BAREKENG: Journal of Mathematics and Its Applications
December 2026 Volume 20 Issue 4 Page 3053-3066
P-ISSN: 1978-7227 E-ISSN: 2615-3017
https://doi.org/10.30598/barekengvol20iss4pp3053-3066

HVAC-COOLING TOWER ENERGY CONSUMPTION PREDICTION IN COMMERCIAL BUILDINGS USING ADVANCED NEURAL NETWORK FRAMEWORKS

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Article Info

Article History:
Received: 26th September 2025
Revised: 21st April 2026
Accepted: 1st June 2026
Available online: 1st July 2026

Keywords:
Commercial Buildings;
Deep Learning;
Energy Forecasting;
Gated Recurrent Units;
HVAC.

ABSTRACT

Today, a major area of concern is the huge consumption of energy worldwide. The modern buildings are considered the largest energy consumers. When the energy consumption pattern of buildings is analyzed, attention is diverted towards the "Heating, Ventilation, and Air Conditioning" plant, which is accountable for the maximum consumption of energy in the buildings. This research work proposes a Deep learning framework including variants of Artificial Neural Network (ANN), namely, Recurrent Neural Network (RNN), Long-Short Term Memory (LSTM), and Gated Recurrent Units (GRU) to analyze and predict the abnormal energy consumption of the HVAC plants in commercial buildings. Also, proficient pre-processing, exploratory data analysis, and hyperparameter tuning for the proposed models are the key factors of this research. The proposed models have exhibited significant improvement as compared to the original RNN, LSTM, and GRU models. Different models of GRU were created using different values for hyperparameters, and the results of the experiments performed on the dataset show that one of the models of GRU outperformed the others with the least Mean Squared Errors (0.006) and (0.005) for the two months April and August, respectively. The research reveals that GRU is a better option for time series data analysis and is useful in energy consumption prediction for HVAC plants.

How to cite this article:

M. Pandey, M. Goyal, and M. Arora, "HVAC-COOLING TOWER ENERGY CONSUMPTION PREDICTION IN COMMERCIAL BUILDINGS USING ADVANCED NEURAL NETWORK FRAMEWORKS", *BAREKENG: J. Math. & App.*, vol. 20, no. 4, pp. 3053-3066, Dec. 2026.

Journal homepage: *https://ojs3.unpatti.ac.id/index.php/barekeng/*
Journal e-mail: *barekeng.math@yahoo.com; barekeng.journal@mail.unpatti.ac.id*

Research Article · Open Access

1. INTRODUCTION

In the current era of technology, energy usage is one of the major points of concern, as energy is the most precious resource, and it is generated mostly by the burning of non-renewable energy resources. Thus, there is a need to conserve energy and identify the areas of large energy consumption. It will provide a correct direction where efforts can be applied to conserve the energy, and hence, enormous energy can be saved. There are three broad categories of energy consumption: Commercial Buildings, Industry, and Transportation. Studies [1] and [2] show Buildings as the largest consumers of energy, accounting for over 40% of total energy usage throughout the world. Industries reportedly consume 32% of the total energy, and the remaining 28% energy is consumed in Transportation [3]. According to [4], Industries are transitioning from labor-intensive to electronic and computer-controlled technologies that consume more energy but can be countered with increased efficiency, improved quality, and performance. However, the efforts made to minimize the energy consumption should not compromise the comfort of occupants, particularly in residential and commercial buildings [5].

There are several traditional methods to estimate the consumption of energy in buildings and heating, ventilation, and Air Conditioning plants. These methods can broadly be classified into three categories: Standard mathematical approach followed in the HVAC industry, Simulation tools, and Statistical models. A large number of software or simulation tools have been developed for estimating energy consumption and sustainability in buildings [6], [7]. Another family of methods used for prediction is the statistical methods, including time series analysis. The most popular time-series models are: Autoregressive (AR), Integrated (I), Moving Average (MA) [8], Autoregressive Moving Average (ARMA) [9]. However, each technique has some limitations as simulation tools are time-consuming and require expertise in domain knowledge. Statistical models such as ARIMA tend to miss significant turning points in data. In contrast with traditional methods, Machine Learning-based algorithmic approaches are better and more efficient for HVAC energy predictions.

A large volume of work has been done in the literature related to energy consumption prediction in buildings using various classification techniques like Decision Tree, Support Vector Machine, Linear Regression, Nearest Neighbor, Artificial Neural Network, and others. Additionally, ensemble techniques such as Random Forest and GBM have also been applied for energy forecasting. Similarly, energy prediction in HVAC plants has also been explored using various Regression and classification techniques. Regression techniques were the subject of a number of studies, including the application of Multi-Linear Regression (MLR), Artificial Neural Networks (ANN), and Support Vector Machines (SVM) to degree day analysis with an RMSE below 20% using Support Vector Regression [10]. In addition, the ANN model can also be used to forecast energy consumption in advance stages of complex buildings with a 10% deviation [11]. Some studies combined classification and regression — employing algorithms such as C4.5, Locally Weighted Naïve Bayes, and SVR—to show that occupant behaviour has a significant effect on plug load energy consumption with an accuracy of 90.29% [12]. For HVAC, this led to very iterative models using MLP Neural Networks and Boosting tree algorithms reaching an accuracy of 90% (energy consumption) and 99% (temperature) [13]. In forecasting the energy use of appliances, analyzing the performance of MLR, Random Forest (RF), and Gradient Boosting Machines (GBM), it was found that the most promising results were yielded by GBM with a MAPE of 38.29% [14]. In a study, ANN was found to be more accurate with MAPE = 14.8 against MLR with MAPE = 19.11 [15]. Another research work performed sensor-based energy forecasting of a residential building using SVR and resulted in a Coefficient of Variation = 3.30% [16].

Using an ensemble of multiple modeling techniques, including CART, CHAID, Random Forests (RF), and SVM, total energy savings of 7.66% have been achieved [17]. A study employed RF, and Energy consumption was reduced by 48% for heating and 39% for cooling [18]. In a model developed to provide a fast and economic alternative for energy audit in buildings using Classification (Falling Rule List classifier), ROC AUC = 0.72-0.86 was achieved [19]. Decision Tree employed to develop an energy benchmark to improve the operational rating of office buildings, showing improved operational ratings [20]. A technique developed for HVAC power disaggregation using DT, DA, SVM, and KNN showed an accuracy of 99% for the KNN model for the combined Compressor and AHU model [21]. RF, ERT, KNN, and MLP were applied to construct a component-based ML model developed for energy demand prediction, resulting in prediction errors lower than 8% [22]. A framework developed to estimate HL and CL using Linear Regression and Random Forests resulted in MAE = 0.51 for HL and 1.42 for CL [23]. An approach developed to optimize the total energy consumption of HVAC in office buildings using CHAID, Exhaustive CHAID, BT, RF, MLP, MARSplines, and SVM resulted in average energy savings of 12.4% to 17.4% [24]. Additionally, ensemble-based machine learning techniques such as Random Forest and GBM have also been applied for energy forecasting. Various semi-supervised techniques pertaining to Clustering and Classification, with the combination of Auto-encoder, SVR, and RF, are proposed for anomaly detection in energy consumption. Various ANN-based ensembles have also been explored for energy consumption prediction. Another combination of clustering and classification was employed for cooling control based on occupancy presence. A framework for energy loss prevention during transportation was proposed using semi-supervised learning. In a study, ANN combined with the Electromagnetism-based Firefly optimization algorithm to help Civil engineers design energy-efficient buildings; RMSE, MAE, and MAPE were low compared to other methods [25]. Several other research works [26]-[31] have employed ensemble and semi-supervised models and gained significant results.

Studies show that Deep Learning techniques provide highly accurate solutions to several modern-day problems. This section explains the experimental work performed by various researchers by applying Deep learning techniques for energy prediction. The researchers have performed an in-depth survey of various Deep learning techniques applied for forecasting energy consumption in buildings, with a long-term objective of energy optimization. Another efficient approach explored deep learning methods for Heating and cooling power requirement predictions in buildings, with several benefits of using Deep learning. A number of deep learning models were employed to improve the accuracy and to minimize the errors for energy prediction in buildings. Various hybrid approaches pertaining to deep learning and machine learning are presented for better performance of energy consumption prediction. A large number of researchers [22], [32]-[41] have explored various Deep Learning methods, including CNN, GRU, GAN, LSTM, CRBM, CIFG, and a hybrid of these methods, to create more efficient models in the energy prediction domain.

This research work employs advanced neural network techniques for prediction, which include Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM), and Gated Recurrent Units (GRU). Neural networks and their variants have proven to give significant prediction accuracy. Each of the mentioned deep learning models is quite appropriate for handling time series problems. RNN has a simpler architecture but suffers from the Vanishing and exploding gradient problems. In contrast, LSTM solves the problems faced by RNN but has a complex architecture. GRU has a simplified architecture and trains fast, but exhibits less flexibility than LSTM.

The issue of abnormal energy consumption in commercial buildings has been targeted in this research work. HVAC is mainly accountable for consuming energy in a building. To address this issue, accurate prediction of energy consumption by the HVAC unit is essential so that appropriate measures can be taken to optimize energy usage. The goals of this research include the prediction of energy consumption by HVAC units, preventing the wastage of energy, ensuring the availability of energy for future generations, and preventing the wastage of non-renewable energy sources.

This research also serves some of the objectives of the SDGs framework, particularly related to the use of clean energy (SDG-7), the prediction of energy consumption leads to encouraging responsible consumption and production (SDG-12), and climate action (SDG-13) by reducing the carbon footprint. In the context of commercial buildings, research maps with sustainable cities and communities (SDG 11).

2. RESEARCH METHODS

The research work in this article is based on ANNs. This section starts with explaining ANNs and their various types, followed by the methodology adopted in the research.

2.1 Artificial Neural Networks

ANN is a well-known Machine Learning technique, whose structure is inspired by the biological Neural Network [10]. ANN maps input parameters to one of the output parameters [11]. ANNs are a kind of black-box technique as they are capable of adapting to the underlying system model, in contrast with other conventional Machine Learning algorithms [12]. The output of each neuron can be calculated by Eq. (1).

$$y = f\left(\sum_{i=1}^{n} w_i x_i + b\right), \tag{1}$$

where y, f, w_i, b, n represent the output, the activation function, weight assigned to input x_i, bias, and the number of input instances, respectively.

Fig. 1 shows the internal processing of an ANN with weighted inputs and an activation/Transfer function. The purpose of an activation function is to add non-linearity so that the neural network can learn complex patterns.

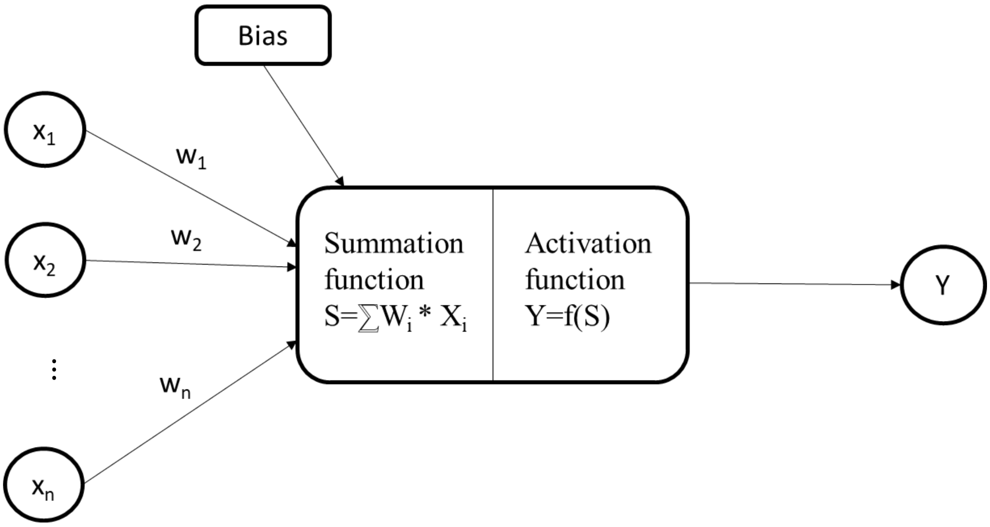

Figure 1. ANN Processing

A few architectures followed in ANNs include the fully connected networks, layered networks, Acyclic networks, feed-forward networks, and others are listed in [13] and [14]. According to [15], ANNs with more than one hidden layer are better in efficiency as compared to single layer networks. One such network is shown in Fig. 2.

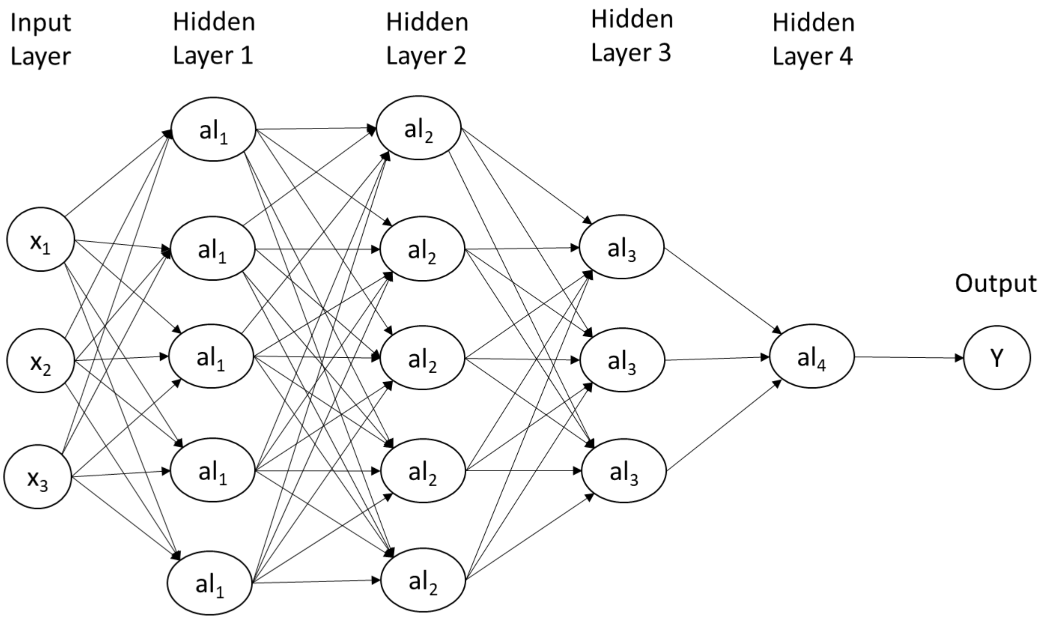

Figure 2. Multi-layer Feedforward ANN

2.2 Advanced Neural Networks

2.2.1 Recurrent Neural Networks

Generally, ANNs use a feedforward architecture that is unsuitable for Time series problems, because ANNs take only the current input for predicting the output. Previous inputs are not considered, resulting in the temporal dependencies between inputs being ignored, which may result in prediction inaccuracy. Therefore, RNN, LSTM, and GRU deep learning architectures are more suitable for handling time series problems. In contrast with ANN and CNN, A Recurrent Neural Network has an important characteristic that the output produced at the previous phase is sent to the input of the current phase [16].

Assume that the input sequence is $(x_{[1]}, x_{[2]}, \dots \dots .., x_{[T]})$ where t is a time step, $t \epsilon 1,2, \dots, T$.

The output sequence is computed as

$$\left(y_{[1]}, y_{[2]}, \dots \dots .., y_{[T]}\right).$$

Each output $y[t]$ is calculated using the inputs $x_{[t]}, x_{[t-1]}, \dots \dots .., x_{[1]}$.

The following Eq. (2) is the equation for a simple RNN.

$$h_t = f(Wx_t + Uh_{t-1} + b), \tag{2}$$

where x_t is the input vector at time t, h_t represents a hidden state, f is the activation function used, W and U are the weights, and b is the bias.

2.2.2 Long Short-Term Memory

Long Short-Term Memory [17] overcomes the RNN's problem of vanishing gradients [18], by training the model on long strings and saving them in memory [19]. Fig. 3 shows the architecture of LSTM.

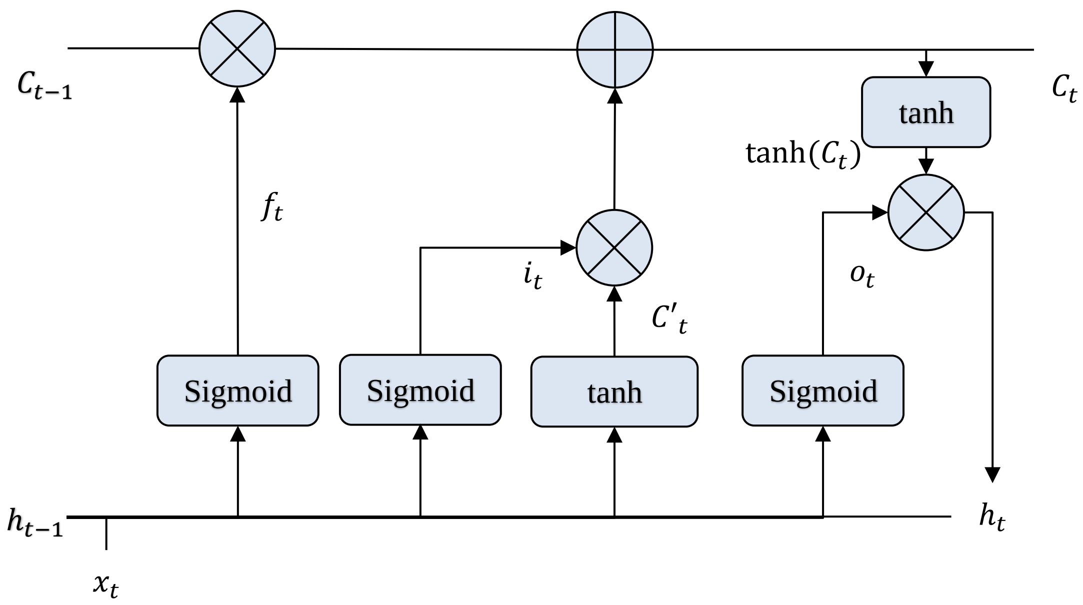

Figure 3. LSTM Architecture

The computations performed in an LSTM cell can be understood by the following equations.

$$i_t = \sigma\left(W_{xi}x_{[t]} + b_{xi} + W_{hi}h_{[t-1]} + b_{hi}\right), \tag{3}$$

$$f_t = \sigma\left(W_{xf}x_{[t]} + b_{xf} + W_{hf}h_{[t-1]} + b_{hf}\right), \tag{4}$$

$$d_t = \tanh\left(W_{xd}x_{[t]} + b_{xd} + W_{hd}h_{[t-1]} + b_{hd}\right), \tag{5}$$

$$o_t = \left(W_{xo}x_{[t]} + b_{xo} + W_{ho}h_{[t-1]} + b_{ho}\right), \tag{6}$$

$$m_{[t]} = f_t * c_{[t-1]} + i_t * g_t, \tag{7}$$

$$h_t = o_t * tan\,h\left(m_{[t-1]}\right). \tag{8}$$

Where i is the input gate, f is the forget gate, o is the output gate, d is the update step, m is the cell memory state, h is the hidden state, σ is the sigmoid activation function, tanh is hyperbolic tanh activation function, $*$ refers to element-wise multiplication, W_x are the input hidden weight matrices, W_h are the hidden-hidden weight matrices, and b_x and b_h are the biases learned during model training.

2.2.3 Gated Recurrent Units

Gated Recurrent Units are a simplified version of the LSTM model [20]. Fig. 4 shows the architecture of GRU.

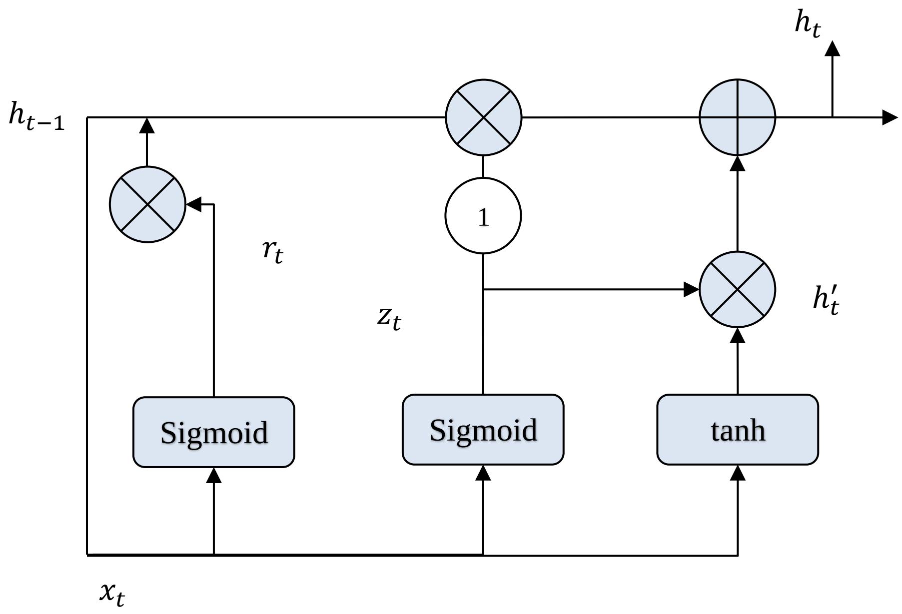

Figure 4. GRU Architecture

The GRU model is described by the following equations [16].

$$z_t = \sigma(W_z x_t + U_z h_{t-1} + b_z)\,, \tag{9}$$

$$r_t = \sigma(W_r x_t + U_r h_{t-1} + b_r), \tag{10}$$

$$h'_t = \tanh(W_h x_t + U_h(h_{t-1} * r_t) + b_h)\,, \tag{11}$$

$$h_t = z_t * h_{t-1} + (1 - z_t) * \hat{\mathrm{h}}_t\,. \tag{12}$$

Where z_t is the vector corresponding to the update gate, r_t is a vector corresponding to the reset gate, h_t is the state vector for the current time frame t.

2.3 Research Methodology

The proposed research work starts with the collection of data from HVAC plants from a commercial building, followed by pre-processing, data partitioning into a 70%-30% ratio, and development of a Deep learning framework, including hyperparameter tuning. Finally, the evaluation of models was done using standard performance metrics, namely RMSE, MSE, MAE, R-squared, and RMSE for GRU. Fig. 5 shows the complete methodology adopted in the research.

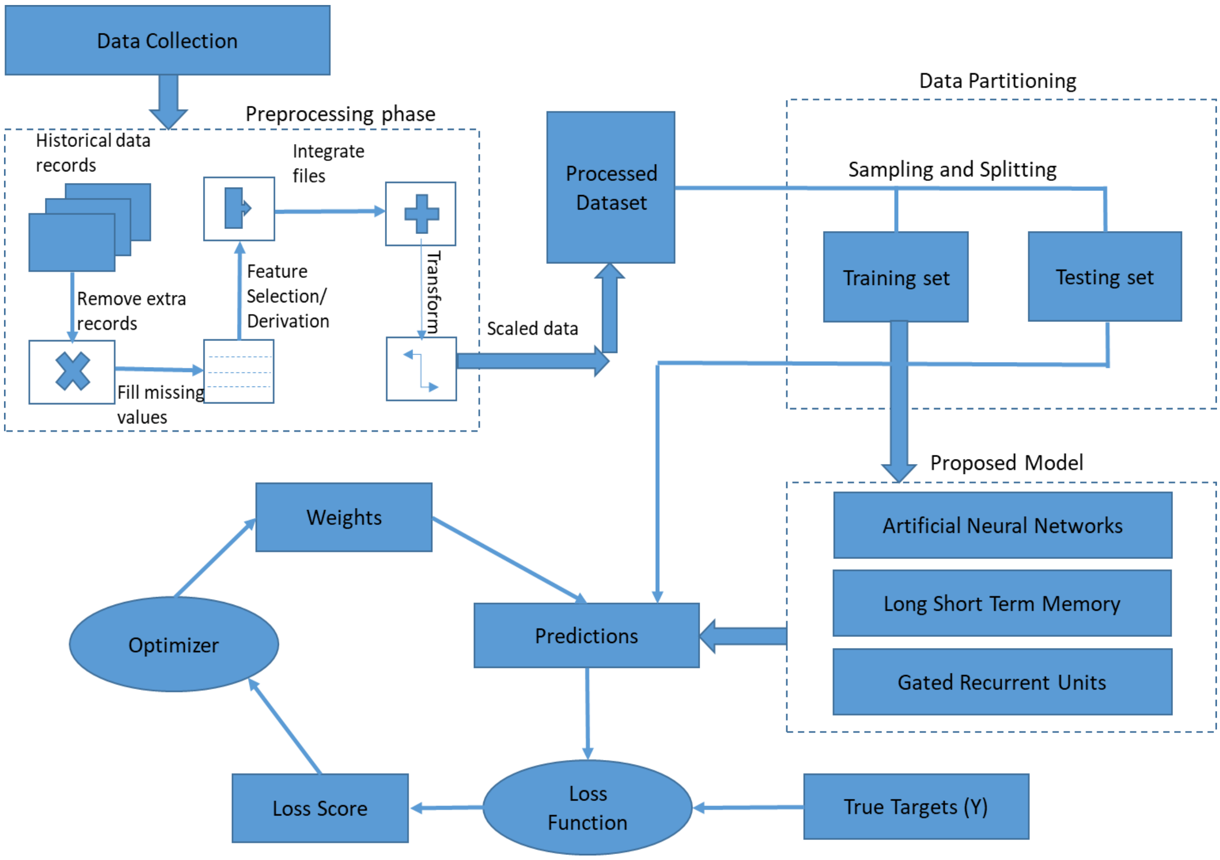

Figure 5. Methodology

The following subsections explain the steps performed under the methodology.

2.3.1 Dataset Description and Exploration

The detailed description of the cooling tower dataset of HVAC plants obtained from a hotel building located in North India is given in Table 1. There are 5 predictors (P1, P2, P3, P4, P5) and 1 target variable (T1) in the dataset. Table 1 gives a description of the parameters used in the dataset along with the units of each [21].

Table 1. Dataset Parameter Description

	Parameter	Description	Unit
P1	DBT(Dry Bulb Temperature)	Ambient temperature	°Celcius
P2	RH(Relative Humidity)	Amount of water vapour in the air relative to its temperature	%
P3	WBT(Wet Bulb Temperature)	Temperature brought down by water evaporation	°Celcius
P4	CT_INLET	Temperature of water entering the Cooling Tower	°Celcius
P5	CT_OUTLET	Temperature of water exiting from the Cooling Tower	°Celcius
T1	CT_POWER	Power consumed by the Cooling Tower	Kilo Watts

2.3.2 Data Cleaning and Wrangling

Data cleaning and wrangling are an integral part of the data modelling life cycle. In this research, several operations have been performed on the dataset, including the removal of extra records, the integration of files, and the replacement of missing values with suitable values as per the patterns of the neighboring data points' values (as the data is a time series). Also, a new parameter has been derived and named Wet Bulb Temperature. This parameter helps in the accurate prediction of Energy consumption. Further, data transformation has been performed, and two csv files were prepared for April and August, respectively [21]. Additionally, Data Scaling has also been applied.

2.3.3 Data Partitioning

After pre-processing, the dataset was ready for further processing. Before applying Deep learning models, the dataset was partitioned into the Training set and Testing set in the ratio of 70%-30%, respectively [22].

3. RESULTS AND DISCUSSION

The models constructed for experimental work and the results obtained have been discussed in this section.

3.1 Model Construction

In this research, GRUs have been applied to the commercial building dataset, and results were recorded for the April dataset, which are shown in Table 2. In total, five models were constructed by varying the number of hidden layers and changing the number of neurons in each layer. Table 3 presents the results of the GRU deep learning algorithm applied to the August dataset. All other hyperparameters, such as the number of models, types, scaling, layers, and neurons, number of epochs, optimizers, and activation functions, were the same as those used for the April dataset.

In this experiment, four Unidirectional and one Bidirectional GRU models were constructed for 50 epochs cycles. Also, ReLu and Adam were used as activation functions and optimizers, respectively. Data scaling has been performed on all models.

3.2 Tuning of Layers and Neurons

Two models, namely model 1 and model 2, consist of three hidden layers, and two models, namely model 3 and model 4, contain two layers. All the models were evaluated on the four performance measures, namely, MAE, RMSE, RMSLE, R-Squared, and MSE (Loss). Hyperparameter tuning was performed, in which different models were constructed, and in each of them, different values for various parameters were tried, and the results were calculated. It is clear from Table 2 that Model 1, with three layers and 128, 64, 32 neurons in each layer, respectively, outperformed the April dataset with the least error values and higher R-squared values. The results for all five models in terms of MSE range between 0.006 and 0.0075, the values for RMSLE are between 0.0037 and 0.0045, and the MAE values vary from 0.0521 to 0.059.

Table 2. **GRU Training Results on April Dataset on Varying Layers and Neurons**

Model	Layers (Neurons)	Loss (MSE)	MAE	RMSE	RMSLE	R-squared
Model 1	3 (128, 64, 32)	0.006	0.0521	0.0776	0.0037	0.6012
Model 2	3 (32, 64, 128)	0.0073	0.0577	0.0855	0.0044	0.5161
Model 3	2 (128, 64)	0.0074	0.0588	0.0862	0.0044	0.5079
Model 4	2 (128, 64)	0.0075	0.059	0.0865	0.0045	0.5048

Similarly, the results of GRU on the August dataset presented in Table 3 also show the MSE values for Models 1 to 5, ranging between 0.0049 and 0.0055, and the MAE values range between 0.0193 and 0.0354. Also, RMSLE varies from .0022 to .0024. It is clear from Table 3 that for the month of August, which is a humidity- based month, the Model 5 outperformed amongst all 5 models with 2 layers and 128, 64 neurons in each layer, respectively.

Table 3. GRU Training Results on August Dataset on Varying Layers and Neurons

Model	Layers (Neurons)	Loss (MSE)	MAE	RMSE	RMSLE	R Squared
Model 1	3 (64, 64, 32)	0.005	0.0248	0.0706	0.0023	0.1031
Model 2	3 (128, 64, 32)	0.0055	0.0354	0.0744	0.0024	0.0063
Model 3	3 (32, 64, 128)	0.005	0.0226	0.0704	0.0023	0.1099
Model 4	2 (128, 64)	0.0049	0.0207	0.0701	0.0023	0.116
Model 5	2 (128, 64)	0.0049	0.0193	0.0699	0.0022	0.1211

3.3 Tuning of Optimizer functions

Table 4 shows the results of April and August months for several performance measures- MSE, MAE, RMSE, RMSLE, and R-squared after optimization using different optimizers- Adam, SGD, RmsProp, and AdaDelta. The MSE values for April range between 0.0048 and 0.0054, and for August, the range of values is 0.0022-0.0027. RMSE values are just the square root of MSE values. MAE values range between 0.0446 and 0.0482 for April and between 0.0149 and 0.0214 for August. The range of RMSLE values is 0.003-0.0034 for April and 0.0009-0.0011 for August. R-squared values range between 0.6091 and 0.6507 for April and between 0.0872 and 0.2476 for August. It is evident from the table that the results obtained from the AdaDelta optimizer are slightly better compared to other optimizers for all performance measures, with minimum errors and with higher values of R-squared.

Table 4. Training Results Using Optimizers for April and August Data

Loss	MSE		MAE		RMSE		RMSLE		R Squared	
Optimizers	**Apr**	**Aug**	**Apr**	**Aug**	**Apr**	**Aug**	**Apr**	**Aug**	**Apr**	**Aug**
Adam	0.0054	0.0027	0.0482	0.0214	0.0733	0.0517	0.0034	0.0011	0.6091	0.0872
SGD	0.0049	0.0026	0.0465	0.0197	0.0701	0.0511	0.0031	0.0011	0.6427	0.1102
RmsProp	0.0049	0.0023	0.0451	0.0159	0.0703	0.0475	0.0031	0.0009	0.6401	0.2298
AdaDelta	0.0048	0.0022	0.0446	0.0149	0.0693	0.047	0.003	0.0009	0.6507	0.2476

Fig. 6 graphically represents the results of Table 4.

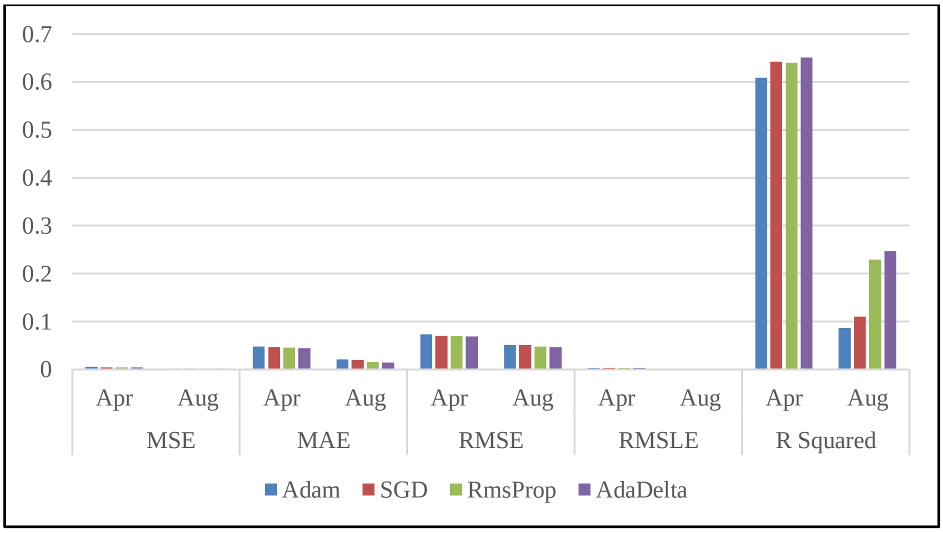

Figure 6. Graphical Representation of Optimizer Results

3.4 Comparison with other ANN models

The results of three models, namely LSTM, GRU, and ANN, have been compiled in Table 5 and Table 6 for April and August, respectively. All the models are Unidirectional. Scaling of data has been performed before model construction. The model evaluation has been conducted using well-known performance metrics, namely, MAE, MSE, RMSE, and R-squared. It is clear from Table 5 and Table 6 that the loss (MSE) is minimum for both months.

Table 5. Comparison of ANN with LSTM and GRU for April

April					
Model	**Layers (Neurons)**	**MAE**	**Loss (MSE)**	**RMSE**	**R Squared**
LSTM	3 (128, 64, 32)	0.0711	0.0114	0.1066	0.1908
GRU	3 (128, 64, 32)	0.0521	0.006	0.0776	0.6012
ANN	2 (128, 64)	0.0584	0.0072	0.0849	0.4759

Table 6. **Comparison of ANN with LSTM and GRU for August**

August						
Model	**Scaled Data**	**Layers (Neurons)**	**MAE**	**Loss (MSE)**	**RMSE**	**R Squared**
LSTM	Yes	3 (32, 64, 128)	1.5425	0.0146	0.0062	0.0618
GRU	Yes	2 (128, 64)	0.0193	0.0049	0.0699	0.1211
ANN	Yes	3 (32, 64, 128)	0.0217	0.0028	0.053	0.0426

The graphical representation of the results of Table 5 and Table 6 is shown in Fig. 7 and Fig. 8, respectively. Fig. 7 shows three bars, corresponding to the results of LSTM, GRU, and ANN, respectively. The performance metrics, MAE, MSE, and RMSE, should ideally be low, whereas R-squared should be high. All evidence shows that the performance of GRU is better and acceptable for the energy prediction in HVAC systems.

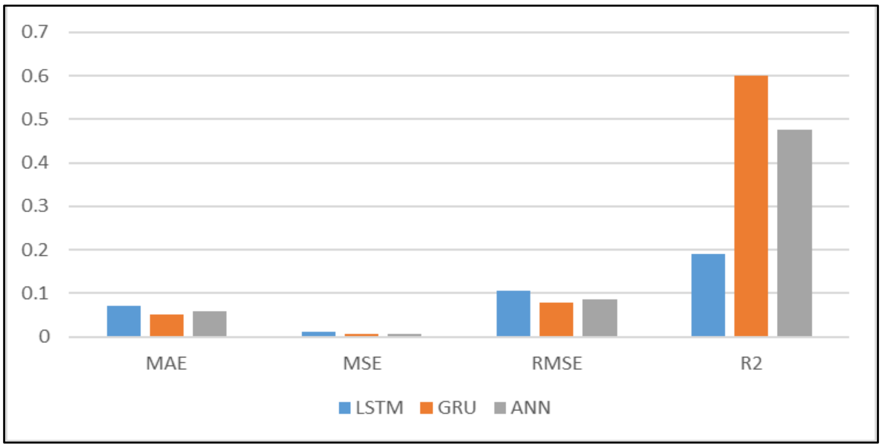

Figure 7. Comparison of ANN with LSTM and GRU (April)

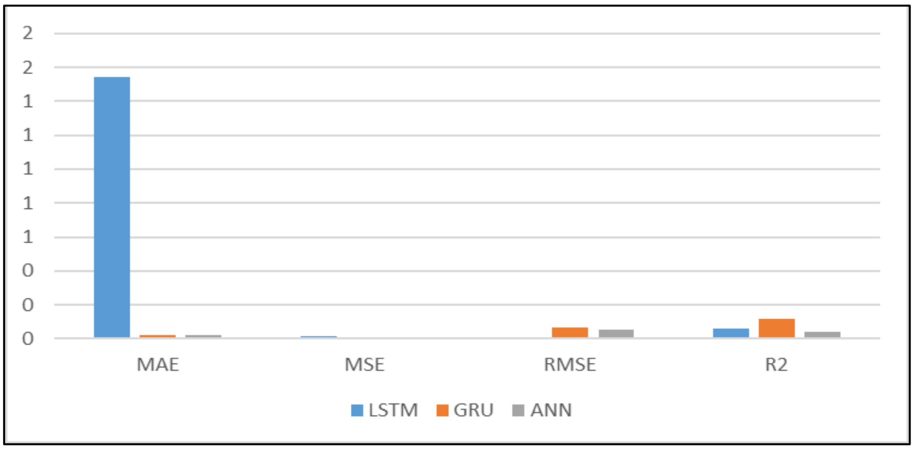

Figure 8. Comparison of ANN with LSTM and GRU (August)

4. CONCLUSION

The accurate prediction of actual energy consumed can be beneficial for HVAC system designers to design the architecture of systems, which ultimately can save huge investments and conserve energy. In this research, a deep learning framework has been proposed for the accurate prediction of energy consumption due to HVAC plants for a commercial building dataset (hotel building). Several models of GRU have been developed after hyperparameter tuning. The following are the conclusions of this research: (1) Neural Network architecture is one of the better choices for energy forecasting, particularly for energy consumption prediction for HVAC plants. (2) Further, Deep Learning algorithms and Gated Recurrent Units are sufficient to handle time series datasets, and with the lowest error function values. (3) The GRU performed better with higher accuracy. (4) Since the results of the GRU model outperformed in this research, the model can be used for predicting energy in similar buildings in the future. However, (5) the scope of this research was limited to the analysis of Cooling Tower data of the HVAC plant, but in the future, other components, such as Chillers data, can be analyzed for better prediction of the energy consumed by HVAC plants. It can be concluded that the proposed approach can be employed for predicting energy in similar buildings.

Author Contributions

Mrinal Pandey: Conceptualization, Formal Analysis, Investigation, Project Administration, Validation, Writing - Review and Editing. Monika Goyal: Data Curation, Methodology, Resources, Writing - Original Draft. Mamta Arora: Software, Visualization. All authors discussed the results and contributed to the final manuscript

Funding Statement

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

Acknowledgment

The authors sincerely appreciate the valuable comments and constructive suggestions provided by the reviewers.

Declarations

The authors declare no competing interests.

Declaration of Generative AI and AI-assisted Technologies

Generative AI tools (e.g., ChatGPT) were used solely for language refinement, including grammar, spelling, and clarity. The scientific content, analysis, interpretation, and conclusions were developed entirely by the authors. All final text was reviewed and approved by the authors.

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