ENERGY CONSUMPTION OPTIMIZATION OF SMART LANDSCAPE LOW-CARBON BUILDINGS BASED ON DEEP LEARNING

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Abstract. To address the issue of insufficient accuracy in traditional building energy consumption prediction models, this paper proposes a landscape architecture energy consumption prediction method based on a Temporal Convolutional Network (TCN). The method innovatively integrates depthwise separable convolutions and attention mechanisms, thereby reducing model complexity while enhancing its generalization capability. Experimental validation demonstrates that this approach achieves a Mean Absolute Percentage Error (MAPE) of 1.69% on public energy consumption datasets, outperforming other baseline models and surpassing classical prediction methods, providing reliable support for energy conservation and emission reduction in landscape architecture.
Keywords: *temporal convolutional network, energy consumption prediction, deep learning, attention mechanism, low-carbon buildings*

Introduction

As sustainable development draws an increasing global attention, energy conservation and emission reduction in the construction sector have become pivotal in achieving the dual carbon goals. Horticultural architecture, as an integral component of building types, faces particularly significant energy consumption issues. Accurate prediction of energy consumption in horticultural buildings is of paramount importance for optimizing energy management and formulating effective energy-saving strategies (Cabeza et al., 2013; Charles et al., 2019). Early research on building energy consumption prediction primarily relied on traditional statistical methods, such as multiple linear regression (Marill, 2004) and grey prediction models (Zeng et al., 2019). Although these methods, based on simple mathematical models, offer the advantages of low computational complexity and strong interpretability, they exhibit notable limitations when dealing with highly nonlinear and dynamic energy consumption data (Amasyali and El-Gohary, 2018). Building energy consumption data are influenced by a multitude of intricate factors, including environmental conditions, architectural characteristics (such as building structure, area, and orientation), and user behavior (such as equipment usage habits and daily routines). Traditional statistical methods struggle to effectively capture these underlying interactions (Liu et al., 2019), leading to limited prediction accuracy, thus failing to meet the demands of practical applications.

In recent years, deep learning technology, with its formidable ability to model nonlinear relationships, has made significant strides in building energy consumption

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prediction. Models such as Multi-Layer Perceptrons (MLP) (Karlik and Olgac, 2011), Recurrent Neural Networks (RNN), and Long Short-Term Memory networks (LSTM) (Park et al., 2021) and Gated Recurrent Units (GRU) (Zainuddin et al., 2021), have demonstrated the capacity to autonomously learn complex features and patterns within data. MLP, through nonlinear transformations across multiple neurons, can perform intricate feature mappings on input data, but it lacks the capability to effectively capture temporal dependencies in time series data. RNN and its variants introduce gating mechanisms (Yuan et al., 2019) in LSTM and GRU, which effectively address the issues of gradient vanishing and explosion in RNNs, thereby enabling better learning of long-term dependencies within long sequences. These models have achieved favorable results in building energy consumption prediction. However, they exhibit high computational complexity and lengthy training times when dealing with long sequences, and their ability to extract local features remains relatively weak.

To further enhance the accuracy and efficiency of building energy consumption prediction, researchers have continuously explored novel methodologies and techniques. Convolutional Neural Networks (CNN) (Shin et al., 2016), renowned for their exceptional performance in image and signal processing, have gradually been introduced into the field of building energy consumption prediction. CNN can autonomously extract local features, possessing strong feature extraction capabilities and computational efficiency. However, traditional CNNs are unable to fully leverage temporal information when processing time series data, thereby impacting prediction accuracy. Temporal Convolutional Networks (TCN), as an emerging deep learning model (Fan et al., 2023), combine the convolutional operations of CNNs with the temporal processing capabilities of RNNs, offering fresh perspectives for building energy consumption prediction. TCN, through dilated convolutions, expands the receptive field, efficiently capturing long-range dependencies while supporting parallel computation, significantly enhancing model training efficiency. TCN is suitable for real-time prediction tasks, but in practical applications, its predictive performance still requires improvement when faced with insufficient historical energy consumption data and diverse, complex data features.

Addressing the aforementioned challenges, this paper proposes a novel method for building energy consumption prediction based on an Improved Temporal Convolutional Network (ITCN). The objective of this study is to propose an improved Temporal Convolutional Network (TCN) model that integrates depthwise separable convolution and attention mechanisms for building energy consumption prediction, validate its performance on public datasets, and provide actionable energy-saving suggestions for low-carbon landscape buildings.

Materials and methods

Temporal convolutional network

A Temporal Convolutional Network (TCN) is a deep learning model designed for processing sequential data (Bi et al., 2021), leveraging the advantages of Convolutional Neural Networks (CNNs) to handle time series information. TCN expands its receptive field through the use of dilated convolutions, enabling it to efficiently capture long-range dependencies, while also supporting parallel computation, making it suitable for real-time prediction and generation tasks.

The convolution operation serves as the bedrock of TCN and can be expressed as *Equation (1)*.

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$$y(t) = (x * w)(t) = \sum_{i=0}^{k-1} x(t-i) \cdot w(i) \quad \text{(Eq.1)}$$

Here, t represents the current time step. x is the input sequence, k is the size of the convolutional kernel, and w stands for the weights.

Causal convolution ensures that the model relies only on past inputs and not on future inputs. This is achieved by adding appropriate padding in the convolution operation.

$$y(t) = (x * w)(t) = \sum_{i=0}^{k-1} x(t-i) \cdot w(i) \quad \text{(Eq.2)}$$

Dilated convolution expands the receptive field by inserting zeros between the kernel elements, without increasing the number of parameters (Wang et al., 2019). This approach enables the model to capture broader temporal or spatial dependencies while maintaining its parameter count. The fundamental structure of dilated convolution is illustrated in *Figure 1*, and its mathematical representation is given as *Equation (3)*:

$$y(t) = (x * w_d)(t) = \sum_{i=0}^{k-1} x(t-d \cdot i) \cdot w(i) \quad \text{(Eq.3)}$$

Here, d signifies the expansion factor.

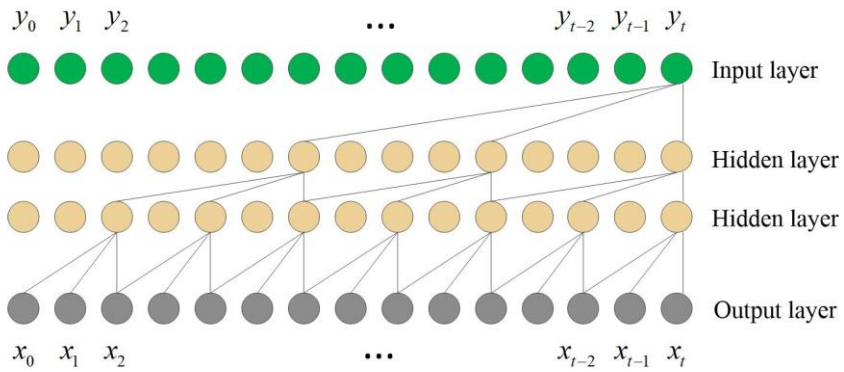

Figure 1. *Dilated causal convolution architecture*

Residual connections alleviate the issue of vanishing gradients by adding the input directly to the output. A typical residual block consists of two convolutional layers, an activation function, and a residual connection, which can be expressed by the *Equation (4)*:

$$y = \text{ReLU}(x + \text{Conv}(\text{ReLU}(\text{Conv}(x)))) \quad \text{(Eq.4)}$$

Here, Conv signifies the convolution operation, and ReLU denotes the activation function.

The schematic diagram of the TCN is illustrated in *Figure 2*. This model employs a synergistic approach by combining dilated convolutions and residual connections to construct a time series prediction model. Its architecture typically consists of multiple

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stacked dilated convolution layers, each endowed with varying dilation rates to capture information across diverse temporal scales, thereby effectively expanding the model's receptive field. Additionally, TCN integrates residual or skip connections to mitigate the vanishing gradient issue prevalent in deep networks and expedite the training process. The model is constructed through the stacking of multiple residual blocks, employing batch normalization and ReLU activation functions to accelerate convergence and enhance the model's nonlinear expressive capabilities. Finally, a fully connected layer is utilized to map features to the predicted outcomes.

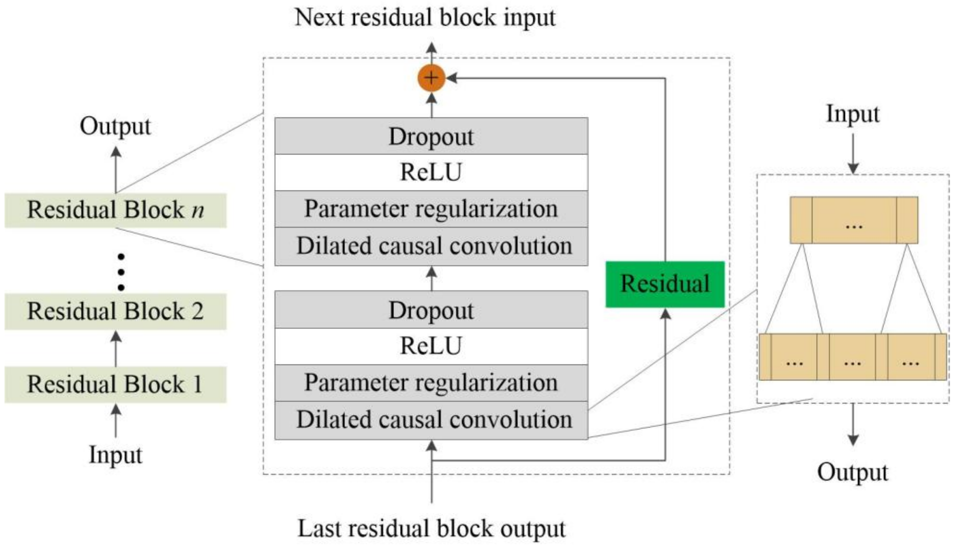

Figure 2. *The fundamental structure diagram of TCN*

Adaptive parametric ReLU

APReLU (Adaptive Parametric ReLU) is an enhanced ReLU activation function (Wang et al., 2024) that bolsters the model's expressive power by incorporating adaptive parameters. After the input features pass through the APReLU activation, the slope of the negative part is governed by a learnable multiplicative coefficient, enabling the model to adapt more effectively to varied data distributions. The processed feature maps are typically fed into a Global Average Pooling (GAP) layer, yielding a one-dimensional vector, which is subsequently utilized for classification or other tasks, as illustrated in *Figure 3*. The formula for the APReLU activation function is expressed as follows:

$$y = \max(x, 0) + \alpha \cdot \min(x, 0) \quad \text{(Eq.5)}$$

Here, x and y denote the input and output vectors, respectively, while α represents the multiplicative coefficient.

Depthwise separable convolution

Depthwise Separable Convolution (DSC) is an optimized convolution operation (He et al., 2023), frequently employed in the architecture of deep learning neural networks, to diminish computational load and the parameter count. *Figure 4* illustrates the process of depthwise separable convolution. In this method, a convolution kernel is applied to each

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channel of the input separately. It initially performs convolution operations on each channel of the input feature maps independently, through depthwise convolution, and subsequently combines these channel outputs via pointwise convolution, to craft the final output. This technique markedly reduces the number of parameters and computational requirements within neural networks, thus enhancing operational efficiency while aiding in the preservation of model performance, and is commonly found in lightweight network architectures.

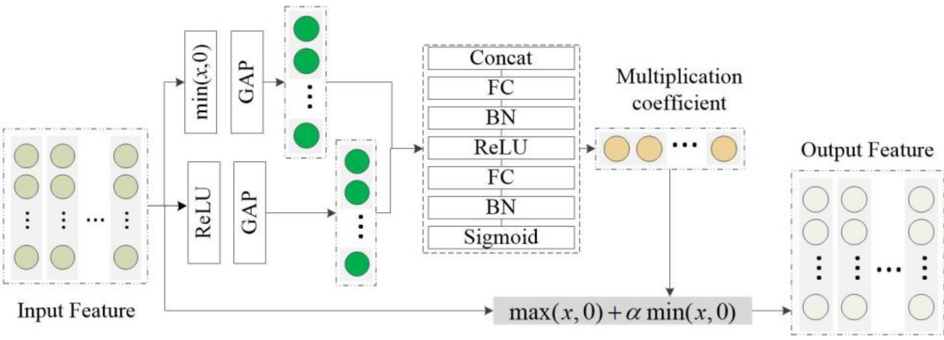

Figure 3. *The architecture of the APReLU network*

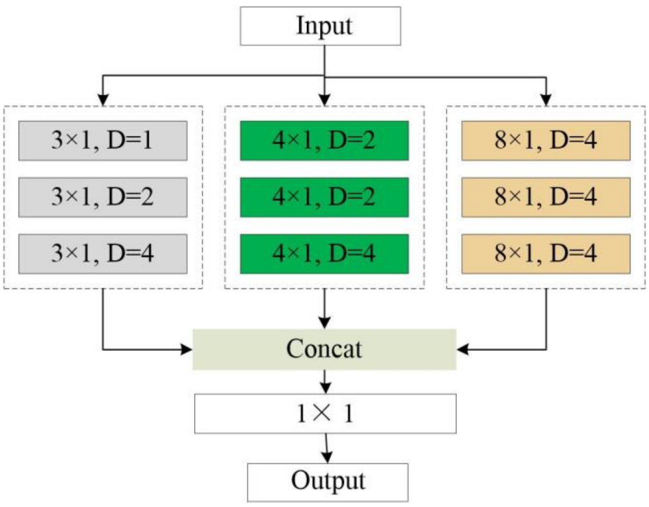

Figure 4. *The fundamental principle of depthwise separable convolution*

Convolutional attention mechanism

The Convolutional Attention Mechanism integrates spatial attention and channel attention (Niu et al., 2021), effectively capturing significant features across both spatial and channel dimensions within Convolutional Neural Networks (CNNs). Spatial attention underscores the importance of features at various locations within an image, whereas channel attention emphasizes the significance of different feature channels. The fusion of these two mechanisms enables the model to focus more acutely on crucial areas and feature channels, thereby enhancing its representational capacity.

Channel attention strengthens the model's feature representation by concentrating on the salience of different feature channels. This mechanism achieves its objective through the application of Global Average Pooling (GAP) and Global Max Pooling (GMP) on the

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input feature maps, producing one-dimensional vectors that represent the average and maximum values of each channel, respectively. These vectors are then processed through Fully Connected (FC) layers to compute the weights for each feature channel. By doing so, the model can better focus on feature channels that carry substantial information, thus elevating its overall performance, shown as *Equation (6-8)*.

$$GAP(F) = \frac{1}{H \times W} \sum_{i=1}^{H} \sum_{j=1}^{W} F(i,j) \quad \text{(Eq.6)}$$

$$GMP(F) = \max_{i,j}\left(F(i,j)\right) \quad \text{(Eq.7)}$$

$$M_c(F) = \sigma\left(MLP\left(GAP(F)\right) + MLP\left(GMP(F)\right)\right) \quad \text{(Eq.8)}$$

Here, F denotes the input feature map with a channel dimension of $H \times W$; MLP signifies a Multi-Layer Perceptron; and σ represents the activation function.

The spatial attention mechanism calculates the average and maximum values across different positions of the feature map to generate a spatial attention map, thereby enhancing the model's focus on significant spatial regions.

The average and maximum values of the spatial mapping of the input feature map are denoted as F_{avg}^{ch} and F_{max}^{ch} respectively, where C is the number of channels, and H and W represent the height and width. These vectors are subsequently processed to create a spatial attention map, which guides the model to concentrate on more critical areas within the image, ultimately improving the model's performance.

$$F_{avg}^{ch} = \frac{1}{C} \sum_{k=1}^{c} F_k(x,y) \quad \text{(Eq.9)}$$

$$F_{\max}^{ch} = \max_{k}\left(F_k(x,y)\right) \quad \text{(Eq.10)}$$

$$\boldsymbol{M}_s(\boldsymbol{F}) = \boldsymbol{\sigma}\left(f^{14}\left(\left[\boldsymbol{F}_{avg}^{ch}; \boldsymbol{F}_{\max}^{ch}\right]\right)\right) \quad \text{(Eq.11)}$$

Here, f^{14} denotes a one-dimensional causal convolution with a kernel size of 14.

This study employs a multi-head attention layer for regression learning to extract global features of building energy consumption and construct dependencies across different dimensions of the data (Feng and Cheng, 2021). The multi-head attention mechanism, by utilizing multiple attention heads in parallel, is capable of learning rich feature representations in distinct representational subspaces, thereby more effectively capturing the dependencies within the data.

For a given input X, multi-head attention obtains the query vectors Q, key vectors K, and value vectors V through linear transformations.

$$Q_i = XW_i^Q \quad \text{(Eq.12)}$$

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$$K_i = XW_i^K \quad \text{(Eq.13)}$$

$$V_i = XW_i^V \quad \text{(Eq.14)}$$

In the Equation (12-14), W_i^Q, W_i^K and W_i^V are the parameter matrices associated with the i -th attention head. For each head i, the formula for computing the attention mechanism is:

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V \quad \text{(Eq.15)}$$

Herein, d_k denotes the dimension of the key. The multi-head attention layer enables the parallel use of multiple attention heads, each capable of learning distinct feature subspaces. The core formula is presented as follows:

$$\text{MultiHead}(Q, K, V) = \text{Concat}(\text{head}_1, \text{head}_2, ..., \text{head}_h)W^O \quad \text{(Eq.16)}$$

Herein, Concat denotes the concatenation of all head outputs; head refers to the individual attention heads, of which there are h in total.

ITCN for building energy consumption forecasting

The factors influencing building energy consumption are multifaceted, encompassing dynamic changes across various temporal scales. To incorporate the impact of multiple factors and to predict building energy consumption more accurately, environmental conditions, building characteristics, and user behaviors should be considered comprehensively. To achieve more precise predictions of building energy consumption using various neural network architectures, it is essential to account for the dynamic variations at multiple temporal scales, such as solar radiation and temperature fluctuations.

Building energy consumption is affected by a multitude of factors, including environmental conditions, building characteristics, and user behaviors. For a more accurate prediction of energy consumption in buildings, the dynamic changes across multiple time scales, such as solar radiation and temperature variations, must be taken into consideration. To address the issue of model overfitting due to the lack of historical data in building energy consumption predictions, we introduce depthwise separable convolution and attention mechanisms to enhance the Temporal Convolutional Network (TCN). Depthwise separable convolution reduces the number of parameters and computational complexity by decomposing standard convolutions, thereby improving model efficiency. The attention mechanism, through adaptive weighting, focuses the model on critical features, enhancing its representation and improving generalization performance under data scarcity. By integrating these approaches, an efficient energy consumption prediction model can be constructed, with input features comprising historical consumption data, weather data, and user behavior data, ultimately yielding

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forecasts of future energy consumption. The architectural prediction model proposed in this study, based on the improved temporal convolution model, is illustrated in *Figure 5*.

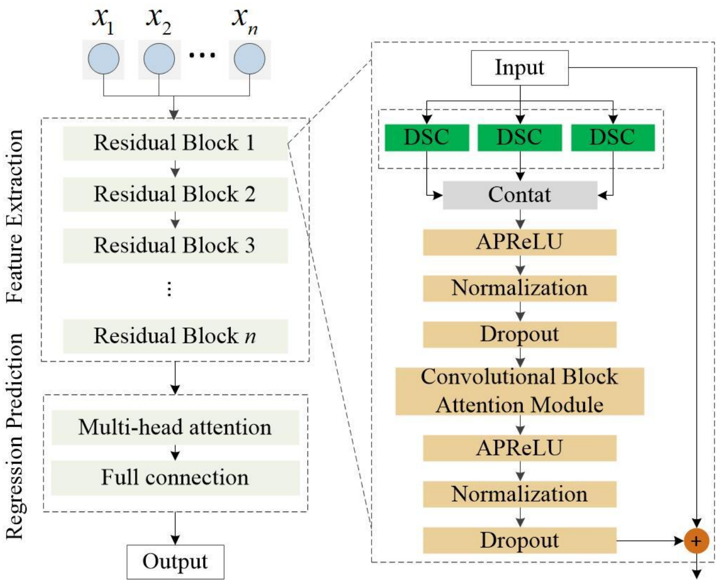

Figure 5. *The Enhanced time-domain convolutional model for forecasting energy consumption*

Results

Data set and evaluation index

This study harnesses a publicly accessible dataset of building energy consumption from U.S. commercial and industrial sites (https://trynthink.github.io/buildingsdatasets), which encompasses historical energy usage data, weather information, and building characteristic details across various commercial and industrial structures. The input features include historical energy consumption (kWh), weather data (temperature in °C, solar radiation in W/m², humidity in %), and building characteristics (e.g., floor area in m², building orientation, insulation type). The dataset primarily consists of CSV files, documenting energy consumption readings, corresponding meteorological data, and building attributes for each site. During the data preprocessing phase, an initial step of data cleansing was undertaken to address missing values and anomalies. To enhance the efficiency and efficacy of model training, normalization was applied to numerical features, scaling them to a consistent range.

In the model training phase, the dataset was bifurcated into training and testing subsets, in an 80% to 20% ratio. The training subset was employed for optimizing model parameters, utilizing Mean Absolute Error (MAE) as the loss function, and the Adam optimizer was implemented for gradient descent to update the parameters. During the model validation phase, the testing subset was utilized to assess the generalization performance of the model. Key evaluation metrics included Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE). The hyperparameter settings for the training model are detailed in *Table 1*.

$$MAE = \frac{1}{N}\sum_{i=1}^{N}| y_i - \hat{y}_i | \quad \text{(Eq.17)}$$

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$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2} \quad \text{(Eq.18)}$$

$$MAPE = \frac{100}{N}\sum_{i=1}^{N}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \quad \text{(Eq.19)}$$

Here, y_i represents the actual values, $\hat{y}_i$ signifies the predicted values, and N denotes the total number of samples.

Table 1. *Hyperparameter settings for the model*

Hyperparameters	Value
Optimizer	Adam
Maximum Epochs	100
Early Stop Loss	0.05
Learning Rate	0.001
Dropout	0.4

Prediction results and comparative experiments

To substantiate the superiority of the proposed algorithm, this study conducted comparative experiments against several classical algorithms, including Support Vector Machines (Chandra and Bedi, 2021), Extreme Learning Machines (ELM) (Wang et al., 2022), and Long Short-Term Memory Networks (LSTM) (Wang et al., 2023). Specific evaluation metric values are presented in *Table 2*.

Table 2. *Effectiveness comparison of various prediction models*

Models	MAE	RMSE	MAPE
SVM	11.94	19.31	26.27
ELM	9.62	15.23	12.09
LSTM	3.2	8.92	2.95
TCN	1.92	5.393	1.69

Based on the predictive outcomes, SVM exhibits a relatively higher Mean Absolute Error (MAE) of 11.94 in this energy consumption prediction experiment. This substantial error may be attributed to the intricate and fluctuating nature of the energy consumption data, rendering it challenging for SVM to accurately discern the underlying patterns. ELM, a single-hidden-layer feedforward neural network, boasts a faster learning rate and demonstrates improvements over SVM; however, it still manifests certain prediction deviations. This could be due to its relatively simplistic structure, which limits its capacity to learn complex features inherent in the energy consumption data. On the other hand, LSTM, particularly adept at handling long-term dependencies in sequential data, achieved a MAPE of 2.95% in the current experiment, showcasing commendable performance.

In comparison, the enhanced TCN significantly outperforms across various metrics, including MAE, RMSE, and MAPE. These results substantiate the efficacy of incorporating these mechanisms, which have substantially augmented the model's

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comprehension and predictive capabilities regarding energy consumption data, enabling a more precise capture of energy consumption trends. The depthwise separable convolutions facilitate extracting features at various scales, thereby enriching the feature representation. Furthermore, the attention mechanism autonomously learns the importance of different segments within the data, allowing the model to concentrate more intensely on pivotal features. This dual enhancement improves the model's ability to discern complex patterns and crucial information within the energy consumption data, thereby elevating the overall prediction accuracy.

Figure 6 presents the predictive outcomes of the proposed algorithms, contrasting actual energy consumption with predicted values while delineating the error margins. The comparative experimental results indicate that the enhanced TCN excels in metrics such as MAE, RMSE, and MAPE, thereby validating the efficacy of the introduced mechanisms in augmenting the model's comprehension and predictive capabilities concerning energy consumption trends, with greater precision in capturing the fluctuations of energy usage. Given its enhanced ability to learn data characteristics, the improved TCN exhibits reduced reliance on specific data distributions, thereby demonstrating superior generalization capabilities in diverse scenarios or with novel data, ensuring more stable and reliable predictive outcomes.

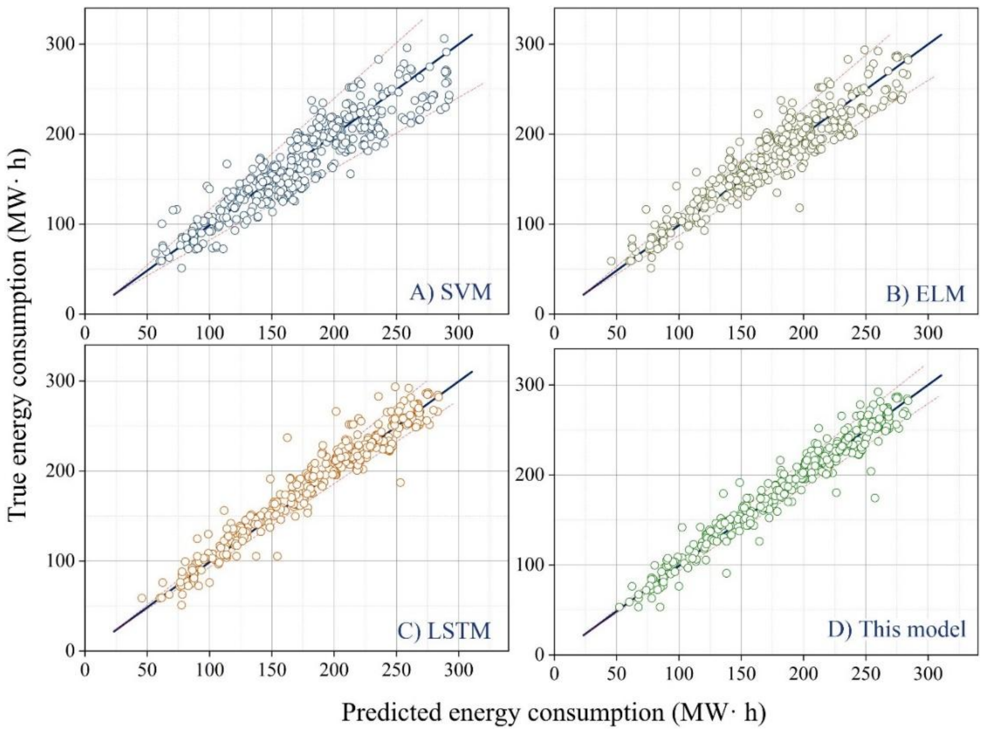

Figure 6. *Comparison results between the proposed model and other models*

Discussion

The case study building is a two-story office building with a total area of 800 m², located in a temperate climate zone. It features double-glazed windows, 200 mm wall insulation, a rooftop PV system, and a central HVAC system. The garden area includes LED landscape lighting and an automated irrigation system. *Figure 7* illustrates the forecasted energy consumption results for a garden building over a week, revealing a

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pronounced cyclical pattern. The structure encompasses green spaces, gardens, and office areas. The energy consumption in the office zones is significantly influenced by the routine of daily operational activities, exhibiting higher usage during office hours on weekdays, primarily due to the extensive operation of lighting, air conditioning, and computer equipment. Conversely, the consumption drops notably during the nighttime rest periods when most devices are powered off. The energy expenditure in the garden areas is predominantly affected by weather conditions, such as the sprinkler and lighting systems. While garden lighting contributes marginally to total energy consumption, its usage patterns—especially during overcast days or for aesthetic enhancement—can lead to non-negligible cumulative energy use over time.

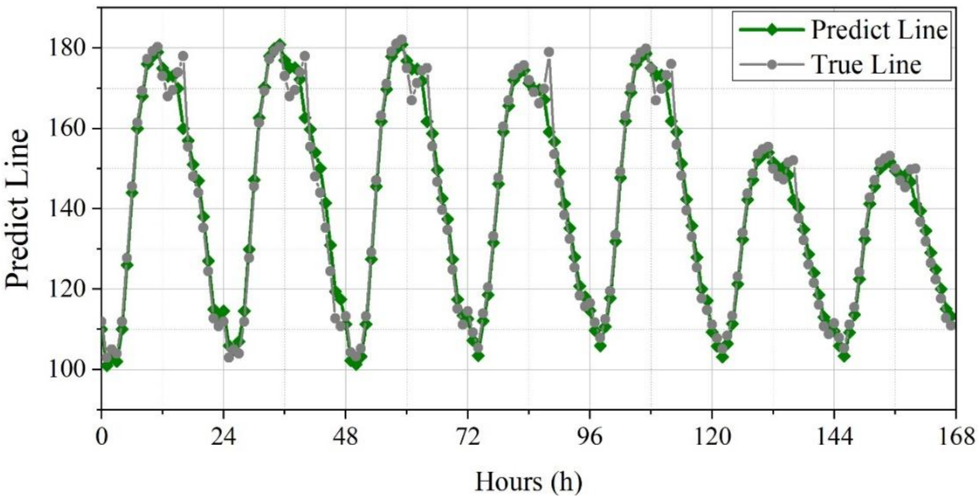

Figure 7. *Energy consumption forecast of a building for one week*

According to the predictive model proposed in this paper, which incorporates information such as weather data, it is observed that the forecasted energy consumption trends align closely with the actual trends, indicating that the model can effectively capture the general pattern of energy consumption changes. However, discrepancies still exist in the specific numerical values. Based on the energy consumption predictions, the following primary areas of energy use and suggestions for energy conservation and carbon reduction can be summarized.

In the realm of energy consumption within landscape architecture, several key patterns emerge: During the daytime business hours on weekdays, the energy expenditure in office areas peaks, largely attributable to the substantial usage of lighting, air conditioning, and computer equipment, resulting in the office buildings frequently operating at full capacity during this period. While nighttime consumption is comparatively lower, a certain level of energy expenditure still persists. On weekends, with a significant reduction in office activities, the frequency of equipment usage within the buildings drops markedly, leading to a decrease in overall energy consumption. However, the maintenance equipment for green spaces and gardens, such as sprinkler systems and landscape lighting, still necessitates operation, thereby ensuring that energy consumption on weekends, though minimal, does not diminish to zero. Furthermore, the energy consumption in green spaces and gardens primarily centers around irrigation systems, landscape lighting, and

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maintenance equipment, with the operational timings and frequencies of these devices exerting a notable influence on the overall energy expenditure.

To this end, suggestions for energy conservation and carbon reduction are proposed: During the daytime business hours on weekdays, intelligent control systems can be employed based on predictive analysis of building energy consumption to regulate the usage of lighting and air conditioning, thereby mitigating unnecessary energy waste. Additionally, employees are encouraged to employ energy-efficient devices, such as low-power computers and energy-saving lighting fixtures. During the nighttime, aside from essential security systems and a portion of the lighting, other non-essential equipment should be diligently shut down, a practice that can be facilitated through timed switches or intelligent control systems. For green spaces and gardens, the operational timings of sprinkler systems can be optimized, opting for nighttime or early morning irrigation to curtail water and electricity consumption. Moreover, for these areas, the adoption of water-saving irrigation techniques and intelligent landscape lighting systems can be pursued to minimize water and electricity waste, while regular maintenance of equipment ensures their efficient operation. Through these measures, the overall energy consumption of the building can be effectively reduced, thereby achieving the objectives of energy conservation and carbon reduction, and fostering sustainable development.

Conclusion

This paper presents a method for transfer prediction of building energy consumption based on a temporal convolutional network, effectively addressing the low prediction accuracy of deep learning models when historical energy consumption data is scarce. By integrating depthwise separable convolutions and attention mechanisms, the model not only reduces parameters and minimizes the risk of overfitting but also enhances its feature extraction capabilities and adaptability to varied building energy consumption data. Experiments validated the superiority of this method across multiple datasets, demonstrating higher prediction accuracy and better generalization. This research provides new technical approaches for the energy efficiency optimization of low-carbon buildings in smart gardens, contributing to energy conservation and emission reduction, and facilitating the realization of dual carbon strategic goals. Looking ahead, we will further refine the model architecture and explore additional application scenarios to extend its impact in broader building energy-saving domains.

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