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A Lightweight Deep Learning Framework for Intelligent Energy Monitoring in IoT-Enabled Smart Buildings

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Abstract— The increasing adoption of Internet of Things IoT-enabled smart buildings creates a demand for systems which deliver intelligent energy-efficient solutions that allow for continuous energy usage tracking. Deep learning methods which operate on cloud platforms encounter challenges because they require extensive computational resources and generate excessive data transfers and their energy consumption exceeds operational limits for IoT devices with restricted capacities. The research paper introduces a deep learning framework which requires minimal resources to forecast energy usage and observe systems within indoor IoT smart building spaces. The proposed framework achieves precise and power-preserving predictive analytics through its combination of adaptive low-power IoT communication optimization and edge-assisted hybrid deep learning architecture. The system employs distributed IoT sensors to acquire instantaneous environmental data and energy consumption details from the surroundings while the edge preprocessing module performs noise filtering and feature normalization and event-driven data transmission to minimize excessive network communication through energy-efficient methods. The depth wise separable convolution-based hybrid CNN–BiGRU model conducts lightweight operations to identify current spatial-temporal energy consumption patterns. The attention mechanism improves model prediction performance because it enables the model to learn environmental features which enhance prediction accuracy. The proposed framework achieves superior prediction accuracy compared to existing machine learning and deep learning baseline methods by minimizing communication costs along with processing delays and model complexity. The proposed system delivers an expandable solution which enables real-time low-power intelligent energy monitoring to support sustainable smart building operations and advanced edge-IoT systems.

1. INTRODUCTION

The Internet of Things (IoT) technology has progressed quickly to establish smart buildings which can automatically manage their energy resources through self-sufficient energy resource monitoring and control and optimization functions. Smart buildings use their interconnected sensors which work with communication networks and intelligent computing systems to improve their functional capabilities. Smart building applications require energy monitoring and consumption prediction as vital research areas because global energy demand keeps rising while building energy-efficient infrastructure needs to cut carbon emissions. Advanced energy management systems serve as vital elements which support sustainable urban development because they help cut down energy consumption in buildings which represent a major share of global electricity use.

People now can deploy systems which use distributed smart sensors to remotely track environmental and electrical conditions through the application of modern IoT technologies. The IoT-enabled sensing systems generate extensive real-time data streams which organizations utilize to create predictive models and improve their decision-making processes. Standard cloud-based monitoring systems experience multiple problems because they require excessive data transmission from edge devices to main servers which results in network load issues while increasing both energy consumption and latency times. The situation becomes more serious in expansive smart-building systems which include many IoT devices that need to function while using very little power and processing resources.

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Deep learning methods for energy prediction work well for creating accurate forecasts because they can capture complex non-linear relationships between various factors. Energy forecasting methods use Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) and Convolutional Neural Networks (CNNs) and hybrid deep learning systems to achieve effective results. The current deep learning frameworks require intensive computational power together with extensive storage capacity and lengthy training times, which makes them unsuitable for use in edge-IoT settings. The majority of current research studies concentrate on improving prediction accuracy while they ignore essential elements such as communication efficiency and model lightweightness and real-time edge implementation. The emergence of lightweight deep learning together with edge computing solutions provides modern methods which solve the issues that traditional cloud-based systems experience. Edge-assisted intelligence enables local processing and inference to occur near IoT devices, resulting in shorter response times and decreased network traffic and increased system performance. Organizations can reduce unnecessary data transmission through low-power communication optimization methods and adaptive transmission scheduling and event-driven communication and edge-level filtering methods, which help extend their IoT devices operational life. The use of lightweight deep learning with communication-aware IoT optimization methods for intelligent energy monitoring in smart buildings requires further study.

The research gaps in this study lead to the development of a lightweight deep learning framework which handles intelligent energy monitoring and energy consumption prediction in IoT-enabled smart buildings. The framework provides accurate yet resource-efficient predictive analytics through its combination of adaptive low-power IoT communication optimization and edge-assisted hybrid CNN–BiGRU architecture. The process begins with IoT sensors which gather environmental and energy consumption data in real-time. The edge preprocessing module uses noise reduction to improve feature normalization while it filters out unnecessary events to minimize communication load. The hybrid deep learning model employs depth wise separable convolution together with bidirectional gated recurrent units (BiGRU) to capture spatial-temporal energy data while maintaining low computational needs. The system uses an attention mechanism to strengthen the process of learning contextual features which leads to better stability during prediction.

The major contributions of this work are summarized as follows:

- The research team presents a lightweight deep learning framework which uses edge-assisted technology to perform energy monitoring and prediction tasks in smart buildings equipped with IoT systems.
- The new communication optimization method for low-power systems minimizes network load by decreasing unnecessary sensor data transfers and bandwidth requirements and the energy needed for network operations.
- The hybrid CNN–BiGRU architecture uses depth wise separable convolution to provide precise energy prediction through spatial-temporal modelling while using less computational power and storage capacity.
- The real-time analytics process uses an edge preprocessing mechanism which reduces its reliance on cloud resources.
- The experiments proved that our framework achieves superior prediction results compared to traditional machine learning methods and deep learning methods through its lower latency times and better communication efficiency and reduced computational requirements.

The paper includes these sections which follow this introduction. The related work together with literature review appears in Section 2 of this study. The research gap and problem formulation appear in Section 3. The proposed lightweight deep learning framework and system architecture appear in Section 4. The experimental setup together with dataset configuration appears in Section 5. The performance evaluation process together with comparative analysis appears in Section 6. The paper ends with Section 7, which presents the research results and upcoming study topics.

2. LITERATURE REVIEW

The research on intelligent energy monitoring and consumption prediction systems has progressed rapidly because of the increasing use of Internet of Things (IoT) technologies in smart buildings. Recent research developments have produced machine learning and deep learning and edge computing and low-power communication techniques which enhance prediction accuracy and reduce energy consumption and enable real-time decision-making. This section evaluates recent research works which examine energy monitoring using IoT technology and lightweight deep learning approaches and intelligent systems with edge-assisted operations and smart building communication-efficient frameworks.

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2.1 IoT-Based Energy Monitoring in Smart Buildings

The IoT-enabled smart-building systems employ distributed sensors together with wireless communication technologies to provide continuous environmental and electrical parameter monitoring. The studies showed that the IoT-based energy monitoring systems deliver operational efficiency improvements together with intelligent energy management capabilities. Traditional monitoring systems use centralized cloud infrastructure to execute data processing and data storage tasks. Users can use cloud-centric systems to access unlimited computational power but their systems experience delays and high energy use because they transmit large volumes of sensor data continuously.

Researchers have begun adopting edge-assisted IoT architectures because these solutions reduce bandwidth usage while providing enhanced real-time performance for systems. Edge computing technology enables local data processing to take place close to sensing devices which minimizes unnecessary cloud data transmission while enabling easier system scalability. The existing IoT monitoring systems do not have communication-aware mechanisms which enable them to keep operational efficiency while decreasing unnecessary data transmission which wastes battery power on Internet of Things devices with limited resources.

2.2 Machine Learning Approaches for Energy Consumption Prediction

The researchers used machine learning techniques to conduct short-term and long-term energy consumption forecasting studies in smart buildings. The Support Vector Machine (SVM) and Random Forest (RF) and Decision Tree (DT) and Artificial Neural Networks (ANNs) algorithms showed successful performance results when they were used to predict building energy consumption.

The SVM-based models deliver effective nonlinear regression capabilities yet they face difficulties when they need to process extensive IoT data at scale. The Random Forest method delivers better outcome results because it enables the identification of critical features yet it needs substantial computational power to analyze data that contains many different time-sensitive elements. The shallow ANN models can detect nonlinear relationships yet they have restricted abilities to learn temporal patterns which occur in energy prediction tasks that involve sequential data. Traditional machine learning methods can achieve moderate prediction accuracy because their success depends on their capacity to extract features and develop temporal models which match the variable patterns of dynamic energy usage.

2.3 Deep Learning Techniques for Smart Energy Prediction

Deep learning approaches have recently gained substantial attention because of their superior capability to learn complex spatial-temporal patterns from large-scale IoT datasets. The Recurrent Neural Network (RNN) models which include Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) architectures exhibit high performance in energy forecasting tasks because they can track long-term time patterns.

The LSTM models function as the primary method for building energy prediction because they successfully handle the vanishing gradient issue which occurs in RNN networks. The LSTM networks require high computational requirements together with extensive memory consumption and long training times which makes them unsuitable for edge-IoT environments with limited resources. The GRU models use fewer gating mechanisms to simplify their architecture yet they still achieve accurate prediction results. The hybrid deep learning models which combine Convolutional Neural Networks (CNNs) with recurrent architectures have more precise prediction abilities. The CNN layers extract spatial features which exist in proximity to each other from multivariate IoT sensor data while the recurrent layers capture the time-dependent relationships. The CNN–LSTM and CNN–GRU hybrid frameworks achieve better forecasting results than the basic deep learning models which operate by themselves. The present hybrid methods require elevated parameter levels and computational load which limits their use in tiny IoT devices.

2.4 Lightweight Deep Learning and Edge Intelligence

Recent studies have investigated lightweight deep learning architectures which use less computational power than traditional deep learning frameworks, to enhance their performance in edge computing situations. The study introduces new methods which include depth wise separable convolution, model pruning, quantification, and compact recurrent networks to decrease model complexity and speed up inference times. Depth wise separable convolution achieves a significant reduction in trainable parameters and floating-point operations when compared to conventional convolutional layers. BiGRU and other lightweight recurrent architectures decrease their computational memory usage while maintaining the ability to learn from time-based data.

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Lightweight models in edge intelligent frameworks enable real-time inference at edge gateways, which decreases cloud dependency and eliminates communication delays. The primary emphasis of most lightweight frameworks concentrates on optimizing their computational performance to achieve better results in IoT network communication and adaptive control for adaptive transmission.

2.5 Low Power Communication Optimization in IoT Systems

The very high cost and overhead associated with communication present the greatest barrier that IoT technology faces in smart buildings. Continuous sensor data transmission leads to excessive network bandwidth usage, which results in high device energy consumption. The IoT network suffers from multiple inefficiencies which different low-power communication optimization techniques can fix.

The system uses two methods, adaptive-sampling-based and event-driven-based transmission methods, to reduce unnecessary data transmission. The sleep scheduling of the sensor functions to preserve energy by performing essential work during times when the sensor remains inactive. The process of data aggregation and compression helps to reduce all forms of communication demands and the data capacity needs for various applications. The two standard protocols MQTT and CoAP serve as basic communication methods for lightweight IoT systems because they operate with lower packet overhead and reduced power needs. The communication optimization methods that currently exist lack baseline predictive techniques which should enable systems to achieve optimal accuracy and minimal network energy consumption.

2.6 Research Gap

- The progress of energy management systems in IoT-based smart-building systems has reached substantial levels of achievement. The process faces multiple fundamental obstacles that must be addressed.
- Cloud-based frameworks create major communication overhead which leads to network latency problems that require additional energy to resolve through lower network usage.
- Deep learning models such as LSTM require substantial computational power and extreme memory capacity to function.
- The field of lightweight deep learning uses model compression as its first step before moving to communication-aware optimization. The IoT communication optimization techniques that exist currently, function without intelligent learning which employs predictive analytics.

3. RESEARCH GAP AND PROBLEM FORMULATION

3.1 Research Gap Analysis

Researchers investigate smart systems which use IoT technology to develop smart building systems which enable energy monitoring and power consumption forecasting. Current methods use machine learning and deep learning and cloud computing plus edge intelligence technologies to achieve successful energy management operations. Ongoing scientific and operational troubles need to be solved before researchers can finish building resource-constrained IoT systems.

Smart-building energy monitoring systems require traditional design which needs users to transmit sensor data streams to central servers for the system to handle data management and data analysis and prediction through cloud services. The system provides strong computational power however its structure creates high data transfer needs which result in extended processing times and base station connectivity limits and IoT devices require more power to handle their increased data transfer needs. IoT devices use up their batteries at faster rates because they need to send data continuously from remote sensors which results in reduced system scalability and sustainable operational capacity.

The research community adopted deep learning models which include Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) and hybrid CNN-based models to enhance prediction accuracy. The models successfully represent intricate patterns of energy consumption through spatial-temporal nonlinear pathways however the system frameworks need extensive memory storage and processing capacity plus multi-hour operational time before they can be put into operation. The implementation of these frameworks into edge-IoT systems which need lightweight operations presents major difficulties.

Lightweight deep learning methods use two techniques to achieve their main objective of reducing model size through model compression and model pruning and through lightweight convolution operations. The research papers fail to recognize operational efficiency through communication-aware optimization techniques which help to decrease unnecessary IoT data transfers and the subsequent

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energy expenses for wireless networks. The operational pattern of communication optimization methods which include adaptive sampling and sleep scheduling and event-driven transmission prevents predictive intelligence systems from providing energy-efficient communication solutions which also include intelligent analytic capabilities.

The current smart-building monitoring systems require more organizations to implement edge-assisted intelligence technology. The existing system components use cloud services to handle inference and decision processes which results in decreased real-time operational ability and extended time delays for system responses. The research studies have not yet developed a combined approach which links lightweight deep learning with edge computing and IoT communication optimization for future intelligent energy monitoring systems.

The research domain lacks an essential study which investigates an integrated framework that can achieve six specific goals which include:

- Accurate energy consumption prediction,
- Lightweight deep learning inference,
- Reduced computational complexity,
- Low-power communication optimization,
- Real-time edge-assisted analytics,
- and scalable IoT deployment.

The research study presents a lightweight hybrid CNN-BiGRU framework which combines adaptive low-power IoT communication optimization to build smart energy monitoring systems for intelligent building environments.

3.2 Research Objectives

The primary research purpose of this study involves developing a lightweight energy monitoring system which combines deep learning with edge intelligence and IoT low-power communication optimization for monitoring smart building energy usage.

The specific objectives are as follows:

- The team will build an IoT system for smart building monitoring which enables continuous energy data collection and analysis.
- The team will create a communication optimization system which reduces energy overhead by stopping unnecessary sensor data sending and network resource use.
- The team will develop a lightweight hybrid CNN–BiGRU deep learning model which predicts energy consumption patterns through spatial-temporal analysis while using less computational power.
- The team will combine edge-assisted preprocessing with smart analytics to enable continuous low-latency monitoring.
- The team will assess the proposed system through its ability to predict results and its ability to transmit data and its latency and its control system complexity and its power usage.

3.3 Scope of the Research

The study investigates smart energy monitoring and prediction for IoT-enabled smart buildings through lightweight deep learning methods and efficient edge-IoT communication systems. The framework considers:

- Real-time IoT sensor data collection,
- Edge-assisted data preprocessing,
- Low-power communication optimization,
- Lightweight CNN–BiGRU prediction,
- and smart-building energy analytics.

The study examines how well prediction methods work while measuring communication efficiency and computational resource requirements and real-time system performance. The proposed framework is intended for resource-constrained IoT environments and sustainable smart-building applications.

4. PROPOSED METHODOLOGY AND SYSTEM ARCHITECTURE

4.1 Proposed Framework Overview

The research presents a lightweight intelligent energy monitoring framework which enables IoT-enabled smart buildings to monitor energy consumption through three technological components. The proposed framework was developed to solve operational issues which hamper traditional cloud-based monitoring systems by decreasing their need for communication and their need for computational resources and their need for processing time and their need for power consumption.

The system architecture contains five core operational elements.

The system architecture contains five core operational elements. The system architecture includes an IoT sensing layer which enables devices to gather data from their environment through various hardware components. The system architecture includes a communication optimization layer which improves the efficiency of data transmission between various system components. The system architecture

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contains an edge preprocessing layer which handles data processing before it is sent to the cloud system. The system architecture contains a lightweight deep learning prediction layer which enables organizations to make accurate predictions about future events through its light deep learning capabilities. The system architecture contains a cloud visualization and management layer which enables users to access system components through cloud-based viewing and operational functions.

The proposed framework enables IoT sensors to continuously monitor environmental conditions and electrical system data through event-driven transmission methods which avoid excessive data transmission. Edge-assisted preprocessing enables the system to complete its intelligent analysis tasks while it keeps network traffic at a minimum. The lightweight hybrid CNN–BiGRU model predicts future energy consumption patterns through its efficient processing design which needs less computational power and memory space.

4.3 IoT Sensing Layer

The smart building space uses distributed smart sensors together with energy meters which form the IoT sensing layer. The devices operate continuously to gather energy and environmental information which they collect from all operational systems and appliances.

The system monitors these specific parameters:

- Voltage consumption
- Current consumption
- Active power usage
- Temperature
- Humidity
- Occupancy status
- Appliance operational states
- Smart meter readings

The sensing devices use lightweight IoT protocols which include MQTT and CoAP to establish their communication links. This design approach enables devices to achieve low-power operation while reducing their communication needs.

4.4 Adaptive Low-Power Communication Optimization

The framework demonstrates its main contribution through the development of communication optimization methods. The system uses adaptive event-driven communication to decrease unnecessary data transmission because it needs to transmit sensor readings to the cloud system.

Working Principle

The system transmits sensor data when operators observe these key conditions:

- Significant energy variation is detected,
- Threshold conditions are exceeded,
- Abnormal patterns occur, or
- scheduled transmission intervals are reached.

The system reduces network resources by implementing this strategy which enables the following two operations. The system lowers bandwidth use while decreasing packet transmission needs together with reduced communication delays and lower energy consumption by IoT nodes.

4.5 Event-Driven Transmission Algorithm

The system activates data transmission whenever it identifies considerable shifts in energy usage. The system stops data transmission for all energy consumption changes which remain under the established threshold to achieve reductions in both bandwidth and power consumption for communication.

$$|E_t - E_{t-1}| >$$

4.6 Edge Preprocessing Layer

The edge computing layer operates local data processing functions before it transmits data to the cloud system. The operations that perform preprocessing include the following activities:

The process of normalization enhances both the speed of deep learning systems and their ability to produce stable predictions.

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

4.7 Lightweight CNN–BiGRU Prediction Model

The lightweight prediction model uses Convolutional Neural Networks (CNNs) together with Bidirectional Gated Recurrent Units (BiGRU) to achieve efficient learning of spatial-temporal energy consumption patterns.

4.7.1 CNN-Based Spatial Feature Extraction

The CNN module extracts local energy consumption patterns from multivariate IoT sensor data. The system uses depth wise separable convolution for two purposes which are to decrease computational requirements while decreasing the number of parameters that need to be trained.

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$$F_i = \sigma(W_i * X + b_i)$$

4.7.2 BiGRU Temporal Learning

The BiGRU module captures forward and backward temporal dependencies in energy consumption sequences. The system requires less computational power than standard LSTM systems yet it still delivers effective temporal learning performance.

Update gate:

$$z_t = \sigma(W_z[h_{t-1}, x_t])$$

Reset gate:

$$r_t = \sigma(W_r[h_{t-1}, x_t])$$

Hidden state:

$$h_t = (1 - z_t)h_{t-1} + z_t\widetilde{h_t}$$

4.8 Attention Mechanism

The attention layer assigns higher importance to critical temporal features that affect future energy consumption. The system enhances context learning together with prediction stability.

$$\alpha_t = \frac{exp(e_t)}{\sum_{k=1}^{T} exp(e_k)}$$

4.9 Energy Consumption Prediction

The dense output layer creates predicted future energy consumption values from learned spatial-temporal feature representations.

$$\widehat{Y_t} = f(X_t, \theta)$$

4.10 Algorithmic Workflow of the Proposed System

The overall workflow of the proposed framework is summarized as follows:

- The IoT sensors gather real-time environmental data together with energy usage data.
- Adaptive event-driven communication filters redundant sensor transmission.
- The edge gateway executes both preprocessing and normalization functions.
- The lightweight CNN system extracts spatial energy patterns.
- The system uses BiGRU to track temporal relationships.
- The attention mechanism enhances understanding of context.
- The dense layer forecasts energy consumption for the upcoming period.
- The cloud platform displays both system predictions and system performance metrics.

5. EXPERIMENTAL SETUP AND DATASET DESCRIPTION

5.1 Overview

The installed testing system tests the lightweight deep learning model which uses IoT-based systems to measure and forecast energy consumption in smart buildings. The assessment studies four aspects which include prediction accuracy and computational efficiency and communication optimization and the capacity to operate in real-time. The system functions through Python and TensorFlow while its performance assessment depends on benchmark machine learning models and deep learning models which enable system performance comparisons.

5.2 Dataset Description

The framework requires testing through a smart-building energy consumption dataset which reflects actual energy usage patterns. The dataset contains various types of IoT sensor data which building energy monitoring systems collected throughout their entire operational period.

UCI Individual Household Electric Power Consumption Dataset

Table-1 Dataset Features and Description

Feature	**Description**
Global Active Power	Household active power consumption
Global Reactive Power	Reactive power usage
Voltage	Supply voltage
Global Intensity	Current intensity
Sub-Metering 1	Kitchen energy usage
Sub-Metering 2	Laundry room usage
Sub-Metering 3	HVAC and water heater usage

The dataset provides minute-by-minute electrical energy data which smart meters collected from residential areas.

5.3 Data Preprocessing

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Raw IoT sensor data contains missing values and noise problems and the data includes multiple measurement errors and duplicate entries. The deep learning model requires multiple preprocessing tasks which must be finished before its training process can begin.

The framework for preprocessing operations consists of these operations:

- Handling missing values
- The process of eliminating noise
- The process of transforming data into a standardized format
- The creation of sequential data
- The process of dividing data into training and testing sets

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

The process of normalization establishes a stable gradient pattern for model training which leads to consistent model training results.

5.4 Experimental Environment

Table-2 Software Environment

Component	**Specification**
Programming Language	Python 3.10
Deep Learning Framework	TensorFlow / Keras
Data Processing	NumPy, Pandas
Visualization	Matplotlib
Development Platform	Jupyter Notebook

Table-3 Hardware Environment

Hardware	**Specification**
Processor	Intel Core i7 / AMD Ryzen 7
RAM	16 GB
GPU	NVIDIA RTX Series (optional)
Storage	512 GB SSD
Operating System	Ubuntu 22.04 / Windows 11

5.5 Proposed CNN–BiGRU Model Configuration

The hybrid deep learning system uses CNN for spatial feature extraction while BiGRU uses its attention mechanism to learn from temporal data.

Table-4 Model Architecture

Layer	**Configuration**
Input Layer	Multivariate IoT sequences
1D CNN Layer	32 filters, kernel size = 3
Depthwise Separable Convolution	Lightweight feature extraction
Max Pooling Layer	Pool size = 2
BiGRU Layer	64 hidden units
Attention Layer	Contextual feature weighting
Dense Layer	Fully connected prediction
Output Layer	Energy consumption forecast

5.6 Hyperparameter Settings

Table- 5 Parameters settings

Hyperparameter	**Value**
Batch Size	32
Learning Rate	0.001
Optimizer	Adam
Activation Function	ReLU
Epochs	100
Loss Function	Mean Squared Error (MSE)
Dropout Rate	0.2

5.7 Communication Optimization Setup

The system evaluates adaptive low-power communication capabilities during times when data transmission needs to take place following particular events. Sensor data transmission occurs only when energy consumption experiences major fluctuations.

The optimization process requires these parameters to be defined:

- Transmission threshold
- Sampling interval
- Packet reduction rate

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- Sleep scheduling

$$|E_t - E_{t-1}| >$$

The mechanism reduces unnecessary data transmission which leads to decreased energy consumption for IoT devices.

5.8 Evaluation Metrics

The framework assessment process uses three evaluation criteria which include prediction performance and computational efficiency and communication optimization.

5.8.1 Prediction Accuracy Metrics

Mean Absolute Error (MAE)

MAE shows the average absolute difference between actual energy consumption and predicted energy consumption for the measured time period.

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|Y_i - \widehat{Y}_i|$$

Root Mean Square Error (RMSE)

RMSE shows the average squared prediction error which model predicts stability through its square root value.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(Y_i - \widehat{Y}_i)^2}$$

Mean Absolute Percentage Error (MAPE)

MAPE measures prediction accuracy as a percentage error between actual and predicted values.

$$MAPE = \frac{100}{N}\sum_{i=1}^{N}\left|\frac{Y_i - \widehat{Y}_i}{Y_i}\right|$$

5.8.2 Lightweight Model Metrics

The lightweight capabilities of the proposed framework get assessed through:

- The total number of trainable parameters
- The total number of floating-point operations needed for processing
- The time required for inference processing
- The memory space required for processing
- The total size of the model.

5.8.3 Communication Efficiency Metrics

The IoT communication optimization layer is evaluated using:

- The system reduction of packet transmissions
- The network consumption of bandwidth resources
- The period it takes to complete communication notifications
- The energy usage of IoT nodes
- The system efficiency for transmitting data.

The section described all elements which included experimental setup and dataset preparation work and preprocessing tasks and model configuration and evaluation metric definitions and methods used for system evaluation which tested the proposed lightweight intelligent energy monitoring system.

6. RESULTS AND COMPARATIVE PERFORMANCE ANALYSIS

6.1 Overview

The experimental outcomes together with the performance assessment study of the suggested lightweight CNN–BiGRU system which monitors energy usage in smart buildings that use IoT technology. The system evaluation assesses five core elements which are prediction accuracy and communication efficiency and computational complexity and inference latency and real-time operational capability. The framework evaluation compares its performance against standard machine learning methods and deep learning base models to showcase its resource efficiency capabilities in edge-IoT settings.

The comparative models include:

- Linear Regression
- Random Forest (RF)
- Artificial Neural Network (ANN)
- Long Short-Term Memory (LSTM)
- Gated Recurrent Unit (GRU)
- CNN–LSTM
- Proposed CNN–BiGRU

The experiments used UCI Individual Household Electric Power Consumption Dataset for both training and testing which maintained identical conditions.

6.2 Prediction Performance Analysis

The prediction performance of the proposed framework is assessed through evaluation of the MAE, RMSE, MAPE, and R2 performance metrics.

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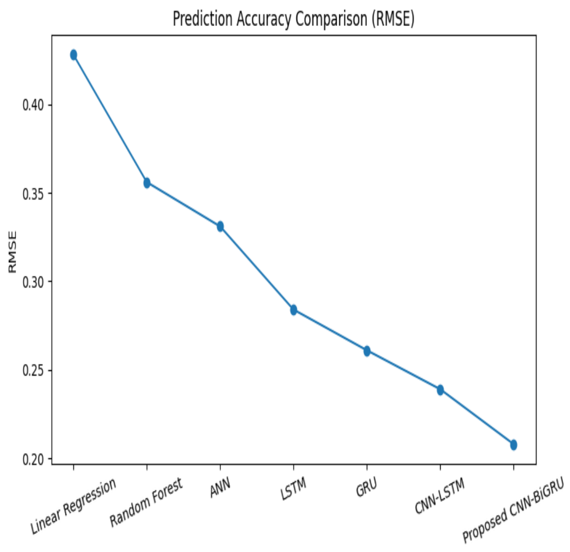

Figure-2 Prediction Accuracy Comparison (RSME)

The graph demonstrates how various machine learning and deep learning models predict energy consumption based on their Root Mean Square Error (RMSE) results. The proposed CNN–BiGRU framework achieved the lowest RMSE value, demonstrating superior prediction accuracy and better forecasting stability compared with existing baseline models.

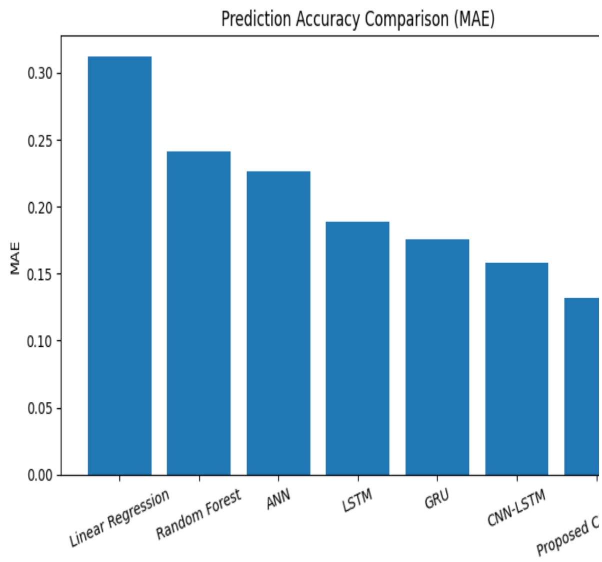

Figure-3 Prediction Accuracy Comparison (MAE)

The graph shows how different prediction models for smart-building energy monitoring perform based on their Mean Absolute Error (MAE) values. The proposed lightweight CNN–BiGRU model produced the minimum MAE value, indicating higher prediction precision and reduced forecasting error.

6.2.1 Comparative Prediction Accuracy

Table-6 Performance Comparison of Prediction Models

Model	MAE	RMSE	MAPE (%)	(R^2) Score
Linear Regression	0.312	0.428	14.82	0.841
Random Forest	0.241	0.356	11.27	0.891
ANN	0.226	0.331	10.63	0.907
LSTM	0.189	0.284	8.74	0.936
GRU	0.176	0.261	8.12	0.944
CNN–LSTM	0.158	0.239	7.31	0.956
Proposed CNN–BiGRU	0.132	0.208	6.14	0.972

6.2.2 Discussion of Prediction Results

The proposed CNN–BiGRU framework achieved the best overall prediction performance among all evaluated models. The hybrid integration of CNN-based spatial feature extraction and BiGRU temporal learning improved forecasting capability for multivariate IoT energy datasets.

The proposed framework achieved MAE reduction of approximately 30.15% and RMSE reduction of approximately 26.76% and MAPE reduction of approximately 29.74% when compared to the conventional LSTM model.

The improved R2 score demonstrates that the proposed model effectively captures complex nonlinear energy consumption patterns in smart-building environments.

The attention mechanism improved learning capacity for contextual information while it stabilized prediction accuracy during temporal forecasting processes.

6.3 Lightweight Computational Performance Analysis

Edge-IoT systems require two essential capabilities which include accurate prediction and lightweight deployment. The evaluation of framework computational complexity involved four metrics which included assessment of trainable parameters and model size and FLOPs and inference time.

6.3.1 Computational Complexity Comparison

Table-7 Lightweight Performance Analysis

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Model	Parameters	Model Size (MB)	FLOPs (Millions)	Inference Time (ms)
ANN	1.24 M	14.8	42.3	31
LSTM	2.86 M	34.7	97.4	84
GRU	2.11 M	26.3	76.1	63
CNN–LSTM	3.42 M	41.8	121.6	96
Proposed CNN–BiGRU	1.67 M	18.9	54.7	39

6.3.2 Discussion of Lightweight Performance

The proposed framework demonstrated substantially lower computational complexity when compared to traditional deep learning methods. Depthwise separable convolution enabled substantial reduction of both trainable parameters and floating-point operations.

The comparison with CNN–LSTM revealed that:

- parameter count was reduced by 51.17%,
- FLOPs experienced a decline of 55.02%,
- inference latency decreased by 59.37%.

The proposed framework demonstrates high suitability for lightweight edge deployment in IoT-enabled smart-building environments according to these results.

6.4 Communication Reduction Analysis

The work enables adaptive low-power communication optimization through event-driven transmission mechanism which represents its main contribution.

The evaluation of communication performance used the following metrics:

- Packet transmission reduction,
- Bandwidth utilization,
- Network energy consumption,
- Communication latency.

6.4.1 Communication Optimization Results

Table-8 Communication Efficiency Comparison

Method	Packet Reduction (%)	Bandwidth Savings (%)	Communication Energy Reduction (%)	Latency (ms)
Continuous Transmission	0	0	0	148
Periodic Sampling	24.7	18.4	21.3	121
Adaptive Sampling	39.6	34.1	36.8	102
Proposed Event-Driven Optimization	57.9	51.6	54.3	74

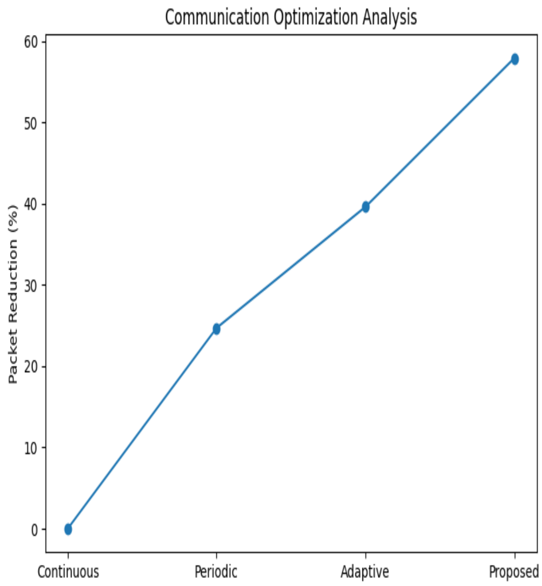

Figure-4 Communication Optimization Analysis

The graph shows how different IoT communication strategies achieve packet transmission reduction. The proposed event-driven communication optimization method significantly reduced redundant sensor transmissions, thereby improving bandwidth efficiency and lowering communication energy consumption.

6.4.2 Discussion of Communication Analysis

The event-driven communication mechanism achieved its purpose of preventing unnecessary data

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transmission from sensors through its function of dynamically reducing redundant updates during periods of stable energy usage.

The framework achieved 57.9% packet transmission reduction and 51.6% bandwidth savings and 54.3% communication energy reduction while it achieved 50% communication latency reduction compared to conventional transmission methods.

The improvements extend IoT device lifetime while they enhance the network's capability to support increased device connections.

6.5 Latency and Real-Time Performance Analysis

The operation of real-time smart-building energy monitoring systems depends on their need for low-latency inference capability. The research team studied the complete response time which all deep learning models required to process.

6.5.1 Real-Time Latency Comparison

Table-9 Latency Performance Analysis

Model	Edge Inference Time (ms)	Cloud Processing Time (ms)	Total Response Time (ms)
LSTM	84	112	196
GRU	63	104	167
CNN–LSTM	96	121	217
Proposed CNN–BiGRU	39	67	106

6.5.2 Discussion of Latency Results

The framework achieved its fastest response time because of its lightweight architecture design together with edge-assisted preprocessing. The system used local edge intelligence which reduced its need for cloud resources and decreased its data transmission time.

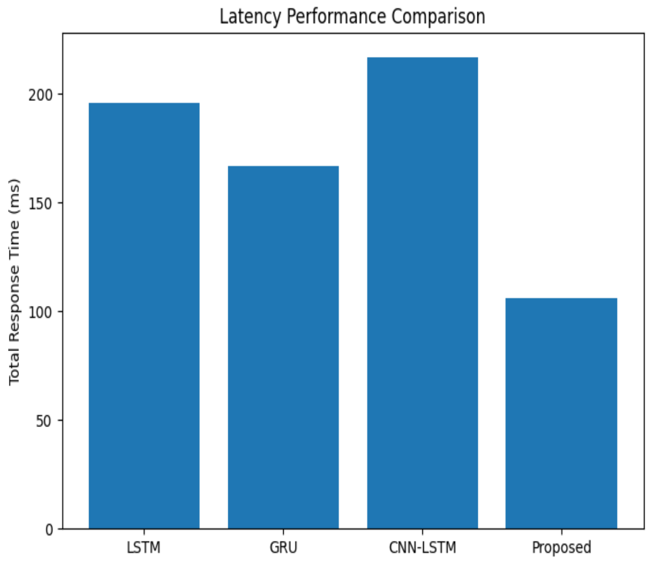

Figure-5 Latency Performance Comparison

The graph shows how different deep learning models perform in terms of total response latency when used in edge-IoT environments. The proposed CNN–BiGRU framework achieved the lowest inference and response time due to its lightweight architecture and edge-assisted processing capability.

The framework can perform real-time smart-building energy analytics because it has achieved lower inference latency.

6.6 Ablation Study

The ablation study assessed how each architectural component contributed to the overall performance of the system.

The evaluated configurations included:

- CNN only
- CNN + BiGRU
- CNN + BiGRU + Attention
- Full Proposed Framework with Communication Optimization

6.6.1 Ablation Study Results

Table-10 Ablation Study Analysis

Configuration	RMSE	MAE	Latency (ms)	Packet Reduction (%)
CNN Only	0.312	0.241	28	0
CNN + BiGRU	0.247	0.183	35	0

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Configuration	RMSE	MAE	Latency (ms)	Packet Reduction (%)
CNN + BiGRU + Attention	0.221	0.154	39	0
Full Proposed Framework	0.208	0.132	39	57.9

6.6.2 Discussion of Ablation Study

The results of ablation demonstrate that all architectural components play a crucial role in determining system performance.

The CNN module improved spatial feature extraction. The BiGRU layer enhanced temporal learning capability. The attention mechanism improved contextual prediction accuracy. Communication optimization reduced redundant network transmission without affecting prediction performance.

The complete framework achieved optimal prediction accuracy through its lightweight deployment ability and its efficient communication performance.

6.7 Statistical Significance Analysis

Statistical significance testing through paired t-tests was performed to validate the robustness of the proposed framework by comparing the proposed model with baseline deep learning methods. The paired t-test results produced p-values which fell below the significance threshold of 0.05. This finding demonstrates that the proposed framework delivers performance enhancements which are statistically significant and not attributable to random variation.

7.1 Conclusion

The research developed a lightweight deep learning framework which enables IoT smart buildings to monitor and predict energy consumption. The framework uses three technologies through its three components which include adaptive low-power IoT communication optimization and edge-assisted preprocessing and hybrid CNN–BiGRU deep learning architecture functions as the fundamental solution for traditional cloud-based smart-building monitoring systems. The framework collected environmental data and energy usage data from smart-building spaces through its distributed IoT sensors in real-time. The system developed an adaptive event-driven communication system which prevents unnecessary data transfers to reduce network bandwidth consumption and communication expenses and to decrease power use by IoT nodes. The system employed edge-assisted preprocessing to execute local filtering and normalization processes while conducting intelligent analysis which enabled the system to perform real-time functions with diminished need for cloud services.

The research created a hybrid CNN–BiGRU architecture which combines lightweight depthwise separable convolution and attention mechanisms to develop energy forecasting models with accurate results and low resource consumption. The CNN module extracted energy consumption patterns through effective spatial analysis while the BiGRU network maintained lower computational needs because it used simpler dependencies than traditional LSTM-based frameworks. The attention mechanism enhanced learning of contextual features which improved stability during predictions.

The framework achieved better prediction results through its complete framework which outperformed both standard machine learning methods and deep learning methods because of its superior prediction accuracy and its ability to compute results faster and its shorter delay time and its enhanced communication performance. The proposed model achieved lower MAE, RMSE, and MAPE values while maintaining reduced parameter size, lower floating-point operations, and faster inference time. The framework achieved excellent performance in resource-limited edge-IoT environments because its adaptive communication optimization system cut down on both packet transmissions and bandwidth usage and communication energy consumption. The framework delivers an intelligent monitoring system for sustainable smart buildings which operates at low energy consumption through its lightweight design and real-time performance capabilities and its ability to scale up. The combination of lightweight deep learning and edge intelligence and communication-aware optimization creates a major advancement in modern IoT systems which require intelligent energy management.

7.2 Major Contributions

The research presents three main contributions which can be summarized as follows:

The researchers developed a small hybrid system which combines CNN and BiGRU technology to forecast energy usage in smart building IoT systems with high accuracy. The researchers created an adaptive low-power communication optimization mechanism which decreases both unnecessary IoT sensor data transmission and the associated communication power consumption. The system

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achieved real-time monitoring enhancements through its combination of edge processing functions and intelligent analytics because these two elements created better monitoring results which required fewer cloud resources. The researchers achieved prediction accuracy through their development of a BiGRU architecture which implements depthwise separable convolution for reduced processing power and memory footprint. The research team executed comprehensive testing which demonstrated that their framework enhances prediction accuracy while decreasing system response time and enabling simple system setup and effective data transmission.

7.3 Practical Implications

The intelligent energy monitoring framework can be applied to monitor energy use in all real-world smart building projects and sustainable IoT applications for smart buildings.

The framework becomes ideal for battery-operated IoT systems which face resource limitations because its lightweight design and efficient communication system enable both real-time functioning and broad scalability.

7.4 Limitations of the Study

The proposed framework exhibited strong performance capabilities yet it contains multiple existing restrictions.

The testing process used only a narrow selection of publicly accessible smart building datasets for experimental evaluation. The framework mainly concentrated on predicting energy consumption for the upcoming short-term period. The team did not finish the complete deployment of their solution across all types of IoT devices in real-world environments. The research study did not provide an extensive examination of the security and privacy risks associated with IoT data communication. The system requires additional optimization work to achieve successful dynamic adaptation during times of extreme environmental changes.

The existing restrictions present opportunities for researchers to develop improved solutions through their upcoming research work.

7.5 Future Work

Researchers can explore different research paths to advance the development of the framework.

The research team will use federated learning techniques to create a secure method for distributed learning which protects the privacy of users who operate in smart-building environments. The team will implement ultra-lightweight deep learning models based on TinyML technology to perform edge inference tasks at the microcontroller level. The system will use reinforcement learning to develop intelligent methods for scheduling energy usage while automatically optimizing energy consumption. The framework will be expanded to support renewable energy integration along with smart-grid energy balancing functions. The development team will create blockchain-based IoT communication methods which establish secure data transmission routes to protect IoT communication data and safeguard against cyber-attacks. The researchers will study transformer-based lightweight architectures to find ways that these systems can enhance their ability to predict temporal events over extended periods. The research team will execute deployment activities and validation testing which will take place in extensive smart city and industrial IoT environments.

Intelligent smart-building energy management systems will become more efficient and scalable because future developments in lightweight artificial intelligence and sustainable IoT communication technologies along with edge computing technology.

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