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Heating-Cooling Monitoring and Power Consumption Forecasting Using LSTM for Energy-Efficient Smart Management of Buildings: A Computational Intelligence Solution for Smart Homes

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Abstract: Energy management in smart homes is one of the most critical problems for the Quality of Life (QoL) and preserving energy resources. One of the relevant issues in this subject is environmental contamination, which threatens the world's future. Green computing-enabled Artificial Intelligence (AI) algorithms can provide impactful solutions to this topic. This research proposes using one of the Recurrent Neural Network (RNN) algorithms known as Long Short-Term Memory (LSTM) to comprehend how it is feasible to perform the cloud/fog/edge-enabled prediction of the building's energy. Four parameters of power electricity, power heating, power cooling, and total power in an office/home in cold-climate cities are considered as our features in the study. Based on the collected data, we evaluate the LSTM approach for forecasting parameters for the next year to predict energy consumption and online monitoring of the model's performance under various conditions. Towards implementing the AI predictive algorithm, several existing tools are studied. The results have been generated through simulations, and we find them promising for future applications.

Key words: design-builder; Besos; smart cities; smart building; neural network; Long Short-Term Memory (LSTM)

1 Introduction

The increase in the number of industries due to the expansion of the industry has made environmental issues more pressing today. According to Ref. [1], if air pollution is not decreased by 2030, an oxygen kit will be necessary to breathe comfortably since the air would be toxic. Artificial Intelligence (AI) is predicted to be used more in the future to tackle environmental-related problems. For example, Ref. [2] stated that the usage of remote-controlled robots would be expanded to include building and system maintenance in hazardous situations.

Nowadays, researchers have considered different techniques to increase the number of Electric Vehicles (EVs) in the city and make them optimize to reduce the negative impact of using vehicles in cities[3, 4]. In this

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case, one could theoretically achieve better results by optimizing the techniques considered by Akbarzadeh et al.[5]

The different buildings are also considered during these years, such as making hospitals smarter by considering the Internet of Things (IoT) and machine learning techniques, such as the system developed by Refs. [6–8]. In addition, cloud computing can be used to manage the data when data collection saves a huge amount of data, like the research done by Khan et al.[9] Moreover, to solve environmental problems, many solutions can contribute to reducing air pollution in major cities, for example, using an EV, which provides many advantages. As stated by Ref. [10], EV is a technology that eliminates the local Nitrogen Oxide (NO_x) and delicate Particulate Matter (PM) emissions. However, expanding the public transport system and increasing the number of EVs on the market play a crucial role in reducing air pollution. One of the most important factors is the optimization of buildings, which is crucial because Ref. [11] stated that smart buildings can be a solution that not only reduces costs and carbon footprint, but also positively affects the environment. To make a building more intelligent, IoT-based technologies might be useful for online monitoring and controlling building energy consumption. By adding sensors and a gateway, it is possible to monitor the cooling and heating of the interior temperature and adjust the cooling and heating power in an energy-efficient manner. For instance, if a household forgets to turn off an additional light before leaving home, he/she may either utilize the application, or the light can be turned off automatically. IoT helps intelligent buildings with security, automated administration, and online control, improving energy efficiency, safety, usability, and accessibility[12, 13]. Machine learning is another branch of research that may be used for smart building. The objective is to forecast what will occur in the next year. In this situation, it is feasible to determine the amount of energy required for each building's cooling, heating, electricity, and total power. By making smarter decisions regarding heating and lighting use based on the various needs of a building's occupants, machine learning has the potential to improve energy management and reduce a building's carbon footprint[14–16].

This study seeks to simulate an office in a city with a cold climate in order to comprehend four distinct characteristics, namely power heating, power electricity, power cooling, and total power, and to assess a time series method in the case of the forecast for the following year. Figure 1 depicts an overview of the stages, from designing an office to collecting data and making predictions based on that information.

2 Data Collection

Understanding the various stages of the project is the first step in evaluating and predicting the under investigation parameters. This research includes the following steps shown in Fig. 1. Utilizing the DesignBuilder program, create an office. After that, generate two office configurations with Controlled Natural Ventilation (CNV) enabled or disabled and their corresponding *. idf files using DesignBuilder. Then, run simulations using Besos for each configuration's energy requirements, altering three parameters: Window-to-Wall Ratio (WWR) from 10% to 90%; two shading modes (on/off); and three insulation thicknesses (0.001, 0.05, 0.2). All cases will be input into Besos to determine

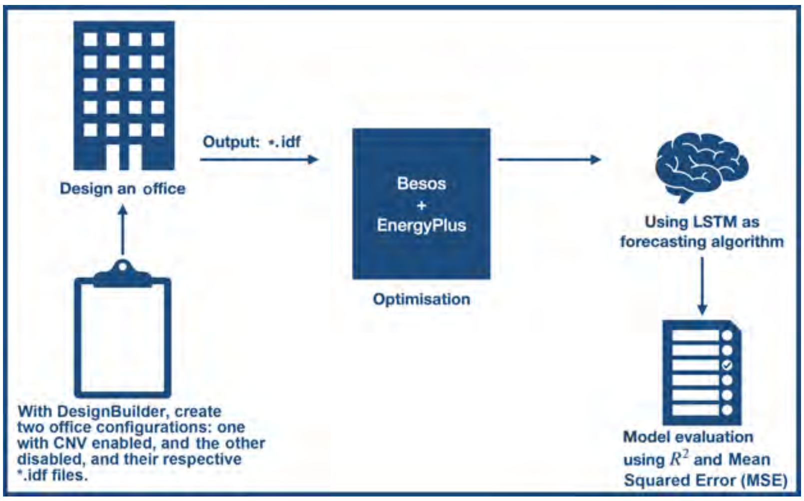

Fig. 1 Summary of three main steps of method.

the ideal values that minimize energy use. Moreover, utilizing EnergyPlus to conduct a dynamic energy simulation to get hourly energy consumption figures, and in the last step, use Long Short–Term Memory (LSTM) to forecast the energy consumption estimates for the following year.

2.1 DesignBuilder

DesignBuilder is an EnergyPlus-based software application for measuring and controlling energy, carbon, lighting, and comfort[17–19]. The designed office under study is located in Winnipeg, Manitoba province, Canada, with a total net area of 4036.47 square feet. This office is divided into two zones with twelve windows, two floors, two roofs, and seven walls. The year-round cold is one factor that led to Winnipeg's selection. Winnipeg is one of the coldest cities on the globe, according to Ref. [20]. This is important since people's energy consumption habits vary greatly in regions with unpredictable weather. In an environment with moderate temperatures, energy is predicted to be used for power cooling in the spring and summer and heating in the autumn and winter. However, this is not the case for places such as Winnipeg. According to Ref. [21], the maximum April temperature in Winnipeg is 10 ℃, indicating that power heating is more likely than power cooling. This phase results in various *. idf files, essential for initiating the next stages, namely, Besos and EnergyPlus.

2.2 Besos and EnergyPlus

Besos is a Python library with the latest version of 2.1.3. It is defined by different modules to model and optimize buildings to assist academics and engineers in constructing more sustainable and district-integrated structures[22]. Besos is used to conduct several simulations with changing parameters, as stated in Table 1, to determine the building's energy usage.

Describing the parameters is essential to understanding why they should be considered. Windows have a significant impact on the performance of a structure[23]. It implies that changing the number or size of windows may alter a home's energy consumption. In the same building, when the window width is N centimetres, the indoor temperature may be close to the outside temperature, and vice versa when the window width is $N - M$ centimetres. This is why window consideration is necessary. WWR quantifies the proportion of window area to the external wall area of a structure[24]. It is calculated as follows:

$$\mathrm{WWR}(\%) = \frac{\sum \text{Glazing area}\,(\mathrm{m}^2)}{\sum \text{Gross exterior wall area}\,(\mathrm{m}^2)} \tag{1}$$

The total area of the walls separating the building's interior and exterior is the building's gross exterior wall area. The glass portion of a building's facade or internal surfaces is referred to as glazing[25]. By adding 10% in each stage, this paper varies the WWR between 10% and 90%; one parameter helps run the Besos. Another parameter is Shading, defined as blocking the sun's rays in the building. The exterior shading of the facade is a crucial method to improve a building's energy efficiency in a subtropical area[26]. Understanding that the installation of shading can affect the amount of artificial lighting in the building is critical to realizing why Shading plays a crucial role in smart buildings. The energy required for artificial lighting is shown in the following:

$$W_{[\mathrm{kW\cdot h/year}]} = W_L + W_P \tag{2}$$

where W_P is the amount of energy required for emergency lighting and lighting control systems, and W_L is the amount required to ensure that the intended illumination requirements are met. W_L and W_P are calculated in the following:

$$W_L = \frac{P_N F_C F_O (t_D F_D + t_N)}{1000} \tag{3}$$

where,

- P_N is the total installed lighting power (W);
- F_C is the constant illuminates factor;
- F_O is the occupancy dependence factor;
- t_D is the daylight time usage (h);
- F_D is the daylight dependence factor;
- t_N is the non-daylight time usage (h).

$$W_P = \frac{P_{PC}(t_Y - t_0) + P_{em} \times t_{em}}{1000} \tag{4}$$

where,

- P_{PC} is the power needed for all control systems, such as emergency and standby (W);
- t_Y is the standard year time (h);
- t_0 is the annual operating time (h);
- P_{em} represents the total charging power installed for the emergency lighting (W);
- t_{em} is the emergency lighting charge time (h).

Controlling shading smartly may increase the amount of sunshine to maintain warmer internal temperatures and spread the light. The climate of the area where the building is located is one factor that should be considered. Reference [27] claimed that shading control can be

Table 1 Parameters configuration.

WWR	Shading	Insulation thickness (m)
0%–90%	On and off	0.0001–0.3500

classified into three groups. Optimizing the shading is crucial for warmer climates. In a mixed environment, it is possible to shade the building in the summer and let the sun in during the winter. Ultimately, it is preferable to reduce shading in a cold area. Given that Winnipeg is a cold climate and the building under study is an office, it is assumed that by employing the shade off, the amount of sunlight may rise and make the interior warmer than the exterior. If people do not shade throughout the day, the temperature may drop from the absence of sunshine, and artificial lighting use may grow.

Insulation thickness is the last characteristic examined in this study. Understanding the U-value, which evaluates how efficient a material is as an insulator[28], is preferable before deciding on the insulation thickness. The lower the U-value, the better for the best insulating materials close to zero[29]. The method for calculating U-value is shown in the following:

$$U = \frac{1}{R_{SI} + R_{SC} + R_A + R_i} \tag{5}$$

where,

- R_{SI} is the thermal resistance of the internal surface ($\mathrm{m}^2\cdot$ K/W);
- R_{SC} is the thermal resistance of the outside surface ($\mathrm{m}^2\cdot$ K/W);
- R_A is the thermal resistance of unvented air cavities;
- R_i is the thermal resistance of building components i ($\mathrm{m}^2\cdot$ K/W).

The energy consumption required to keep the internal temperature within comfortable ranges can be seen with Besos. Of course, the energy needed also depends on the outside temperature, which is supplied to the simulation as input with an *. epw file containing various information about the outside temperature for a chosen city. Other factors include,

- the schedule (here are working hours);
- the surfaces' transmittance; and
- the building's occupancy (including the number of people and machines like computers that naturally emit heat).

Engineers, architects, and researchers can be estimated parameters such as energy consumption for heating, cooling, etc. by considering EnergyPlus[30]. One of the project's goals is to simulate a building's complete data monitoring system, so the ideal total energy usage simulation was run using the Besos settings. After the simulation, it is feasible to anticipate how much energy will be used in the upcoming year. Figures 2–5 represent the data collected from Besos and EnergyPlus, with the y-axis demonstrating energy usage in the kWh unit and the x-axis representing the data based on the hourly data for one year.

3 Forecast Algorithm

The performance gap is defined as the discrepancy between the current level of performance and the one that is desired[31]. According to Ref. [32], the amount of energy used in buildings accounts for forty percent of the total energy used in the United States. Modelling and projecting building energy consumption is vital for

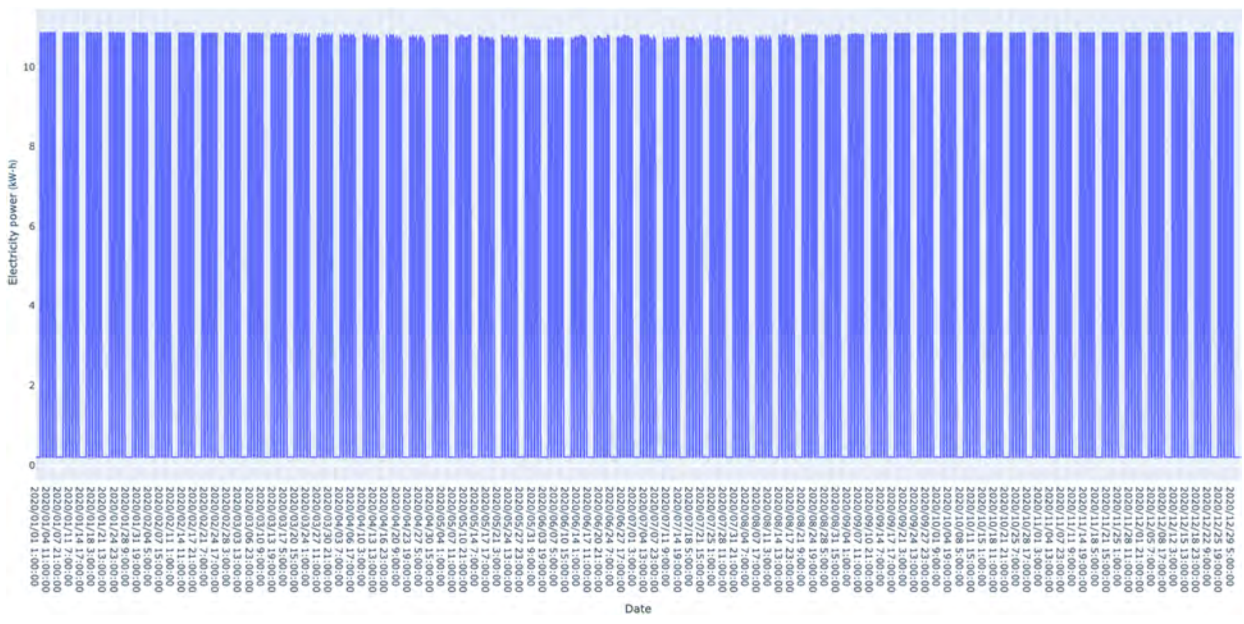

Fig. 2 Collected data of electricity power.

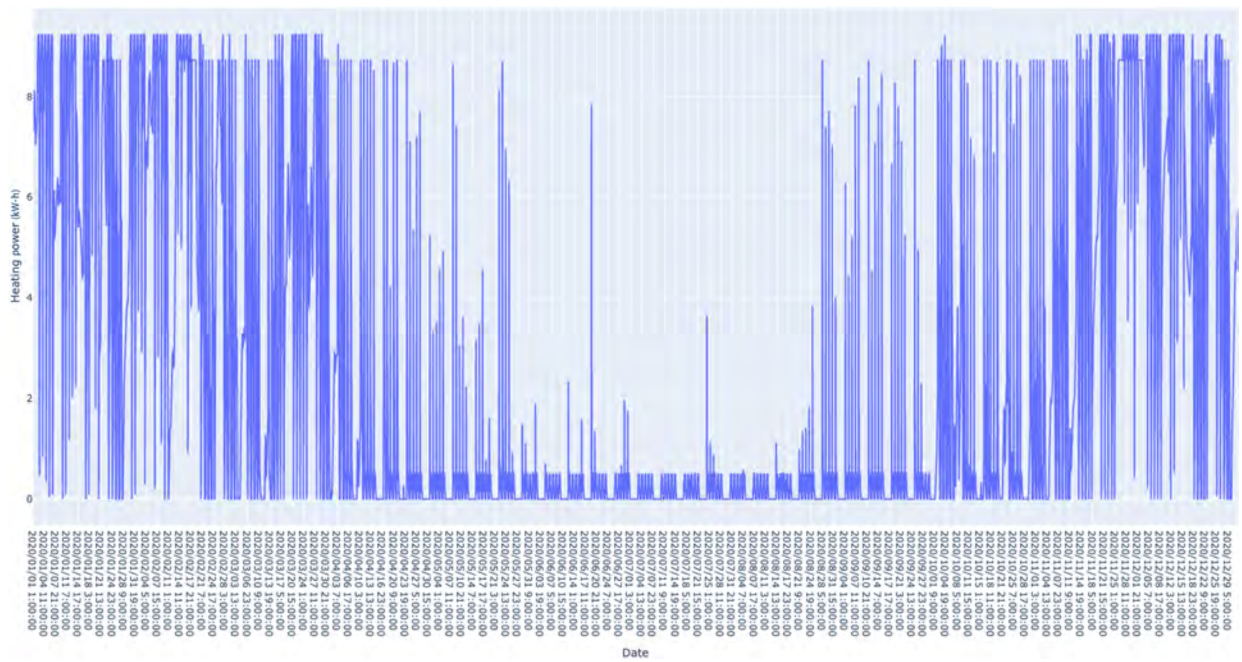

Fig. 3 Collected data of heating power.

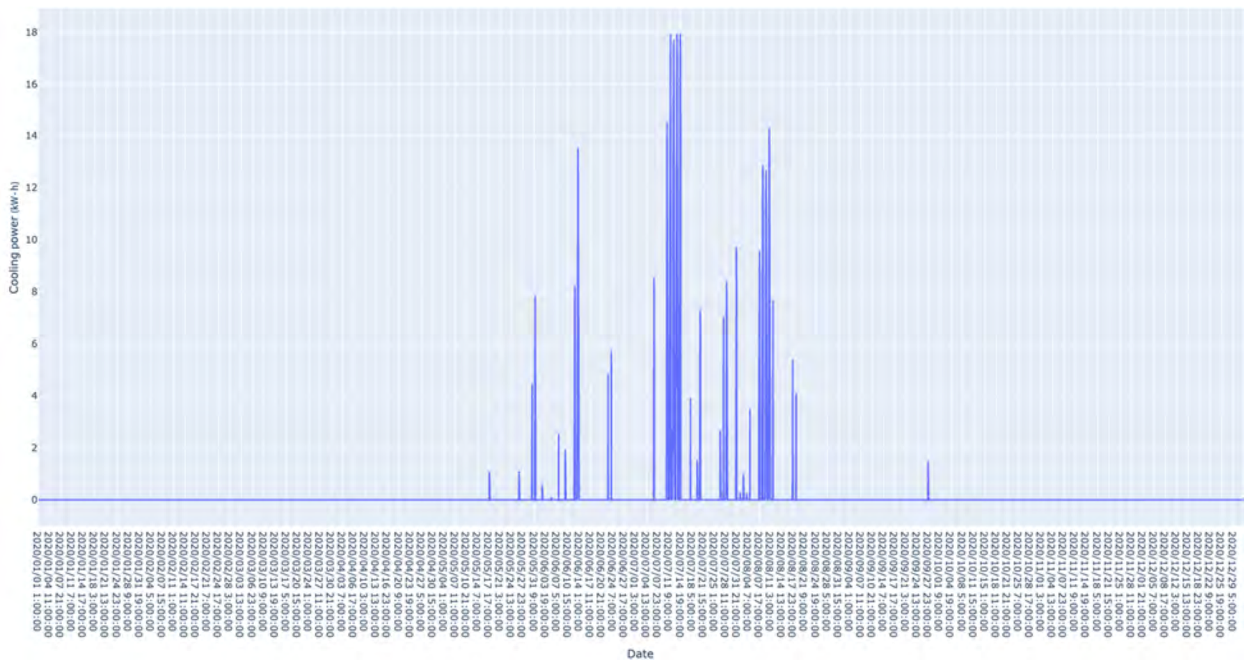

Fig. 4 Collected data of cooling power.

addressing building energy efficiency issues and meeting the present difficulties of human comfort. Urbanization growth is one of the major reasons for the increase in energy consumption[33]. To better understand, it is necessary to comprehend the methodologies used to anticipate the building's energy consumption; as Ref. [34] stated, AI and machine learning have been proposed for forecasting buildings' energy consumption and performance.

3.1 Summary of forecasting

The first step is understanding the difference between prediction and forecasting, and why forecasting is considered in this paper. The available dataset is time series, defined as recording the data over time[35]. For example, the data are recorded hour by hour in a year. A forecast is a computation or assessment that combines

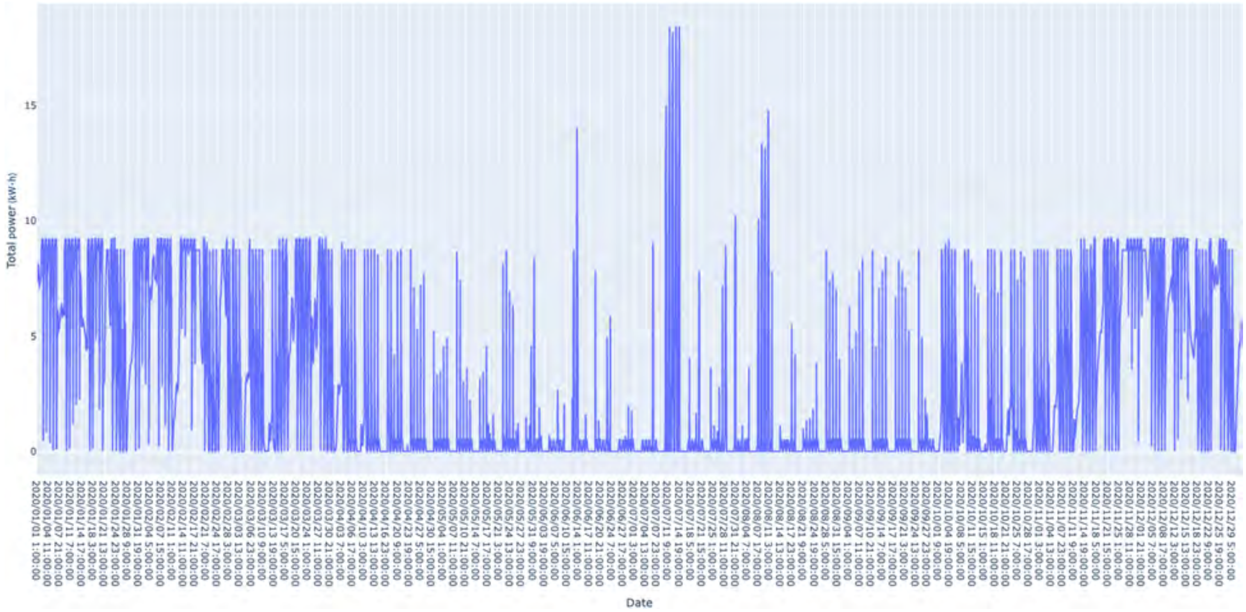

Fig. 5 Collected data of total power.

information from past occurrences and current trends to predict the result of a future event. At the same time, a prediction states that something will occur in the future regardless of the availability of past knowledge[36]. This study focuses on forecasting power consumption based on hourly data gathered over the period of a year; hence, the time series issue is the emphasis of this research. Before comparing alternative methodologies, summarized in Table 2, it is essential to recall the purpose of the study. Each machine learning and neural network is tailored to a certain study area.

3.2 SVM

The SVM method aims to discover a hyperplane in N-dimensional space, where N is the number of features to classify the data points separately[37]. It is, nevertheless, mainly employed to solve classification problems[38]. SVM employs the kernel technique to accomplish the goal of applying a linear decision boundary to high-dimensional data. SVM has based on the premise that the classifier is simple. The method for calculating the estimated class as a function is denoted in the following:

$$\hat{y} = w^{\mathrm{T}}x + w_0 \tag{6}$$

where $\hat{y}$ is the predicted class label, w represents the weight vector and w_0 is the bias term, and x is the input feature vector. Through the kernel trick it is possible to generate high-dimensional features. Ideally, a decision on a given test vector x should not depend on all vectors in the training set, but only on a select few. This approach reduces the computational complexity and localizes the decision-making, meaning that the classifier uses training set vectors similar to x to determine x's class. Considering this, let's introduce the function $L(y,\eta)$, as shown in the following:

Table 2 Under study algorithms.

Support Vector Machine (SVM)
Gaussian Process (GP)
Artificial Neural Network (ANN)

$$L(y,\eta) = \max(0, 1 - y\eta) \tag{7}$$

where $L(y,\eta)$ represents the loss function, which calculates the difference between the actual output y and the predicted output η. The goal of the SVM is to minimize this loss function, thereby enhancing the model's prediction accuracy.

It turns out that minimizing Eq. (8) is proportioned to minimizing this loss function which depends on the loss function plus a regularization term, essentially penalizes weighted vectors with a very large norm,

$$\min_{w,w_0} \frac{1}{2}||w||^2 + c\sum_{i=1}^{N} \max(0, 1 - y_i\eta_i) \tag{8}$$

After that, end up with a solution with the form expressed in the following:

$$\hat{w} = \sum_{i=1}^{N} \alpha_i x_i, \text{with } \alpha \text{ spare} \tag{9}$$

where vector $\hat{w}$, which is needed to set up the classifier, is a linear combination of the training vectors x_i with coefficients α_i (a sparse vector is a vector that has most coefficients α_i equal to zero) and this leads to a classification stated in the following:

$$\hat{y}(x) = \operatorname{sgn}(\hat{w}_0 + \hat{w}^{\mathrm{T}} x) = \operatorname{sgn}(\hat{w}_0 + \sum_{i=1}^{N} \alpha_i x_i^{\mathrm{T}} x) \tag{10}$$

Results in Ref. [39] demonstrate that the SVM approach might achieve more accuracy and generalization than the Back-Propagation (BP) neural networks model, which is excellent for constructing cooling load prediction models. Moreover, Ref. [40] compared four algorithms for predicting cooling in the office building in Guangzhou, China,

- Back Propagation Neural Network (BPNN);
- Radial Basis Function Neural Network (RBFNN);
- General Regression Neural Network (GRNN);
- SVM.

However, all of them are appropriate for building cooling load prediction; SVM and GRNN methods can reach better accuracy. Reference [41] applied a parallel implementation of the SVM approach to estimate energy consumption in several buildings utilizing massive time-series information for the first time. Numerous research studies have forecasted the power consumption in buildings, as observed in mentioned articles, but other approaches must be included to compare them ideally since the considered dataset consists of data for both power heating and cooling, and the data simulated just for one year and for one building.

3.3 GP

When the Gaussian probability distribution is generalized, GPs are considered, which can be a foundation for advanced non-parametric machine learning classification and regression techniques[42]. If the joint probability density function of the random variables $X(t_1), X(t_2), \ldots, X(t_N)$ is Gaussian for any value of N, a random process is Gaussian, as stated in the following:

$$f_X(x_1, x_2, \ldots, x_N; t_1, t_2, \ldots, t_N) = \frac{1}{\sqrt{(2\pi)^N \det(R)}} \mathrm{e}^{x} \tag{11}$$

where,

- x is equal to $-\frac{1}{2}[x-m]^{\mathrm{T}} R^{-1} [x-m]$;
- $x = [X(t_1), X(t_2), \ldots, X(t_N)]^{\mathrm{T}}$ is the column vector of random variables;
- x is the column vector $[x_1, x_2, \ldots, x_N]^{\mathrm{T}}$;
- m is the mean of the column vector;
- R is the covariance matrix.

In building energy modelling, ideal values for several parameters are often uncertain, such as envelope insulation. While accounting for uncertainty, Ref. [43] proposed a scalable probabilistic framework enabling large-scale expenditures in energy retrofitting buildings. Additionally, Ref. [9] provided a framework for GP modelling to calculate energy savings and uncertainty rates in measuring methods, they claim that GP models may capture complicated nonlinear and multi-variable interactions and multi-resolution energy behaviour patterns in contrast to linear regression. Since GP models are created within a Bayesian framework, they may account for many sources of uncertainty more systematically. Under the specific condition, the performance of the GP is acceptable, but here is another question: is the GP the best option if there is a limit of uncertainty in the data set?

3.4 ANN

Neural networks' novel techniques can be seen in different fields of studies[44]. The ANN phrase is taken from biological neural networks, which are responsible for the development of the structure of the human brain[45]. The reason why a typically more sophisticated model is considered, and also a model whose parameters are calculated automatically, will be defined in the following. Suppose a simple problem in machine learning, "digit recognition" (the situation that is given some handwritten digits and set up a classifier to classify the ten possible classes); it is pretty hard to relate these small pictures to a statistical distribution. It is also hard to describe this to a computer[46].

Figure 6 shows the neural network learns the model (not related to a statistical distribution, but it is a numerical model that computes some function, which is used as a classifier). The neural network automatically computes the $f(x)$ parameters. Consequently, a classifier is a sophisticated, which is a multidimensional function with several inputs (vectorized data samples) and outputs (class probabilities). Reference [47] considered neural network to anticipate annual consumption, which exemplifies an ANN strategy based on a supervised Multi-Layer Perceptron (MLP) network for electrical energy consumption forecasting, and

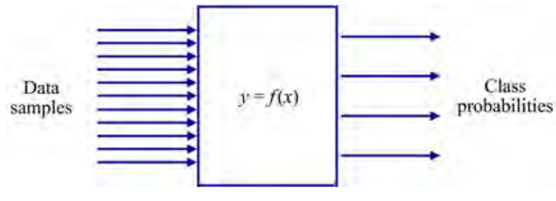

Fig. 6 Neural network example.

demonstrates that it can estimate annual consumption with reduced error. In addition, Ref. [48] evaluated several building energy consumption forecast algorithms for residential structures. Their findings indicated that deep neural networks and ANN have the highest performance accuracy, with ANN requiring less training time than deep neural networks.

4 Data Processing

Data was procured as described in Section 2 after processing through DesignBuilder, Besos, and EnergyPlus. Table 3 presents a segment of the dataset, featuring six entries from June 15, 2022 at different times. "Time" relates to the hour-by-hour simulation parameter. t_{in} and t_{out}, represent the inside and outside temperatures, respectively. PH is the heating power (in kW·h), PC is cooling power (in kW·h), PE is the electricity power (in kW·h), and PT is the total power (in kW·h). In the end, the dataset consists of 8 columns and 8760 rows, representing a year's worth of simulated data.

4.1 Data correlation

One of the steps to understanding a dataset more effectively is to consider the correlation between different parameters. For example, it is necessary to understand the relationship between cooling power and inside or outside temperature. Data correlation is defined as finding the linear relation between two variables. Assume the situation in which a random vector, in this example, has only two entries that $X = [x_1, x_2]$. It is easier to talk about the lack of correlation, meaning if x_1 and x_2 are statistically independent, it is clear that there should be no relationship between those values; or in other terms, the value of random variable x_1 as a piece of knowledge should not say anything about the value that x_2 takes. For example, looking at the pixels of an image, they are typically similar between adjacent pixels and neighbouring pixels. So it is possible to say that there is some statistical correlation between the values of those two pixels modelled by two random variables x_1 and x_2, and a tool should be considered. The correlation coefficient measures the amount of correlation between two random variables. The correlation coefficient is in the interval $[-1, +1]$. If the correlation coefficient equals zero, there is no correlation between random variables. If it is equivalent to $+1$, it means they have a considerable correlation. If it equals -1, there is a correlation between x_1 and $-x_2$. Figure 7 represents the correlation between

Table 3 Dataset example with six entries.

Time	t_{in} (℃)	t_{out} (℃)	PH (kW·h)	PC (kW·h)	PE (kW·h)	PT (kW·h)
10:00:00	22.8	14.19	0.51	0.0	10.73	0.51
11:00:00	22.8	14.55	0.51	0.0	10.71	0.51
12:00:00	23.01	14.89	0.38	0.0	10.7	0.38
13:00:00	23.05	14.81	0.38	0.0	10.7	0.38
14:00:00	22.97	14.57	0.51	0.0	10.7	0.51

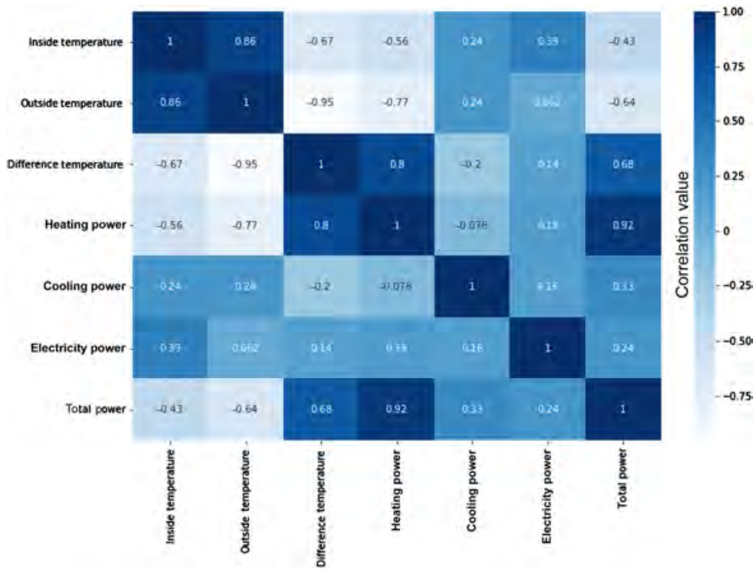

Fig. 7 Correlation between data available in the dataset.

data available in the dataset.

To forecast each parameter of the power cooling, power heating, total power, and power electricity, it needs to understand the most relevant features based on Fig. 7. This process, named feature selection, can be helpful in reduction of the computational time and improving model performance by reducing the number of input variables.

4.2 LSTM

The technique used to predict the parameters is LSTM. It is the RNN architecture used in deep learning. LSTM is an RNN architecture that shows temporal sequences and long-range dependencies more precisely than conventional RNNs. After understanding the appropriate algorithm to forecast the dataset and determine the correlation between data, it is time to understand the LSTM configuration. This method forecasts power cooling, heating, electricity, and total power in an office building in Winnipeg, Canada.

4.3 Activation functions

Two activation functions are considered in this paper, Sigmoid and Tanh. Sigmoid formula is in the following:

$$S(x) = \frac{1}{1+\mathrm{e}^{-x}} \tag{12}$$

where $S(x)$ is a sigmoid function.

The input to the function is simply a linear combination of the input plus the bias. When the input is largely negative or positive, the function goes to zero or one; however, the transition between zero and one is smooth.

The chosen activation function is both continuous and differentiable. This characteristic means that even slight changes to the weights within the neural network can result in substantial variations in the output. In contrast, the hyperbolic tangent is an alternative activation function that has a link to the sigmoid function, as shown in the following:

$$\sigma = \frac{1+\tanh(\frac{z}{2})}{2} \tag{13}$$

The key difference lies in the output range; unlike the Sigmoid function that varies between 0 and 1, the hyperbolic tangent function's output ranges from -1 to $+1$. The Tanh function has a derivative of up to 1.0, which makes parameter changes far more relevant; this makes the Tanh function virtually always superior to the Sigmoid function as an activation function for hidden layers.

4.4 Number of epochs

Another parameter that needs setting is the number of epochs, which represents complete passes through the training dataset[35]. Figure 8 illustrates the required number of epochs for the total power. After approximately ten epochs, the behavior stabilizes, as evidenced by the intersection between the training loss and validation loss curves. However, we set the epoch value to 50 for the total power as the decrease in loss is still ongoing. While increasing the number of epochs can lead to longer computation time, the effect on the model's performance may be minimal, rendering the trade-off acceptable. Figure 9 indicates the electricity power epochs behaviour, where the situation is more or less similar to the total power. The difference is that after ten epochs, there are no changes in the case of training and validation loss. The number of epochs for power electricity is equal to 25. As Fig. 10 represents, the number of epochs for the heating power has a different story, where after ten epochs, there is a slight decrement in the performance. For heating power, 50 is considered the number of epochs. Cooling power epochs

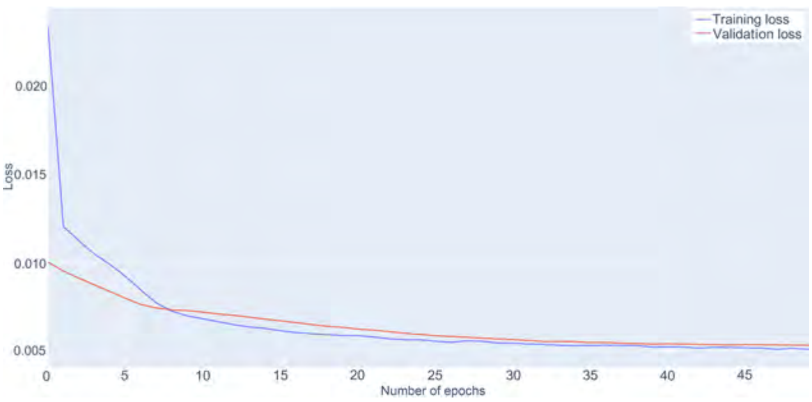

Fig. 8 Training loss vs. validation loss for total power.

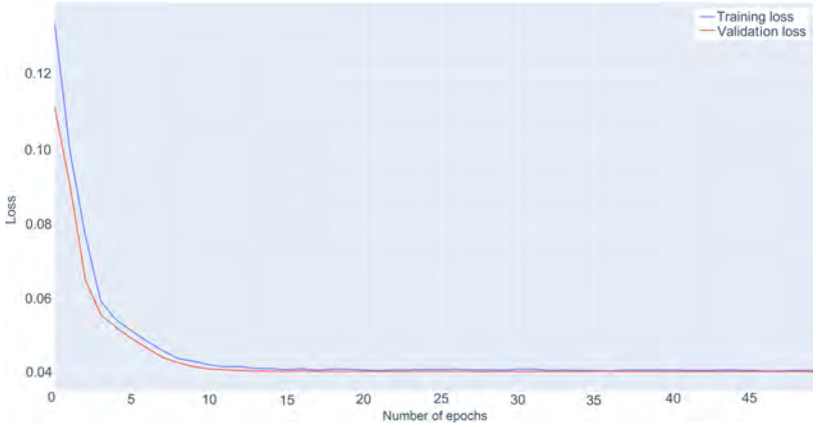

Fig. 9 Training loss vs. validation loss for electricity power.

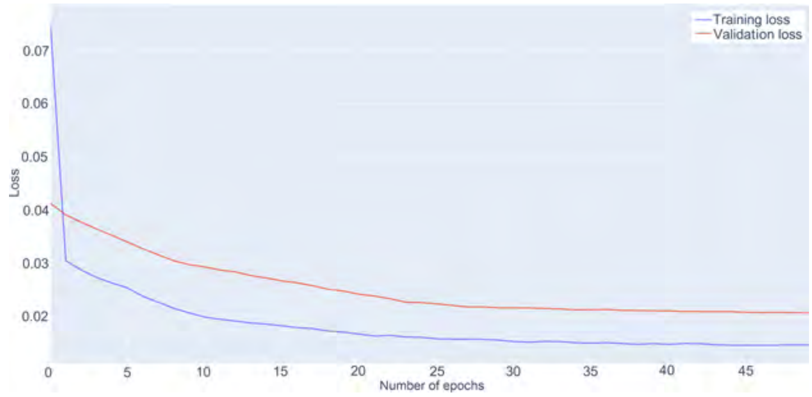

Fig. 10 Training loss vs. validation loss for heating power.

are represented by Fig. 11, where the performance is unacceptable since the lack of available data resulted in that. As the data is related to the cold climate, most days, there is no cooling power in the office.

4.5 Model evaluation

This paper considered R_2 and MSE as metrics to evaluate model performance. The MSE, presented in Eq. (14), is commonly used to assess the quality of the model's predictions. A smaller MSE value indicates a better estimation. In this equation, n is the number of data points, AE_i represents the actual or observed values, and PE_i denotes the predicted or estimated values from the model. The difference between these two values, $AE_i - PE_i$, indicates the error of each prediction. The squaring operation penalizes larger discrepancies more severely than smaller ones, highlighting the model's ability to avoid large errors.

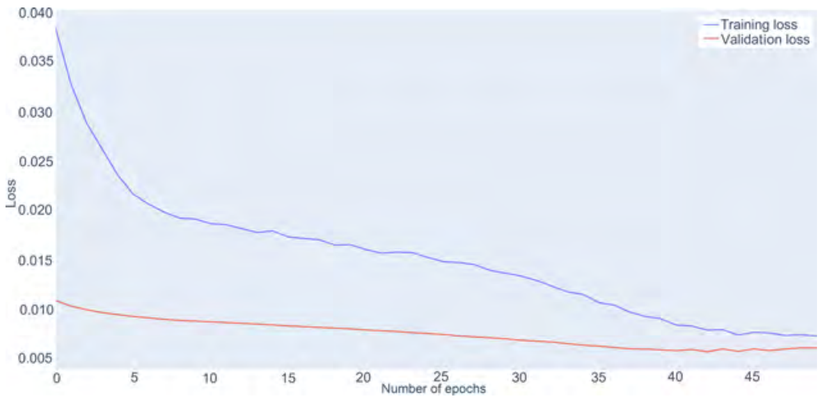

Fig. 11 Training loss vs. validation loss for cooling power.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(AE_i - PE_i)^2 \tag{14}$$

where AE_i is the actual value at the i-th instance and PE_i is the predicted value at the i-th instance by the model. On the other hand, R_2 is also considered, which is defined in Eq. (15).

On the other hand, R^2 is also considered, which is defined in the following:

$$R^2 = 1 - \frac{\sigma_e^2}{\sigma_y^2} = 1 - \frac{\sum_{n=1}^{N}[\hat{y}(n) - y(n)]^2}{\sum_{n=1}^{N}[y(n) - \overline{y}]^2} \tag{15}$$

R^2 should be as close as possible to 1.

5 Results and discussion

This paper's collected data are excessively significant since they include all energy consumption-related characteristics, including cooling power, heating power, electricity power, and total power. In addition, the city under study is one of the coldest places in the world, which may affect people's energy consumption for factors such as cooling power. In this situation, the expectation is whether the provided data and the performance of the LSTM are adequate. Comparing original and forecasted data demonstrates, as shown in Fig. 12, that the performance of electricity power is acceptable. Table 4 presents the model assessment based on the MSE and R^2, which are 4.46 and 0.82 for electricity power, respectively. The result can be attributed to the consistent availability of hourly electricity power data throughout the year. However, the model's performance may be influenced by the absence of heating power usage data during warmer months in the workplace. This lack of data during high-temperature periods could potentially affect the model's predictive accuracy. However, heating power's MSE and R^2 are 2.76 and 0.78, respectively. This demonstrates the LSTM's adequate performance. Figure 13 contrasts the original and prediction of the model for heating power. Cooling power is the most difficult aspect of this paper since, in a cold region, cooling power reduces daytime consumption. Consequently, data for the fall and winter and specific days of such months are unavailable. MSE is estimated to be 3.76 using LSTM, whereas R^2 is 0.72. As shown in Fig. 14, cooling power has the lowest performance of all factors studied in this study, confirming once again that increasing the number of data also enhanced the model's performance. The total power result is illustrated in Fig. 15, in which the performance is more similar to the heating power, with the MSE equals to 2.76 and R^2 equals to 0.78.

Table 4 Model evaluation.

Energy characteristic	MSE	R^2
Electricity power	4.46	0.82
Heating power	2.91	0.77
Cooling power	3.76	0.72
Total power	2.76	0.78

6 Conclusion

Technology use might result in a mix of benefits and drawbacks. Controlling the energy that people use daily is one thing that must be done to stop the destruction of the environment. In this particular scenario, some research areas, such as machine learning and IoT, play an essential role. Smart building is one topic that contributes to solving the problems related to using energy in buildings. The model evaluation of the LSTM represents that the RNN algorithm has an acceptable result since its accuracy is in a good range for different cases. In this paper, RNN is also considered a method to forecast data related to energy consumption.

The paper's primary issues pertain to two distinct topics. Initially, we chose a city with mostly low temperatures throughout the year, which may result in data unavailability for cooling energy consumption. Therefore, we analyzed the LSTM algorithm when imperfect data was supplied. In addition, the workplace's heating, cooling, and energy usage are evaluated so that the most accurate projections may be made for the next years. In this instance, the performance of the LSTM was thoroughly evaluated in various conditions. For future expansions, it is strongly suggested to test LSTM in a city with hot temperatures to establish if LSTM's performance is acceptable.

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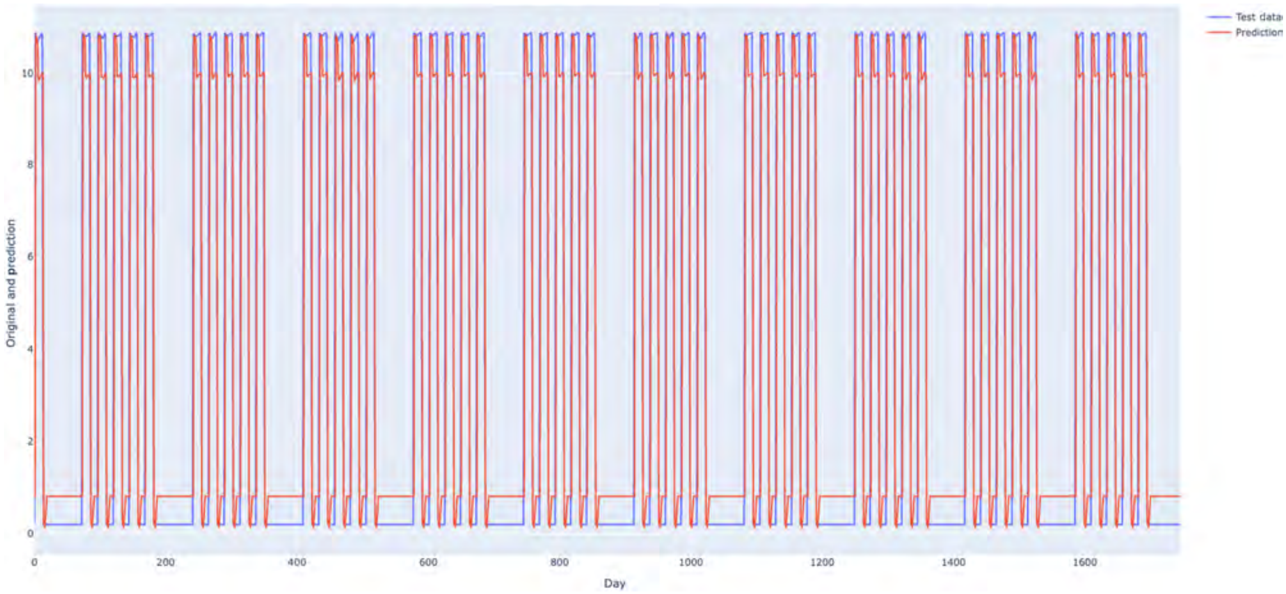

Fig. 12 Original vs. prediction for power electricity.

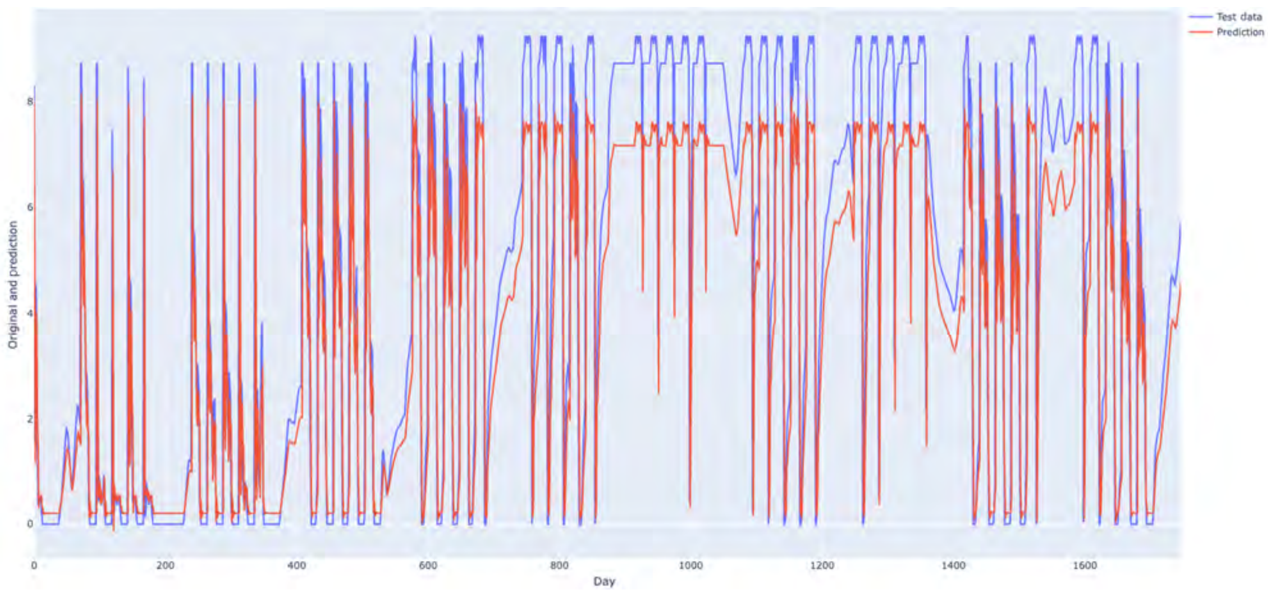

Fig. 13 Original vs. prediction for heating power.

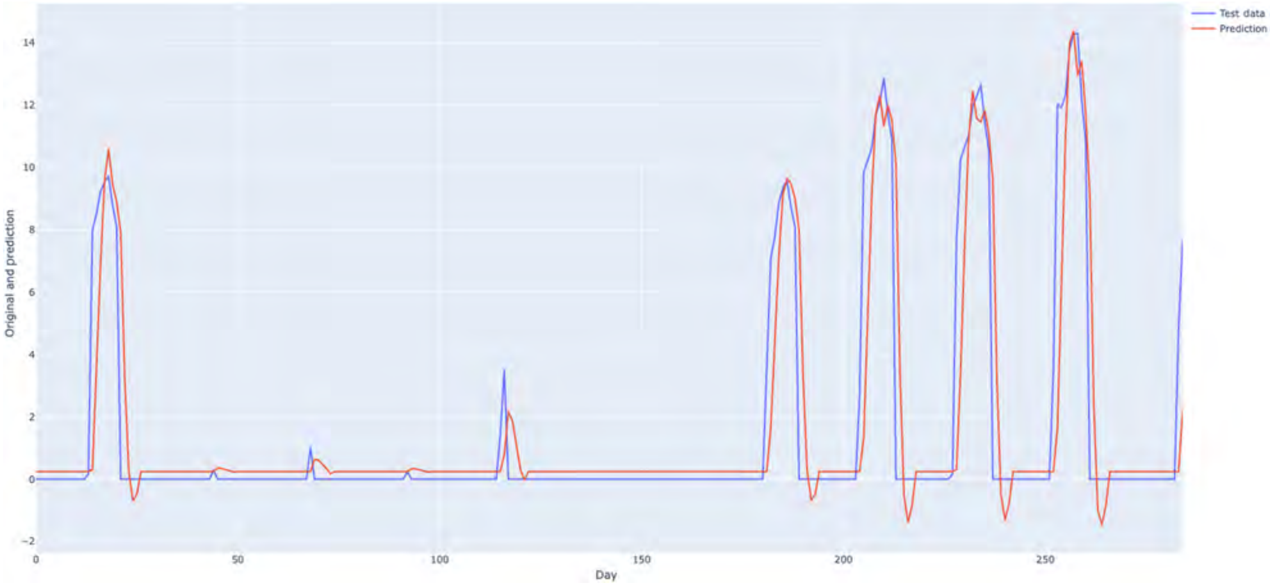

Fig. 14 Original vs. prediction for cooling power.

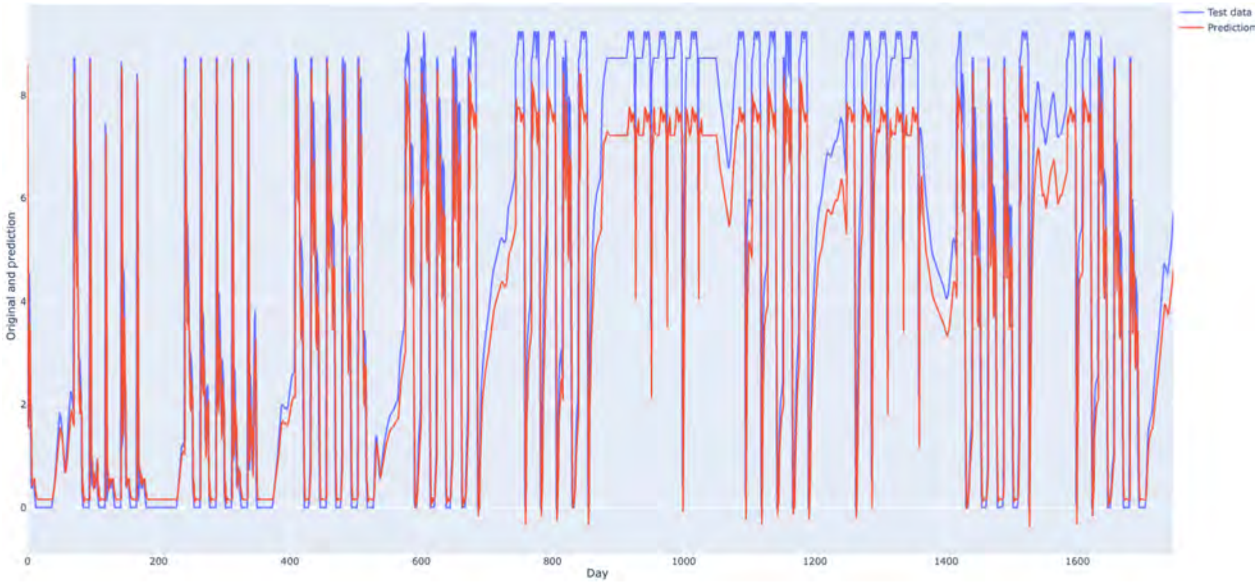

Fig. 15 Original vs. prediction for total power.

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