

# Multi-Objective Prediction of Building Loads Based on Similar Days Considering Window Inconsistency<sup>#</sup>

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## ABSTRACT

To address the limitations that traditional time series methods and regression analysis struggle to characterize the nonlinearity, dynamics, and uncertainty of building energy consumption, and that existing deep learning prediction models suffer from the issue of window inconsistency, this study proposes a multi-objective prediction method for building loads based on similar days that accounts for window inconsistency. The primary goal of this method is to achieve accurate prediction of both the total building load and chiller energy consumption. The implementation process of the proposed method is as follows: First, combined with the meteorological features and date attributes of the day to be predicted, 100 similar days are selected to construct a matched training dataset; Second, three parallel convolutional channels (for meteorological data, temporal information, and historical load) are designed to extract features, followed by cross-dimensional fusion of these features; Finally, the fused features are input into the X-LSTM-Transformer model: the X-LSTM component captures long-term dependencies, while the Transformer component focuses on key time nodes. Experiments were conducted using one year of measured data from an office building. The results indicate that, For the total building load prediction: MAE = 6.138, RMSE = 7.623,  $R^2 = 0.979$ ; For the chiller energy consumption prediction: MAE = 4.097, RMSE = 6.358,  $R^2 = 0.956$ . The predicted values show high consistency with the actual measured values. Compared with the X-LSTM-Transformer model without the similar-day strategy, as well as benchmark models including CNN-Attention-LSTM, Bi-LSTM, and LSTM, the proposed method demonstrates significantly superior prediction accuracy.

**Keywords:** Building load; X-LSTM-Transformer; Similar days

## NONMENCLATURE

### Abbreviations

X-LSTM	Long Short-Term Memory
MAE	Mean Absolute Error
RMSE	Root Mean Squared Error

## 1. INTRODUCTION

With the advancement of society and economic development, building energy consumption has exhibited a rapid growth trend. In China, building energy consumption accounts for 21% – 21.7% of the country's total energy consumption<sup>[1]</sup>. As a major component of national energy consumption, research on building energy consumption holds significant practical significance and economic value. Accurate and effective building energy consumption prediction serves as the core foundation for achieving building energy efficiency<sup>[2]</sup>.

Building energy consumption prediction has gradually become a research hotspot in the academic community. In the field of short-term energy consumption prediction, traditional techniques primarily rely on time series methods<sup>[3]</sup> and regression analysis methods<sup>[4]</sup>, which have been initially applied in practical engineering scenarios. However, the energy consumption characteristics of building systems inherently exhibit complex characteristics such as nonlinearity, dynamics, and uncertainty. Traditional linear modeling techniques struggle to accurately characterize these features, resulting in their prediction accuracy and response efficiency being unable to meet the high-precision requirements of current building energy conservation management and control<sup>[5]</sup>.

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With the continuous iteration and optimization of artificial intelligence algorithms, data-driven technologies have gradually become the core focus of research in the prediction field [6], and building energy consumption prediction models based on deep learning have emerged accordingly. Specifically, Reference [7] proposed a CNN-RNN hybrid model for building energy consumption prediction by leveraging the feature extraction advantages of convolutional neural networks (CNNs) and the capability of recurrent neural networks (RNNs) in time-series data learning. This model not only improved prediction efficiency but also maintained favorable prediction accuracy. Reference [8] constructed a building energy consumption prediction model by integrating the attention mechanism with the LSTM neural network; this model can more accurately capture information critical to prediction results while effectively reflecting the variation trends of building energy consumption data.

Reference [9] completed the prediction of building heating load without considering climatic information. Reference [10] realized the prediction of building heating load demand using a backpropagation neural network (BPNN). Reference [11] constructed a load prediction model by combining long short-term memory (LSTM) with the adaptive boosting (AdaBoost) algorithm, achieving the prediction of loads in urban residential areas. Reference [12] proposed a two-stage neural network prediction framework, adopting a two-stage mode where "climatic variables are predicted in the first stage, and the prediction results of climatic variables are used as input in the second stage" to complete short-term electrical load prediction.

While significant progress has been made in existing studies, the issue of window inconsistency has not been addressed. In load prediction, window inconsistency refers to the phenomenon where the time window used for analysis in the prediction process mismatches the feature window of actual load changes. This mismatch prevents the model from accurately capturing the core variation patterns of the load and ultimately leads to prediction deviations. To address the aforementioned window inconsistency issue, this study proposes a multi-objective prediction method for building loads based on similar days that considers window inconsistency. The specific research roadmap is as follows:

**Accurate Similar-Day Selection:** To address the insufficient window consistency in the similar-day selection process, this study comprehensively considers the meteorological features and date attributes of the day to be predicted, selects the 100 most similar days

from historical data, and constructs a training sample sequence with a window matching the prediction scenario.

**Multi-Dimensional Feature Fusion:** Multiple convolutional channels are designed, including a meteorological feature channel, a temporal feature channel, and a historical load channel, to perform targeted local extraction of different types of features. Subsequently, deep cross-dimensional feature fusion is achieved through feature concatenation and a weight layer, fully exploiting multi-dimensional information in the data.

**Construction of Multi-Objective Prediction Model:** The fused features are input into an improved X-LSTM-Transformer hybrid model. By utilizing the self-attention mechanism of the Transformer module, the model dynamically captures the feature contribution weights of key time nodes. Ultimately, multi-objective collaborative prediction of the energy consumption of building chillers and the total load of the entire building is realized, significantly enhancing the model's ability to characterize complex energy consumption patterns.

## **2. ESTABLISHMENT OF THE MULTI-OBJECTIVE BUILDING LOAD PREDICTION MODEL**

### *2.1 Multi-Column Convolutional Channels for Feature Extraction and Feature Fusion*

To achieve multi-objective collaborative prediction of building chiller energy consumption and total building load, the input data in feature processing typically includes multi-dimensional features such as meteorological features, temporal features, and historical load features. These different types of features exhibit significant differences in terms of their physical meanings, temporal patterns, and influence mechanisms on energy consumption.

When extracting features, a single convolutional channel tends to confuse features across different dimensions, leading to the loss of key information and failure to fully retain the unique representations of each type of feature. To address this issue, this study proposes a multi-column convolutional channel strategy for feature extraction. By designing dedicated convolutional channels for different types of features, targeted extraction of local features is realized, laying a foundation for subsequent cross-dimensional feature fusion and long-term temporal modeling.

In response to the attribute differences among the three types of features, three parallel and parameter-independent convolutional channels are constructed.

Each channel processes only one type of feature, thereby maximizing the retention of key local information. The parameter configuration of the multi-column convolutional channels is shown in Table 1.

Although the features output by the multi-column convolutional channels have achieved targeted extraction of local information, cross-dimensional synergy must be realized through a fusion strategy.

Table 1 Parameter Configuration of Multi-Column Convolutional Channels

Convolutional Channel Type	Input Features
Meteorological Feature Channel	Air temperature, relative humidity, et al.
Temporal Feature Channel	Hourly encoding, date type, et al.
Historical Load Channel	Total building load, chiller energy consumption, et al.

To eliminate the isolation of features output by the multi-column convolutional channels and adapt to the differentiated prediction requirements of the dual targets (total building load and chiller energy consumption), the following steps are implemented:

First, through feature concatenation, the outputs of the meteorological channel, temporal channel, and historical load channel are aligned by time steps and concatenated along the feature dimension to form a fused feature matrix. This operation fully retains the original local features of each channel to avoid information loss. Subsequently, a target-aware weight layer is introduced. A weight matrix is defined, and the weights are normalized to the [0,1] range using the Sigmoid function. This layer dynamically allocates the contribution of different features to the dual targets, generating two target-specific feature matrices. Finally, standardized features are output through the convolution kernel.

### 2.2 X-LSTM Model

Although the Long Short-Term Memory (LSTM) model addresses the gradient vanishing problem of Recurrent Neural Networks (RNNs) to a certain extent, it still suffers from limitations such as restricted flexibility in information storage, limited storage capacity, and weak parallelization capabilities when handling complex long-term dependency tasks.

xLSTM (eXtended Long Short-Term Memory) is an extended and optimized version of the traditional LSTM. It aims to break through the bottlenecks of the traditional LSTM — including restricted information storage flexibility, limited capacity, and weak

parallelization—and enhance its performance in large-scale deep learning. By extending the gating mechanism and introducing temporal attention factors, xLSTM optimizes long-term temporal modeling. This enables it to effectively capture the long-term dependencies of building energy consumption and adapt to the standardized temporal features output by the multi-column convolutional channels.

### 2.3 Establishment of the Energy Consumption Prediction Model

By integrating similar-day selection, multi-column convolutional channel-based feature extraction and fusion, and the X-LSTM-Transformer hybrid model, a multi-objective building energy consumption prediction model is constructed (as illustrated in Figure 1). The specific workflow is as follows:

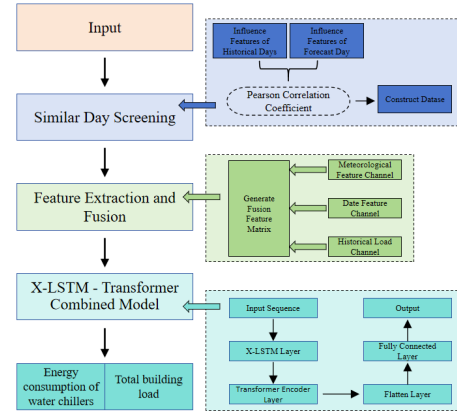


Figure 1 Energy Consumption Prediction Model

First, the input layer inputs time-series data including meteorological, temporal, and historical load features, providing raw information support for subsequent analysis. Among these features: meteorological features cover air temperature, relative humidity, etc.; temporal features include hour, date type, etc.; historical load features involve the total building load, chiller energy consumption, etc., from previous time periods.

Second, aiming at the problem of insufficient window consistency during similar-day selection, the similar-day screening step comprehensively considers the meteorological features and date attributes of the day to be predicted. By calculating the Pearson correlation coefficient, the 100 most similar days are selected from historical data to construct a new training sample sequence, which optimizes the matching degree between the training data and the prediction scenario.

Third, the multi-column convolution and feature fusion layer uses three parallel convolutional channels, namely the meteorological feature channel, temporal

feature channel, and historical load channel, to perform targeted local extraction of meteorological, temporal, and historical load features respectively, and outputs feature matrices of corresponding dimensions. Subsequently, deep fusion of multi-channel features is conducted to generate a fused feature matrix suitable for dual-objective prediction.

Then, in the X-LSTM-Transformer hybrid model layer: the fused feature sequence is first input into the X-LSTM layer, which captures long-term dependency relationships by virtue of its extended gating and temporal attention factors; next, the sequence passes through the Transformer encoder layer, which focuses on the feature contributions of key time nodes through the self-attention mechanism to generate attention-enhanced features specific to the targets; finally, the features are processed via a flatten layer and fully connected layers.

Last, the multi-output layer is designed with two independent fully connected output heads, which output the predicted value of total building load and the predicted value of chiller energy consumption respectively, realizing dual-objective collaborative prediction.

### 2.4 Evaluation Metrics

To assess the prediction accuracy of the proposed prediction method in this study, three evaluation metrics are selected: mean absolute error (MAE), root mean squared error (RMSE), and coefficient of determination ( $R^2$ ).

## 3. EXPERIMENTAL VALIDATION

### 3.1 Experimental Data and Environment

The experimental data are derived from the measured data of a large-scale office building from August 2019 to June 2020, with a sampling interval of 30 minutes. The data include three categories of core features: meteorological features (air temperature), temporal features, and load & energy consumption data features.

The experimental platform in this study adopts a Windows 10 64-bit operating system, equipped with an Intel i7-11400 CPU. During the implementation of the prediction model, Python 3.8 was used for programming, and the TensorFlow framework was employed to implement the proposed algorithm.

### 3.2 Feature Analysis

To clarify the degree of influence of each feature on the prediction of total building load and chiller energy

consumption, an analysis of feature importance was conducted, and the results are shown in the figure 2.

For the total building load prediction:

The importance of chiller energy consumption is significantly prominent, making it the core influencing feature; Chilled water flow also exhibits high importance and plays a key role in predicting the total building load; Features such as month, hour, cooling water temperature, and day of the week have relatively low importance and exert a weak influence on the total building load prediction.

For the chiller energy consumption prediction:

Chilled water flow ranks first and is the most critical feature; Chilled water temperature and outdoor temperature also have a certain degree of importance and exert a relatively obvious influence on the chiller energy consumption prediction; By comparison, features such as hour, month, and day of the week have lower importance and their roles in the chiller energy consumption prediction are relatively limited.

In summary, there are obvious differences in the importance of different features in the prediction of total building load and chiller energy consumption. Features such as chiller energy consumption and chilled water flow play more critical roles in their respective prediction scenarios.

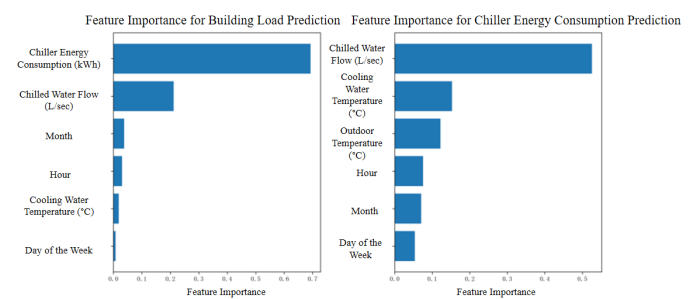


Figure 2 Feature Analysis

## 4. RESULTS

In this study, the measured data from May 26 to June 1, 2020 (a total of 7 days) were selected as the test set to conduct dual-objective prediction of total building load and chiller energy consumption, thereby verifying the model performance.

### 4.1 Building Load Prediction

The building load prediction results are shown in Figure 3. The trends of the actual values and predicted values are highly consistent, with only slight deviations observed during the peak hourly load periods of the day. However, the overall fluctuation trend is completely synchronized with the changes in the actual load, which

verifies the model's ability to capture short-term dynamic changes.

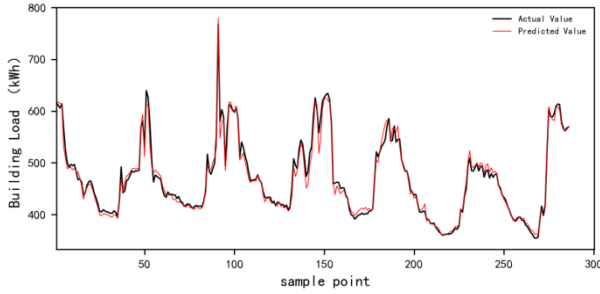


Figure 3 Building Load Prediction Results

The prediction scatter plot is shown in Figure 4. In the figure, the predicted values and actual values are closely distributed along the red dashed line ( $y = x$ ), and the blue scatter points are highly clustered on both sides of the diagonal. This intuitively reflects the high consistency between the model's predictions and the actual values.

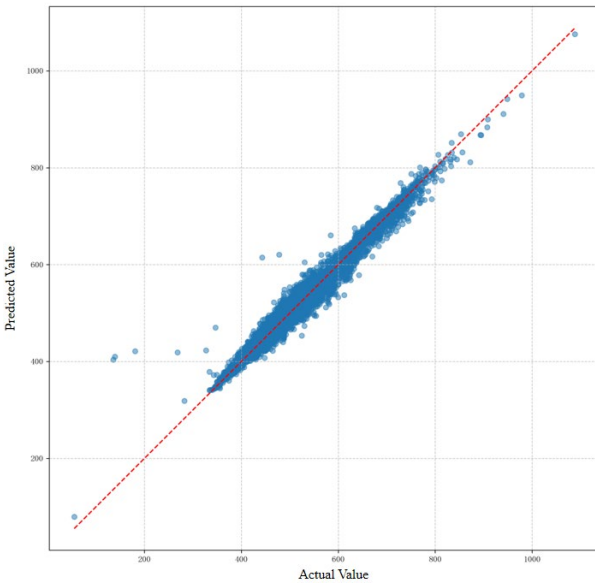


Figure 4 Scatter Plot of Building Load Prediction

From the perspective of quantitative indicators: the MAE, RMSE, and  $R^2$  for total building load prediction are 6.138, 7.623, and 0.979, respectively. These results indicate that the model achieves high overall prediction accuracy and excellent fitting performance for building load.

#### 4.2 Chiller Energy Consumption Prediction

The chiller energy consumption prediction results are shown in Figure 5. The matching degree between the predicted values and actual values also performs excellently: during the periods when the chiller operates at full load, the deviation between the predicted values and actual values is less than 5 kWh. This indicates that the model can accurately capture the intra-day

fluctuations and inter-day differences in chiller energy consumption.

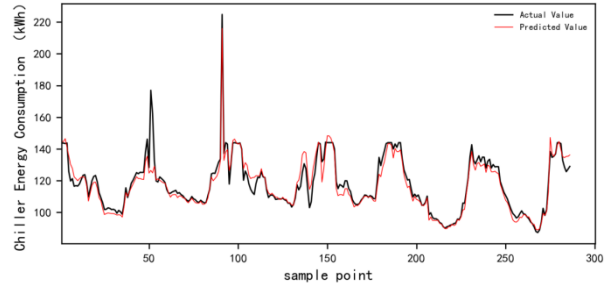
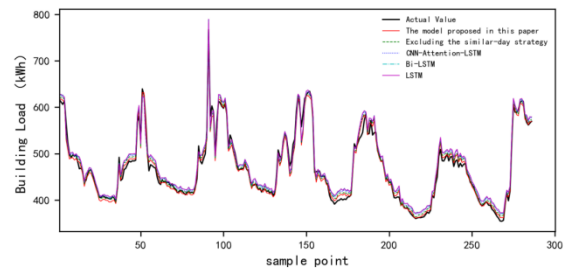


Figure 5 Chiller Energy Consumption Prediction Results

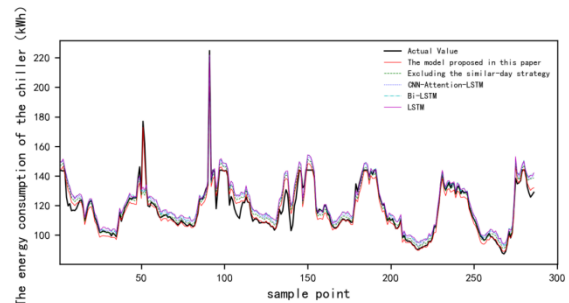
## 5. DISCUSSION

To further verify the superiority of the energy consumption prediction model proposed in this study, mainstream models in the field of building energy consumption prediction — including CNN-Attention-LSTM, Bi-LSTM, and LSTM were selected as comparison models. Additionally, the X-LSTM-Transformer hybrid model without the similar-day strategy was also included for comparison.

Performance comparison experiments were conducted under the same experimental data and environment. Each model was run independently 10 times, and the average metrics on the test set were taken as the final results. The comparison results are shown in Figure 7. It can be intuitively observed from the figure that the proposed X-LSTM-Transformer model exhibits a significantly higher degree of alignment between its prediction results and the actual values than the other comparison models.



(a) Building Load



(b) Chiller Energy Consumption

Figure 6 Comparison Experiments

The prediction performance metrics of different models are presented in Table 2. As can be seen from Table 2, all metrics of the proposed model in this study are significantly superior to those of the comparison models.

Fig. 2 Accuracy Distribution

Evaluation Metrics	Building Load Prediction			Chiller Energy Consumption Prediction		
	MAE	RMSE	R <sup>2</sup>	MAE	RMSE	R <sup>2</sup>
Proposed Model in This Study	6.138	7.623	0.979	4.097	6.358	0.956
Model Without Considering the Similar-Day Strategy	8.107	10.812	0.975	4.233	6.494	0.932
CNN-Attention-LSTM	9.829	12.243	0.972	4.436	6.872	0.926
Bi-LSTM	11.185	13.321	0.967	4.758	7.034	0.912
LSTM	11.791	13.832	0.964	5.074	7.152	0.901

## 6. CONCLUSIONS

This study proposes a multi-objective prediction method for building load based on similar days that accounts for window inconsistency, achieving accurate prediction of total building load and chiller energy consumption. The core conclusions are as follows:

Similar-day selection integrates meteorological and date attributes to select 100 similar-day samples, enabling window feature matching between training data and prediction scenarios. Compared with models without similar-day selection, prediction errors are significantly reduced.

Multi-column convolution provides dedicated extraction pathways for meteorological, temporal, and historical load features, while the target-aware weight layer dynamically allocates feature contribution degrees. Compared with single-convolution-channel models, feature utilization efficiency is fully improved.

The LSTM model captures cross-day and cross-week long-term dependencies, and the Transformer enhances the feature weights of key time periods based on the self-attention mechanism. Together, they collaboratively achieve comprehensive characterization of long-term patterns and short-term dynamics.

In future research, we will focus on the adaptive optimization of similar-day selection, the improvement of model generalization ability, and the design of lightweight architectures. The goal is to improve the method system to adapt to more building energy-saving scenarios.

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