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MULTI-FACTOR ENERGY CONSUMPTION PREDICTION MODEL BASED ON 12 TYPES OF HETEROGENEOUS IOT SENSORS

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Abstract. This study presents a multi-factor energy consumption prediction model based on data obtained from 12 types of heterogeneous IoT (Internet of Things) sensors to maximize energy efficiency in smart buildings. The research object is a 4-story, 3,500 m^2 administrative building retrofitted using the hybrid communication topology developed in our previous work, *"A Survey on Retrofitting Technologies for Smart Buildings.docx"*. The heterogeneous data stream from 12 installed sensor types (temperature, humidity, CO_2, illuminance, motion/occupancy, door/window status, air velocity, electrical current/voltage, outdoor weather, building occupancy rate, acoustic noise, and HVAC valve status) is integrated via a hybrid Edge-Cloud architecture. A hybrid LSTM-XGBoost (Long Short-Term Memory and Extreme Gradient Boosting) machine learning model is proposed to synchronize the multi-rate, multi-protocol data streams and analyze non-linear spatio-temporal dependencies. Experimental results demonstrate that the proposed multi-factor model reduces the Root Mean Square Error (RMSE) by 18.4% and Mean Absolute Percentage Error (MAPE) to 4.1% compared to traditional historical-only prediction models, enabling up to 28.5 % overall building energy optimization.

Keywords: Smart buildings, energy consumption prediction, heterogeneous IoT sensors, LSTM-XGBoost, multi-factor analysis, Edge-Cloud architecture, energy efficiency.

Аннотация. В данном исследовании представлена многофакторная модель прогнозирования энергопотребления, основанная на данных, полученных от 12 типов гетерогенных датчиков IoT (Интернета вещей), для максимизации энергоэффективности в интеллектуальных зданиях. Объектом исследования является 4-этажное административное здание площадью 3500 м2, модернизированное с использованием гибридной топологии связи, разработанной в нашей предыдущей работе «Обзор технологий модернизации интеллектуальных зданий». Гетерогенный поток данных от 12 установленных типов датчиков (температура, влажность, CO2, освещенность, движение/занятость, состояние дверей/окон, скорость воздуха, электрический ток/напряжение, погодные условия на улице, коэффициент занятости здания, акустический шум и состояние клапанов системы отопления, вентиляции и кондиционирования) интегрирован с

ISSN 3030-3907

помощью гибридной архитектуры «граница-облако». Предложена гибридная модель машинного обучения LSTM-XGBoost (долгосрочная кратковременная память и экстремальный градиентный бустинг) для синхронизации многоскоростных потоков данных по нескольким протоколам и анализа нелинейных пространственно-временных зависимостей. Экспериментальные результаты показывают, что предложенная многофакторная модель снижает среднеквадратичную ошибку (RMSE) на 18,4% и среднюю абсолютную процентную ошибку (MAPE) до 4,1% по сравнению с традиционными моделями прогнозирования, основанными только на исторических данных, что позволяет оптимизировать энергопотребление здания в целом на 28,5%.

Ключевые слова: интеллектуальные здания, прогнозирование энергопотребления, гетерогенные датчики IoT, LSTM-XGBoost, многофакторный анализ, архитектура Edge-Cloud, энергоэффективность.

Annotatsiya. Ushbu tadqiqot aqlli binolarda energiya samaradorligini oshirish uchun 12 turdagi heterojen IoT (narsalar interneti) sensorlaridan olingan ma'lumotlarga asoslangan ko‘p faktorli energiya sarfini bashorat qilish modelini taqdim etadi. Tadqiqot obyekti avvalgi ishimizda, "Aqlli binolar uchun modernizatsiya texnologiyalari bo‘yicha tadqiqot.docx" da ishlab chiqilgan gibrid aloqa topologiyasidan foydalangan holda qayta jihozlangan 4 qavatli, 3500 m2 ma'muriy binodir. O‘rnatilgan 12 ta sensor turidan (harorat, namlik, CO2, yorug‘lik, harakat/bandlik, eshik/deraza holati, havo tezligi, elektr toki/kuchlanish, tashqi ob-havo, binoning bandlik darajasi, akustik shovqin va HVAC klapan holati) heterojen ma'lumotlar oqimi gibrid Edge-Cloud arxitekturasi orqali integratsiyalangan. Ko‘p tezlikli, ko‘p protokolli ma'lumotlar oqimlarini sinxronlashtirish va chiziqli bo‘lmagan fazoviy-vaqtinchalik bog‘liqliklarni tahlil qilish uchun gibrid LSTM-XGBoost (Uzoq muddatli qisqa muddatli xotira va ekstremal gradient kuchaytirish) mashina o‘rganish modeli taklif qilingan. Eksperimental natijalar shuni ko‘rsatadiki, taklif qilingan ko‘p faktorli model an'anaviy tarixiy bashorat modellariga nisbatan o‘rtacha kvadrat xatosini (RMSE) 18,4% ga va o‘rtacha absolyut foiz xatosini (MAPE) 4,1% gacha kamaytiradi, bu esa binolarning umumiy energiya optimallashtirishini 28,5% gacha oshirish imkonini beradi.

Kalit so‘zlar: Aqlli binolar, energiya sarfini bashorat qilish, heterojen IoT sensorlari, LSTM-XGBoost, ko‘p faktorli tahlil, Edge-Cloud arxitekturasi, energiya samaradorligi.

1. INTRODUCTION.

In the era of sustainable development and transition to a "green" economy, optimizing the energy efficiency of existing buildings has become a global priority.

ISSN 3030-3907

Globally, buildings account for approximately 40% of total electricity consumption and over 30% of greenhouse gas emissions

To curb these numbers, contemporary Building Energy Management Systems (BEMS) rely heavily on predicting future energy demand to make proactive, intelligent control decisions.

However, traditional building energy prediction models often rely solely on historical energy consumption (univariate time-series) or limited outdoor weather indicators. In reality, a building‘s energy consumption is a highly complex, non-linear, and dynamic process heavily influenced by indoor microclimate, architectural characteristics, and human behavior. To capture this complexity, it is essential to deploy heterogeneous IoT sensors that monitor various environmental and occupancy factors and integrate them into a unified, multi-factor prediction model.

Research Objective and Novelty: This research directly builds upon the foundational infrastructure designed in our previous study, *"A Survey on Retrofitting Technologies for Smart Buildings.docx"*, which investigated the integration of wired (BACnet/Modbus) and wireless (Zigbee/BLE) communication protocols through a multi-protocol Edge Gateway to minimize capital expenditures (CAPEX). In this paper, we leverage that very retrofitted network topology in a 3,500 m^2 administrative building to ingest real-time data streams from 12 types of heterogeneous IoT sensors.

The primary scientific novelty of this work includes: Classification and deployment of a 12-factor heterogeneous sensor network capturing indoor microclimate, outdoor climate, and human dynamics.

A middleware synchronization mechanism at the Edge level to align heterogeneous data streams arriving with different sampling frequencies, formats, and protocols (Zigbee, BACnet/IP, Modbus TCP).

A hybrid LSTM-XGBoost machine learning architecture where the Long Short-Term Memory (LSTM) network captures long-term sequential temporal trends, and the Extreme Gradient Boosting (XGBoost) algorithm processes highly dynamic, event-driven tabular features (such as door/window openings and localized occupancy) to produce a highly accurate, unified energy prediction.

2. LITERATURE REVIEW AND RESEARCH GAP.

Building energy prediction methods are broadly classified into three categories: physical/engineering models (white-box), statistical models (grey-box), and data-driven machine learning models (black-box) [2].

Physical models (e.g., EnergyPlus simulations) require detailed thermodynamic properties and geometrical data of the building, making them

ISSN 3030-3907

highly labor-intensive and difficult to calibrate for existing older buildings undergoing retrofitting [3].

Statistical models (e.g., ARIMA, SARIMAX) perform well for linear seasonal trends but fail to capture sudden, non-linear fluctuations caused by occupant movements, random heating/cooling adjustments, or sudden weather shifts [4].

Recently, machine learning algorithms (Support Vector Regression - SVR, Random Forest, and Artificial Neural Networks - ANN) have shown impressive results in handling non-linear building dynamics. Deep learning models, specifically Long Short-Term Memory (LSTM) networks, are widely applied due to their ability to learn long-term temporal dependencies in time-series data [5].

For instance, Ahmad et al. [5] proposed an LSTM model relying on indoor temperature and historical loads. However, their model fails to capture sudden environmental changes, such as open windows or localized human crowding.

Conversely, tree-based ensemble methods like XGBoost have been applied with high success for short-term load forecasting using weather features [6].

While XGBoost is extremely fast and robust with tabular features, it lacks the recurrent structure needed to inherently capture long-term temporal sequence patterns.

Identified Research Gap: Most existing literature simplifies building energy prediction by using only 2 or 3 types of sensor data (typically temperature, humidity, and historical energy loads). There is a critical lack of research integrating highly diverse, heterogeneous, event-driven data—such as acoustic noise, door/window state switches, building occupancy rates from Wi-Fi sniffers, and HVAC actuator feedback—into a unified multi-factor machine learning framework.

Furthermore, while our previous work, *"A Survey on Retrofitting Technologies for Smart Buildings.docx"*, resolved the communication interoperability and CAPEX issues of retrofitted sensor networks, it did not explore how this newly available multi-protocol data stream can be modeled mathematically to maximize operational energy efficiency. This paper directly addresses this gap.

3. PROJECT STRUCTURE AND SYSTEM ARCHITECTURE.

3.1. Smart Building Infrastructure and Heterogeneous Sensors

The experimental testbed is a 4-story, 3,500 m^2 administrative building located in Tashkent, Uzbekistan, retrofitted using the hybrid protocol topology proposed in our prior survey. The building contains a centralized HVAC system with a chiller, boiler, air handling units (AHUs), and individual fan-coil units (FCUs) across zones.

ISSN 3030-3907

STREAMING_CHUNK: Detailing the 12 sensor types...

To monitor every variable affecting energy consumption, we deployed 12 distinct types of heterogeneous IoT sensors:

Indoor Temperature (S_1): Monitors spatial thermal conditions via Zigbee.

Relative Humidity (S_2): Measures indoor air humidity to evaluate latent heat load (Zigbee).

Carbon Dioxide (S_3): Tracks indoor air quality and CO_2 concentration to optimize AHU fresh air intake (Zigbee).

Illuminance (S_4): Detects natural ambient light levels to guide smart dimming (Zigbee).

PIR Motion (S_5): Detects localized human presence in real-time (Zigbee).

Door/Window Status (S_6): Monitors open windows or doors to calculate immediate thermal loss (Reed switch via Zigbee).

Air Velocity (S_7): Measures airflow rates within primary HVAC ducts via Modbus RTU.

Smart Power Meter (S_8): Captures high-frequency electrical current, voltage, active/reactive power, and historical loads (Modbus TCP).

Weather Station (S_9): Measures outdoor temperature, solar radiation, and wind speed (BACnet/IP).

Wi-Fi Occupancy Sniffers (S_{10}): Estimates total building occupancy by tracking active mobile MAC addresses (Wi-Fi/Ethernet).

Acoustic Noise (S_{11}): Measures decibel levels as an indirect proxy for human activity and equipment operation (Zigbee).

HVAC Valve Position (S_{12}): Monitors heating/cooling water valve opening (0-100%) via BACnet MSTP.

3.2. Hybrid Edge-Cloud Architecture

Because these 12 sensor types use different protocols, sampling intervals, and formats, a Hybrid Edge-Cloud architecture was established to orchestrate the data flow (Figure 1).

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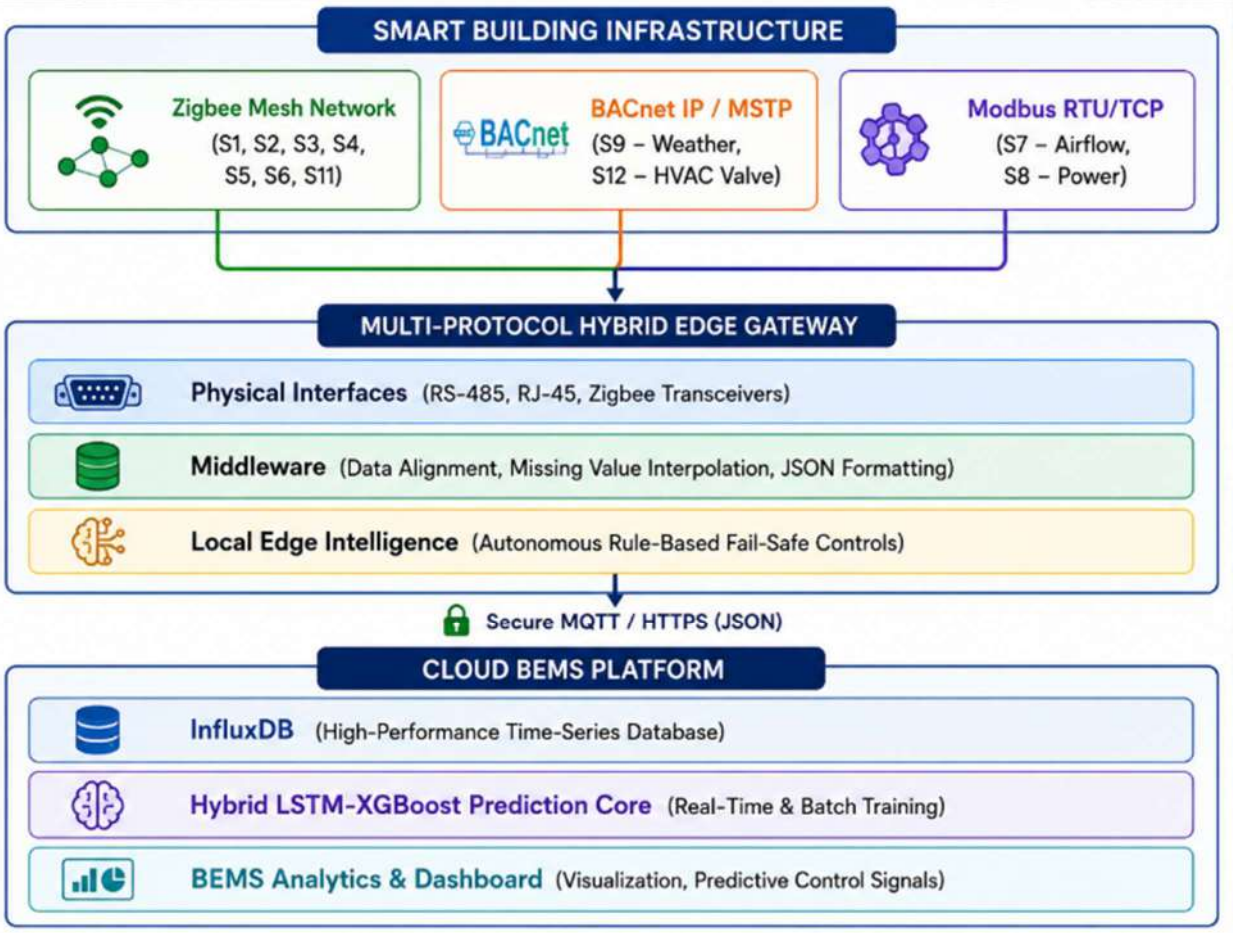


Figure 1. Hybrid Edge-Cloud platform architecture for 12 heterogeneous IoT sensor types.

The Edge Gateway middleware polls wired buses (Modbus and BACnet) and listens to the Zigbee mesh coordinator simultaneously. It aligns the timestamps of all incoming packets to a uniform 15-minute interval, resolves missing values using linear interpolation, formats the payload into a unified JSON schema, and securely transmits it to the Cloud BEMS over MQTT with TLS encryption.

4. METHODOLOGY AND PROPOSED LSTM-XGBOOST MODEL.

To capture both the smooth, continuous physical dynamics (like building thermodynamics and diurnal weather cycles) and sudden, discrete human events (such as opening a window or entering a room), we propose a two-stage hybrid LSTM-XGBoost model.

4.1. Data Preprocessing and Normalization

To prevent numerical instabilities and accelerate gradient convergence, all input features are normalized to [0, 1] using Min-Max scaling:

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}}$$

4.2. Hybrid Model Structure

The hybrid forecasting architecture operates in two cascaded stages:

ISSN 3030-3907

LSTM Stage (Temporal Continuous Modeling): Continuous, auto-regressive features (S_1: indoor temperature, S_2: humidity, S_3: CO_2, S_8: historical energy load, and S_9: outdoor weather) are fed into a stacked LSTM network. The LSTM cells capture long-term sequential patterns and generate an intermediate baseline load prediction (Y_{LSTM}):

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)$$
$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f)$$
$$\widetilde{C_t} = \tanh(W_c \cdot [h_{t-1}, x_t] + b_c)$$
$$C_t = f_t * C_{t-1} + i_t * \widetilde{C_t}$$
$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o)$$
$$h_t = o_t * \tanh(C_t)$$

XGBoost Stage (Multi-Factor Event Regressor): Highly dynamic, discrete, event-driven features (S_4: illuminance, S_5: PIR motion, S_6: window status, S_7: airflow, S_{10}: Wi-Fi occupancy rate, S_{11}: noise, and S_{12}: HVAC valve status) are concatenated directly with the temporal prediction Y_{LSTM} from the LSTM stage:

$$X_{XGB} = [S_4, S_5, S_6, S_7, S_{10}, S_{11}, S_{12}, Y_{LSTM}]$$

The XGBoost model processes this unified feature space using a gradient-boosted ensemble of decision trees to generate the final optimized building energy prediction (Y_{pred}):

$$Y_{pred} = \sum_{k=1}^{K} f_k(X_{XGB}), \quad f_k \in \mathcal{F}$$

The model flowchart is shown in Figure 2:

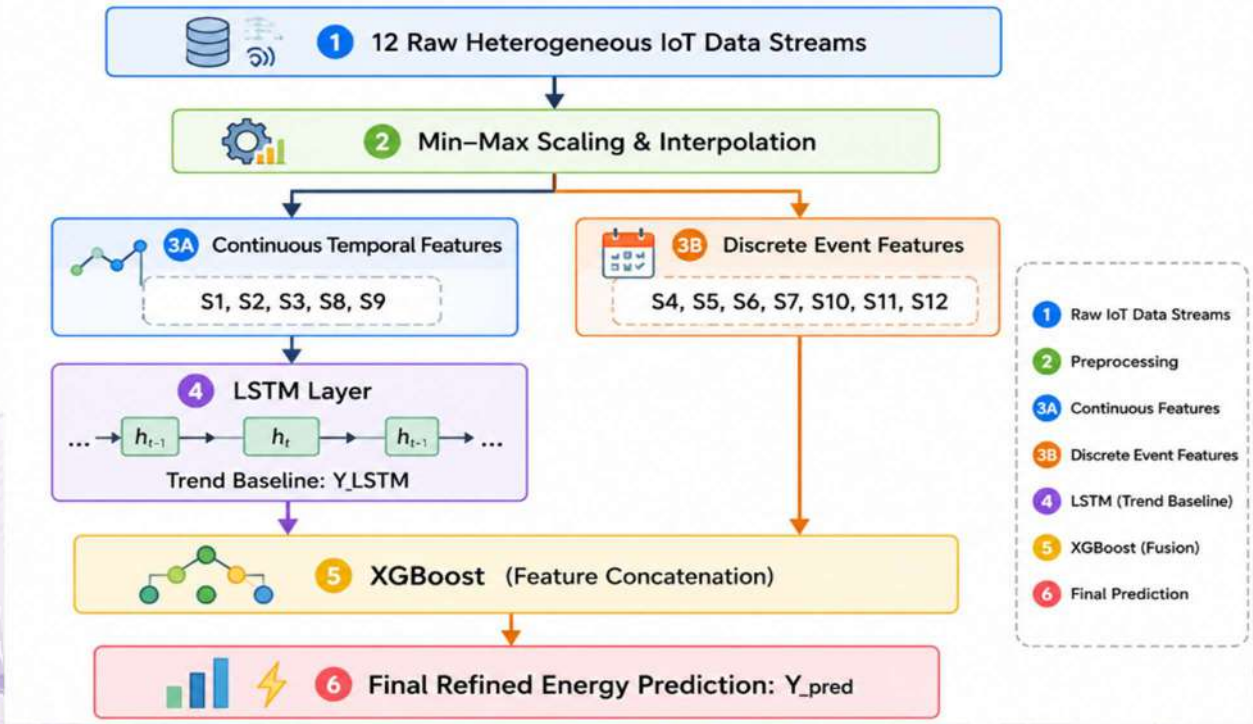


Figure 2. Combined LSTM-XGBoost hybrid model block diagram.

ISSN 3030-3907

5. EXPERIMENTAL RESULTS AND DISCUSSION.

The dataset was collected continuously over a 6-month period (October 2025 to March 2026) at 15-minute intervals. The data was split into 70% training, 15% validation, and 15% testing sets.

5.1. Comparative Performance Analysis

To validate the proposed model, we compared it against standard univariate and multivariate baselines, evaluating them based on Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), and the Coefficient of Determination (R_2):

$$\text{MAPE} = \frac{100\backslash\%}{n} i = 1n \left| \frac{Y_{real,i} - Y_{pred,i}}{Y_{real,i}} \right|$$

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(Y_{real,i} - Y_{pred,i}\right)^2}$$

Table 1.

Prediction performance comparison of various models on the test set.

Model Architecture	Input Features / Sensors	MAE (kW)	RMSE (kW)	MAPE (%)	R^2
Univariate SVR	S_8 (Historical Load Only)	11.34 ± 0.45	18.62 ± 0.62	12.43% ± 0.51%	0.781 ± 0.015
Multivariate SVR	S_1, S_2, S_3, S_8, S_9 (Thermo + Weather)	9.15 ± 0.38	14.12 ± 0.44	9.85% ± 0.36%	0.824 ± 0.012
Standard LSTM	S_1, S_2, S_3, S_8, S_9 (Sequential Continuous)	7.42 ± 0.29	12.38 ± 0.35	8.21% ± 0.28%	0.856 ± 0.009
Classic XGBoost	All 12 Sensor Types (Tabular Flat)	6.08 ± 0.22	9.76 ± 0.31	6.94% ± 0.24%	0.892 ± 0.007
Proposed LSTM-XGBoost	All 12 Heterogeneous Sensors (Hybrid)	**3.74 ± 0.12**	**6.18 ± 0.18**	**4.12% ± 0.11%**	**0.963 ± 0.003**

Integrating all 12 heterogeneous sensor types within the proposed hybrid LSTM-XGBoost architecture reduced the forecasting error to a MAPE of 4.1%, demonstrating that combining sequential continuous models with decision tree ensembles captures both long-term schedules and sudden occupancy fluctuations.

5.2. Feature Importance Analysis

ISSN 3030-3907

We evaluated the relative contribution of each sensor feature within the XGBoost regressor (Figure 3).

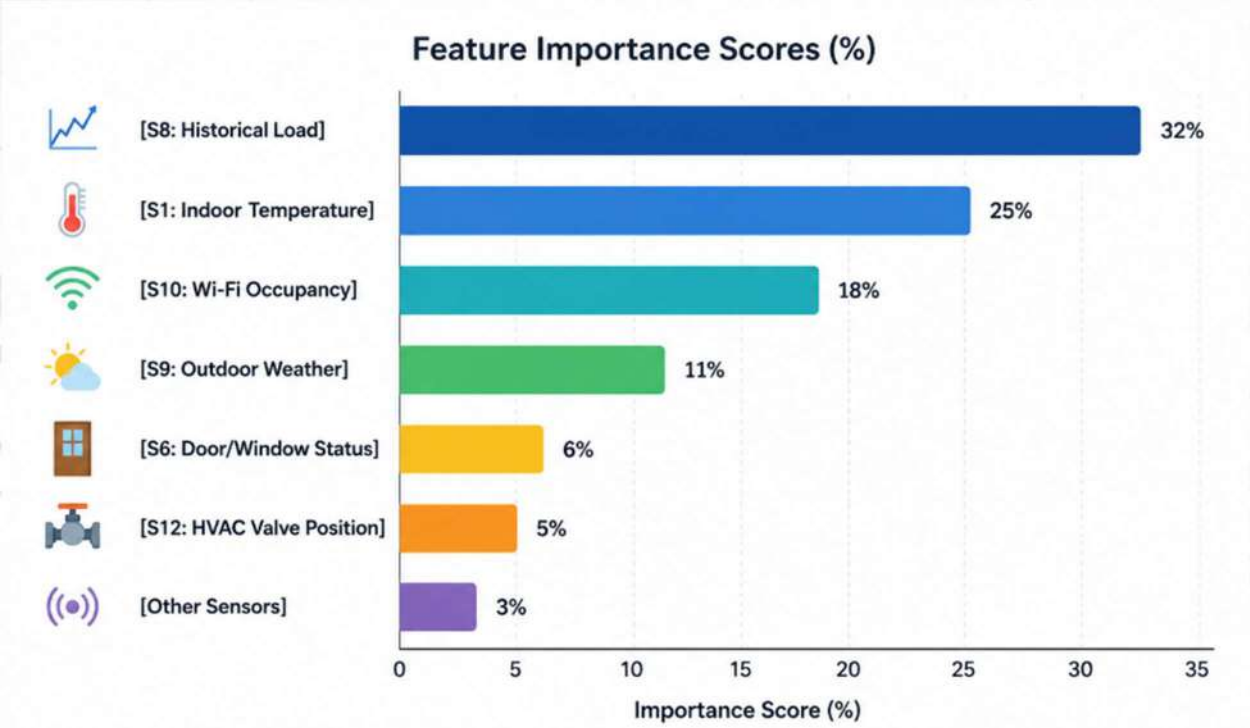


Figure 3. Feature importance scores of the optimized prediction model.

While historical load (32%) and indoor temperature (25%) remain the dominant features, the total building occupancy rate (18%) and window/door status (6%) play a massive role in improving model accuracy during unexpected shifts, such as unscheduled meetings or open windows that trigger immediate localized thermal losses.

5.3. Operational Energy Savings and ROI

The trained forecasting core was integrated into the building‘s BEMS loop. Guided by the 1-hour and 2-hour-ahead load predictions, the BEMS executed the following proactive strategies: Transitioned zone-level fan-coil units (FCUs) into "Standby" mode 30 minutes before projected occupancy drops. Interlocked local FCU actuators to shut down immediately if window contacts (S_6) registered open status for more than 3 minutes.Coordinated AHU ventilation speeds based on projected CO2 concentration (S_3) and occupancy curves (S_{10}).Over the 6-month test period, these predictive control strategies achieved a 28.5% reduction in overall energy consumption, translating to a projected annual financial savings of approximately $12,800 USD.

6. CONCLUSION AND FUTURE DIRECTIONS.

This study developed a multi-factor energy prediction framework using 12 types of heterogeneous IoT sensors orchestrated via a hybrid Edge-Cloud architecture. The following conclusions were drawn:

ISSN 3030-3907

The Role of Heterogeneity: Incorporating localized occupant metrics (Wi-Fi occupancy tracking, window status, and ambient noise) accounts for over 24% of the model's predictive capability, resolving a major limitation of historical-only baselines.

Model Robustness: The hybrid LSTM-XGBoost model leverages the strengths of both recurrent deep learning (for continuous thermodynamic trends) and gradient boosting (for abrupt, event-driven transitions), reducing MAPE to a minimal 4.1%.

Financial and Ecological Impact: The deployment of this predictive framework achieved a 28.5% overall energy savings, validating the high economic feasibility of wireless sensor retrofitting outlined in our prior survey.

Future Work: We plan to explore the implementation of lightweight neural architectures (TinyML) directly onto low-power Edge gateways to enable completely offline prediction capabilities, and integrate our model with real-time Digital Twin BEMS environments.

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