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Comparasion of HVAC Energy Consumption Prediction in an Academic Building using LSTM and DNN

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ABSTRACT

Energy consumption information is a collection of information obtained from datasets that is useful for making decisions for energy conservation. In this paper, we proposed a modern approach based on LSTM and DNN. While many researchers have employed these methods for predicting energy consumption of HVAC, this paper seeks to compare their efficacy to determine which is superior. The comparative analysis in question employs accuracy metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R-squared (R^2) values. Furthermore, the accuracy metric outcomes indicate that the LSTM method surpasses the DNN approach in terms of the R-squared (R^2) value, with respective scores of 0.941 and 0.782. Meanwhile, for other accuracy metrics, the DNN method outperforms LSTM. Nevertheless, the performance of the two proposed methods is excellent, as evidenced by the R-squared (R^2) value exceeding 0.75, which aligns with modeling standards observed in numerous research studies.

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1. INTRODUCTION

Global warming has become an important problem which is largely influenced by increasing concentrations of CO2 dioxide carbon emissions in the air. CO2 emissions are caused by excessive energy use, especially in academia, recidential and commercial buildings [1,2]. Approximately 36% of the world's energy consumption and 38% of carbon emissions can be attributed to the building sector [3]. In Indonesia, a commitment has been made to achieve a 29% reduction in carbon emissions by 2030, employing measures focused on energy conservation. Additionally, there is a specified target to attain 23% utilization of new renewable energy by the year 2025. Considering the current condition and a goal to achieve carbon reduction and energy conservation by 2030, we are faced with the formidable challenge of diminishing building energy consumption and mitigating building carbon emissions [4]. The largest energy consumption in building systems is the HVAC (Heating, Ventilation, and Air Conditioning) system with approximately 40-60% according to the type of building [5], this is the focus of researchers in making efforts to increase building energy efficiency [6]. Many studies related to energy management systems in building have been carried out espicially in HVAC system [7-9].

The forecasting of building energy holds significant importance in the realms of energy saving by planning, management, and conservation. This is crucial as it facilitates the provision of precise solutions for demand response on the supply side [10,11]. The utilization of machine learning methods to the control and optimization of HVAC systems is emerging massively in the current era. Many studies show that machine learnig is used to prediction, which this method can be classified into white-box, black-box, and grey-box approaches [12,13]. Simplify, In the realm of predicting building energy

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consumption, black box models prove more adept at swiftly generating accurate forecasts compared to grey and white box models. Analyzing and mining extensive datasets within black-box models allows for bypassing the impact of real assumptions on predictions especially in electricity energy consumption load [14]. Black-box models can be sub-divided into non-deep learning and deep learning models [15].

Deep learning models possess the ability to comprehend intricate nonlinear connections, exhibit outstanding predictive precision, and are especially beneficial for scrutinizing extensive datasets related to building energy. They proficiently grasp prolonged dependencies and temporal dynamics, thereby enhancing the accuracy of predictions, particularly in the context of time-series forecasts. Common deep learning models encompass Artificial Neural Networks (ANN), Deep Neural Networks (DNN), recurrent neural networks (RNN), Long Short-Term Memory (LSTM), and gate recurrent units (GRU). Das et al. [16] employed a Long Short-Term Memory (LSTM) model for forecasting electricity consumption in residential environments. This was done to comprehend the usage patterns of residents and offer energy management solutions aimed at optimizing electricity utilization. Salam and El Hibaoui. [17] proposed a hybrid model, incorporating both neural network and Long Short-Term Memory (LSTM), which was developed with the aim of constructing effective models for predicting electricity consumption.

As we know, the LSTM neural network constitutes a type of recurrent neural network, featuring LSTM cells employed as hidden layers. The recurrent neural network (RNN) incorporates the notion of time series into its network structure design, enhancing its adaptability in the analysis of time series data. Additionally, the long short-term memory (LSTM) neural network addresses issues such as gradient disappearance, gradient burst, and inadequate long-term memory capacity observed in RNN. This enables LSTM to effectively utilize long-distance time information [18,19]. This neural network is widely using and successful outcomes have been attained in the prediction of building energy consumption. [20, 21]. While, the utilization of the deep neural network (DNN), a widely embraced artificial intelligence model, has been prevalent in various prior studies to create surrogate models, leading to notable success. In recent years, much research in DNN models has been developed in various energy applications such as prediction of HVAC energy consumption in a residential dormitory through the application of Deep Neural Network by opening window impact [22]. Alcántara et al. [23] deployed DNN for prediction interval of energy sources. DNN has the ability to increase the relevance of deep neural networks (DNN) in probabilistic forecasting due to its capacity to estimate prediction intervals accurately based on events that occur periodically. Therefore, forecasting HVAC system consumption will accurate, because the input layer is highly influenced by many events intermittent such as weather conditions, irradiance, wind and occupancy.

This research is proposed to analyze and compare both DNN and LSTM machine learning for prediction of consumption energy HVAC. In recent years, DNN has become more popular than the traditional ANN method, which is often applied to HVAC systems [24-26]. The main objective of this paper focuses on analyzing the application of DNN and LSTM machine learning for accurate prediction of HVAC energy consumption. That is possible to analyze energy conservation strategies and plans which can increase the efficiency of building consumption. In summary, in the realm of HVAC building optimization, control, and optimal control, machine learning finds extensive application across diverse phases encompassing planning, operation, and maintenance. In the next step, the results of both DNN and LSTM will be comparing by metric accuration tools. This paper utilized the Mean Squared Errot (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE) and R-Squared (R^2) as a performance criterion for evaluating model results. Additionally, this research using Isolation Forest anomaly detection in data preparation step which is traditional techniques.

2. RESEARCH METHOD

This research uses the HVAC electricity consumption energy of Labtek XIX FIBRC SBM-ITB building as a case study object, which this building is used for academic activities and lectures by SBM students. In this paper, the data access of lake data of database Sielisa ITB (electricity and water system) obtains by connected to localhost Management Energy Laboratory. Figure 1 illustrates the research framework designed for predicting electrical energy consumption. This study employs Deep Neural

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Network (DNN) and Long Short-Term Memory (LSTM) machine learning tools. The performance outcomes of each tool will be systematically examined and compared through accuracy metrics.

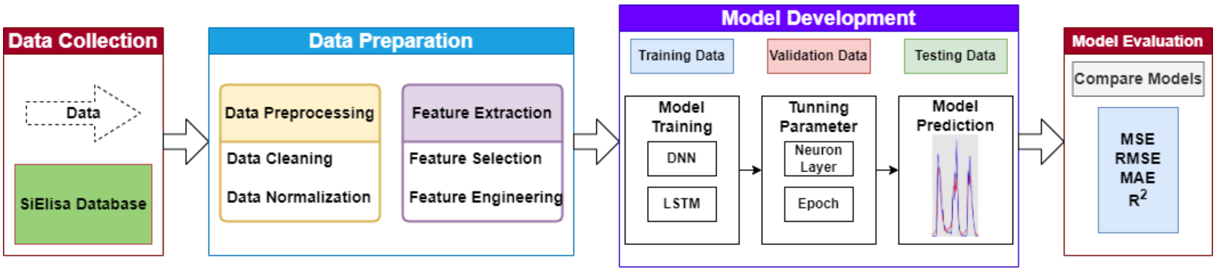

Figure 1. Framework for predicting electricity consumption in HVAC-SBM building energy

2.1. Data Collection

The first stage, Figure 1 describes how collected to the lake data within the (electricity and water system) SiElisa ITB database, which pertains to electricity and water systems, is facilitated through connection to the Management Energy Laboratory hosted on localhost. The research solely utilizes electricity consumption data sourced from the Advanced Metering Infrastructure (AMI) installed within the building. This data encompasses various electricity consumption categories such as lighting, HVAC (only AC), and other systems. The AMI system only records electricity usage in 3 phases (R, S, T) so it requires data processing in the datalake using the equation:

$$P_{AC} = (V_R I_R P_{f1}) + (V_S I_S P_{f2}) + (V_T I_T P_{f3}) \quad kW \tag{1}$$

Were P_{HVAC} represent HVAC electrical load, V (voltage) and I (Current) in each phase, divided by P_f (power factor). Further, The HVAC electricity consumption used is the entire building which is responsible for academic, office, library and administrative activities.

2.2. Data Preparation

In this paper, we used anomaly detection techniques for data cleaning. The Isolation Forest, commonly referred to as iForest, introduces a methodology involving the creation of an ensemble comprising iTrees tailored to a specific dataset. In equation (2), Anomalies are recognized as instances exhibiting notably shorter average path lengths within these iTrees. Anomalies are identified within hourly data using a sensitivity parameter setting of 1 percent, or a contamination value of 0.01, along with specified parameters including max features set at 0.3, max samples at 0.8, and n_estimators at 400. Equation (2) indicates that when we set $k = 1$, the isolation forest identifies a data point as an outlier if the function $E(t, M, k)$ for a larger range of k (greater than 1) considers it to be an outlier based on the sample dataset. Where t signifies the total number of trees, M denotes the overall number of binary splits executed during the search process, and k represents the size of the final node.

$$E(t, M, k) = \frac{1}{t} \sum_{i=1}^{t} \begin{cases} \sum_{j=1}^{M} 1 + c(0), & k = 1 \\ \sum_{j=1}^{M} 1 + c(k), & k \neq 1 \end{cases} \tag{2}$$

Additionally, holidays are predefined within the program to exclude anomalies recognized by ITB academics from the calendar system. Specifically, these holidays span from December 20th to January 16th for the semester break, April 19th to 25th for Eid holiday, and June 6th to August 20th, 2023, for the academic semester break. Following the completion of statistical analysis utilizing the isolation forest model, the subsequent steps will involve the removal of outliers and the normalization of data.

Furthermore, in this data preparation stage, we introduce novel features that impact the temporal dynamics of HVAC systems or physical variable features such as solar radiance, temperature and humidity environmental. For this paper, these features play a critical role in predicting output targets, particularly considering the geographical context of the research conducted in tropical countries. Meanwhile, time lagging techniques are employed to generate new features by incorporating data from the preceding one hour (P_{AC} $(t-1)$)and two hours (P_{AC} $(t-2)$). Table 1 illustrates the features employed in this research. While, the prediction model incorporates timeseries attributes including

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month, day, hour, and minute, resulting in a total of nine input features which the output target of the model is the prediction of HVAC power consumption (P_{AC}(t)).

Table 1. Features on LSTM and DNN model

Features	Models	
	LSTM	DNN
Minute	√	√
Hour	√	√
Day	√	√
Month	√	√
$irr\ (t)$	√	√
$T_{amb}\ (t)$	√	√
$H_{amb}\ (t)$	√	√
$(P_{AC}\ (t-1))$	√	√
$(P_{AC}\ (t-2))$	√	√
Target		
$(P_{AC}\ (t))$	√	√

2.3. Model Development

The subsequent stage involves developing a data-driven model for predicting HVAC electrical load, utilizing a hybrid architecture comprising LSTM and DNN layers. As we know, the LSTM neural network constitutes a type of Recurrent Neural Network (RNN). Meanwhile, DNN models has been developed in various energy applications such as prediction of HVAC energy consumption.

1) LSTM

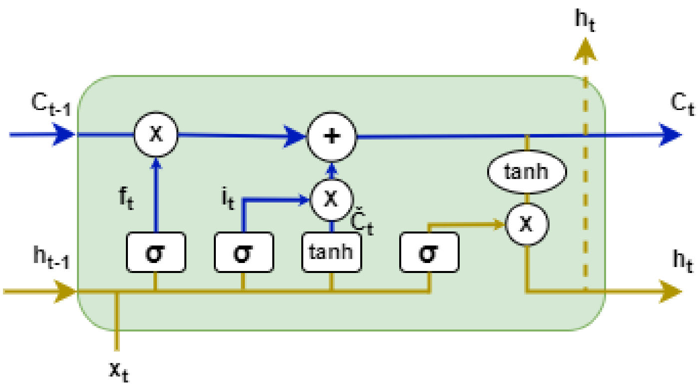

Figure 2. LSTM cell to overcome of limitation RNN

Simplify, Figure 2 show the model of LSTM which takes in previous cell state (C_{t-1}), previous cell output (h_{t-1}), and current input vector (x_t) as input parameters. It then generates the current state (C_t) and output vector (h_t) for the subsequent cell. The initial layer incorporates a forget gate, which applies a linear transformation to the current of input vector and previous states using a sigmoid function (r). This linear transformation can be written in the form (3), which gate outputs either 0 or 1, where 1 indicates to retain the state, and 0 indicates to 'discard and erase it' [27].

$$f_t = \sigma(W_f.[h_{t-1}, x_t] + b_f) \tag{3}$$

Next step in this cell, the "current state layer" operates, wherein another sigmoid function is employed. This function accepts both the previous cell output and the current input vector, conducting further linear transformations on them, which denotes in equation:

$$i_t = \sigma(W_i.[h_{t-1}, x_t] + b_i) \tag{4}$$

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Ultimately, this layer incorporates a gate of hyperbolic tangent that reads the previous cell output and current input vector. It produces a candidate value (Č) which is subsequently added to the cell state update process by (5).

$$\check{C}_t = tanh(W_c.[h_{t-1}, x_t] + b_t) \quad (5)$$

While, the current state undergoes an update by incorporating the previous cell state and the current candidate value, (6).

$$C_t = f_t . C_{t-1} + i_t . \check{C} \quad (6)$$

Lastly, the current output vector, ht, is computed by applying a linear transformation through a sigmoidal function to the previous cell state and current input vector. The resulting output is then passed through a hyperbolic tangent function to normalize the values between (-1, 1), which is written in mathematically in (7) and (8).

$$o_t = \sigma(W_0[h_{t-1}, x_t] + b_0)_t \quad (7)$$

$$h_t = o_t . tanh(C_t) \quad (8)$$

2) DNN

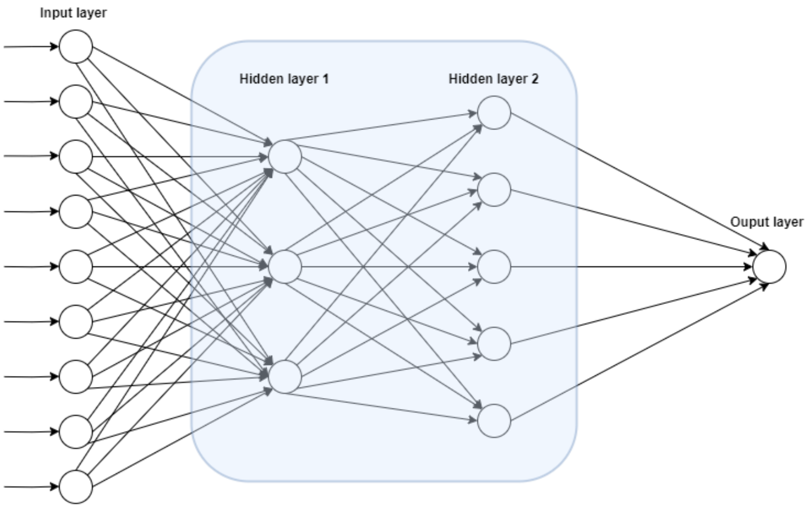

Figure 3. DNN layers and configuration

Figure 3 represents a specific architecture within artificial neural networks characterized by numerous layers comprising interconnected neurons or nodes. DNNs are termed "deep" due to their substantial layering, enabling them to effectively capture intricate patterns within data. Within the DNN framework, each layer of neurons serves to process and refine information before transmitting it to subsequent layers. In this research, the initial layer is denoted as the input layer which consists of nine input variables. Then the cover layer is the target output layer. Meanwhile, the intermediate layer is called the hidden layer which consists of 3 hidden layers 1 and 5 hidden layers 2. This study constructs a Deep Neural Network (DNN) model and evaluates the loss function during DNN training, employing the mean-squared error (MSE) metric. The MSE formula utilized in this research is as follows:

$$\mathcal{E}_{mse} = \frac{1}{d_{out}} \frac{1}{n^{\mathbb{L}}} \sum_{j=1}^{d_{out}} \left| \mathcal{N}_j^{ref}(\mathcal{L}) - \mathcal{N}_j(\mathcal{L}) \right|^2 \quad (8)$$

Where $\mathcal{N}_j^{ref}(\mathcal{L})$ denotes the corresponding reference solutions and $\mathcal{N}_j(\mathcal{L})$ $(j = 1, \ldots, d_{out})$ denotes j component of the output achieved during dimensional output d_{out} from DNN when a set of inputs $\mathcal{L}$ is given [28].

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2.4. Model Evaluation

To evaluate the precision of the prediction, it is imperative to establish the metrics for evaluating the performance of the two models. This facilitates tracking the progression of estimated accuracy values over time. Four standard evaluation metrics are employed for assessment, as defined below:

- Mean Squared Error (MSE):

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(x_i - y_i)^2 \tag{9}$$

- Root Mean Squared Error (RMSE):

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(x_i - y_i)^2}{n}} \tag{10}$$

- Mean Absolute Error (MAE):

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|x_i - y_i| \tag{11}$$

- R-squared (R^2):

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(x_i - y_i)^2}{\sum_{i=1}^{n}(x_i - \bar{y})^2} \tag{12}$$

3. RESULTS AND DISCUSSION

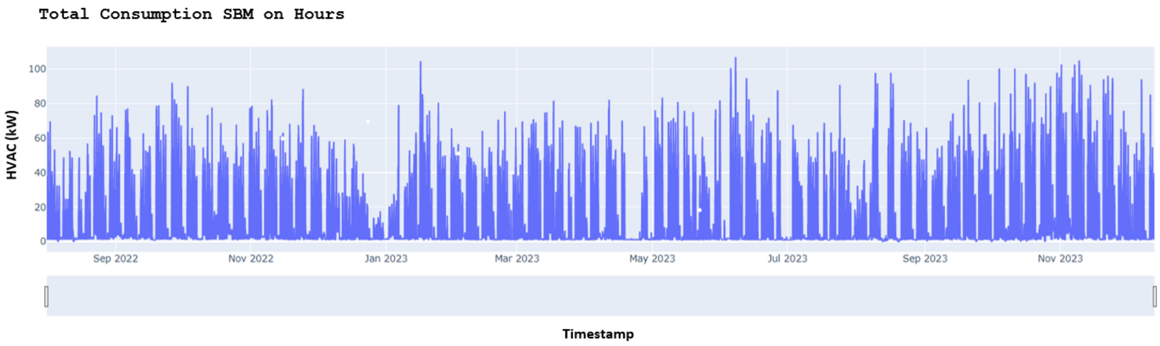

Figure 4. Dataset of HVAC electricity consumption in 2022 until 2023

Time series data is employed in this study to capture the normal building usage activities post the Covid-19 pandemic. Through rigorous outlier anomaly detection techniques, the data has been thoroughly cleaned and verified to ensure its reliability and accuracy for analysis. In this case study, this paper only focusing on the HVAC total consumption energy from September 2022 until November 2023 which represents by Figure 4. The main focus of this article is on the HVAC system, particularly on understanding and managing its electricity consumption. One significant aspect of this involves recognizing and eliminating outliers in the data by Isolation Forest anomaly detection to ensure its cleanliness and accuracy. That will help in identifying patterns and factors that influence HVAC electricity usage comprehensively.

3.1. LSTM results

The training loss of model depicted in Figure 5 reveals a significant difference in the number of epochs between LSTM and DNN, where the model shows high training loss. Despite both models employing two hidden layers, the LSTM model exhibits notably fewer epochs compared to the DNN counterpart which only used 150. Specifically, the first layer comprises 64 neurons, while the second layer consists of 32 neurons. For training purposes, the dataset is partitioned into three categories of data: 70% for training data, 20% for validation data, and 10% for testing data, following standard procedures in research papers.

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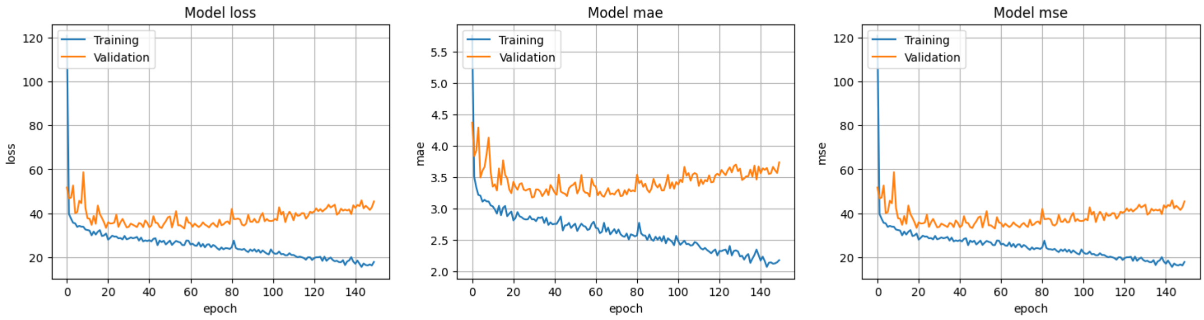

Figure 5. Training loss model of LSTM

As we know, the testing data used for the LSTM model that has been created is 10%, which is equivalent to 50 days of the total data These predictions will be validated using some of the same accuracy metrics in the DNN, while the performance results of each machine learning can be analyzed. Figure 6 presents the LSTM prediction outcomes, utilizing 1199 testing data points from the overall dataset. Additionally, the figure showcases the error percentage generated per unit time. Indirectly, the LSTM model yields a relatively high error rate over time. Nevertheless, it is imperative to note that several other accuracy metrics will be employed to ascertain the viability of this model.

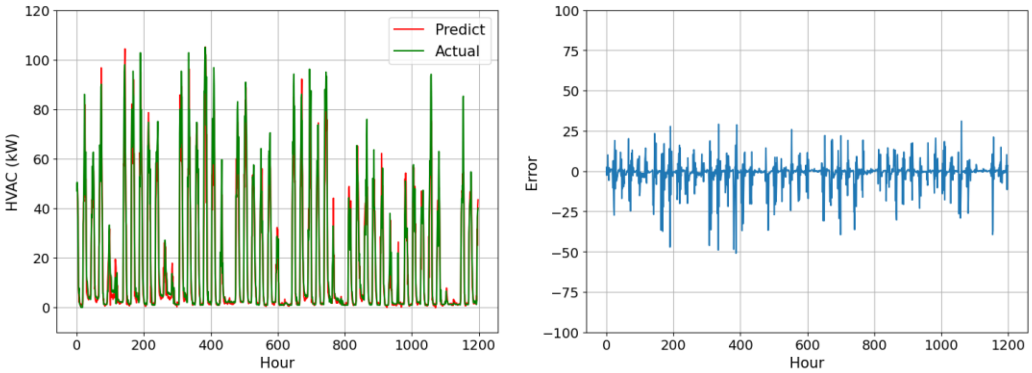

Figure 6. Prediction of HVAC electricity energy by LSTM model

3.2. DNN results

The reliability and accuracy of Deep Neural Network (DNN) models show significant consistency depending on the dataset used during the training, validation, and testing phases. With 9 sets of input variables across hidden layers 1 and 2, the DNN application aims to provide precise predictions despite the inherent volatility of the input data, characterized by variables such as solar radiation, outdoor temperature, and outdoor humidity.

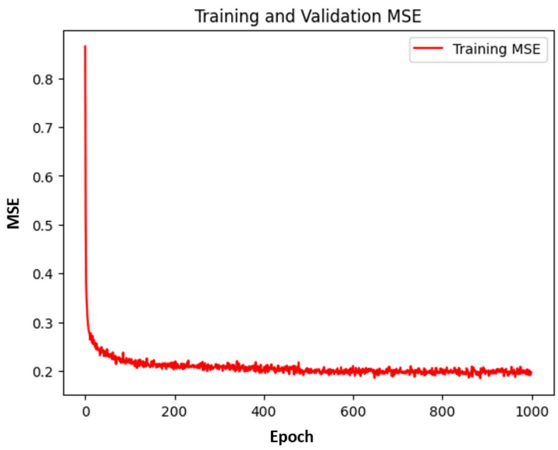

Figure 7. Training loss model of DNN

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Figure 7 illustrates that the loss function or training data of DNN is lower than that of LSTM. This difference may be due to the much higher number of epochs for DNN, which is 1000 compared to model previously only 150 epochs. While, Figure 8 shows the DNN prediction outcomes utilizing 10% of the test data, equivalent to 50 days, spanning from October 23, 2023, to December 12, 2023. The results of model prediction data indicates that the training model adequately predicts the energy load of HVAC electricity consumption during weekends, especially on Saturdays and Sundays, despite the absence of holiday contextual features in the model input. Moreover, the model demonstrates reasonably accurate predictions for weekdays, even amidst numerous holidays present throughout the entire dataset.

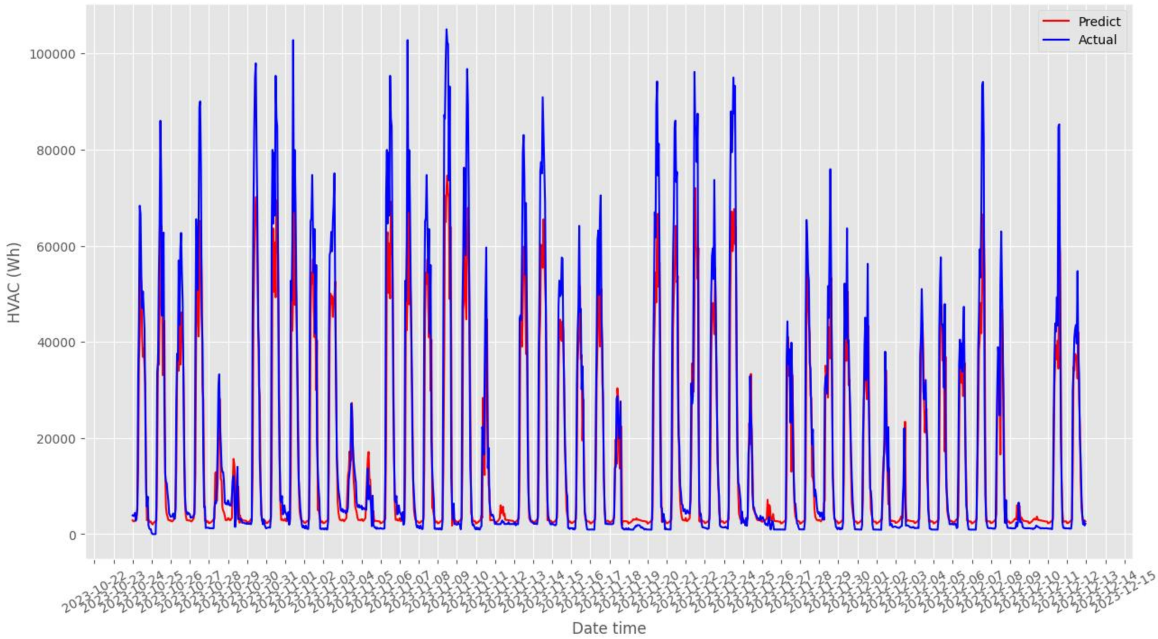

Figure 8. Prediction of HVAC electricity energy by DNN model

3.3. Metric Accuration

Table 2 provides a comprehensive overview of the errors observed in the second test for both LSTM and DNN models. The prediction efficacy of each model is evaluated through metrics such as MAE, MSE, RMSE, and R^2. This analysis allows for a thorough consideration of the various advantages and disadvantages inherent in each model, thereby facilitating the identification of the optimal model for predicting HVAC loads, particularly for university buildings.

Table 2. Metric accuration evaluation both LSTM and DNN model

Metric Accuration	Models	
	LSTM	DNN
MAE (Wh)	0.552	0.277
MSE (Wh)	25.42	0.236
RMSE (Wh)	5.042	0.486
R^2 (%)	0.941	0.782

4. CONCLUSION

The task of energy prediction is crucial in our daily lives due to its significant economic advantages and its potential to advance energy conservation efforts. While various methods have been suggested to predict energy consumption, traditional approaches often struggle because they overlook hidden periodic patterns in the data. This study aims to compare two modern techniques, Long Short-Term Memory (LSTM) and Deep Neural Network (DNN), in addressing this challenge. The methodology involves selecting nine additional factors and analyzing the time series data associated with energy consumption for modeling purposes. The key findings of this research are outlined as follows.

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- The LSTM method demonstrates superior predictive performance compared to DNN, as evidenced by the high R-squared value of 0.941. This phenomenon is likely attributable to the LSTM model's larger number of cells or neurons. However, despite its higher R-squared value, other error metrics indicating accuracy display considerably larger values compared to those of the DNN method.
- Meanwhile, the DNN method outperforms in terms of error metrics used for accuracy assessment. The respective MAE, MSE, and RMSE values are 0.277, 0.236, and 0.486.

In addition, both methods are suitable for predicting fluctuating energy consumption, primarily because their R-squared values meet the standard requirements, namely R-squared greater than >0.75. Furthermore, when predicting electrical energy consumption in other machine learning techniques, particularly for systems like HVAC, where values tend to fluctuate, it is advisable to incorporate additional features such as holidays, weekdays, and weekends. This inclusion helps provide a more comprehensive understanding of the training data model.

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