Proceedings of the 4th International Conference on Mechatronics and Smart Systems
DOI: 10.54254/2755-2721/2026.35329

Smart Building Cooling Load Prediction Based on GWO-CNN-LSTM

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Abstract. To improve the energy-saving effect of buildings, we need to know how much electricity will be used in advance; that is, we should be able to accurately predict the electricity demand of different branches. However, due to the irregular and complex changes in the time of electricity demand, it is very difficult to accurately forecast the cooling load. Therefore, a combination of forecasting methods was used in this study to solve this problem, and the results are as follows: First, a detailed 3D model of the building is constructed to collect all kinds of data on cooling load, and then a new method integrating Grey Wolf Optimizer (GWO), Convolutional Neural Networks (CNN) and Long Short-Term Memory networks (LSTM) is trained and tested; this method has been named the GWO-CNN-LSTM model, and it can solve problems such as irregular timing and prediction difficulty. After training, a simple optimization algorithm is employed to automatically tune the hyper-parameters of the combined network and connects the feature extraction part with the memory function of the sequence processor; through this combination, the model can better seize not only the long-term trend but also a short-term fluctuations of load data, and it has performed reasonably well compared to previous reference models and generated slightly more accurate calculations; thus, it can be concluded that this GWO-CNN-LSTM forecasting approach is relatively reliable and can provide data support for optimising AC system operation and promoting building energy conservation.

Keywords: cooling load, load prediction, forecasting, GWO-CNN-LSTM model

1. Introduction

Getting the building's cooling needs right is a must, as it can save energy and help the heating and cooling equipment work normally ; as many papers have pointed out, older methods that use physics rules to predict these requirements do have a solid foundation,they consume too much computer resources and take too long to run; therefore, they can not meet the demand for speed in real construction work [1-4]. Because of this, people began to focus on ways that simply learn from old data, and this has become the main way researchers work now to predict building energy consumption, even these smart computer models have a significant problem: how well they perform depends greatly on how you set their parameters, and manual adjustment is often just a guess, leading to uncertain results, some people have tried using smart search techniques such as PSO or GA to tune these parameters, no one has genuinely applied the Grey Wolf Optimizer, or GWO, in

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combined with CNN and LSTM for cooling load prediction, and systematic comparisons with other hybrid models remain limited comparison with other combined setups [5-8].

This paper attempts to build one of these mixed models and calls it GWO-CNN-LSTM, hoping it will work; the main additions are two parts: first, it uses the GWO trick to automatically set the best knobs for the CNN-LSTM network to try and speed up the training and improve the accuracy of the guesses; Second, it places this model alongside simple ones such as plain LSTM or plain CNN to see if it can better capture both the slow changes and the sudden jumps in the cooling data [9, 10].

2. Process design

2.1. Multi-software modeling process

Workflow has been built to use SketchUp, OpenStudio and EnergyPlus for building an energy model; SketchUp is used as a drawing environment to create the 3D shape of a building, and it can be easily connected with the OpenStudio add-on to add other information, such as building materials and thermal zones; OpenStudio is in the middle, and based on using the 3D model as input, various parameters of the building are set, such as how the building envelope is constructed, what internal internal loads, operating schedules and HVAC layouts are configured to generate simulation input files simulation are generated, then EnergyPlus is employed to perform calculations and determine energy consumption and loads based on factors such as heat transfer, air movement and system logic, etc., so the entire process is relatively easy to operate and avoids manual data entry errors.

2.2. Convolutional neural network

A Convolutional Neural Network (CNN) is a particular kind of feedforward neural network that has a convolutional part, pooling sections and fully connected layers; it has the characteristics of local connections, shared weights and pooling steps to reduce overall complexity and the total number of parameters, enabling effective extraction of position-invariant features through hierarchical learning and achieving some success and breakthroughs in the field of picture recognition and object detection, a drawing of the structure of architecture is shown in Figure 1 [11, 12].

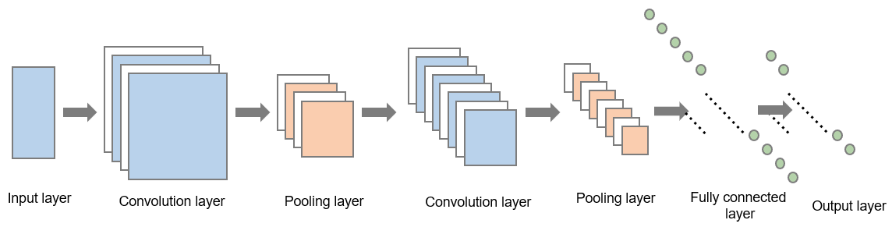

Figure 1. CNN architecture

2.3. LSTM neural network

LSTM has been used to address the problem of vanishing or exploding gradients during training, and it has a gate structure; that is to say, there is a memory component called the cell state. By performing various operations on the cell state over time, some information can be retained, updated or forgotten; thus, this network has the ability to learn long-term dependencies in sequential data. The structure of a single LSTM unit is shown in Figure 2 [13, 14].

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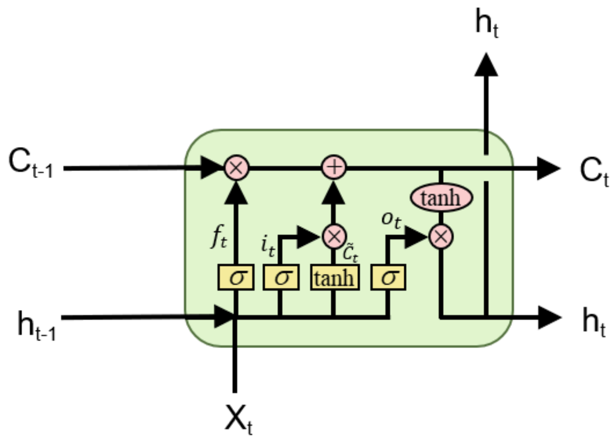

Figure 2. Framework of the LSTM basic unit

The forget gate of one LSTM basic cell determines how much of the previous memory should be kept in the last memory state, and the input gate decides how much date to the current state; the candidate part provides new data for memory update. Through this gated flow, the unit can remember important timing information and block irrelevant or redundant data.

The amount of cooling load at different times is often caused by many reasons, such as changes in the external environment, people's use of the building and various activities carried out by occupants; thus, it is irregular and difficult to predict. Given that LSTM networks are capable of handling long-term dependencies in data, they can identify periodic cycles and the long-term effects of weather fluctuations; therefore, models based on LSTM have achieved good results in predicting cooling loads accurately [15, 16].

2.4. Grey Wolf Optimizer

Mirjalili and others proposed the Grey Wolf Optimizer, or GWO for short, which is essentially a way to find good answers by imitating the behaviour of grey wolves in nature, and this method has been popular because it is simple to use, easy to implement, and requires relatively few parameter adjustments; therefore, it has been applied extensively in all sorts of applications [17, 18]. Within this framework, each wolf represents a potential solution being tested, the prey is the desired optimal solution we aim to find, and all the wolves are ranked based on their fitness; among them, the top one is designated as alpha, the next two as beta and delta, and all others as omega, and during the search, the top wolves guide the omegas to move towards the good areas. The whole search has three sections, which are to circle the prey, to hunt it actively, and to move in for the attack; in the first part, the wolves move based on where they believe the prey is, although no one knows the exact location, so the algorithm only uses the top three wolves to guess the position; then, in the hunting stage, the rest of the pack follows the direction of the alpha, beta, and delta wolves, which helps the search cover new areas and also inspect nearby spots, and finally, in the attack phase, the area being observed shrinks gradually with each step, forcing everyone to get closer to the best answer they have found.

Given all of the above, by learning how grey wolves rank each other and hunt together, GWO can also do a good job finding an optimal combination of model parameters; therefore, in this paper, an optimizer is used to tune the main knobs of the prediction setup to improve the accuracy of the guesses and maintain overall stability of the system [19, 20].

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3. Simulation analysis and discussion

3.1. Load simulation

A 3D building model was made in SketchUp, and then this model was imported into OpenStudio; at that time, many other information, such as the outside structure and material, thermal performance, internal load distribution, operation schedule, etc., were introduced as input for simulation [21]. In Table 1, the location of this simulation was set as 39.8° N, 116.47° E, and the simulation was run from April 1st to the end of September; a VAV system with reheat was employed, and some components such as a chiller, heating and cooling coils, speed-changing pumps and fans, a boiler, and a cooling tower were added ; the entire floor area is 123.68 square meters, with a length of 13.35 meters and a width of 6.68 meters; In Figures 3 and 4, the EnergyPlus model built with SketchUp is presented.

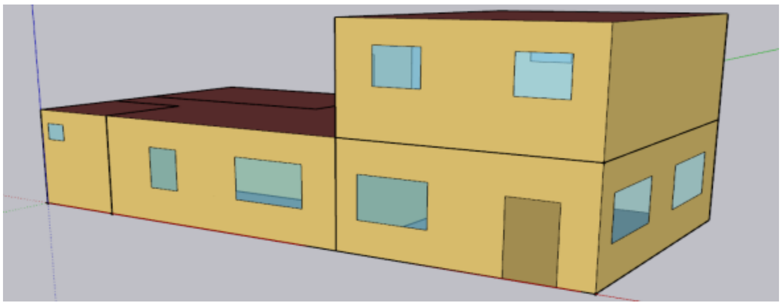

Figure 3. Model of a building (front view)

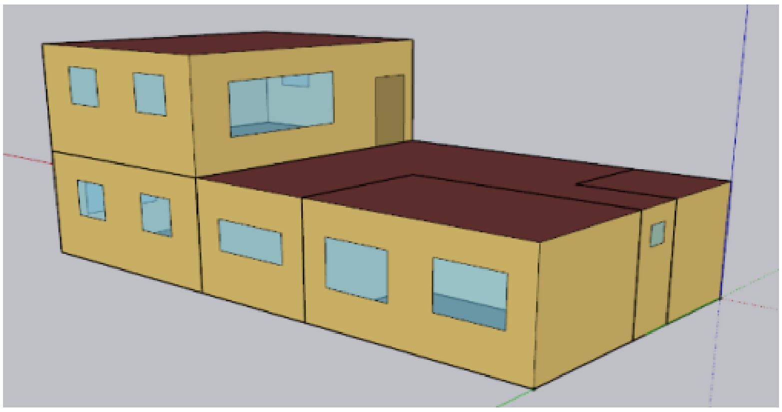

Figure 4. Model of a building (rear view)

Table 1. Simulation parameters used in AnyCasting

Integration	Feed stock	Bulk (mm)	Density (kg/m³)	Thermal permeability [W/(m·K)]	Heat capacity [J/(kg·K)]	Thermal transmittance W/(m²·K)
	EPS Insulation Board	40	30	0.042	1380	
Outer wall	Cement mortar	25	1800	0.93	1050	0.79
	Reinforced concrete	200	2500	1.74	1050	

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Table 1. (continued)

Roof	Fine aggregate concrete	40	2300	1.51	920	0.77
	Extruded Polystyrene Board	40	30	0.042	1380	
	Cement mortar	20	1800	0.93	1050	
	Cement slag	30	1300	0.52	980	
	Reinforced concrete	120	2500	1.74	920	
Floor	Concrete slab	120	2500	1.74	925	1.32
	Vapor barrier	30	30	0.047	1460	
	Particle layer	50	2500	1.74	925	
	Screed	20	1800	0.93	837	
	Cement mortar	20	1800	0.93	1050	
Interior wall	Autoclaved aerated concrete	200	760	0.25	1000	1.19
	Cement mortar	20	1800	0.93	1050	

In Figure 5, the building's simulated cooling load profiles are displayed.

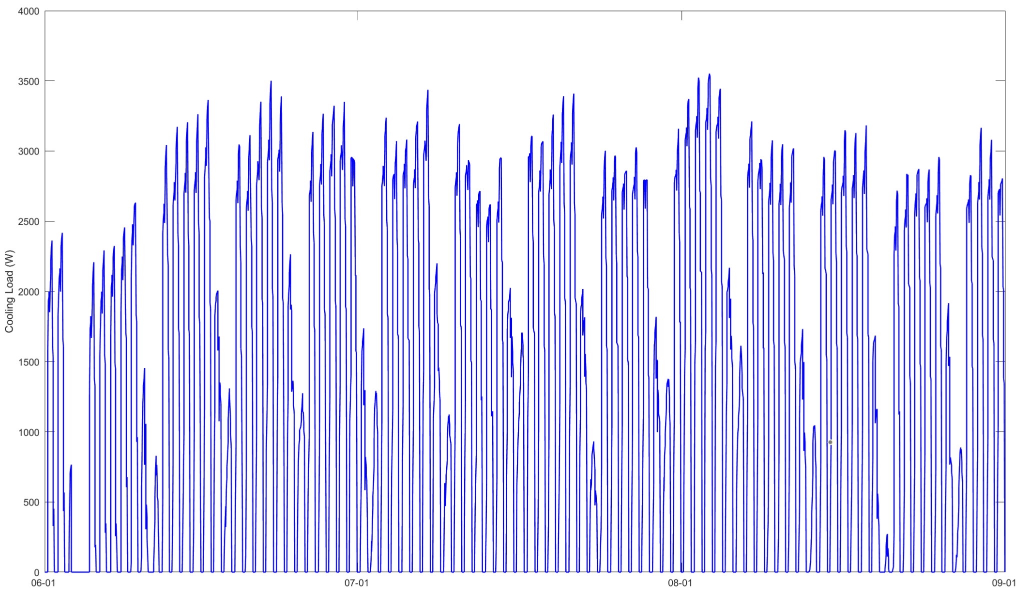

Figure 5. Building cooling load simulation

Later, for the cooling load forecasting section, the researchers took the data from the summer months in the study area as June, July and August, to construct and test the prediction model.

3.2. Factor selection for cooling load forecast

When building a data analytics , one must select suitable input variables to improve the accuracy of the prediction and enhance the performance of the model with new data; the Pearson correlation coefficient is a numerical rule used to identify which input variables are closely associated with building cooling loads, and this number can indicate changing factors; it will always be between -1

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and 1; if the number is closer to 1, the correlation is strong; if it is positive, the two factors move together; otherwise, if it is negative, they move in opposite directions. After examining the numbers, seven factors were selected as the input variables due to their close correlation with the cooling load; they are the load from one hour ago (0.921), two hours ago (0.816), the total sunlight reaching the ground (0.628), the outside air temperature (0.613), scattered sunlight (0.558) and outside temperature from the previous hour (0.534) [22], and these results are shown in Figure 6.

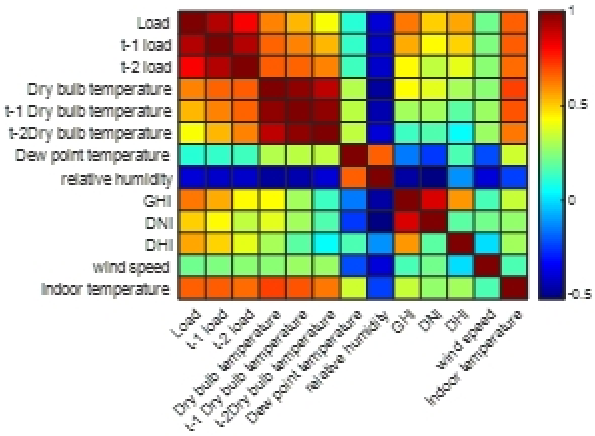

Figure 6. Pearson correlation heatmap

3.3. Comparative analysis

As shown in the three models in Figure 7, GWO had the best performance with an R^2 of 0.9118; it is close to the fluctuations of the actual load, can handle both sudden increases in demand and periods of low demand reasonably well, and maintains accuracy over time with a relatively small error. LSTM was the second best, with an R^2 of about 0.886; although it can capture the general trend, it has some issues in responding to abrupt changes and extreme points compared with GWO; CNN performed poorly and reached only 0.6409, showing a weak fit; its predictions often fell short during peak load times and missed minor patterns, so it was not very in line with the actual data; overall, GWO was more reliable for forecasting cooling load, LSTM did moderately well, and CNN did not appear to be suitable unless significant redesign or more extensive training was carried out.

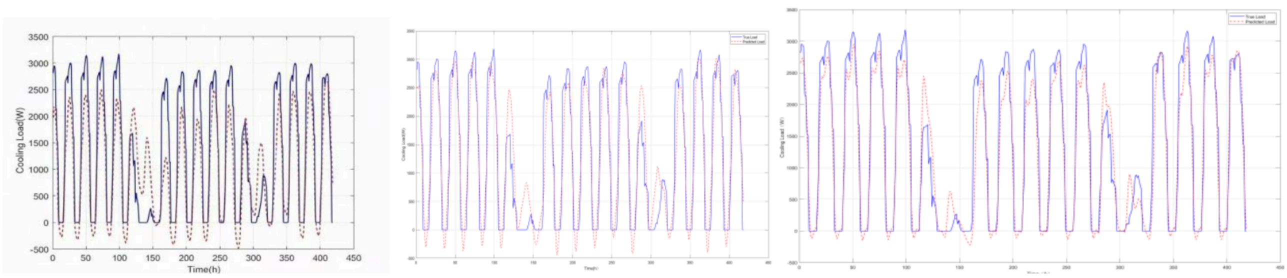

Figure 7. Comparative analysis of GWO, LSTM, and CNN in cooling load prediction

4. Conclusions

A new model, GWO-CNN-LSTM, has been constructed in this paper to predict the cooling demand of buildings, and a 3D model was also built with SketchUp, and the necessary data were obtained through simulating, (GWO) was used to optimize the parameters of the CNN-LSTM network to help the model capture local details and long-term trends in the data, and after comparison with other

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methods such as a simple LSTM, basic CNN-LSTM and PSO-tuned versions, it was found that the new model performs better; these results show that it can be used as a data-driven method to achieve achieve more accurate cooling load prediction and support building energy conservation.

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