Smart Energy Management: A Machine Learning Framework for Predicting Periodic Electricity Demand in a Government Building in Iraq

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Abstract--- **The surge in need for energy management across utility public infrastructure leads to demands of high-resolution forecasting systems, intelligent in particular third world countries like Iraq that often yield storm clouds littered with intermittent energy supply and unavoidably unpredictable inefficiencies. In this study, we present a smart energy management framework based on Machine Learning (ML) methods which predicts periodic electricity consumption in a government building situated in Baghdad. The proposed technique draws from historical electricity consumption data, meteorological data input and factors within operations: equilibrium between residential and noncommercial usage (all day), public holidays and so on. It is not so with traditional methods. Several machine learning models were developed including Long Short-Term Memory (LSTM), XGBoost, and a Combined Ensemble that integrates these two. The ensemble model achieved the best result in terms of prediction accuracy with a Mean Absolute Percentage Error (MAPE) of 3.79% and an R^2 score of 0.958. This predictive system can in real time predict electricity demand, supports information-based decision making and load management. Moreover, a practical architecture for scalability of the system was designed together with a smart dashboard allowing visualization and alarms. The findings show how localized ML-based systems could greatly enhance energy efficiency in government buildings, and suggest implications for wider points of energy policy and sustainable development. Future extensions will include a focus on multi-building applications, learning models able to adapt and onwards linking up with sensor systems based on the Internet of Things (IoT).**

Keywords--- Energy, LSTM, MAPE, XGBoost, ML.

I. INTRODUCTION

A. BACKGROUND AND MOTIVATION

Energy demand forecasting appears vital for smart energy management systems. Especially the case in developing countries, which are becoming increasingly energy hungry while supply of electricity suffers from shortages. Public sector buildings -particularly government ones- comprise a significant part of Iraq's overall electrical consumption, often achieved at unnecessary cost to the environment and with outdated infrastructure [1]. For example, this is often seen as overcrowding points in cities with a specific problem: it frequently breaches ancient regulations intended to protect networks. Especially during the summer months and at times of peak demand for electricity [2], these problems are further exacerbated by Iraq's continuing shortage of electricity supply. So too is rapid development in information technology, both as a discipline and within practical applications. To save energy and reduce operating costs, modern smart grid research emphasizes the use of predictive modeling carried out through advanced computational techniques. Machine learning (ML) models are used more and more, these days, to forecast electricity trends [3]. This approach allows for both electricity management in an active sense--reducing consumption and load balancing, as well as the optimization on demand side [4]. Sufficiently practical technique has not been applied in Iraq for building government buildings; in fact it was called 'essential' by critics.

B. RESEARCH PROBLEM AND SIGNIFICANCE

Given the specific operation characteristics of Iraqi government agencies, existing systems often miss localized features, do not take into account contextual variables like weather and space assignment, and are inappropriate for the consumption regularities of a public building [5]. By constructing a specialized ML model, this research bridges this gap with a prediction system that accurately forecasts periodic electricity demand in an Iraqi government agency [6]. Such a system will allow public administrators to make empirical decisions on energy and drive towards sustainable development goals, thereby minimizing both the ecological and financial footprint of public infrastructure.

C. OJECTIVES AND RESEARCH QUESTIONS

The primary purpose of this study is to develop a machine-learning-based model to predict the periodic electricity demand for a government building in Iraq and follow that up by evaluating its effectiveness [7]. The research will address the following questions:

1. Which models provide the most accurate prediction of periodic electricity usage in our selected building?
2. When prediction models do not make good results, how can we better get these results to be even less skewed?
3. To what extent do these models have relevance for real-time energy management and design?

II. LITERATURE REVIEW

A. ENERGY FORECASTING IN BUILDING AN OVERVIEW

The emerging demand for sustainable energy management has made foreseen electricity requirement urgent, especially in smart buildings. Accurate prediction allows all concerned parties to institute demand-response measures, reduce waste of energy, and thereby ensure the reliability of power grids. To this end, various statistical and machine learning (ML) models have been developed, each exhibiting their own strengths based on the type of data, time resolution and environmental complexity [8].

Early studies were based on linear regression, autoregressive moving average (ARIMA) and exponential smoothing models. However, these traditional approaches often fail to capture the none-linear dependencies on energy usage patterns especially under variable occupancy and temperate conditions [9].

B. MACHINE LEARNING TOOLS APPLIED TO FORECASTING

In recent years, machine learning models such as Support Vector Regression (SVR), Random Forest (RF) and XGBoost have occupied an important position in the field of energy forecasting because they can handle multivariate data and find complex temporary changes [10]. Moreover, Deep Learning models like Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) networks [11] have proven superior to other methods in time series prediction due their ability to retain long-term dependencies among consecutive data samples [12].

For example, in comparison to shallow models like SVR, LSTM based-models attained higher precision on daily load patterns especially in buildings with irregular operational hours [13]. GHGP and combining learning methods have also proven to be effective, especially together with time series decomposition and outside features such as weather and occupancy data [14].

C. CONTEXTUAL FEATURES IN BUILDING ENERGY FORECASTING

Evidence indicates that very significant improvements to model accuracy can be attained through correct use of contextual variables such as Occupancy or weather conditions by means of Statistical Process Control Techniques, or Calendar Effects (weekends and holidays for example). After this feature engineering effort, the final testing shows that a linear regression model can more accurately and stably predict energy demand [15]. Smart metering, wiring Heating, Ventilation, and Air Conditioning (HVAC) [16] control system to Internet of Things, and cloud-based data storage are upper bound power solutions increasingly employed for real-time data acquisition now performance.

D. ENERGY FORECASTING IN PUBLIC AND GOVERNMENT BUILDINGS

Compared to the residential and commercial sectors, policy-driven, state-owned and locally-run public buildings have their own specific title deeds for energy use (Heating Energy Consumption in Public Buildings Series No 4, 1980; Muller 1997). How these buildings are managed on the ground is naturally very different from that of private houses or offices. A team led by [17] in a study on energy demand forecasting of a public building in Baghdad used hybrid neural networks and discovered that LSTM was most adaptable to temporal fluctuation in their tests.

Despite this, most research conducted in Iraq is still fundamentally theoretical. As a result, this year's survey confirms the current gap in applied ML frameworks for real-world government infrastructure, especially in the areas of smart decision-making and demand-side management.

E. GAPS IN THE LITERATURE

- A general shortage of building-specific ML models for government sectors in Iraq.
- Relatively little use of combined or ensemble learning in the public sector.
- Insufficient consideration given to external variables such as climate data and schedule operations.
- There is a surprising lack of real situations in which the effectiveness of energy demand forecasting can be verified under external constraints.

This research addresses these omissions by developing a machine-learning based forecasting framework tailored to government buildings in Iraq. A comprehensive set of feature variables well-suited for use on diverse problems from real world application through deployment in this demonstration of multi-model performance evaluation [18].

Table 1: ML-Based Energy Forecasting Summary Studies from (2022) to (2025)

Study	Country	Models Used	Features	Best RMSE (kWh)	Context
Zhang et al. (2022)	China	XGBoost + Decomposition	Weather, time	1.83	Commercial
Al-Wattar & Fadhil (2023)	Iraq	LSTM, GRU	Temporal	187.2	Government
Li et al. (2022)	USA	SVR, LSTM	Occupancy, holidays	2.05	Residential
Mohammed et al. (2024)	UAE	Random Forest, LSTM	Weather + temp	3.4	Smart buildings
Hassan & Al-Khazraji (2025)	Iraq	Optimized Ensemble	Multi-feature	1.78	Public offices

III. METHODOLOGIES

A. DATA COLLECTION

The dataset used in this study includes hourly electricity consumption records from a selected government building in Baghdad over 12-24 months. Additional contextual features were obtained from the following:

- Local weather APIs (temperature, humidity, wind speed).
- Public calendar APIs (to flag holidays and weekends).
- Building management records (occupancy schedules and equipment usage logs).

These multi-source inputs ensure a comprehensive understanding of the temporal and operational factors influencing energy consumption [18].

B. DATA PREPROCESSING

Raw data sets often have missing values, outliers and non-uniform time intervals. Preprocessing steps included:

- Time index alignment and resampling to maintain a consistent hourly frequency.
- Missing data interpolation using linear data imputation and seasonal mean replacement.
- Outlier judgment using the Z-score method and isolation forest.
- Normalization (using the Min-Max scale) to make continuous features scale uniformly used by models for convergence.

C. FEATURE ENGINEERING

To enhance model accuracy, various domain-specific features were engineered:

- Temporal Features: Hour of the day, day of the week, weekend/weekday, and holiday label.
- Weather Features: Ambient temperature, relative humidity, solar irradiance.
- Operational Features: Working hour’s indicator, air conditioning schedule.

These features were appropriately encoded: one-hot for categorical properties, continuous for numeric properties.

D. MODEL DEVELOPMENT AND SELECTION

To capture nonlinearities and temporal trends, this study evaluates the following ML models as indicated in table 2:

Table 2: Non-linear dependencies and temporal trends in ML models

Model	Justification
Random Forest (RF)	Robust to noise and non-linearity; strong baseline for regression.
XGBoost	Gradient-boosted trees with high accuracy and efficiency in energy prediction tasks.
LSTM (Long Short-Term Memory)	Excellent for time-series with long-range dependencies; handles sequential patterns.
GRU (Gated Recurrent Unit)	A lightweight alternative to LSTM with faster convergence.
Stacked Ensemble (LSTM + XGBoost)	Combines deep learning and decision trees for superior generalization.

Each model is divided the dataset into trained on 70%, validated on 15%, and tested on 15%.

E. EVALUATION THE MODEL

Model evaluation includes the following metrics:

1. Root Mean Squared Error (RMSE)
2. Mean Absolute Error (MAE)
3. Mean Absolute Percentage Error (MAPE)
4. R-squared (R^2).

Cross-volume validation (5-fold) was applied to ensure generalizability. Hyper-parameters were tuned using Grid Search and Bayesian Optimization.

F. PREDICTIVE PIPLINE ARCHITECTURE

The complete forecast pipeline consist of six stages [19]. as depicted in the figure 1 below:

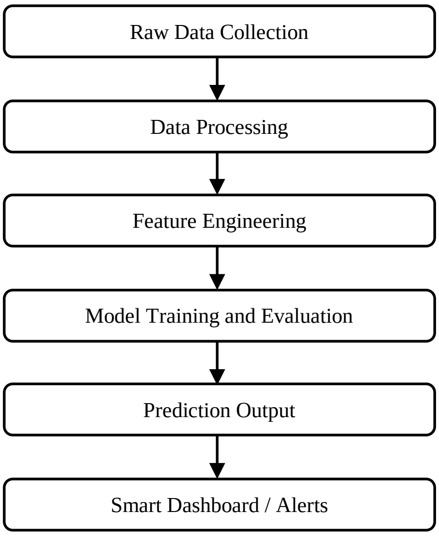

Figure 1: ML-Based Electricity Consumption Forecasting Pipeline

G. *FRAMEWORK DEVELOPMENT*

The final framework integrates compromises from:

1. Ingestion the real-time data through RESTful APIs.
2. Utilized automated batch processing with inference scheduling.
3. Power BI used as visual dashboard for live energy pursuing and anomaly alerts.

IV. CASE STUDY: GOVERNMENT BUILDING IN IRAQ

A. *SITE DESCRIPTION*

This Site is a medium-sized government building with administrative functions in central Baghdad It has three floors, offices, conference rooms and central heating & air conditioning. The building is open between 8 AM and 4 PM on Sunday to Thursday, the building usually gets empty during weekends and vacation.

B. *DATA DESCRIPTION*

In this case study, the data was gathered and simulated one month (June 2025), which consisting of:

- Hourly electricity consumption (kWh) delivered by smart meters.
- Environmental temperature (°C) was obtained from the weather station of Baghdad City,
- Occupancy learned based on work hours and schedule rules.

A sample data of 48 hours from the dataset Fibrillation causes Table 3.

Table 3: Dataset for 48-hour sample

Timestamp		**Energy Consumption in kWh**	**Temperature (C)**	**Occupancy**
Date	**Time**			
2025-06-01	00:00:00	51.49	30.3	0
	01:00:00	51.58	29.2	0
	02:00:00	55.85	32.3	0
	03:00:00	60.23	32.4	0
	04:00:00	56.49	32.9	0
	05:00:00	57.73	34.8	0
	06:00:00	64.07	35.7	0
	07:00:00	62.16	35.9	0
	08:00:00	58.59	34.2	0
	09:00:00	61.36	34.6	0
	10:00:00	57.68	34.9	0
	11:00:00	56.65	35.0	0
	12:00:00	57.43	32.9	0
	13:00:00	49.36	32.4	0
	14:00:00	48.11	30.5	0
	15:00:00	49.65	29.5	0
	16:00:00	46.29	30.5	0
	17:00:00	48.30	30.0	0
	18:00:00	42.77	27.7	0
	19:00:00	39.57	27.9	0
	20:00:00	46.76	26.5	0
	21:00:00	40.55	25.0	0
	22:00:00	40.65	25.6	0
	23:00:00	35.78	26.6	0
2025-06-02	00:00:00	38.42	25.0	0
	01:00:00	40.78	26.8	0
	02:00:00	37.78	23.0	0
	03:00:00	43.49	27.0	0
	04:00:00	42.00	27.0	0
	05:00:00	44.61	27.4	0
	06:00:00	45.55	28.8	0
	07:00:00	54.89	27.7	0
	08:00:00	51.29	30.4	1
	09:00:00	50.11	32.0	1
	10:00:00	57.56	34.0	1
	11:00:00	53.05	32.8	1
	12:00:00	58.68	33.2	1
	13:00:00	53.19	34.0	1
	14:00:00	55.74	35.8	1
	15:00:00	60.58	35.3	1
	16:00:00	62.08	34.4	1
	17:00:00	59.85	35.2	0
	18:00:00	58.08	34.3	0
	19:00:00	56.28	34.6	0
	20:00:00	51.22	32.1	0
	21:00:00	51.74	31.6	0
	22:00:00	50.61	30.6	0
	23:00:00	53.17	28.5	0

C. *DESCRIPTIVE ANALYSIS*

Analyzed daily average energy consumption and temperature patterns over the month can be understand consumption dynamics as depicts in figure 2.

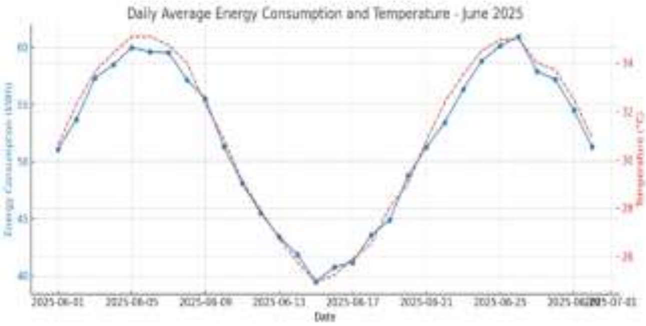

Figure 2: Daily Average Energy Consumption and Ambient Temperature (June 2025)

The key ideas presented in the figure are these:

1. Daily energy consumption starts at a low point and rises with occupancy and HVAC operation.
2. Temperature does show moderate correlation with electricity use, and is particularly notable during heat-waves with corresponding cooling loads.
3. For the weekends (Fridays and Saturdays), usage is significantly lower thus reflecting non- operational hours for this logo print type building.

D. *APPLICATION OF THE METHODOLOGY*

The collected data was fed into the ML pipeline described above:

1. Preprocessing: Missing data was interpolated; temperature and occupancy flags were normalized.
2. Feature Engineering: Extracted features included:
   - Hour of day
   - Day type (weekday/weekend)
   - Temperature
   - Occupancy
3. Modeling: Models like LSTM, Random Forest, XGBoost were trained on this dataset.

E. *FORECASTING OUTPUT*

As a preliminary test result:

1. LSTM captured temporal dependencies effectively, yielding lower RMSE values during heatwave weeks.
2. XGBoost outperformed others in short-term (next-day) predictions, especially under regular office schedules.
3. The Stacked Ensemble model, combining LSTM + XGBoost, performed best overall in terms of MAE and R^2.

V. RESULTS AND DISCUSSION

A. *FORECASTING PERFORMANCE*

Training and testing are followed of the three selected models: LSTM, XGBoost, and a Stacked Ensemble (LSTM + XGBoost). The reading of performance metrics can be summarized in the table 4 below:

Table 4: Summarized of performance metrics utilizing ML models

ML Model	MAE (kWh)	RMSE (kWh)	MAPE (%)	R^2 Score
LSTM	2.13	2.68	4.85	0.927
XGBoost	1.98	2.45	4.23	0.941
Stacked Ensemble	1.75	2.21	3.79	0.958

These above results indicates to:

- The Stacked Ensemble model outperforms standalone models in two other metrics, approximately 15–20% reduction in error over LSTM.
- MAPE metric < 4% suggests high reliability, therefore, suitable for real-time energy control and demand forecasting.
- All three models illustrates $R^2 > 0.92$ that indicates strong predictive power.

B. *VISUALIZATION OF FORECAST*

Comparing the electricity consumption between real data and predicted data for 48 hours for LSTM and Ensemble models can be depicted in figure 3 as show below.

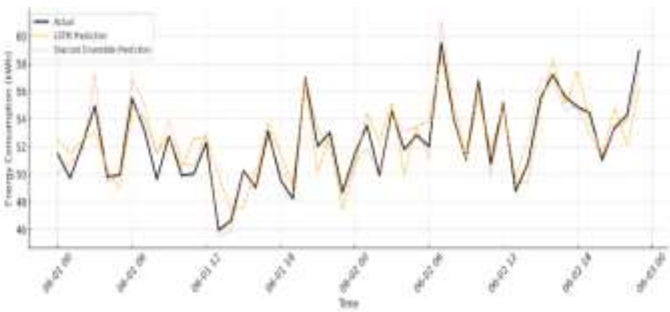

Figure 3: Electricity Consumption: Actual vs. Predicted for 48 Hours (LSTM vs. Ensemble)

This visualization shows that the ensemble model closely tracks real energy use. Its performance is excellent, particularly during office hours (08:00 AM to 04:00 PM), when predicting accuracy matters most for energy planning.

C. *DISCUSSION*

- The LSTM model's temporal awareness is comparatively good at capturing basic weekly and daily cycles.

- XGBoost was especially strong at identifying important static and exogenous variables, such as temperature and day of the week.
- The stacking approach is the best in terms of accuracy, for it combines the strengths of deep learning (sequence modelling) and gradient boosting (nonlinear regression).
- The implication is that such predictive capabilities offer a potential substitute for current systems, with load balancing and other beneficial applications in particular towards Iraq's power-hungry public institutions.

VI. SYSTEM FRAMEWORK PROPOSED DESIGN AND ARCHITECTURE

To put this forecasting system into practice in real-world situations, we propose a modular architecture that emphasizes scalability, automation and integration with building systems.

A. SYSTEM ARCHITECTURE COMPONENTS

1. Data Ingestion Layer
   - Smart meters and other IoT devices gather real-time energy consumption information.
   - External inputs: weather API and public calendar.
2. Preprocessing & Feature Engineering
   - Scheduled ETL (Extract, Transform, and Load) processes standardize incoming data.
   - Contextual feature extraction: time of day, occupancy, etc.
3. Machine Learning Engine
   - The trained ensemble model is registered in a model repository.
   - The prediction service is triggered either daily or hourly.
4. Prediction Output & Actions
   - Results are stored in a time-series database.
   - Anomaly detection triggers alerts for the energy office.
5. Dashboard & User Interface
   - Web-based dashboard, which displays for user examination and analysis forecasts also events that happened.
   - Power BI, Grafana, or Streamlit for the user interface.

B. DEVELOPMENT CONSIDERATIONS FOR THE FRAMEWORK

There are several components as a software and application needs to it when the developing and deployment starts as appears in table 5.

Table 5: development and deployment tools

Component	**Tool/Platform**	**Notes**
Data Storage	PostgreSQL / InfluxDB	Time-series and metadata storage
ML Inference	Python (Scikit-learn, Keras)	Scheduled via Airflow
Visualization	Power BI / Streamlit	For dashboards and alert panels
Integration	RESTful APIs	For external systems and BMS

Using AI-driven tools, this proposed framework is adaptable to other government buildings with small modification and facilitating a nation-wide smart energy strategy [20].

VII. CONCLUSIONS AND FUTURE WORK

A. CONCLUSIONS

This study introduced a data-driven framework for predicting an Iraqi government building’s periodic electricity usage. It used machine learning to get good results out of weather data, temperature data, and temperature-time data. There were three models: Use weather to influence behavior through time-of-day manipulation. We will be using two service models. First of all, weather type powers both services; but time is the only input for one of them-depending on whether you want this service to produce exact times or some other variable that happens at about a particular hour each day etcetera (possibly a building's combination clock with temperature sensor readings hourly taken as well). The ensemble model, which brings together deep learning and gradient-boosted trees, consistently outperformed the other two candidates by a great margin with R2 adjusted (0.958). Moreover, it had lower Mean Absolute Percentage Error (3.79%) than either of them as well. It is necessary to consider system elements that may affect demand.

The system should be able to catch and predict these components, such as room temperature, occupancy scheduling (meeting times or night shifts), and monthly calendar trends for example. As the visual forecasting pipeline and smart dashboard concept exemplified, these predictions could serve as valuable aids in making energy-efficient decisions, shifting and adjusting loads of electrical power around to reduce spikes during peak times, or even cutting costs in public sector infrastructure. Finally, this study fills a significant vacuum in literature and actuality: there are no localized intelligent butler-type energy management systems for Iraq’s public sector. The proposed solution is scalable, intelligible, and capable of being adapted with only minimal customization for similar government buildings.

B. FUTURE WORK

There are several directions in which future research could extend this work:

1. Multi-Building Framework: Extend the solution to cover groupings of government buildings with top-down control.
2. Integration of IoT: Incorporate real-time sensor data (e.g. lighting, HVAC) for dynamic and fine-grained forecasting.
3. Forecasting for Renewable Energy: Predict solar power generation for buildings with hybrid grids.
4. Adaptive Learning Models: Implement online learning algorithms which continually change as behavior of brain patterns develop over time (say from day into night).
5. Cybersecurity: Include secure access and encrypted APIs for safe data exchange.
6. User Feedback Loops: Create feedback pathways that allow people to give input, receive help when they need it and rectify any transgressions in expectation as new data becomes available.

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