Journal of Network Intelligence ©2025 ISSN 2414-8105
Taiwan Ubiquitous Information Volume **10**, Number **1**, February **2025**

Energy Efficiency Prediction of Assembled Concrete Buildings Based on Deep Recurrent Neural Networks

Cun-Li Shen*

Architectural Engineering Institute
Chongqing Industry & Trade Polytechnic, Chongqing 408000, P. R. China
shencunli_edu@163.com

Huan-Bin Zhang

College of Information Science
Adamson University, Ermita, 1000 Metro Manila, Philippines
td0508@163.com

*Corresponding author: Cun-Li Shen
Received March 1, 2024, revised May 30, 2024, accepted July 2, 2024.

Abstract. *Assembled concrete buildings usually have better thermal insulation and sealing properties, which can effectively reduce building energy consumption and carbon emissions during the production phase. By studying and predicting the energy-saving performance of assembled concrete buildings, it can provide designers with a more accurate assessment of energy consumption. However, the energy-saving performance of assembled concrete buildings is affected by a variety of factors, and the prediction of energy-saving needs to take into account the interactions of multiple factors, which requires a high level of model accuracy. Therefore, this work proposes a deep recurrent neural network-based energy efficiency prediction for assembled concrete buildings. First, the construction process of assembled buildings is divided into five stages according to the modelling principles. According to the characteristics of each stage, the calculation methods of carbon emissions of the five sub-parts were established, and the carbon emission factors corresponding to different subjects were sorted out, which were used as the theoretical basis of the subsequent carbon emission prediction model. Then, Antisymmetric Recursive Neural Network (ARNN) is used to build a deep learning environment for building energy efficiency prediction. Meanwhile, after analysing the working principle of the attention mechanism in deep learning, it is proposed that Global Attention Mechanism (GAM) is introduced in ARNN, so that the model pays more attention to the part of the input sequence with important information. Finally, the proposed GAM-ARNN model is compared with a variety of other prediction models through 15 assembly building case base data. The experimental results show that the proposed GAM-ARNN model is the optimal model, and the error between its predicted data and the measured data of the carbon emission factor method is 1.19%, which is significantly lower than that of other prediction models.*
Keywords: Assembly building; Energy efficiency prediction; Deep recurrent neural network; ARNN; Attention mechanism

1. **Introduction.** With the intensification of global climate change and energy crisis, the construction industry is under tremendous pressure to reduce energy consumption and minimize environmental impacts [1, 2]. For this reason, energy-efficient buildings have become an important trend in global building development, and assembled concrete

buildings have attracted much attention due to their fast construction, low energy consumption, and low life cycle cost. Assembled buildings are constructed by prefabricating building components in a factory and then transporting them to the site for assembly, as a way to shorten the construction cycle and reduce energy loss and environmental pollution caused by on-site construction [3]. However, accurately predicting the energy consumption of assembled concrete buildings plays a crucial role in achieving energy-saving goals, guiding energy-saving design and evaluating energy-saving effects [4]. Therefore, investigating how to accurately predict the energy consumption of assembled concrete buildings has become an important issue in this field [5], especially predicting the energy consumption under the changing building operation environment and uncertain natural climate conditions.

An in-depth study of energy efficiency prediction of assembled concrete buildings can not only help building designers and builders to optimize building design and select more efficient materials and technologies [6, 7], but also provide empirical support for policy makers to develop more reasonable energy efficiency standards and codes. In addition, because of the tremendous advancement of technology in artificial intelligence in recent years, how to use advanced machine learning models, such as BP neural networks, to improve the accuracy and generalization ability of prediction models has become a hot research issue in related fields. The application of such methods not only promotes the development of intelligent building technology, but also has important theoretical and practical significance in promoting sustainable building practices and achieving the goal of green and low-carbon development. Therefore, this study aims to explore the use of deep recurrent neural networks to establish an energy-saving prediction model for assembled building projects and carry out example measurements through Python software modeling, with the aim of accurately and effectively predicting carbon emissions in the materialization phase.

1.1. **Related work.** At present, foreign scholars have conducted a large number of studies on the management of building energy efficiency [8, 9, 10], mainly focusing on the following carbon emission measurement and influence factors.

The term "building construction process" refers to the process of constructing a structure from the ground up. This process includes the stages of producing and processing building materials, transporting building materials, and constructing the building on-site. One of them is the manufacturing stage of construction materials, which is responsible for a greater share of the total carbon emissions across the whole life cycle. One of the most important aspects of energy efficiency management is the investigation of methods for reducing carbon emissions throughout the building construction process. Jaillon and Poon [11] studied the energy-saving aspects and environmental impacts of an assembled building and concluded that the environmental impacts were 72% during the raw material production phase and 23% during the use phase. The construction and end-of-life recycling phases contributed very little to the total impact as they accounted for 1% and 3% respectively. Matic et al. [12] discussed the carbon emissions of a single assembled building using the carbon emission factor method. In order to simplify the carbon emissions of the physical phase, they were converted into those of the manufacturing of construction materials, building materials transportation and construction building, and the emission reduction effect of projects with different assembly rates was analyzed according to the consumption of reinforcement bars, concrete consumption, etc. Duan et al. [13] used the Life Cycle Assessment (LCA) to establish a quantitative measurement model of carbon emissions, and classified the physical phase into the production of raw materials, manufacture of components or materials processing, transportation on-site assembly and construction.

Research has found that the key point of efficient energy saving and carbon reduction is to implement the factors that affect energy consumption and carbon emission. Most of the studies have analyzed a certain part of energy consumption and carbon emissions from a whole life cycle perspective. Liu et al. [14] proposed an energy saving and carbon emission reduction influencing factor system based on Building Information Modelling (BIM) by combining construction dynamic simulation and using IT tools to analyze the energy saving performance in terms of building design. Tan et al. [15] constructed a BIM based conceptual model for carbon emission measurement in the whole life cycle [16] of assembly projects. Fitriaty and Shen [17] used Revit software to build a model to estimate the energy consumption by predicting the number of photovoltaic panels required for a net-zero-energy building in order to achieve a balanced energy consumption. Xu and Yuan [18] improved the envelope design parameters, optimized the floor plan layout and utilized natural ventilation to effectively reduce the carbon emissions of the building. Sun [19] developed a building energy consumption prediction model based on the BP neural network, and the results showed that the relative error between the predicted output of the BP neural network and the simulated value was within 4%.

Deep Recurrent Neural Networks (DRNN) have a significant advantage over traditional BP neural networks in terms of their ability to model time-series data [20, 21]. DRNNs are particularly good at dealing with time-series data because they can convey information in the temporal dimension, thus capturing the time-dependence and dynamics in the data. DRNNs can continually update their state to reflect the latest received information, which is particularly valuable for real-time energy consumption prediction. In BP networks, it is usually necessary to retrain the entire model to adapt to new data, which is a more static process [22].

1.2. **Motivation and contribution.** Since building energy consumption prediction often involves time-series data (e.g., historical energy consumption records, time-dependent environmental variables, etc.), DRNN are able to model such dependencies more accurately. DRNN are able to automatically extract and learn higher-order features from raw data through their multilayer architecture. In the context of energy efficiency prediction for assembled concrete buildings, this capability is particularly beneficial in discovering and modeling complex and non-linear patterns in energy consumption behavior, which are difficult to capture by BP neural networks. Therefore, this paper computationally uses DRNN for energy efficiency prediction of assembled concrete buildings. The main innovations and contributions of this work include:

(1) Aiming at the problem of theoretical support for the carbon emission prediction model, this paper makes modifications on the basis of the theory of carbon emission coefficient, gives the calculation method of carbon emission of five subcomponents, and analyzes the carbon emission factors corresponding to human beings and machinery.

(2) For the problem of selecting the influencing factors of the energy-saving model, the literature analysis method is used to initially find the factors affecting the carbon emissions of assembled buildings. Then, according to the results of the correlation test, the strength of the correlation between the influencing factors and carbon emissions is judged. Finally, 8 key influencing factors are screened out from 23 influencing factors of carbon emission.

(3) Aiming at the problem of low prediction accuracy of traditional BP neural network models, it is proposed to use Antisymmetric Recursive Neural Network (ARNN) to build a deep learning environment for building energy efficiency prediction. At the same time,

it is proposed that Global Attention Mechanism (GAM) is introduced in ARNN. Factors such as floor area and number of building floors are used as input variables of the GAM-ARNN model, and the unilateral carbon emissions from building production buildings are used as output indicators.

2. Principles related to energy efficiency in assembled concrete buildings.

2.1. Calculation of carbon emissions during construction. The energy saving modelling of assembled concrete buildings mainly addresses the issue of carbon emissions. In the construction process of assembled buildings, the types of materials and data sources are not easy to determine, and there are many unpredictable situations, so the carbon emission study is a cumbersome process. The accurate collection of carbon emission data must be based on the characteristics of the assembled building, and it must be clear that the key point of measurement is the determination of the calculation method and carbon emission factor in the construction process. Assembled concrete buildings generate carbon emissions at multiple stages throughout their life cycle.

Directly calculating the carbon footprint of a building at different stages will help to further evaluate its sustainability. In this paper, we refer to the formulas used in life cycle assessment and use the energy consumed in the production, transportation and construction of materials, combined with their carbon dioxide equivalents, to obtain the carbon emissions at different stages. The basic principle of the carbon emission factor method is as follows:

$$C = A \times f \tag{1}$$

where C denotes total carbon emissions; A denotes consumption data for each phase of activity; and f denotes the carbon emission factor.

In this paper, the carbon emission coefficient is used as the theoretical basis to study the carbon emission of assembled concrete buildings. According to the specific needs of the research project, modifications are made on the basis of the theory of carbon emission coefficient, as follows.

$$C = C_1 + C_2 + C_3 + C_4 + C_5 \tag{2}$$

where C denotes the total carbon emission during the construction process; C_i represents the carbon emission in the stage i, $i = 1, 2, \dots, 5$.

It can be seen that the carbon emissions of assembled concrete buildings during the construction process mainly involve the following stages.

(1) Raw material production stage

The raw material production phase includes the production of concrete raw materials (cement, sand, aggregates, etc.), which are usually accompanied by energy consumption and emissions. This phase is calculated as follows:

$$C_1 = \sum Q_a \times EF_a \tag{3}$$

where C_1 denotes the total carbon emission in the production stage of raw materials; Q_a denotes the demand of the a-th building material; EF_a denotes the carbon emission factor of the a-th material.

(2) Raw material transport phase

The transport of raw materials from the place of production to the site consumes a certain amount of energy, for example, the process of transporting materials such as cement and aggregates. In the study, secondary transport and vehicle return trips are ignored. The default length of construction materials is 40 kilometres when the actual distance of transport of building materials is uncertain.

$$C_2 = \sum Q_b \times L_b \times EF_b \tag{4}$$

where C_2 denotes the total carbon emission at the material production stage; Q_b denotes the consumption of the b-th building material; L_b denotes the transport distance of the b-th building material; and EF_b denotes the carbon emission factor of the b-th building material.

(3) Production stage of assembled concrete components

The production phase of assembled concrete components includes the production and installation process of assembled concrete components, which involves energy consumption and emissions, especially for production processes and equipment. BIM software can be used to derive formwork quantities, component quantities and reinforcement quantities. The consumption data for the prefabricated component production stage is obtained by converting according to the corresponding quotas. Carbon emissions at this stage include the centralised processing of ready-mixed concrete at the component plant.

$$C_3 = Q_c \times EF_c + \sum Q_d \times EF_d + \sum Q_e \times EF_e \tag{5}$$

where C_3 denotes the total amount of carbon emissions in the prefabricated component production stage; Q_c denotes the number of working days of assembly workers in the prefabricated component production stage; EF_c denotes the carbon emission factor of assembly workers in the prefabricated component production stage; Q_d denotes the consumption of construction materials of category d; EF_d denotes the carbon emission factor of construction materials of category d; Q_e denotes the consumption of equipment and machines of category e; EF_e denotes the carbon emission factor of equipment and machines of category e.

(4) Precast transport phase

Carbon emissions from the transport of prefabricated components refer to the horizontal transport of prefabricated components on the road from the component plant to the construction site. Because prefabricated components are large in size and are not easy to transport, load and unload, they are usually transported close to the component plant. According to the survey results, the reasonable transport distance is 50-120 km, and in this study, the basic transport distance is 100 km by default, regardless of the type of components.

$$C_4 = \sum Q_f \times L_f \times EF_f \tag{6}$$

where C_4 denotes the total carbon emission in the prefabricated parts transport stage; Q_f denotes the consumption of the f-th construction material; L_f denotes the transport distance of the f-th construction material; and EF_f denotes the carbon emission factor of the f-th construction material.

(5) On-site assembly construction stage

Carbon emissions during the on-site assembly construction phase are created by the on-site construction of concrete and the on-site assembly construction of precast elements.

$$C_5 = Q_g \times EF_g + \sum Q_h \times EF_h + Q_i \times EF_i + \sum Q_j \times EF_j \tag{7}$$

where Q_g denotes the number of working days of workers in the concrete pouring project; EF_g denotes the carbon emission factor of workers in the concrete pouring project; Q_h denotes the consumption of mechanism in the category h of concrete pouring project;

EF_h denotes the carbon emission factor of machinery and equipment in the category h of concrete pouring project; Q_i denotes the number of working days of workers in the precast installation project; EF_i denotes the carbon emission factor of workers in precast component installation projects; Q_j denotes the consumption of equipment and machinery of category j in precast component installation projects; EF_j denotes the carbon emission factor of equipment and machinery of category j in precast component installation projects.

2.2. **Carbon emission factors.** "Carbon emission factor" means a numerical coefficient used to calculate and estimate direct or indirect greenhouse gas emissions from an activity. For example, if the combustion of one ton of coal produces about 3 metric tons of carbon dioxide, the carbon emission factor for coal is 3 tons of CO_2 per ton of coal. The carbon emission of construction machinery is related to its frequency of use, working hours and fuel type. Transport equipment includes all kinds of lorries, cranes, transport ships, etc., which are used for transporting raw materials and equipment in the construction process. Carbon emissions from transport equipment mainly originate from exhaust gas emissions from fuel combustion, including carbon dioxide, nitrogen oxides, and so on. For different types of machinery, their carbon emission factors will vary, so the type of energy consumed needs to be considered in the calculation process. The carbon emission factors for machinery and transport equipment are calculated as follows:

$$EFN = \sum QN_i \times EFN_i \tag{8}$$

where QN_i denotes the i-th consumed energy type; EFN_i denotes the carbon emission factor of the i-th energy source.

3. **Construction of energy efficiency prediction models for assembled concrete buildings.**

3.1. **Analysis of influencing factors for energy saving modeling.** In this work, the carbon emission factor method is applied to analyse the energy efficiency of 15 assembled concrete building cases, and the most influential energy efficiency influencing factors are summarised, thus providing input parameters for the subsequent deep recurrent neural network prediction model.

This paper uses literature analysis to accurately and objectively find the factors affecting carbon emissions from assembly buildings. Firstly, the scope of the carbon emission problem of assembled buildings is clarified, as well as the related keywords. For example, the keywords "assembly building", "carbon emission", "influencing factors", etc. are used to search relevant literature. Then, academic databases (e.g. Google Scholar, Web of Science, Scopus, etc.) or library resources were used to search for literature related to carbon emissions from assembly buildings. Search according to the keywords and filter the literature related to this work. Read the screened literature, focusing on the descriptions, analyses and discussion sections of the literature on the factors affecting carbon emissions from assembly buildings. Summarise and refine the carbon emission influencing factors of assembled buildings involved in each literature, including factors in various aspects of the production stage, transport stage, construction stage and use stage, and categorise and summarise them.

The correlation between the influencing factors and carbon emissions of assembled buildings was examined using the Spearman rank correlation coefficient of SPSS.20 software. The linear relationship between them was assessed by calculating the correlation coefficient. According to the results of the correlation test, the strength of the correlation between each influence factor and carbon emissions is judged. When the significance

$p < 0.05$, the correlation is considered significant, indicating that the factor is significantly related to carbon emissions. Eventually, 8 key influencing factors were screened out from 23 influencing factors of carbon emissions, as shown in Table 1.

Table 1. Key Influences on Energy Efficiency and Carbon Reduction

Serial number	**Variable name**	**Factor name**
1	X_1	Building area
2	X_2	Storey
3	X_3	Building height
4	X_4	Labour consumption
5	X_5	Reinforcing steel consumption
6	X_6	Concrete consumption
7	X_7	Prefabricated building block
8	X_8	Mechanical consumption
9	Y	Unilateral carbon emissions

3.2. **Deep recurrent neural network.** DRNN is a neural network model that combines deep learning and RNN for processing sequence data and capturing long-term dependencies in sequences [23, 24]. Compared to traditional RNN models, DRNN increases the depth of the model by stacking multiple recurrent layers, which improves the model's ability to model sequence data. DRNN creates a depth structure by stacking multiple recurrent layers (RNN layers or LSTM layers) together [25]. Each loop layer accepts the hidden state of the previous moment as input and outputs the hidden state of the current moment, by which the sequence data is processed step by step.

Antisymmetric Recursive Neural Network (ARNN) is a neural network structure for processing sequence data [26], which is mainly used to learn long-term dependencies in sequence data. Compared with the traditional RNN or LSTM, ARNN solves the problems of gradient vanishing and gradient explosion to a certain extent, and is able to better capture the features in sequence data. Therefore, this paper tries to adopt ARNN to achieve energy efficiency prediction of assembled concrete buildings.

ARNN is a tree-based neural network that represents the syntactic structure of an input sequence by recursively combining subtrees. Each node has a vector representation of its own features and builds up the overall representation by combining the representations of the sub-nodes. ARNN takes full advantage of ordinary differential equation stability to capture long-term dependencies in time series data. An ordinary differential equation is a special kind of dynamic system that contains only one variable, namely time t. The first order ordinary differential equation is shown below:

$$h'(t) = f(h(t)) \tag{9}$$

When time $t \geq 0$, then $h(t) \in \mathbb{R}^n$, $\mathbb{R}^n$ denotes the n-dimensional Euclidean space; and f is the mapping from the open domain in $\mathbb{R}^{n+1}$ to $\mathbb{R}^n$.

The problem of solving a function $h(t)$ given an initial condition $h(0)$ is known as the initial value problem for a differential equation. However, for most ordinary differential equations there is no analytical solution. It is common to use numerical methods to discretise a continuous problem, and then find a numerical solution for the discrete nodes as an approximate solution to the ordinary differential equation. The forward Euler method is the most representative numerical solution method.

In the forward Euler method, if the derivative of the function $h(t)$ at the point $t-1$ is replaced by a two-point equation.

$$h'(t-1) \approx \frac{h(t) - h(t-1)}{\varepsilon} \tag{10}$$

where ε is a positive number that converges to 0 infinitely. Replacing $h(t)$ with an approximation of h_t, the initial value problem becomes.

$$\begin{cases} h_t = h_{t-1} + \varepsilon f(h_{t-1}) \\ h_0 = h(0) \end{cases} \tag{11}$$

where ε is called the step size.

Then, for the ordinary differential equation $h'(t) = \tanh(Wh(t))$, the approximate solution obtained using the forward Euler method is.

$$h_t = h_{t-1} + \varepsilon \tanh(Wh_{t-1}) \tag{12}$$

Equation (12) can be viewed as a RNN without input data. Here h_t is the hidden state at step t, W is the model parameter, and ε is the hyperparameter. This provides a general framework for designing recurrent neural network structures via discrete ordinary differential equations.

In numerical analysis, stability theory studies the stability of solutions of ordinary differential equations when the initial conditions are subjected to small perturbations. That is, a solution to an ordinary differential equation is considered stable when the long-term behaviour of the system is independent of the initial conditions. Ideally this means that the real part of the eigenvalues of the Jacobi matrix is made to approximate 0, i.e. the system is critically stable. Under such conditions, the system is able to remain stable while maintaining long-term dependence on the inputs. The eigenvalues of the antisymmetric matrix, on the other hand, are all 0 or purely imaginary, so that the antisymmetric matrix can be used to construct the ideal ordinary differential equation.

$$h'(t) = \tanh\left((W_h - W_h^T)h(t) + V_h x(t) + b_h\right) \tag{13}$$

where $(W_h - W_h^T)$ is the antisymmetric matrix.

Discretising Equation (12) using the forward Euler method gives ARNN as follows:

$$h_t = h_{t-1} + \varepsilon \tanh\left((W_h - W_h^T)h_{t-1} + V_h x_t + b_h\right) \tag{14}$$

where $h(t) \in \mathbb{R}^n$ is the hidden state at moment t; $x(t)$ is the input term at moment t; $W_h \in \mathbb{R}^{n\times n}$, $V_h \in \mathbb{R}^{n\times m}$ and $b_h \in \mathbb{R}^n$ are the parameters of the network; ε is a hyperparameter indicating the learning rate of the neural network.

Since the antisymmetric matrix $W_h - W_h^T$ has only $\frac{n(n-1)}{2}$ degrees of freedom, it can be parameterised as an upper triangular matrix with the main diagonal elements all being 0 when implementing the building energy efficiency prediction model, which reduces the model parameters of ARNN by half, and makes the learning efficiency higher.

3.3. **ARNN with global attention mechanism.** In this paper, ARNN is used to implement energy efficiency prediction for assembled concrete buildings. However, ARNN may suffer from the local attention problem when dealing with long sequence data, i.e., the model only focuses on part of the input data to play a role in the prediction, while ignoring other important information. Therefore, this paper proposes to introduce the global attention mechanism into ARNN and proposes GAM-ARNN. GAM-ARNN model can dynamically adjust the attention weights according to different parts of the input data in order to capture the key features in the whole sequence. The GAM model can help the ARNN model to pay more attention to the parts of the input sequence that have important information, thus improving the learning efficiency and generalisation capability, as shown in Figure 1.

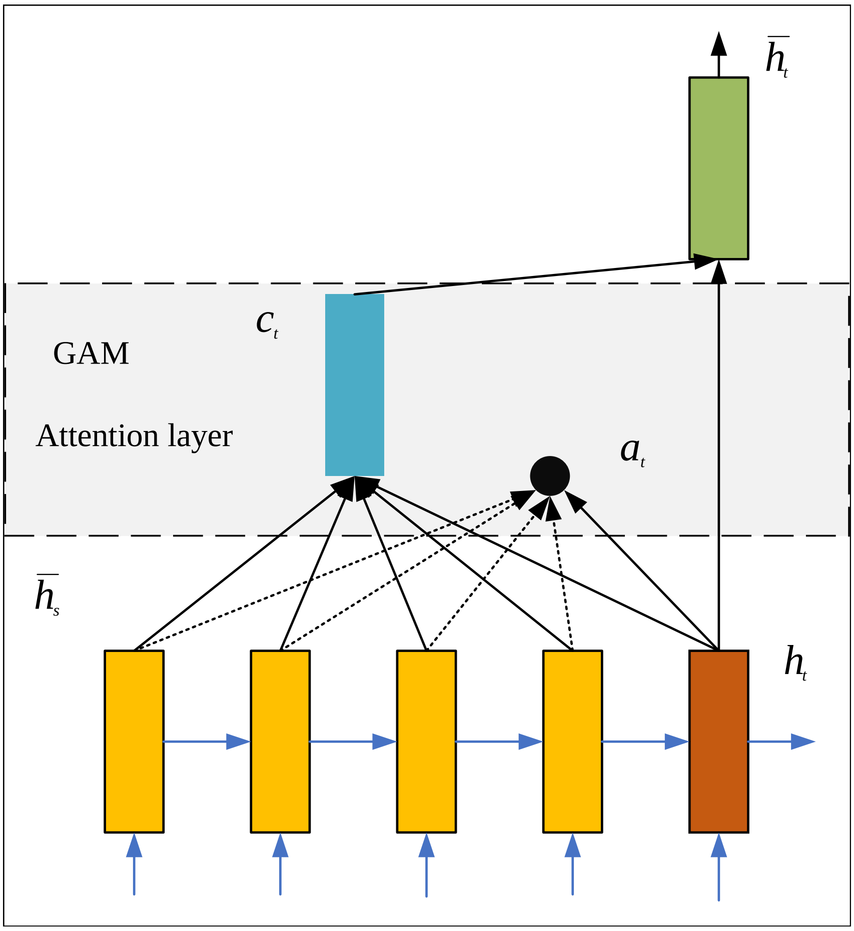

Figure 1. Global attention mechanism

The global attention mechanism adds an attention layer on top of ARNN, where $\bar{h}_s$ is the source hidden state, h_t is the current target hidden state, a_t is the alignment weight, c_t is the context vector, and $\bar{h}_t$ is the attention hidden state. The attentional model calculates the similarity between the current target state h_t and all source states $\bar{h}_s$ at time t using a scoring function as follows.

$$\text{score}(h_t, \bar{h}_s) = v_a^T \tanh\left(W_a \begin{bmatrix} h_t \\ \bar{h}_s \end{bmatrix}\right) \tag{15}$$

Two fully connected layers are used to implement this network in the scoring function, where the output of the first layer and the output of the second layer correspond to the dimensions of the ARNN hidden layer. After obtaining the scores, the alignment weights a_t can be computed using the softmax function.

$$a_t(s) = \frac{\exp\left(\text{score}(h_t, \bar{h}_s)\right)}{\sum_{s'} \exp\left(\text{score}(h_t, \bar{h}_{s'})\right)} \tag{16}$$

The vector c_t can be obtained by computing the weighted average of the weights a_t and the hidden state $\bar{h}_s$. A simple fully connected layer is used to combine the information of both the given target hidden state h_t and the vector c_t to find the attention hidden state $\bar{h}_t$.

$$\bar{h_t} = \tanh\left(W_c[c_t; h_t]\right) \tag{17}$$

For the calculated attention hidden state $\bar{h_t}$, the prediction probability is generated by a softmax layer, so as to complete the task of predicting the energy saving of the building.

$$p(y_t|y_{<t}, x) = \text{softmax}\left(W_s\bar{h_t}\right) \tag{18}$$

3.4. **GAM-ARNN based energy saving prediction.** The GAM-ARNN model, which consists of normalised data inputs, was used. Factors such as floor area and number of building floors are used as input variables to the GAM-ARNN model, and the unilateral carbon emissions during the construction of the assembly building are used as output indicators. Training in the GAM-ARNN model and comparing the prediction results of this model with the actual values are carried out to prove the effectiveness of the proposed deep recurrent neural network with real data.

The variability between the carbon emission factors and the individuality between the samples of each assembly building project, such as the number of floors in layers, floor area in planes, and prefabrication rate in percentages, may cause the data results to be imprecise and reduce the accuracy of the model. Normalising the training data was done to reduce the variability of each category factor.

$$\bar{x_i} = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}} \tag{19}$$

Normalisation was applied to the raw data of the influencing factors and carbon emissions involved in the prediction based on Equation (18), making the data critical between $[0, 1]$. The physical carbon emissions of the assembled buildings obtained after normalisation were used as training objects for the GAM-ARNN model.

$X1, X2, X3, X4, X5, X6, X7, X8$ are taken as input factors. The descriptions of the eight input factors are shown in Table 1. The GAM-ARNN model obtains the weight coefficients of the output values by continuously adjusting the parameters of the output layer and the input layer during the operation, making the overall gradient in a decreasing trend, and on the basis of which, we get the expected carbon emissions from the assembly building project. The energy-saving prediction model of assembled concrete buildings based on GAM-ARNN is shown in Figure 2.

4. Experimental results and analyses.

4.1. **Experimental configuration and training.** In order to obtain the data required to build the carbon emission prediction model for the assembly building chemical phase, a total of 15 assembly building case base data were collected in this work. Based on the quantities obtained from the BIM model, the consumption of building materials in the production phase of the demonstration project was converted. During the construction of the project, the transport process of building materials is mainly the carbon emissions formed by the energy consumption generated by the use of transport vehicles to transport the building materials used in the cast-in-place phase from the production site to the mixing workshop.

Based on the above GAM-ARNN model, 12 out of 15 sets of case data are selected as the training set and the remaining 3 sets are used as the test set. The Pytorch 1.8 framework is used in the experiments to implement the model proposed in this paper, and training and testing are performed. The operating system is Ubuntu 18.04, the GPU is NVIDIARTX 3090, the processor is Intel(R) Xeon(R) Glod 5218 R, and the memory is 64 G. The parameters of the GAM-ARNN model are shown in Table 2.

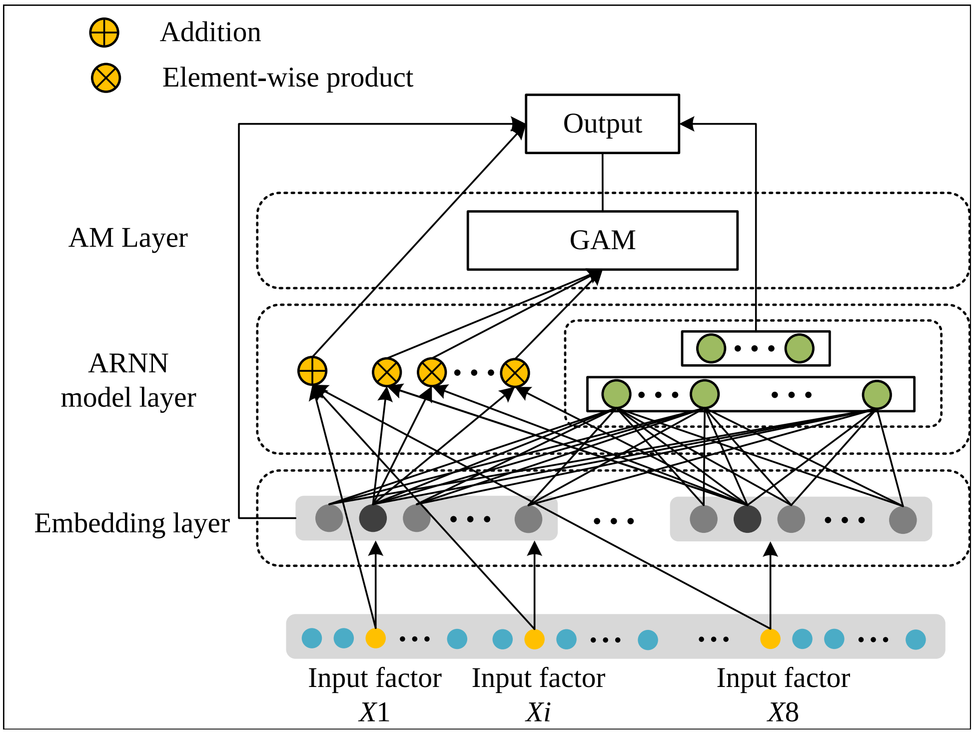

Figure 2. GAM-ARNN based energy efficiency prediction model for assembled concrete buildings

Table 2. Training parameters for the GAM-ARNN model

Parameters	**Numerical value**
Learning rate	0.0001
Batch size	32
Arnn number of hidden layers	512
Loss function	Cross-cutting
Optimiser	Adam
Number of generations	50

The trends of loss values versus accuracy for the training and test sets are shown in Figure 3 and Figure 4, respectively.

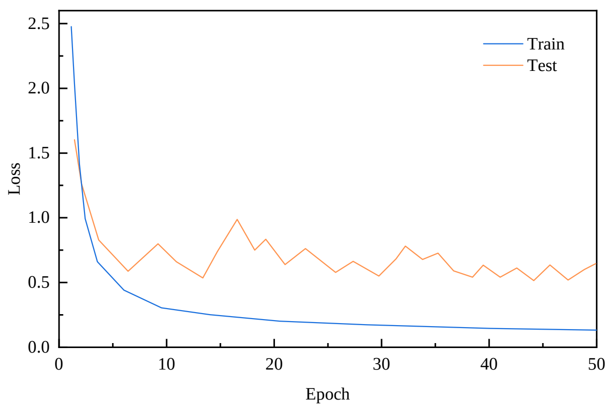

Figure 3. Change in value of losses

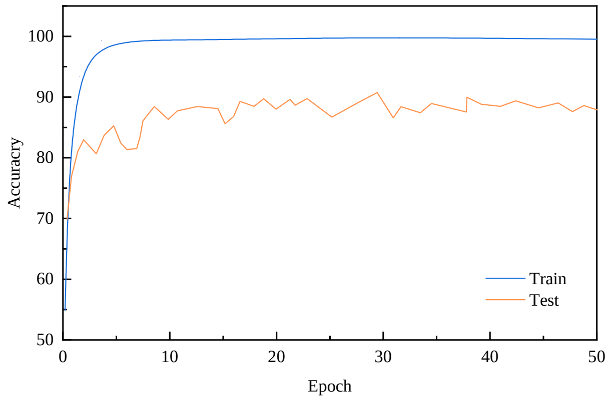

Figure 4. Change in value of accuracy

4.2. **Analysis of carbon emission prediction results.** The unilateral carbon emissions of assembled buildings predicted by a number of different models are compared and the results are shown in Table 3.

Table 3. Unilateral Carbon Emissions from Assembled Buildings Predicted by Different Models

Predictive modelling	**Unilateral carbon emissions** t	**Error** (%)
Carbon emission factor method	1058.07	/
DNN	1039.96	-8.87
Bi-LSTM	1029.22	-6.43
GRU	1019.32	-5.51
CNN+LSTM	1009.97	-4.61
ARNN	983.93	-3.74
GAM-ARNN	1058.07	-1.19

It can be seen that the error between the data predicted and analysed by the GAM-ARNN model and the measured data by the carbon emission factor method is 1.19%, which is significantly lower than the other prediction models.The comparison between the ARNN model and the GAM-ARNN model is regarded as an ablation experiment of the attention mechanism module. It can be seen that the prediction accuracy of the model with the added global attention mechanism is higher than that of the model without the added attention mechanism. This is due to the fact that the GAM-ARNN model's performance improvement is greater for long sequence sample data, proving that the attention mechanism can help the ARNN model to pay more attention to the parts of the input sequence with important information, thus improving the generalisation ability for different influencing factors.

5. **Conclusion.** In this work, a method for predicting energy efficiency of assembled concrete buildings based on the GAM-ARNN model is proposed. Modifications were made based on the theory of carbon emission factor, and the calculation method of carbon emission of five subcomponents was given. The carbon emission factors corresponding to human and machinery were analysed. Literature analysis was used to initially find the factors affecting the carbon emission of assembled buildings. Then, based on the results of the correlation test, 8 key influencing factors were screened out from 23 influencing factors of carbon emission. ARNN is used to build a deep learning environment for building energy efficiency prediction. At the same time, it is proposed to introduce GAM

in ARNN. 8 key influencing factors are used as input variables of GAM-ARNN model, and unilateral carbon emissions during the construction of assembled buildings are used as output indicators. The experimental results show that the error between the GAM-ARNN model and the carbon emission factor method is 1.19%, which is significantly lower than other prediction models. The ablation experiment of the attention mechanism module verifies the effectiveness of the global attention mechanism.

Acknowledgment. This work was supported by Chongqing Municipal Education Commission Science and Technology (No. KJQN202303606).

REFERENCES

[1] L. Pérez-Lombard, J. Ortiz, and C. Pout, "A review on buildings energy consumption information," Energy and Buildings, vol. 40, no. 3, pp. 394-398, 2008.
[2] A. Allouhi, Y. El Fouih, T. Kousksou, A. Jamil, Y. Zeraouli, and Y. Mourad, "Energy consumption and efficiency in buildings: current status and future trends," Journal of Cleaner Production, vol. 109, pp. 118-130, 2015.
[3] G. Mihalakakou, M. Santamouris, and A. Tsangrassoulis, "On the energy consumption in residential buildings," Energy and Buildings, vol. 34, no. 7, pp. 727-736, 2002.
[4] X. Cao, X. Dai, and J. Liu, "Building energy-consumption status worldwide and the state-of-the-art technologies for zero-energy buildings during the past decade," Energy and Buildings, vol. 128, pp. 198-213, 2016.
[5] L. Brady, and M. Abdellatif, "Assessment of energy consumption in existing buildings," Energy and Buildings, vol. 149, pp. 142-150, 2017.
[6] B. Kingma, and W. van Marken Lichtenbelt, "Energy consumption in buildings and female thermal demand," Nature Climate Change, vol. 5, no. 12, pp. 1054-1056, 2015.
[7] M. Santamouris, N. Papanikolaou, I. Livada, I. Koronakis, C. Georgakis, A. Argiriou, and D. Assimakopoulos, "On the impact of urban climate on the energy consumption of buildings," Solar Energy, vol. 70, no. 3, pp. 201-216, 2001.
[8] R. Saidur, "Energy consumption, energy savings, and emission analysis in Malaysian office buildings," Energy Policy, vol. 37, no. 10, pp. 4104-4113, 2009.
[9] X. Li, C. P. Bowers, and T. Schnier, "Classification of energy consumption in buildings with outlier detection," IEEE Transactions on Industrial Electronics, vol. 57, no. 11, pp. 3639-3644, 2009.
[10] W. Li, Y. Zhou, K. Cetin, J. Eom, Y. Wang, G. Chen, and X. Zhang, "Modeling urban building energy use: A review of modeling approaches and procedures," Energy, vol. 141, pp. 2445-2457, 2017.
[11] L. Jaillon, and C. S. Poon, "Life cycle design and prefabrication in buildings: A review and case studies in Hong Kong," Automation in Construction, vol. 39, pp. 195-202, 2014.
[12] D. Matic, J. R. Calzada, M. Eric, and M. Babin, "Economically feasible energy refurbishment of prefabricated building in Belgrade, Serbia," Energy and Buildings, vol. 98, pp. 74-81, 2015.
[13] H. Duan, M. Hu, Y. Zhang, J. Wang, W. Jiang, Q. Huang, and J. Li, "Quantification of carbon emissions of the transport service sector in China by using streamlined life cycle assessment," Journal of Cleaner Production, vol. 95, pp. 109-116, 2015.
[14] S. Liu, X. Meng, and C. Tam, "Building information modeling based building design optimization for sustainability," Energy and Buildings, vol. 105, pp. 139-153, 2015.
[15] Z. Tan, H. Liu, and C. Zeleny, "Low-carbon design of public buildings based on BIM," Journal of Mechanical Engineering Research and Developments, vol. 38, no. 1, pp. 105-111, 2015.
[16] M. V. Shoubi, M. V. Shoubi, A. Bagchi, and A. S. Barough, "Reducing the operational energy demand in buildings using building information modeling tools and sustainability approaches," Ain Shams Engineering Journal, vol. 6, no. 1, pp. 41-55, 2015.
[17] P. Fitriaty, and Z. Shen, "Predicting energy generation from residential building attached Photovoltaic Cells in a tropical area using 3D modeling analysis," Journal of Cleaner Production, vol. 195, pp. 1422-1436, 2018.
[18] Z. Xu, and J. Yuan, "A BIM-Based Study on the Sunlight Simulation in Order to Calculate Solar Energy for Sustainable Buildings with Solar Panels," Emerging Solar Energy Materials: IntechOpen, 2018.

[19] H. Sun, "Prediction of building energy consumption based on BP neural network," Wireless Communications and Mobile Computing, vol. 2022, 2022.
[20] L. Mou, P. Ghamisi, and X. X. Zhu, "Deep recurrent neural networks for hyperspectral image classification," IEEE Transactions on Geoscience and Remote Sensing, vol. 55, no. 7, pp. 3639-3655, 2017.
[21] A. Murad, and J.-Y. Pyun, "Deep recurrent neural networks for human activity recognition," Sensors, vol. 17, no. 11, pp. 2556, 2017.
[22] A. Rahman, V. Srikumar, and A. D. Smith, "Predicting electricity consumption for commercial and residential buildings using deep recurrent neural networks," Applied Energy, vol. 212, pp. 372-385, 2018.
[23] T.-Y. Wu, H. Li, S. Kumari, and C.-M. Chen, "A Spectral Convolutional Neural Network Model Based on Adaptive Fick's Law for Hyperspectral Image Classification," Computers, Materials & Continua, vol. 79, no. 1, pp. 19-46, 2024.
[24] S.-M. Zhang, X. Su, X.-H. Jiang, M.-L. Chen, and T.-Y. Wu, "A traffic prediction method of bicycle-sharing based on long and short term memory network," Journal of Network Intelligence, vol. 4, no. 2, pp. 17-29, 2019.
[25] F. Zhang, T.-Y. Wu, Y. Wang, R. Xiong, G. Ding, P. Mei, and L. Liu, "Application of Quantum Genetic Optimization of LVQ Neural Network in Smart City Traffic Network Prediction," IEEE Access, vol. 8, pp. 104555-104564, 2020.
[26] V. Folli, G. Gosti, M. Leonetti, and G. Ruocco, "Effect of dilution in asymmetric recurrent neural networks," Neural Networks, vol. 104, pp. 50-59, 2018.
[27] Z. Liu, L. Li, X. Fang, W. Qi, J. Shen, H. Zhou, and Y. Zhang, "Hard-rock tunnel lithology prediction with TBM construction big data using a global-attention-mechanism-based LSTM network," Automation in Construction, vol. 125, 103647, 2021.