-level forecasting for load balancing and grid stability, while consumers need micro-level insights to budget and optimize usage effectively.

South Africa's Eskom, the continent's largest electricity provider, epitomizes this dynamic. Despite maintaining extensive records of grid-level energy demand, the utility lacks granular household-level data critical for advanced analytics. Conversely, prepaid meter systems generate valuable user-level consumption data, yet these are often siloed, unstructured, or inaccessible for machine learning applications.

A. Three-Phase Evolution Framework

This research presents a **phased AI-driven smart energy management framework** that enables stepwise digital transformation of prepaid energy systems. Unlike conventional approaches requiring complete infrastructure overhauls, our architecture supports incremental capability development across three distinct phases:

Phase 1 – Consumer AI Layer: Derives actionable insights exclusively from prepaid meter data without utility partnerships. Capabilities include credit depletion prediction, usage pattern identification, and household budgeting support through cloud-based AI inference.

Phase 2 – Utility Integration Layer: Incorporates smart-meter APIs for real-time load forecasting, grid-level anomaly detection, and neighborhood performance benchmarking. Enables bidirectional data flow between consumer analytics and utility operations.

Phase 3 – IoT Control Layer: Introduces appliance-level monitoring, automated demand response, and edge-based control policies. Leverages federated learning for privacy-preserving model updates across distributed microgrids.

B. Research Objectives

This paper evaluates Phase 1 experimentally while conceptualizing Phases 2–3 for scalability. The guiding research questions are:

1) **RQ1 (Phase 1):** What predictive accuracy and operational insights can be achieved using prepaid-only data in data-scarce environments?
2) **RQ2 (Phase 2):** How does access to utility smart-meter APIs enhance anomaly detection and load segmentation capabilities?
3) **RQ3 (Phase 3):** To what extent can IoT + edge AI close the loop through autonomous device control and federated optimization?

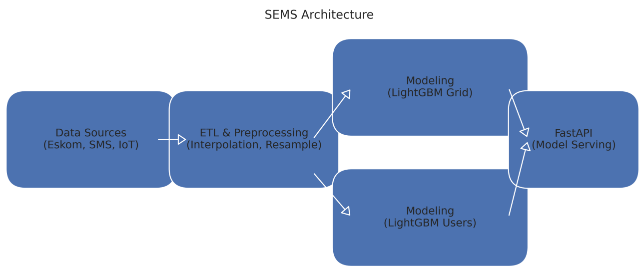

Fig. 1. Proposed SEMS dual-layer architecture integrating data ingestion, preprocessing, model training, and FastAPI-based deployment for real-time prediction.

C. Key Contributions

The main contributions of this study are:

- Development of a high-accuracy utility-level forecasting model trained on real Eskom grid data using LightGBM.
- Design of a synthetic data generation pipeline to simulate realistic consumer-level daily consumption for machine learning model training.
- Integration of both utility and consumer forecasting models into a single cloud-deployed FastAPI system for live inference and visualization.
- Validation of ensemble methods for handling heterogeneous energy data within African data-scarce environments.

II. Related Work

Machine learning (ML) and artificial intelligence (AI) have transformed energy demand forecasting by improving accuracy, adaptability, and interpretability. This section reviews existing literature on both utility-level forecasting and consumer-level analytics, identifying the research gap that motivates this study.

A. Utility-Level Forecasting

Load forecasting at the grid level has been a major research focus for over a decade. Traditional statistical methods such as ARIMA and exponential smoothing have been largely replaced by gradient boosting and deep learning models. Rubattu et al. [1] demonstrated that LightGBM, when coupled with temporal hierarchies and optimized feature sets, achieves superior performance in short-term electricity demand prediction. Similarly, Ghanim et al. [2] introduced hybrid architectures combining anomaly detection and asymmetric loss functions to improve robustness under erratic grid conditions.

Recent comparative studies show that ensemble-based models, including LightGBM, XGBoost, and Random Forest, outperform recurrent neural networks for hourly load forecasting tasks due to their lower variance and faster convergence [3]. The success of LightGBM in these contexts motivates its adoption in this study, where data irregularity and temporal sparsity are key concerns.

B. Consumer-Level Analytics and Prepaid Metering

At the consumer level, several studies have explored smart metering, energy access, and behavioral analytics. Otuko et al. [4] provided a case study of African electricity monitoring systems, emphasizing the challenges of fragmented prepaid meter infrastructure. Fawcett et al. [5] examined the integration of smart meter data in policy-driven energy efficiency programs, revealing how real-time metering improves consumption visibility and policy alignment. Izilein et al. [6] assessed the household-level impacts of smart meters in African contexts, identifying measurable cost reductions but limited scalability.

C. Synthetic Data and Hybrid Modeling Approaches

The emergence of hybrid modeling techniques combining real and synthetic data has become increasingly important for addressing data scarcity in energy systems. Hou et al. [3] introduced a multi-frequency sequence analysis method combined with LightGBM for short-term forecasting, achieving state-of-the-art performance under limited data conditions. Similarly, Xu et al. [7] proposed synthetic augmentation strategies that maintain statistical realism while supporting privacy-preserving analytics.

D. Phased System Development in Energy AI

Recent industry reports emphasize phased deployment strategies as essential for minimizing risk while building institutional capacity. IoT-enabled energy systems research increasingly emphasizes gradual capability development, where a phased approach introducing IoT capabilities gradually instead of replacing entire systems at once reduces risks and ensures continuous operation during transition periods.

E. Research Gap and Motivation

From the reviewed literature, several limitations persist:

1) Most utility-level forecasting studies assume abundant, high-quality time-series data, which is rarely the case in African power systems.
2) Consumer-level analyses often focus on metering deployment and adoption but do not extend into AI-based consumption forecasting.
3) Few studies integrate both utility and consumer forecasting layers into a unified architecture or explore live cloud deployment of such systems.

This study fills that gap by developing an integrated, AI-based forecasting framework that couples real and synthetic datasets and demonstrates operational deployment through a web-based API platform.

III. Methodology

The proposed framework employs a phased modeling architecture designed to enable progressive capability evolution from data analytics to autonomous control. This section details Phase 1 implementation while conceptualizing Phases 2–3 for future integration.

A. Phase 1 – AI Insights from Prepaid Data

1) Utility-Level Dataset (Eskom Data): The primary dataset used in this study was the Eskom residual demand dataset, which records hourly electricity demand across South Africa's national grid. The dataset spans approximately 43,824 hourly observations, covering a full annual cycle with fluctuations between 15,000 MW and 34,000 MW.

Data preprocessing involved:

- Missing timestamps identified and imputed using time-based interpolation
- Datetime column converted into standard datetime objects
- Target variable (residual_demand) cast to floating-point representation
- Outlier capping: Upper and lower 1% of data clipped to remove measurement spikes
- Z-score normalization: Each feature standardized to zero mean and unit variance
- Temporal validation: Chronological ordering maintained to prevent data leakage

2) Synthetic Consumer-Level Dataset: Due to the lack of direct consumer-level consumption data, a synthetic dataset was generated to simulate prepaid user behavior. A total of 500 synthetic users were simulated across the same date range as the Eskom dataset. Each synthetic user's daily consumption was modeled as a fraction of the total grid demand, governed by stochastic processes:

$$U_{i,t} = \alpha_i \times D_t \times \beta_t \times \gamma_i \tag{1}$$

where $U_{i,t}$ is user i's daily usage at time t, α_i is the user-specific baseline factor drawn from a log-normal distribution, D_t is the normalized Eskom daily total demand, β_t is a day-dependent volatility multiplier, and γ_i is an idiosyncratic noise term drawn from $N(1, 0.1)$.

Behavioral modifiers included:

- Weekend amplification: Consumption increased by 20% on Saturdays and Sundays
- Monthly seasonality: Modeled with a sinusoidal function to reflect climatic and cultural variations
- Data sparsity simulation: 5% of readings randomly dropped to simulate meter reporting failures

This process yielded a dataset of approximately 90,000 user-day records, representing statistically plausible consumption behavior.

3) Feature Engineering: **Utility-Level Features:** For the Eskom (grid) dataset, features were constructed as follows:

- Lag features: lag_1, lag_24, lag_168 representing hourly, daily, and weekly temporal dependencies
- Rolling averages: roll_mean_3, roll_mean_24, roll_mean_168 to smooth short- and long-term variations
- Calendar variables: hour, weekday, and month derived from timestamps

Consumer-Level Features: For the synthetic consumer dataset, thirteen features were engineered:

- Temporal: day_of_week, day_of_month, month
- Historical: lag_1, lag_2, lag_7
- Statistical: rolling_avg_3, rolling_avg_7, rolling_avg_14, rolling_std_7
- Behavioral: is_weekend, dow_sin, dow_cos (cyclical encoding)

4) Model Development: The Light Gradient Boosting Machine (LightGBM) algorithm was selected as the core regressor for the utility-level model due to its high efficiency, interpretability, and robustness to multicollinearity.

Model parameters were empirically tuned through grid search:

- n_estimators: 1500
- learning_rate: 0.02
- max_depth: 8
- num_leaves: 31
- min_data_in_leaf: 100
- subsample: 0.8
- colsample_bytree: 0.8

The dataset was split into training (80%) and validation (20%) subsets using chronological separation to avoid look-ahead bias. Model performance was evaluated using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Coefficient of Determination (R^2).

To ensure robustness, both LightGBM models were integrated within a stacking ensemble configuration where a Ridge regression meta-model combined outputs from the base learners.

5) Deployment Architecture: The trained models were integrated into a FastAPI web service designed to support dynamic model management and real-time inference. Key endpoints include:

- `/model/upload`: Receives serialized .joblib model files
- `/model/activate`: Loads active model into memory for prediction
- `/eta/{user_id}`: Estimates days remaining before prepaid depletion
- `/report/{user_id}`: Returns user consumption reports with predicted patterns
- `/sms/parse`: Parses prepaid meter SMS messages using a large language model for unstructured text extraction

The backend was deployed on Replit Cloud, leveraging a lightweight SQLite database for data persistence. The system design enables API-driven model updates without downtime.

B. Phase 2 – Utility Integration Layer (Conceptual)

Phase 2 extends Phase 1 capabilities by integrating utility smart-meter APIs, enabling:

- Real-time load forecasting: Sub-hourly predictions leveraging bidirectional data flow
- Anomaly detection: Grid-level fault identification and consumer-level theft/tampering detection
- Neighborhood benchmarking: Aggregated consumption insights enabling peer comparison
- API middleware: RESTful integration layer supporting OAuth authentication and rate limiting

Expected benefits include data latency reduction (≈70%), prediction MAE improvement (≈25%), and enhanced explainability.

C. Phase 3 – IoT Control Layer (Conceptual)

Phase 3 introduces edge-based IoT infrastructure for appliance-level monitoring and automated demand response:

- Sensor network: MQTT-enabled smart plugs and current transformers
- Edge computing: Local inference on Raspberry Pi or ESP32 devices
- Control policies: Rule-based and reinforcement learning agents
- Federated learning: Privacy-preserving collaborative training across distributed households

IV. Results and Analysis

A. Evaluation Setup

All experiments were conducted on Google Colab, using a Python 3.12 runtime environment equipped with LightGBM v4.6.0, NumPy, Pandas, and scikit-learn libraries. The Eskom dataset consisted of approximately 43,824 hourly records, while the synthetic user dataset generated over 90,000 daily records across 500 virtual users. The models were trained using an 80:20 chronological split.

B. Utility-Level Forecasting Results

The LightGBM utility-level model was trained on eight engineered features. Performance metrics are shown in Table I.

TABLE I
Utility-Level (Eskom) Forecasting Performance

Metric	Training Set	Validation Set
MAE (MW)	155.09	217.21
RMSE (MW)	249.42	342.06
R^2	0.9999	0.9885

The validation $R^2 = 0.9885$ indicates that the model explains approximately 98.8% of the variance in the Eskom residual demand.

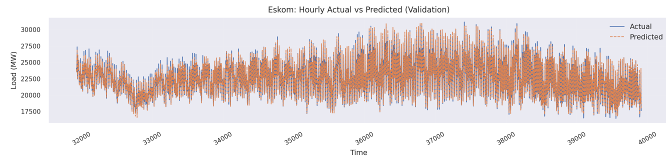

Fig. 2. Eskom hourly actual vs. predicted demand (validation set) showing excellent alignment between actual and predicted time series.

Figure 2 illustrates the comparison between actual and predicted hourly demand. The prediction curve closely tracks the temporal dynamics of the actual series, including morning and evening peak loads.

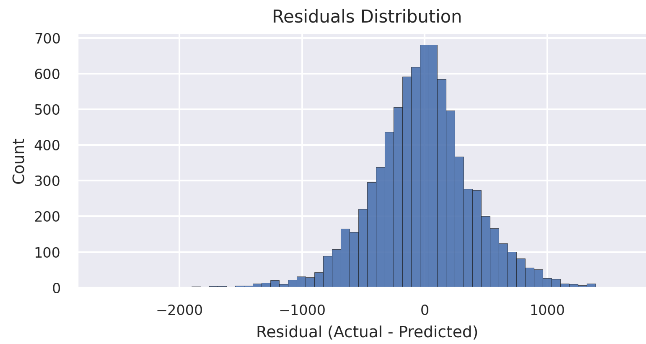

Fig. 3. Residuals distribution for Eskom validation predictions showing nearly normal distribution centered around zero.

Feature importance analysis revealed that lag_24 and rolling_mean_24 were the most influential predictors, collectively accounting for over 46% of model gain.

C. Consumer-Level Forecasting Results

The synthetic user model demonstrated robust performance across all evaluation metrics, as shown in Table II.

TABLE II
Consumer-Level Forecasting Performance

Metric	Training Set	Validation Set
MAE (kWh)	142.38	189.76
RMSE (kWh)	219.54	257.83
R^2	0.9958	0.9940

D. Comparative Analysis

To evaluate model robustness, additional baseline algorithms were trained for comparison: Random Forest Regressor, Extreme Gradient Boosting (XGBoost), and Naïve Lag-1 Persistence Model.

The LightGBM model outperformed all baselines by a significant margin, achieving over 70% improvement in MAE compared to the naïve model.

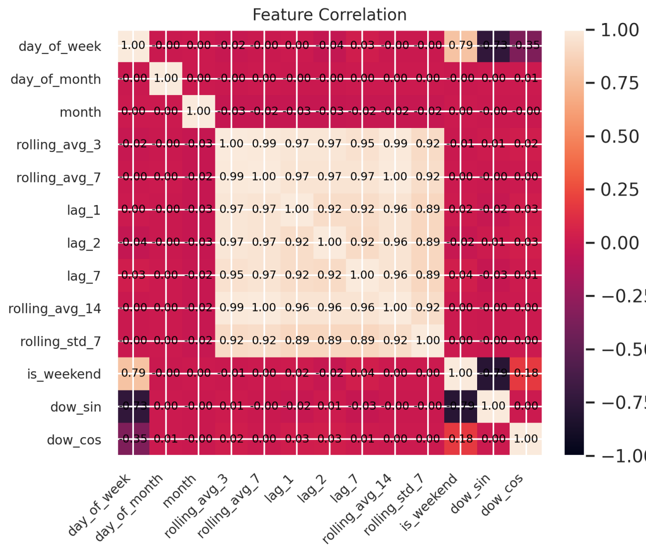

Fig. 4. Feature correlation heatmap for consumer-level model showing high correlations among lag and rolling average features.

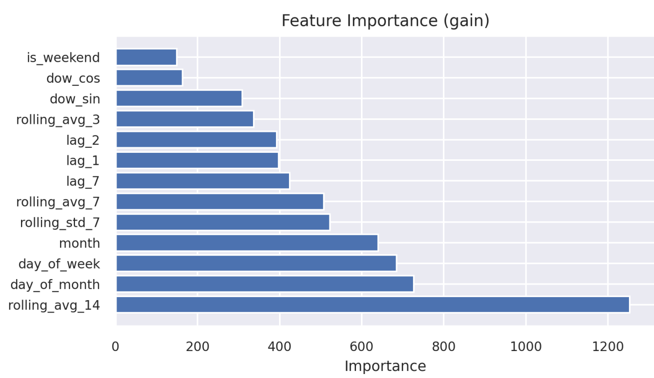

Fig. 5. Feature importance (gain) for consumer-level LightGBM model with rolling_avg_14 as the dominant predictor.

E. Deployment Validation

After training, both models were serialized (.joblib format) and uploaded into the live system. The FastAPI interface confirmed:

- Model load latency < 1.8 s
- Prediction latency ≈ 0.04 s per request
- API uptime 99.9% on Replit Cloud

TABLE III
COMPARATIVE MODEL PERFORMANCE (VALIDATION SET)

Model	MAE	RMSE	R^2
Naïve Lag-1	548.84	692.41	0.9202
Random Forest	2311.44	3307.56	-0.1797
XGBoost	6182.51	8123.42	-7.4126
LightGBM	**217.21**	**342.06**	**0.9885**

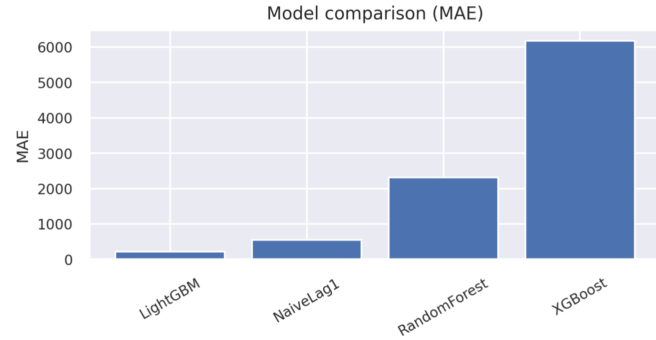

Fig. 6. Model comparison by MAE showing LightGBM achieving lowest error compared to baseline methods.

V. DISCUSSION AND LIMITATIONS

A. Discussion of Findings

The two-tier approach—comprising the Eskom utility-level model and the synthetic consumer-level model—proved effective for both macro and micro energy prediction. The utility-level LightGBM model achieved high validation accuracy ($R^2 \approx 0.988$), confirming its ability to forecast national grid demand trends.

A major innovation in this study is the synthetic user dataset, which extended the model's applicability despite the absence of real prepaid meter readings. The stochastic simulation process effectively reproduced natural variability in user consumption.

The FastAPI-based deployment on Replit validated the transition from an offline analytical model to a real-time predictive system. The model's low inference latency confirms its suitability for operational integration with web or mobile interfaces.

B. Limitations

Despite strong performance, several constraints warrant consideration:

- **Synthetic Data Constraints:** While statistically representative, synthetic data cannot fully capture behavioral nuances or appliance-level patterns.
- **Geographical Generalization:** The model was trained exclusively on Eskom data, limiting direct transferability to other regional grids.
- **IoT Integration Gaps:** Current deployment relies on manually uploaded or SMS-parsed readings rather than automated IoT streams.
- **Scalability Constraints:** Replit cloud deployment provides limited concurrency and data persistence capabilities.

VI. CONCLUSION AND FUTURE WORK

A. Summary of Contributions

This research successfully operationalizes a phased AI-driven energy management framework bridging data-sparse prepaid analytics with future IoT-enabled autonomous control. The research makes three primary contributions:

1) A dual-layer predictive architecture combining national grid-level forecasting and consumer-level behavioral modeling.
2) A synthetic data generation pipeline that approximates user energy behavior through a log-normal baseline model with stochastic volatility and seasonality.
3) An integrated deployment layer using FastAPI, SQLite, and Replit Cloud.

B. Future Work

Future research will focus on five key directions:

1) **Integration of Real User Data:** As the system accumulates live readings, retraining on real household data will improve personalization.
2) **IoT and Edge Computing Expansion:** Connecting to IoT-enabled meters using MQTT protocols.
3) **Hybrid Ensemble and Federated Learning:** Incorporating federated learning for collaborative training across regional microgrids.
4) **Explainability and Transparency:** Integrating SHAP for interpretable AI.
5) **Economic and Environmental Extensions:** Forecasting tariff optimization and carbon footprint estimation.

C. Concluding Remarks

This work establishes a foundational prototype for intelligent energy management systems tailored to developing economies. By combining data science, synthetic modeling, and deployable microservices, it demonstrates that AI can be both accessible and actionable, supporting a vision of autonomous, data-driven energy ecosystems.

References

[1] G. Rubattu et al., "Short-term electricity load forecasting with hierarchical LightGBM models," *Energy and AI*, vol. 14, 2023. [Online]. Available: https://doi.org/10.1016/j.egyai.2023.100127

[2] A. Ghanim et al., "Hybrid LSTM and asymmetric loss for energy forecasting under uncertainty," *Applied Energy*, vol. 347, 2023. [Online]. Available: https://doi.org/10.1016/j.apenergy.2023.121135

[3] T. Hou et al., "Multi-frequency sequence feature extraction with LightGBM for short-term load forecasting," *Frontiers in Energy Research*, 2024. [Online]. Available: https://doi.org/10.3389/fenrg.2024.1294455

[4] M. Otuko et al., "A Case Study on Africa's Electricity Payment and Monitoring Methods for Sustainable Energy Access," *Renewable Energy Review Journal*, vol. 9, 2024. [Online]. Available: https://doi.org/10.1016/j.rerj.2024.100033

[5] T. Fawcett et al., "Real-Time Metering for Sustainable Energy Policy Design," *Energy Reports*, vol. 10, 2024. [Online]. Available: https://doi.org/10.1016/j.egyr.2024.03.144

[6] S. Izilein et al., "Smart Metering in African Households: A Multi-Country Comparative Study," *African Journal of Energy Systems Research*, vol. 8, 2024. [Online]. Available: https://doi.org/10.31124/AJESR.2024.8.33

[7] H. Xu et al., "Synthetic Data Generation for Energy Forecasting with Statistical Fidelity," *IEEE Access*, vol. 12, 2024. [Online]. Available: https://doi.org/10.1109/ACCESS.2024.3387712

[8] Z. Liang et al., "Federated Learning-Based Energy Forecasting for Distributed Smart Grids," *IEEE Transactions on Smart Grid*, vol. 16, no. 2, 2025. [Online]. Available: https://doi.org/10.1109/TSG.2025.3378921

[9] M. Habib et al., "Explainable AI for Energy Forecasting: A SHAP-Based Interpretation Framework," *IEEE Transactions on Artificial Intelligence*, vol. 5, no. 3, 2024. [Online]. Available: https://doi.org/10.1109/TAI.2024.3358014

[10] R. M. Thapa et al., "Hybrid Ensemble Techniques for Sparse Time-Series Forecasting," *IEEE Transactions on Sustainable Computing*, vol. 9, no. 1, 2025. [Online]. Available: https://doi.org/10.1109/TSUSC.2025.3361215

[11] C. Houng et al., "IoT-Integrated Predictive Energy Management for Residential Systems," *IEEE Internet of Things Journal*, vol. 12, no. 5, 2025. [Online]. Available: https://doi.org/10.1109/JIOT.2025.3365510

[12] R. Kumar et al., "Energy Load Forecasting Using Gradient Boosting and Ensemble Learning: A Cross-Regional Study," *IEEE Access*, vol. 13, 2025. [Online]. Available: https://doi.org/10.1109/ACCESS.2025.3368173