

ORIGINAL ARTICLE

Enhanced Electricity Forecasting for Smart Buildings Using a TCN-Bi-LSTM Deep Learning Model

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ABSTRACT

Integration of sensor technology and advanced software empowers consumers to manage energy usage proactively. This proactive approach yields positive impacts at both micro and macro levels, benefiting individuals and contributing to broader environmental conservation efforts. By leveraging predictive models, consumers can make informed decisions that serve their interests and promote a greener and more sustainable future for all. Thus, energy consumption (EC) prediction is crucial for effective resource management. In this study, we propose an innovative deep-learning approach to predict EC, focusing specifically on smart buildings. Our model utilises a hybrid deep learning architecture to effectively capture low and high information patterns present in multivariate time series data of various sensors deployed in smart buildings and numerous influencing factors. To address the nonlinear and dynamic nature of this data, our model combines a deep neural network (DNN) with a deep learning sequential model (DLS). Specifically, temporal convolutional networks (TCN) within the DNN family are employed to extract various trends from the data, while the DLS model, which consists of Bi-directional Long Short-term Memory Networks (Bi-LSTM), is employed to learn and capture these trends effectively. Consequently, we present a hybrid deep learning framework that leverages for learning multivariate time series data related to EC with shared feature representation. To validate our approach, we extensively evaluate our model using a dataset from an office building in Berkeley, California. Experimental results demonstrate that our model achieves satisfactory accuracy in EC prediction. For the 7-h horizon and on multivariate TS data, an R^2 of 0.97 is realised for the proposed model. This is confirmed by the 1.65% improvement in transiting from univariate to multivariate data, which supports using multiple modalities.

1 | Introduction

Energy efficiency involves using less energy to achieve the same or greater output level, making it a critical component of sustainable energy usage. This objective can be accomplished through various methods, including adopting energy-efficient appliances, enhancing building insulation, optimising industrial processes, and promoting energy conservation behaviours (Mathumitha, Rathika, and Manimala 2024; Hernandez et al. 2014). Energy

efficiency offers numerous advantages, such as reducing greenhouse gas emissions, enhancing energy security, lowering energy costs, and improving overall quality of life. It represents a cost-effective approach to combating climate change, as it helps reduce the need for new power plants and transmission lines. Overall, energy efficiency is vital in sustainable energy usage and can significantly decrease energy consumption (EC) while addressing climate change concerns. Inefficient use of electrical devices by occupants is a major source of energy waste, with

buildings accounting for approximately 40%–50% of total energy usage (Mathumitha, Rathika, and Manimala 2024; Hernandez et al. 2014; International Energy Agency (iea) 2022; Jogunola et al. 2022; Al-Shargabi et al. 2022). The operation of lighting, air conditioning, fans and other electronic devices further increases a building's EC, leading to higher carbon dioxide (CO₂) emissions compared to vehicles. Accurately predicting building EC is now feasible and plays a crucial role in managing energy usage effectively to reduce carbon emissions (Jogunola et al. 2022; Al-Shargabi et al. 2022; Cheng, Lim, and Hui 2022).

Advanced technology enables smart buildings to automate and optimise multiple systems and operations, encompassing security, lighting, air conditioning, heating, ventilation and energy management (Al-Shargabi et al. 2022; Cheng, Lim, and Hui 2022; Qiao, Yunusa-Kaltungo, and Edwards 2021). These buildings utilise various sensors, controls and automation systems to gather data on building performance and occupant behaviour. It is then analysed to pinpoint areas for enhancement and streamline building operations. For instance, a smart building might employ occupancy sensors to regulate lighting and temperature settings based on occupancy patterns or utilise predictive maintenance algorithms to detect potential equipment failures in advance (Al-Shargabi et al. 2022; Cheng, Lim, and Hui 2022; Qiao, Yunusa-Kaltungo, and Edwards 2021; Megahed, Abdelkader, and Zakaria 2019). The primary goal of intelligent buildings is to reduce EC while ensuring user comfort (Al-Shargabi et al. 2022; Cheng, Lim, and Hui 2022; Qiao, Yunusa-Kaltungo, and Edwards 2021; Megahed, Abdelkader, and Zakaria 2019). These buildings offer numerous benefits, including improved energy efficiency, enhanced occupant comfort, decreased operational costs, increased productivity, and enhanced building resilience. Moreover, they contribute to reducing greenhouse gas emissions by optimising energy usage and minimising waste. Smart buildings represent a burgeoning trend in the construction and real estate sectors and hold significant potential for enhancing building performance and mitigating EC. Notably, it is projected that buildings will consume over 65.0% of the total available energy between 2018 and 2050. Additionally, CO₂ emissions are anticipated to reach approximately 1.3 billion metric tons by 2030, underscoring the urgent need for environmental conservation efforts (International Energy Agency (iea) 2022; Jogunola et al. 2022). Therefore, precise load forecasting is imperative for smart buildings.

In the contemporary landscape, the Internet of Things (IoT)-based energy management paradigm for smart cities is under scrutiny and exploration. The introduction of enabling edge computing technology is proposed as a pivotal component of the suggested framework (Plageras et al. 2018; Singh et al. 2020). Researchers grapple with the intermittence and uncertainty inherent in the continuous demand for energy power. Reliable energy forecasting is deemed essential to materialise the vision of smart buildings (Liu et al. 2019). Significant attention has been directed towards advancing techniques for representing EC attributes, including Heating, Ventilation, and Air Conditioning (HVAC), electrical utilisation, occupancy count, temperature, weather history and predicting future EC. Studies on EC prediction can be categorised into three main areas based on the load: short-term (ranging from an hour to a week), medium-term (spanning a few months) and long-term (projected over a

year) forecasting (Mughees et al. 2021). Inspired by (Immonen, Kiljander, and Aro 2020), the importance of transparent information, user-friendly interfaces and personalised recommendations are underscored to enable informed decision-making and active consumer engagement in the emerging energy market. EC forecasting has remained a prominent and extensively studied research area for several years.

In the past, research primarily relied on classical statistical methods to forecast EC, employing linear models. Common statistical techniques for EC forecasting included exponential smoothing, autoregressive integrated moving averages (ARIMA), and multiple linear and Gaussian process regression (Hernandez et al. 2014; Chujie, Li, and Zhengjun 2022; Amasyali and El-Gohary 2018). However, these models assumed that the conditional variance of the time series remained constant, which is not applicable in practical EC scenarios. In recent years, researchers have shifted their focus to computational intelligence-based approaches, also known as machine learning methods. This shift has resulted in the development of various data-driven EC forecasting approaches, including ensemble methods, support vector regression (SVR), k-nearest neighbour (k-NN), neural networks (NN) and fuzzy and evolutionary techniques (Hernandez et al. 2014; Al-Shargabi et al. 2022; Chujie, Li, and Zhengjun 2022; Ahmad et al. 2014; Tiwari et al. 2022). The comparative analysis of various machine learning algorithms has been performed to understand the occupant pattern (Elhabyb et al. 2024). Similarly, algorithms like SVR, NN and boosting are employed to perform the study of energy optimization in smart building (Boutahri and Tilioua 2024). Nevertheless, these existing prediction methods, whether statistical or machine learning-based, need to be revised when it comes to dynamic EC conditions. They struggle to capture the nonlinear low and high-frequency characteristics of EC in complex and dynamic energy demand. They are ill-equipped to handle the vast amounts of data present in massive multimodal conditions.

Deep learning (DL) has emerged as a potent tool in data science, facilitating automatic pattern identification and feature extraction through unsupervised/supervised learning (Chaudhari et al. 2023). Consequently, researchers have adopted various optimization algorithms to enhance the performance of Long Short-Term Memory (LSTM) models for short-term EC prediction in modern Spanish society (Torres, Martínez-Álvarez, and Troncoso 2022; Gautam et al. 2024). Similarly, a genetic algorithm has been employed to optimise the time lag and hyperparameters of LSTM, enabling precise short-term EC prediction for residential and commercial buildings (Almalaq and Zhang 2019). A household EC projection routine, leveraging parallel LSTM and singular spectrum analysis, has been proposed to address the volatility of EC data (Jin et al. 2022). Additionally, a deep neural network (DNN)-based EC prediction approach has been developed for the early design phase to aid building designers in forecasting annual EC (Olu-Ajayi et al. 2022). Furthermore, Generative Adversarial Nets (GANs) have been utilised to enrich EC databases and improve the accuracy of EC prediction using a simple NN architecture (Tian et al. 2019). Various approaches, including neural networks (NN), deep extreme learning machines (DELm), and fuzzy systems, have been employed for month and week EC prediction, highlighting the diversity of methods in this field (Fayaz and Kim 2018). Moreover, fuzzy

logic, bat algorithms and DELM have been utilised to optimise EC and achieve acceptable comfort levels for users based on identified user parameters (Shah et al. 2020). Besides, a hybrid convolutional neural network (CNN)-LSTM deep learning model has been developed to extract profound features and then perform the temporal analysis for energy forecasting in the United States (Natarajan et al. 2024) and Pakistan (Ullah et al. 2024). Similarly, CNN-bidirectional LSTM (Bi-LSTM) has been operated on various characteristics of buildings for short-term load forecasting (Sekhar and Dahiya 2023). Short-term forecasting has been constructed using CNN-recurrent NN for identifying hourly EC for smart buildings (Jayashankara et al. 2023).

From the above discussion, it is evident that timely and accurate EC prediction is crucial for efficient energy management. However, existing solutions must be more robust in modelling dynamic, nonlinear, high and low-frequency (HALF) information and temporal data characteristics to predict EC effectively. The multifaceted nature of data significantly influences the outcome of EC projection techniques. Hence, this paper proposes a hybrid deep learning model to address these data characteristics, utilising multivariate time series EC data and automatically identifying sensitive features for EC prediction modelling. Such integration of the multiple modes directly mimics real-world scenarios to improve the measure of predictability under varying environmental contexts. The proposed model extracts and learns the nonlinear HALF features of EC data under multimodal conditions, such as air temperature, solar radiation and HVAC operational data. This novel model aims to enhance the predictive capability of the existing system by combining the temporal convolutional network (TCN) and bidirectional LSTM (Bi-LSTM). The TCN captures both HALF information effectively, identifying diverse trends arising from multimodal operations of smart buildings. In addition, TCN deals with the different time scales in the EC data efficiently and effectively and is an ideal application for real-world scenarios. The feature extraction method that uses TCN is computationally efficient compared to other deep learning frameworks (Liu et al. 2024). To incorporate long-term dependencies for prediction, the Bi-LSTM is subsequently employed on features gathered from various TCNs at the server. Experimental evaluation on the EC time series dataset, comprising multimodal conditions in an office building in Berkeley, California, demonstrates that the hybrid deep learning routine outperforms state-of-the-art models.

The remainder of the paper is structured as follows: Section 2 outlines our proposed prediction methodology, covering the problem statement, motivation, and an overview of the model. Section 3 is devoted to discussing the dataset utilised in our study, along with the various pre-processing operations undertaken. Additionally, we delve into result analysis, comparing both univariate and multivariate approaches, and explore the application of explainable AI techniques. Lastly, in Section 4, we draw conclusions based on our findings and contributions to this research endeavour.

2 | Material and Method

This section provides detailed information about the problem formulation and the proposed method.

2.1 | Problems and Motivations

The statistics of world for the period 1990–2014 are presented in Figure 1a¹. The following are the observations:

- The global GDP and EC enhancement are due to the population's growth by 38.37% as people demand more products, services, and energy.
- The staggering economic improvement and a rising level of productivity are best explained by the fact that the GDP per capita has risen by 153.25%.
- The application of intermittent EC systems and devices correlates with industrialization and new technological achievements, which in turn proved an increase in energy-intensive kind of economic activities.
- That could reflect a rise in the efficiency of energy utilisation or modifications to the primary energy content—for example, the inclusion of more renewable energy sources in the primary energy supply.
- Some of the major environmental problems still exist, but the increase in emissions is less pronounced than the increase in EC.
- It may point to improvements in emission reduction or, probably, cleaner energy utilisation.

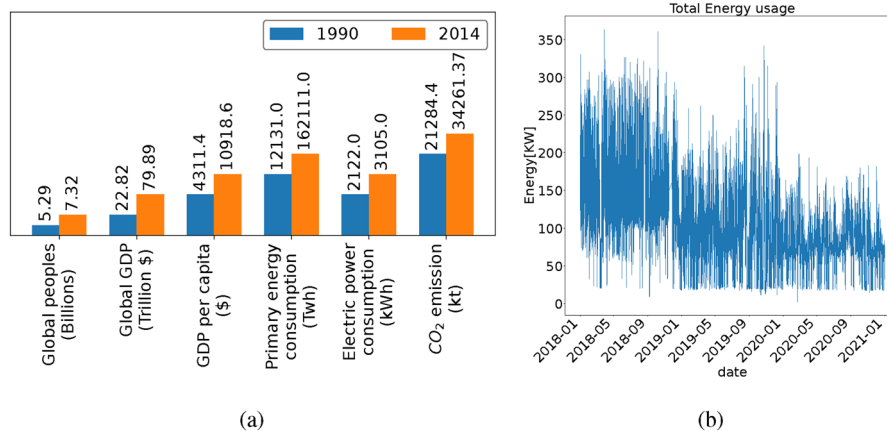


FIGURE 1 | (a) Evolution of world energy. (b) Total EC of office building.

Thus, EC forecasting is essential for proactive energy management and greenhouse gas emission reduction, underscoring the significance of early warning systems. The primary objective is to optimise energy efficiency, improve occupant comfort, reduce operational costs and enhance productivity, ultimately enhancing building resilience at various observation points over specific time intervals. The observation period typically spans 15 min, as determined by sensor systems. Figure 1b depicts a representation of typical EC data.

The EC prediction problem is addressed as follows: The model's development relies on utilising EC time series (TS) data. Let $X = \{x_1, \dots, x_n\}$ represent the EC TS data, covering a time interval T between two consecutive data points x_i and x_j . Given a time T , the projection model expects the EC value at time $T + 1/T + n$. The prediction model factors in various elements, such as air temperature, solar radiation, HVAC operational data and other relevant multimodal conditions, as depicted in Figure 2. Therefore, these data characteristics are integral to the EC forecasting process.

The crucial aspect of EC forecasting involves efficiently processing and capturing the spatial-temporal patterns (STP) of the EC data elements mentioned earlier. Contextual information about the observation sites is inherent in the EC data, and other factors,

such as past conditions, influence future trend development. In essence, the periodic intervals and adjacent data points in the EC TS data often exhibit a strong correlation with each other.

Furthermore, EC data demonstrate sharp non-linearities, especially during transitions from weekdays to weekends, holidays and working hours. EC forecasting is challenging due to the rapid and unpredictable changes in weather conditions and greenhouse gas emissions influenced by numerous factors. Moreover, these factors exhibit non-linear and dynamic behaviour, including temperature, humidity and occupants. The complexity arises from the highly non-linear interactions among these factors, making precise EC prediction for specific times and locations a daunting task. Given the inherent interdependence among these influencing factors, effectively managing and leveraging this interdependence from the multivariate EC TS data presents another significant challenge in EC prediction.

This paper presents a novel EC prediction method leveraging a hybrid deep learning architecture. Handling EC TS data presents challenges due to their diverse statistical characteristics, where different TS exhibit distinct representations and structures. Consequently, traditional shallow machine learning models encounter difficulties in fusion modelling within this

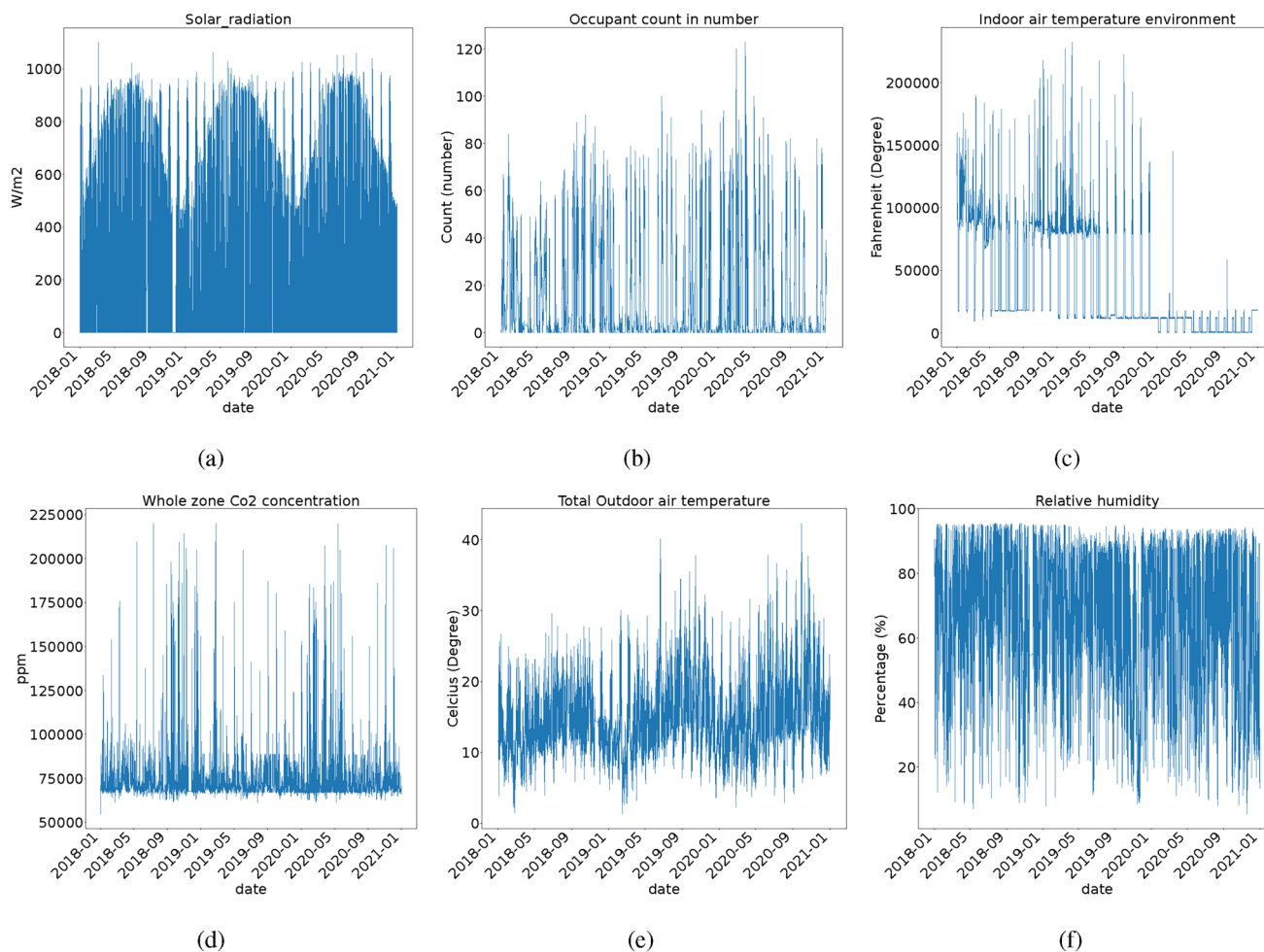


FIGURE 2 | Multimodal conditions of office building: (a) Solar radiation, (b) occupant count, (c) indoor temperature, (d) CO₂, (f) outdoor temperature and (e) relative humidity.

context. To tackle this challenge, researchers have investigated deep learning models, which have demonstrated potential in improving the performance of conventional machine learning models (Jogunola et al. 2022; Al-Shargabi et al. 2022; Cheng, Lim, and Hui 2022; Qiao, Yunusa-Kaltungo, and Edwards 2021).

The proposed hybrid model, that is, TCN-Bi-LSTM, offers remarkable edges over the existing hybrid approaches, particularly regarding its robustness, efficiency and suitability for real-world deployment in EC management:

- The proposed model runs TCN to extract HALF temporal behaviour to allow for the representation of time-variant EC data patterns. This precision is essential for applications where minute-to-minute energy use predictions impact operational efficiency and real-time decision-making.
- TCNs are more robust to varying sequence lengths and better handle data with irregular patterns (He and Zhao 2019; Chen et al. 2020), such as EC data influenced by sporadic user behaviour or weather changes, which are common challenges in real-world deployment.
- Standard LSTMs are efficient for sequential data, but the major bonus of the Bi-LSTM component is that it processes data in forward and backward directions (Graves, Jaitly, and Mohamed 2013). As a result, the model can learn dependencies from past and future TS data points, thus giving it a better ability to learn real-time changes. Therefore, the prediction output is more stable.
- Compared to other hybrid models, the TCN-Bi-LSTM is computationally efficient due to the architecture of TCNs, which use 1D dilated convolutions rather than recurrent connections (Chen et al. 2020). This efficiency makes the model more feasible for deployment in resource-constrained environments, such as edge devices or energy management systems in smart buildings.
- The TCN-Bi-LSTM model is developed to allow entry for data scales as small as residential buildings' and as big as commercial buildings' data scales and different input frequencies. This scalability is important for the effective and practical application of the model in disparate settings.

Therefore, the design of the TCN-Bi-LSTM hybrid model offers a robust solution for the complex real-time energy management requirements, differentiating it from other models with a focus on real-life implementation challenges and proposing the scalability, flexibility and computational effectiveness when implemented in the actual world. adiation, HVAC operational data and other relevant multimodal conditions, as shown in Figure 2. Hence, the data characteristics mentioned are crucial to the process of EC forecasting.

2.2 | Model Overview

Figure 3 illustrates the comprehensive framework of the proposed system, delineating four main tiers and the EC scenario in smart residential sectors. It consists of the following tiers:

- **Data collection tier:** The office building dataset utilised in this study was sourced from Berkeley, California (Luo et al. 2022). The building was constructed in 2015. The building dataset comprises variables representing instrument-produced data values, which change over time. Data collection was conducted through a plethora of IoT sensors integrated into various office-use equipment, primarily detecting properties like temperature, humidity and solar radiation. These IoT sensors continuously monitor the production system, providing data points every 1–15 min. For this study, the sensor data has already been collected and is readily available for analysis.
- **Model development tier:** The model development tier is pivotal in predicting EC and efficiently managing it. To facilitate this process, a cloud server acts as a service provider to consumers. This cloud server stores, analyzes and relays household demand, ensuring a proper energy supply to the respective consumers.
- **IoT-based analytics platform tier:** The IoT-based analytics platform tier is central to the framework, where consumer parties utilise resource-constrained instruments for forecasting their upcoming energy needs. It is noteworthy to mention that specific information on energy production resources falls outside the scope of this article, and we presumptively assume that the grid station obtains sufficient energy from the available resources.
- **Energy consumers tier:** The energy consumers tier has experienced notable advancements in sensor technology and software, empowering end users to forecast their required EC accurately. This capability serves as a valuable preliminary assessment tool for consumers, enabling them to strategically plan their energy usage based on external and indoor multimodal conditions. By leveraging these predictive capabilities, consumers can influence various aspects, including financial management, efficient energy-saving strategies, occupant comfort and global environmental sustainability. Making informed decisions about energy usage not only aids in cost optimization but also contributes to a more environmentally sustainable approach to EC. Ultimately, this integration of sensor technology and software empowers consumers to take a proactive role in energy management and its positive impacts on both micro and macro scales.

2.3 | Energy Consumption Prediction Model

Our framework makes significant technical contributions, primarily centred on predicting future EC from the consumer endpoint. These contributions include reducing prediction error rates by developing the hybrid deep learning model. Several crucial steps are involved in creating a functional trained model applicable to real-world scenarios. The initial step involves pre-processing the raw data from an existing dataset, as detailed in Sub-section 3.1. Subsequently, our novel hybrid deep learning mechanism is implemented to obtain the optimised EC prediction model. The proposed model's process is detailed below, enabling the model to adapt and improve iteratively.

We introduce the EC prediction framework based on a proposed architecture. It combines TCN and Bi-LSTM to address

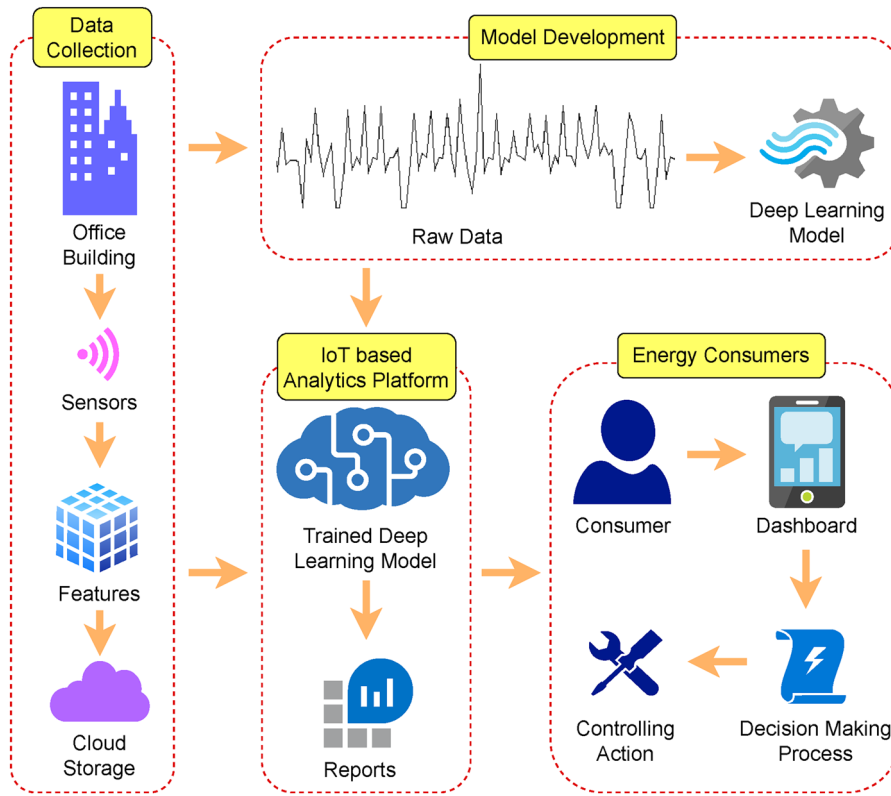


FIGURE 3 | Architectural overview of proposed system.

the spatial-temporal dependence in EC TS data. Because of the interrelationship between local patterns and the LD within the EC TS data, the EC TS is also influenced by other multimodal conditions data, forming inherent interdependencies. Figure 4 provides a graphical illustration of the EC forecasting framework. The overall model comprises two main components: (1) TCN: These layers are responsible for learning HALF correlation features from the TS data. (2) Bi-LSTM: This component extracts LD temporal attributes from the respective TS data. Combining these components allows the proposed model to effectively capture and leverage the patterns present in the EC data, resulting in improved EC prediction performance for buildings.

The initial step involves training the TCN (Chen et al. 2020) to capture the dependency features present in EC TS data. These TCNs are utilised to extract HALF information patterns and identify potential interrelationship features from the TS data of multimodal conditions. Our model receives inputs as multiple 1D TS. Instead of individually learning the features of each TS, we collectively learn from all the TS data across multiple conditions. This approach ensures we efficiently exploit the various patterns and dependencies among the EC data for improved prediction accuracy.

Subsequently, the extracted features, comprising the HALF information trend features and the potential correlation features from multivariate EC TS data are concatenated at the server. This combined feature set is then passed as input into specific bi-directional LSTMs. These bi-LSTMs can learn STP from both past and future contexts by simultaneously processing the TS data in both forward and backward directions. This

bidirectional processing enhances the model's ability to capture and leverage the temporal relationships within the data, leading to more comprehensive and accurate EC prediction. With the input data X , the process of acquiring dependency features from the multivariate TS data can be described as follows:

$$\psi(X) = \psi_K(\dots \psi_2(\psi_1(X, \gamma^{(1)}), \gamma^{(2)}) \dots \gamma^{(K)}) \rightarrow \varpi. \quad (1)$$

In this representation, ψ represents the different operations performed by the TCN at each stage K , and γ represents the TCN's learning parameters for each stage K . The TCN generates the output ϖ , that is, HALF information trend features. Similar to Equation (1), Bi-LSTM learns ϖ with ϕ and ζ , that is, various operations and learning parameters of Bi-LSTM. It is expressed as

$$Bi - LSTM(\varpi, \phi, \zeta) \rightarrow O_t. \quad (2)$$

The objective function of the proposed technique training can be expressed as follows:

$$\underset{\Theta}{\operatorname{argmin}} \Gamma = \frac{1}{m} \sum_{a=1}^l \|\hat{y}_a - y_a\|. \quad (3)$$

The ultimate goal of proposed model training is to minimise the overall error Γ of training samples. In this context, a denotes the number of input samples within a time window and Θ is the learning parameter of the layer. In this manner, the proposed model integrates TCN and bi-LSTM into a hybrid deep learning architecture. This unified framework allows for the

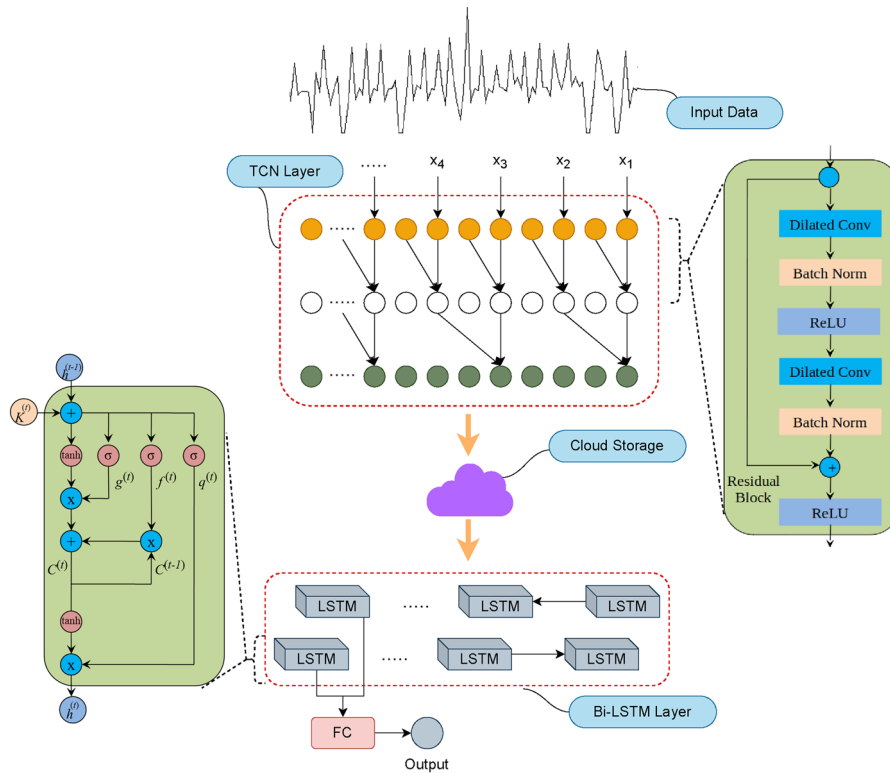


FIGURE 4 | Proposed hybrid deep learning model for EC prediction.

simultaneous extraction of both the HALF pattern and the STP from the multivariate TS data related to EC.

3 | Experimental Setup and Result Discussion

This section provides detailed information about the datasets utilised, the pre-processing steps applied to the data, and the performance metrics used for evaluation.

3.1 | Dataset Description

This investigation utilises the LBNL-ETA dataset, as referenced in the work by Luo et al. (2022). The dataset encompasses a comprehensive set of whole building and end-use energy consumption (EC) information, including occupancy counts, HVAC system working states and environmental characteristics (both outdoor and indoor). The sensor values were collected over 36 months from two office levels covering an area of 2325 m², employing nearly 300 sensors for data collection. The dataset provides valuable insights into the energy usage of various building systems, primarily focusing on three energy-consuming systems: HVAC, electrical and lighting.

3.1.1 | HVAC System

The offices in the building are supplied with heating and cooling through an Underfloor Air Distribution (UFAD) system. This system utilises four rooftop units (RTUs) equipped with a cooling mechanism for the underfloor plenum. It supplies specific column lines and cools the offices on the building's second and ground

floors. During the data collection period from 2018 to 2020, both model-predictive and rule-based (traditional) control modes were employed. In the rule-based mode, each Underfloor Terminal temperature setpoint and the minimum position of the outside air flow damper for the second-story office on Saturdays were determined based on a pre-defined zone temperature setback schedule. On the other hand, the model-predictive mode utilised a maximisation technique to identify the ideal RTU service value in terms of fan speed and air temperature. This determination was made through the real-time state of the system and anticipated disturbances, allowing for more efficient and adaptive control of the HVAC system.

3.1.2 | Lighting Systems

The building's lighting system comprises a dedicated lighting management server, a workstation, and Philips light fixtures. Occupancy detectors (photocell light) are strategically positioned throughout the workplace zones. This combination of sensors facilitates control over the on/off states of lighting zones based on occupancy status. Moreover, manually operated roller shades are installed on windows within offices and conference rooms to regulate natural light. The EC of the lighting system can be monitored and managed through the browser-based Graphical User Interface (GUI) for Lutron Quantum Vue (Lutron 2017).

3.1.3 | Electrical Systems

The building's power supply is facilitated by two transformers, supplying electricity to the main switchboards for both the offices and HVAC systems. The office's main switchboard

distributes power to open and common spaces, rooms and panels. Similarly, another main switchboard powers the building's mechanical equipment, such as air conditioning and geysers. The National Energy Research Scientific Computing Center (NERSC) measures electrical systems at the panel level to monitor and benchmark energy usage in data centres. General electric trip units measure panels for HVAC and lighting.

3.2 | Preliminary Analysis and Data Preparation

Figure 5 illustrates the energy forecasts for the smart building over 3 years, utilising the information used to develop the models. All payloads are combined to obtain the overall EC for the dataset, and 15-min intervals for each day are aggregated. Additionally, the EC data for specific loads, such as HVAC_N, HVAC_S, mels_S, mels_N and lig_S, are resampled daily from 15-min data, and these graphs are displayed in Figure 5. It was observed that in certain instances, sudden declines in consumption occur due to missing data for extended periods, necessitating data pre-processing. Figure 6a exhibits a weekly consumption pattern, resampled using the mean daily consumption. This pre-processing step helps address any irregularities caused by data gaps and ensures a more reliable representation of the EC pattern. By handling these data gaps appropriately, the energy forecasting models can provide more accurate and consistent predictions.

The hourly consumption pattern resampled by the average per-hour consumption reveals a sharp decline in weekend consumption, highlighting the importance of including weekdays as a feature. The abrupt increase in consumption during working hours is depicted in Figure 6b, indicating that using the current hour as a characteristic will enable precise prediction.

During the development prediction process, the following assumptions were considered:

- Energy usage: The data were resampled to 15-min intervals to meet the lag requirement, transforming it from 15-min increments to hourly intervals.
- Minute of the day: Given the dynamic nature of a smart building's electricity consumption throughout the day, one crucial variable for accurate energy forecasting is the minute of the day. Consequently, the minute of the day is represented as an integer from 0 at 12 a.m. and up to 23 for a day on an hourly basis.
- Day type: The data set indicates that EC tends to be lower during the weekend compared to weekdays. Therefore, each weekday is encoded as an integer to aid in energy forecasting, ranging from 0 for Monday to 6 for Sunday. These representations of time-related variables are essential in improving the accuracy of EC predictions.

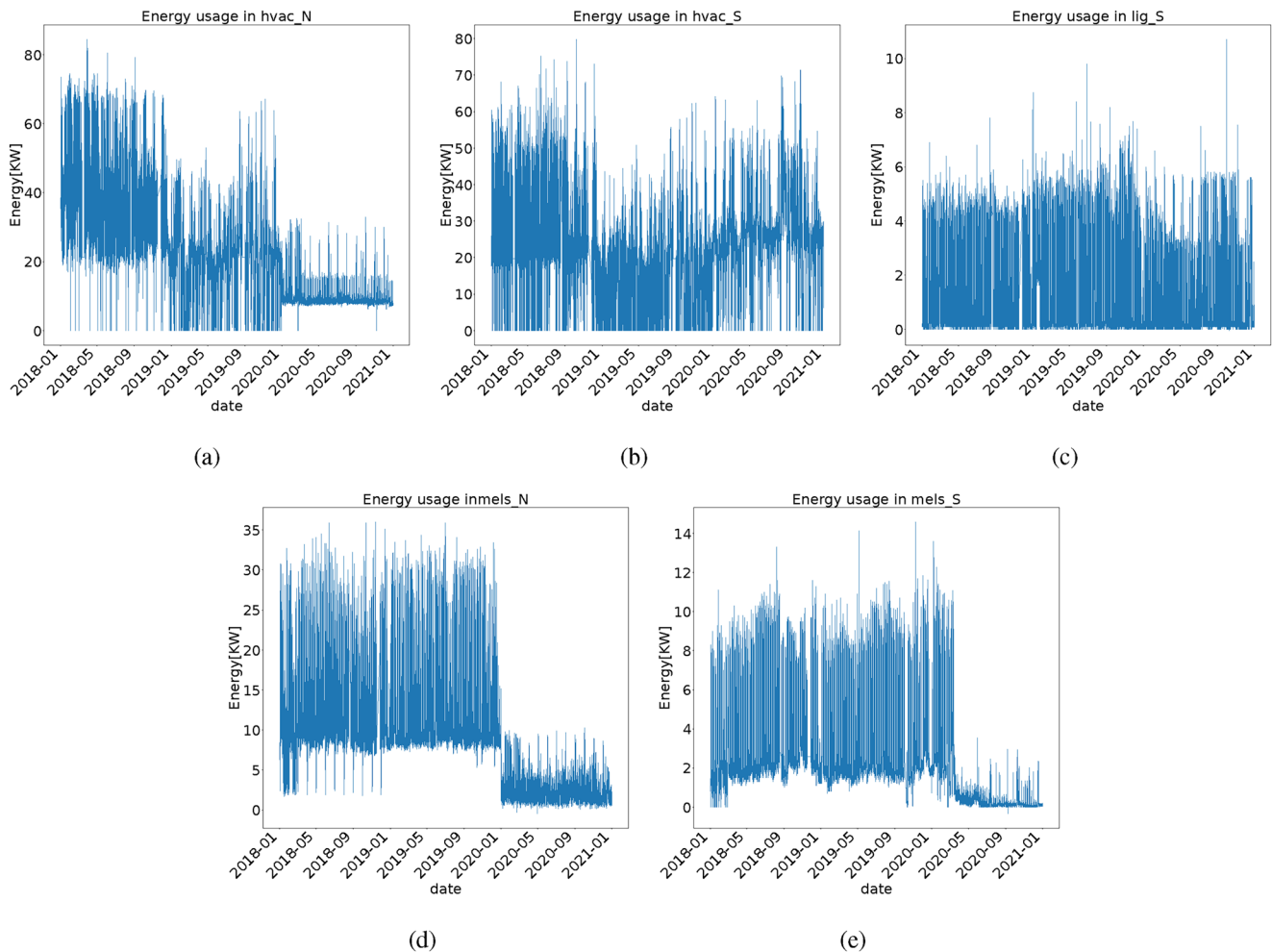
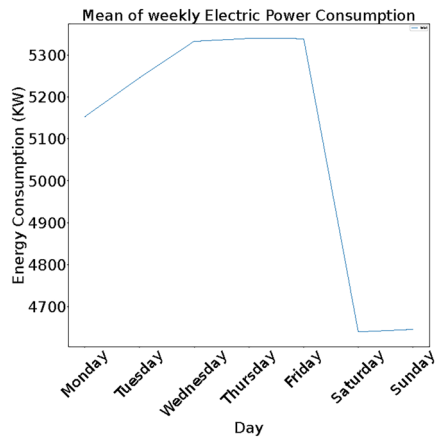
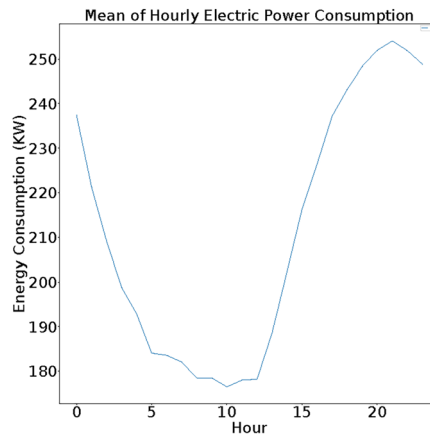


FIGURE 5 | Individuals EC consumption for: (a) HVAC_N and (b) HVAC_S load, (c) lig_S load, (d) mels_N and (e) mels_N.



(a)



(b)

FIGURE 6 | EC on real values in (a) day and (b) hour wise.

3.3 | Data Pre-Processing

The majority of the data for EC was clean, but there were some occurrences of null and negative values that required cleaning in the data set.

3.3.1 | Dealing With Null Values

The data set contains 3180 null entries, with the following breakdown across different categories (N: North and S: South wing of building): miscellaneous electric loads (mels) for mels_S (38 nulls), mels_N (24 nulls), lighting load (lig) for lig_S (34 nulls), HVAC_N (1542 nulls) and HVAC_S (1542 nulls). Because of the small number of null values in the mels_S, mels_N and lig_S categories, with relatively minor gaps between them, we can impute the missing values using the mean value. However, for the larger gaps in HVAC_N and HVAC_S, a supervised learning approach is employed. The features used in this approach include working day, month, lig_S, mels_S and mels_N. The Chi-squared test is applied to select the most relevant features, resulting in the selection of three optimal features. Using gradient boosting regression, the model yields an R^2 value of 0.84 for HVAC_N and 0.72 for HVAC_S, indicating reasonably good predictive performance. This demonstrates the effectiveness of the supervised learning approach in predicting missing values for the HVAC_N and HVAC_S categories.

3.3.2 | Dealing With Negative Values

There are various alternative approaches to address negative values. In this study, the negative values in the dataset were handled by substituting them with their respective previous values. This replacement led to an R^2 value of approximately 0.86, which suits the specific objectives of this study.

Ultimately, the paper focuses on predicting the total power consumption, disregarding individual contributions and summing them up to obtain the overall building's total power. As a result,

the dataset now comprises a time series of the total power of the building, collected at a sampling frequency of 15 min.

3.4 | Result Analysis

The models are evaluated and compared using various window sizes, specifically 4, 12, 20, and 28, along with different time stamps represented in hours, namely 1, 3, 5, and 7. For each timestamp, the best-performing model is selected. This comparison allows us to determine the most effective model for different temporal contexts. Various types of statistical, DL, Machine Learning and hybrid-deep learning (HDL) algorithms are applied in the analysis. To compare the models' performance, three commonly used metrics are considered: Mean Absolute Error (MAE), Root Mean Squared Error (RMSE) and R-squared (R^2). The data set is partitioned in such a way that 90.0% of the data is treated as training data, while the remaining 10.0% is allocated as testing data. The experimental results were obtained on a compute node equipped with a 2.60GHz Intel(R) Core(TM) i7-10750H CPU with six cores and 8 GB of RAM.

3.4.1 | Univariate Machine Learning Model

Table 1 shows the performance of three different models (Linear Regression (LR), ARIMA, and ANN) in terms of three metrics (MAE, RMSE and R^2) at different time horizons (1, 3, 5 and 7h). At the all-time horizon, ANN achieved the lowest MAE, followed closely by ARIMA and then LR. However, at the 1-h time horizon, the MAE value of ANN is followed closely by ARIMA and then LR. Similarly, at all time horizons, ANN consistently achieved the lowest RMSE values, indicating its better performance compared to the other models. At the 1- and 5-h time horizon, ANN had the highest R^2 value, followed by ARIMA and LR. At the 3- and 7-h time horizons, LR consistently achieved the highest R^2 values, indicating its better fit to the data compared to the other models.

Overall, the performance comparison of the models varies depending on the specific metric and time horizon. ANN tends to

TABLE 1 | Lag values of univariate models with error metrics.

Error metric	Models	Lag			
		1h	3h	5h	7h
MAE	LR	8.74512	8.53271	8.86124	8.11642
	ARIMA	8.4851	8.13512	8.43250	7.991
	ANN	8.21412	7.5853	8.181	7.86431
	RNN	7.41153	7.02414	7.92416	7.5112
	LSTM	6.64989	5.95055	7.04188	7.81044
	Bi-LSTM	6.47734	5.67300	6.69240	5.80187
	TCN	4.43684	6.67421	5.48321	5.46874
	CNN-LSTM (Jayashankara et al. 2023)	5.24025	6.38688	7.31434	6.25339
	TCN-RNN (Gautam et al. 2024)	7.54041	6.02413	8.49475	5.97155
	TCN-LSTM (Gautam et al. 2024)	4.225	5.66571	5.48672	4.47624
	TCN-Bi-LSTM	4.44217	4.79700	5.44283	4.10695
RMSE	LR	11.0125	10.4257	10.4581	10.13282
	ARIMA	10.9151	11.7033	10.7450	9.695
	ANN	10.811	10.0812	10.0321	9.2602
	RNN	9.6953	10.4489	9.3073	9.4214
	LSTM	8.4225	8.0277	9.0937	9.8971
	Bi-LSTM	8.3654	7.1703	9.5781	7.1340
	TCN	6.3241	8.1634	8.3420	7.2471
	CNN-LSTM (Jayashankara et al. 2023)	7.1709	8.9409	9.3660	8.7516
	TCN-RNN (Gautam et al. 2024)	9.0866	7.9761	10.8916	7.3169
	TCN-LSTM (Gautam et al. 2024)	6.2470	6.8141	7.3157	5.7747
	TCN-Bi-LSTM	6.1449	6.1208	7.0228	5.418
R^2	LR	0.795	0.827	0.821	0.796
	ARIMA	0.811	0.784	0.81	0.788
	ANN	0.825	0.802	0.84	0.784
	RNN	0.864	0.82	0.863	0.793
	LSTM	0.88	0.876	0.863	0.822
	Bi-LSTM	0.872	0.917	0.867	0.918
	TCN	0.922	0.879	0.883	0.861
	CNN-LSTM (Jayashankara et al. 2023)	0.918	0.877	0.866	0.829
	TCN-RNN (Gautam et al. 2024)	0.865	0.918	0.827	0.881
	TCN-LSTM (Gautam et al. 2024)	0.928	0.93	0.915	0.952
	TCN-Bi-LSTM	0.925	0.927	0.911	0.958

Note: Bold indicates the best results.

perform well in terms of R^2 , while ARIMA shows competitive performance in both MAE and RMSE. LR generally exhibits the least favourable results among the three models, but its performance is still close to that of the other models in some cases. Among all the methods, ANN performance varies significantly with various time horizons for different metrics.

3.4.2 | Univariate DL Model

The comparative analysis of the results for the different DL models (RNN, LSTM, Bi-LSTM and TCN) is provided in Table 1 using various performance metrics and time horizons. Except for the 3-h time horizon, TCN achieved the lowest MAE, followed by

Bi-LSTM, LSTM and RNN. At the 3-h time horizon, Bi-LSTM achieved the lowest MAE, followed by LSTM, TCN and RNN. It is also observed that the MAE value has decreased due to DL models by at least 9.7%, 7.3%, 3.1% and 4.49%, respectively, for time horizons of 1, 3, 5 and 7h compared to machine learning models. Besides, TCN has reduced the MAE value by at least 5.7% compared to DL sequential models like Bi-LSTM, LSTM and RNN for all the time horizons. Among DL sequential models, Bi-LSTM performs better on 1-, 3-, and 7-h time horizons, while LSTM is superior in the 5-h time horizon. But, LSTM and Bi-LSTM MAE values are very close compared to RNN.

At the 1- and 5-h time horizons, TCN had the lowest RMSE value, followed by Bi-LSTM, LSTM and RNN. Hence, TCN has reduced the RMSE value by at least 12.9% compared to DL models. Similarly, at the 3- and 7-h time horizons, Bi-LSTM had the lowest RMSE value, followed by TCN, LSTM and RNN. It drops the RMSE by approximately 1.5% compared to LSTM, TCN and RNN. Like MAE, the DL method reduces the RMSE value in comparison to machine learning models in all time horizons, and it is approximately 1.7%. Similar to the RMSE value, the R^2 value of DL models has shown a matching trend, and both TCN and Bi-LSTM are competing to achieve good performance.

Overall, the performance comparison shows that TCN and Bi-LSTM consistently outperformed the other models across most time horizons and metrics. TCN achieved the lowest MAE and RMSE values and the highest R^2 values, indicating its overall superior performance. Also, noteworthy deviation in the performance between various time horizons is observed for TCN compared to other DL methods for different metrics. Bi-LSTM also demonstrated competitive performance, especially in terms of R^2 . LSTM performed well in R^2 but outperformed TCN and Bi-LSTM in terms of MAE and RMSE. RNN achieved the lowest performance among the four models in most cases.

3.4.3 | Univariate HDL Model

Based on the results obtained from the individual DL models for predicting EC TS data, several hybrid models are proposed in this work to further enhance performance prediction. By designing and implementing these hybrid models, we aim to achieve more accurate and reliable EC forecasts, taking advantage of the complementary characteristics of individual models. Table 1 shows a comparative analysis of the different hybrid models (CNN-LSTM, TCN-RNN, TCN-LSTM and TCN Bi-LSTM) using multiple time horizons and performance metrics. At the 1-h time horizon, TCN-LSTM achieved the lowest MAE and slightly superior to TCN-Bi-LSTM. At the 3-, 5-, and 7-h time horizon, TCN-BiLSTM achieved the lowest MAE, followed by TCN-LSTM, CNN-LSTM and TCN-RNN. However, TCN-Bi-LSTM displays the dominant performance in RMSE and R^2 compared to other hybrid models.

Overall, the performance comparison shows that TCN-LSTM and TCN Bi-LSTM consistently outperformed the other hybrid models across most time horizons and metrics. TCN-Bi-LSTM achieved the lowest MAE and RMSE values and the highest R^2 values, indicating its overall superior performance. Hybridising TCN and Bi-LSTM models exploits TCN's effective

local modelling of temporal dependencies along with the Bi-LSTM's strong long-term memory retention. TCN-LSTM also demonstrated competitive performance, especially in terms of MAE and RMSE values. CNN-LSTM performed well but was outperformed by TCN-based models in most cases. TCN-RNN achieved the lowest performance among the four hybrid models in most cases. Despite its hybrid architecture, the CNN-LSTM model did not surpass the performance of deep learning models like Bi-LSTM.

3.4.4 | Multivariate Machine Learning Model

Table 2 discusses the comparative analysis of the multivariate data set of EC. At the all-time horizon, ANN achieved the lowest MAE, followed by ARIMA and then LR. A similar trend is observed for RMSE and R^2 metrics. LR exhibits a significant variation in MAE and RMSE performance across all time horizons. Overall, the performance comparison shows that ANN consistently outperformed the other models across most time horizons and metrics. The MAE performance of the EC prediction model improved significantly, with an enhancement of at least 13.0% and 12.0% for the 1- and 5-h time horizons, respectively, when using multivariate EC data compared to univariate EC data. A similar kind of enhancement is observed with RMSE and R^2 metrics.

3.4.5 | Multivariate DL Model

Except for the 3-h time horizon, TCN achieved the lowest MAE, followed by Bi-LSTM, LSTM and RNN. At the 3-h time horizon, Bi-LSTM achieved the lowest MAE, followed by LSTM, TCN and RNN. Similar trends are observed for the RMSE and R^2 metrics as well. Overall, the performance comparison shows that TCN consistently outperformed the other models across most time horizons and metrics. TCN achieved the lowest MAE and RMSE values and the highest R^2 values, indicating its overall superior performance for EC forecasting. TCN outperforms the DL sequential model by at least 5.8% in terms of MSE, 7.8% in terms of RMSE and 0.7% in terms of R^2 . Bi-LSTM and LSTM also performed competitively, demonstrating strong predictive capabilities. RNN achieved relatively lower performance compared to the other models in most cases. Indeed, both TCN and Bi-LSTM models using multivariate EC TS data have demonstrated substantial improvements compared to the univariate approach. Specifically, TCN has consistently achieved R^2 values greater than 0.92 across all time horizons, indicating its superior performance in capturing the variations in the EC data. These results highlight the effectiveness of leveraging multivariate information and the capabilities of TCN and Bi-LSTM models in enhancing the accuracy of EC forecasting.

3.4.6 | Multivariate HDL Model

Except for the 1-h time horizon, TCN-Bi-LSTM achieved the lowest MAE, followed by TCN-LSTM, CNN-LSTM and TCN-RNN. At the 1-h time horizon, TCN-LSTM achieved the lowest MAE, followed by TCN-Bi-LSTM, CNN-LSTM and TCN-RNN. At the all-hour time horizon, the models' RMSE scores ranked

TABLE 2 | Lag values of multivariate models with error metrics.

Error metric	Models	Lag			
		1h	3h	5h	7h
MAE	LR	7.14215	8.24051	7.16502	7.86114
	ARIMA	6.975	7.92514	7.1042	7.121
	ANN	6.8102	7.331	6.565	6.86725
	RNN	6.22614	6.41681	6.01244	6.38657
	LSTM	5.42614	4.4275	6.88537	5.74255
	Bi-LSTM	5.39512	4.201	5.3172	5.05974
	TCN	3.6617	5.2041	5.00452	4.09775
	CNN-LSTM (Jayashankara et al. 2023)	4.821	5.4224	6.78438	6.82599
	TCN-RNN (Gautam et al. 2024)	6.9426	5.74359	7.82275	5.13301
	TCN-LSTM (Gautam et al. 2024)	3.1385	4.3182	4.96758	3.61358
RMSE	TCN-Bi-LSTM	3.8158	3.8862	4.66857	3.2016
	LR	10.0074	11.361	10.1792	9.1481
	ARIMA	9.222	9.7793	9.9498	8.805
	ANN	8.4345	9.379	9.595	8.4705
	RNN	8.3625	7.4022	9.2574	8.121
	LSTM	6.8601	6.6709	8.5607	6.39
	Bi-LSTM	7.2083	5.961	7.4296	7.0124
	TCN	5.261	6.5183	6.8465	6.3301
	CNN-LSTM (Jayashankara et al. 2023)	7.6434	7.8437	9.6364	8.4135
	TCN-RNN (Gautam et al. 2024)	7.4875	7.8851	9.1351	7.5585
R^2	TCN-LSTM (Gautam et al. 2024)	5.3082	5.9533	6.0205	5.2585
	TCN-Bi-LSTM	5.0179	5.3207	5.226	4.2051
	LR	0.821	0.752	0.832	0.861
	ARIMA	0.85	0.85	0.836	0.87
	ANN	0.873	0.84	0.85	0.886
	RNN	0.887	0.926	0.859	0.892
	LSTM	0.93	0.911	0.873	0.928
	Bi-LSTM	0.917	0.942	0.915	0.885
	TCN	0.946	0.924	0.922	0.934
	CNN-LSTM (Jayashankara et al. 2023)	0.921	0.906	0.852	0.884
	TCN-RNN (Gautam et al. 2024)	0.928	0.917	0.86	0.926
	TCN-LSTM (Gautam et al. 2024)	0.943	0.95	0.937	0.941
	TCN-Bi-LSTM	0.948	0.951	0.947	0.968

Note: Bold indicates the best results.

from lowest to highest as follows: TCN-Bi-LSTM, TCN-LSTM, CNN-LSTM and TCN-RNN. A similar pattern is observed for the R^2 value, and the best R^2 value of 0.968 is achieved for the 7-h horizon on multivariate TS data. Also, the best R^2 value of 0.952 is attained for a 7-h horizon on univariate TS data. Thus, an overall improvement of 1.65% has been realised by moving from

univariate to multivariate TS data. Overall, the performance comparison shows that TCN Bi-LSTM consistently outperforms the other models across most time horizons and metrics. TCN Bi-LSTM achieved the lowest MAE and RMSE values and the highest R^2 values, indicating its overall superior performance for EC forecasting. TCN-LSTM and TCN-RNN also performed

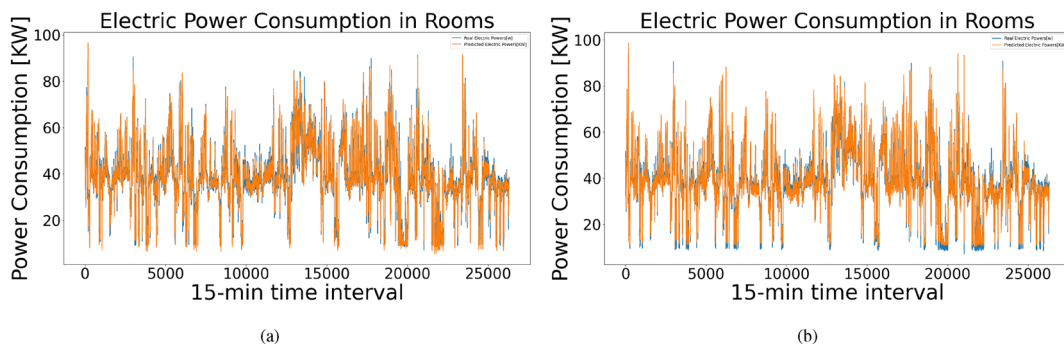


FIGURE 7 | (a) Actual versus predicted graph using TCN-Bi-LSTM on univariate TS data and (b) actual versus predicted graph using TCN-Bi-LSTM on multivariate TS data.

competitively, demonstrating strong predictive capabilities. CNN-LSTM achieved relatively lower performance compared to the other models in most cases.

Figure 7 compares the actual EC values with the corresponding predicted values using the TCN Bi-LSTM model in different scenarios. By comparing Figure 7a,b, we can assess the performance of the TCN-Bi-LSTM model in two different settings: Univariate and multivariate. This comparison enables us to evaluate the model's ability to capture patterns and make accurate EC predictions based on the multivariate input data configuration. The analysis reveals a strong correlation between the projected values and the actual values, indicating that the proposed model exhibits good performance. Figure 8 shows the loss function for the Bi-LSTM model and indicates the quality of training of the classifier.

3.5 | Perspectives

US residential appliances consume approximately 30.0% of electricity, generating around 12.0% CO_2 emissions. HVAC and artificial lighting systems take about 54.0% and 6.0% of total EC in the residential sectors. In the same way, lighting and HVAC systems account for 15.0% and 40.0% of energy used by commercial buildings (de Paola et al. 2014). Thus, for building managers and legislators, putting the suggested approach into practice in smart buildings has several advantages:

1. Improved predictions of EC also provide more accurate spending estimation and long-term forecasting.
2. A shift in demand response strategy made it more promising, balancing demand and supply.
3. Real-time given for EC forecasting provides comfort to occupants, electricity efficiency and timely changes.
4. Interconnection of renewable energy sources is made easier, minimising reliance on non-renewable energy sources.
5. Optimising the EC management improves cost reduction and financial position.
6. Control of energy usage provides useful information for business operations, and efficiency is realised.
7. A reduction in CO_2 emissions and an improved environmental assessment make plans more sustainable and compliant with requirements.

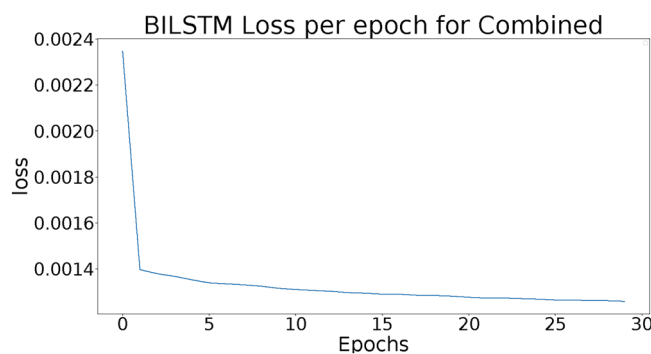


FIGURE 8 | Loss per epoch values for Bi-LSTM model.

In summary, the proposed model enables building managers to make effective decisions for controlling EC and providing sustainable functioning of buildings and resources to promote it while paying attention to the financial result.

4 | Conclusion

In conclusion, the increasing cost of electricity and the depletion of natural resources have become significant challenges in the generation of electricity. To address these issues and promote energy-efficient practices, the development of smart energy-efficient buildings has become a crucial focus. Many countries are actively monitoring and seeking ways to minimise energy costs while promoting environmental sustainability. In this paper, we have proposed various methodologies and their combinations for predicting energy consumption based on time series data. Through extensive testing on different time lags, we have found that our proposed model performs optimally with a 15-min lag. This demonstrates the effectiveness of our approach in forecasting energy consumption accurately. Looking ahead, we have explored various hybrid deep learning algorithms in our research to uncover more hidden features and enhance the accuracy of energy consumption predictions. Through the use of these predictive capabilities, consumers gain the power to directly influence various critical aspects, such as cost control, systematic energy-saving strategies, occupant comfort and global environmental sustainability. With access to informed insights on energy usage, individuals and organisations can optimise costs and adopt a more environmentally sustainable approach to energy consumption.

Additionally, expanding data sets to include diverse electrical products and scenarios will further improve the algorithms' ability to anticipate energy use in smart buildings. By continually refining and innovating our predictive models, we can contribute to the development of more efficient and sustainable energy practices, leading to a brighter and more environmentally conscious future. Subsequent research efforts shall, therefore, be directed towards this improvement based on the area of the geographic location.

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Data Availability Statement

The data that support the findings of this study are openly available in A three-year building operational performance dataset for in at <https://datadryad.org/stash/dataset/doi:10.7941/D1N33Q>, reference number <https://doi.org/10.7941/D1N33Q>.

Endnotes

¹ <https://data.worldbank.org/>.

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