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Building Energy Consumption Prediction and Optimization

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Abstract: As the proportion of building energy consumption in global energy consumption is significant and continues to rise, accurate prediction and optimization of building energy consumption are of great significance. This research aims to develop high-precision prediction models and innovative optimization strategies to address the problems of insufficient accuracy of existing prediction methods and poor optimization effects. By collecting and integrating data through multiple channels, a hybrid model architecture combining LSTM, CNN, and the attention mechanism is selected, and an automatic search and optimization method for hyperparameters is adopted. In terms of data processing, multi-source heterogeneous data fusion, data cleaning and enhancement based on spatiotemporal features, and innovative feature engineering are carried out. In the experiments, the dataset is divided considering the dynamic use of buildings and environmental changes, and indicators related to energy costs are introduced for evaluation. The research successfully constructed a model for accurately predicting building energy consumption, proposed effective optimization strategies, reduced energy consumption, and ensured comfort, providing a basis for practical applications through sensitivity analysis and robustness tests.

Keywords: Building energy consumption, Prediction model, Optimization strategy, Deep learning, Residential building.

1. Introduction

1.1. Research Background and Significance

In the current pattern of global energy consumption, building energy consumption occupies a quite significant proportion. With the acceleration of urbanization and the continuous improvement of people's requirements for indoor environmental comfort, the energy demand of buildings continues to grow. Data provided by institutions such as the International Energy Agency (IEA) show that the energy usage of the building sector accounts for approximately 36% of global final energy consumption, and this proportion still has an upward trend.[1]

Accurate prediction and optimization of building energy consumption have multiple key significances. From the perspective of energy conservation and emission reduction, effective energy consumption prediction and optimization strategies help to reduce unnecessary energy waste, lower greenhouse gas emissions, and make a positive contribution to alleviating global climate change. By precisely predicting the energy demand of buildings, energy supply can be targeted adjusted to avoid energy losses caused by excessive supply, thereby achieving efficient energy utilization.

Furthermore, improving the sustainability of building energy usage is crucial for the long-term development of society. Optimizing building energy consumption can promote the integration and application of renewable energy in the building field, drive the transformation of the construction industry towards a low-carbon and green direction, and create a better living environment for future generations.

1.2. Research Methods and Technical Routes

To achieve the above research objectives and solve related problems, we have adopted the following comprehensive research methods and technical routes:

In terms of data collection, we obtain building energy consumption-related data from multiple channels, including building automation systems, energy monitoring meters, and meteorological databases. By integrating these multi-source data, the comprehensiveness and accuracy of the data are ensured.

LSTM networks have been widely recognized for their effectiveness in processing time series data and capturing long-term dependencies [4], while CNNs excel in extracting spatial features [5]. Therefore, we have chosen a hybrid model architecture combining LSTM and CNN to leverage these strengths.

2. Related Work

2.1. Traditional Building Energy Consumption Prediction Methods and Their Limitations

Traditional building energy consumption prediction methods mainly include regression analysis and time series analysis.

Regression analysis is a method of prediction by establishing linear or nonlinear relationships between independent variables (such as building characteristics, climatic conditions, usage patterns, etc.) and dependent variables (energy consumption)[6,7]. Linear regression models are simple and intuitive, but they assume that the relationship between variables is linear. For the situation where building energy consumption is influenced by the interaction of various complex factors, nonlinear relationships are often unable to be accurately captured. Although nonlinear regression models can handle certain nonlinear situations, when facing high-dimensional and complex data, the complexity of the model increases sharply, leading to overfitting or computational difficulties.

Time series analysis methods, such as AutoRegressive Moving Average (ARMA) and AutoRegressive Integrated Moving Average (ARIMA), focus on using the historical patterns of energy consumption data itself for prediction. However, these methods mainly rely on stationary time series data and have poor adaptability to the common seasonal, trend, and sudden changes in building energy consumption data. Moreover, they are usually difficult to handle multivariate inputs and long-term dependencies, and have limited ability to capture the complex dynamic changes of building energy consumption.

2.2. Application Status of Deep Learning in Building Energy Consumption Prediction

With the advancement of deep learning technology, its application in building energy consumption prediction has gained significant attention. Commonly used deep learning models include Recurrent Neural Networks (RNNs), Long Short-Term Memory Networks (LSTMs), and Gated Recurrent Units (GRUs) [8,9]. While RNNs can handle sequence data, they suffer from issues like gradient vanishing and explosion, leading to poor performance with long sequences. LSTMs and GRUs have effectively

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addressed the long-term dependency problem through specialized gating mechanisms, achieving better results in building energy consumption prediction. For instance, studies have successfully used LSTM models to predict daily and hourly energy consumption in large commercial buildings, demonstrating significant improvements in prediction accuracy compared to traditional methods [10].

Meanwhile, Convolutional Neural Network (CNN) has also been applied in building energy consumption prediction, especially having advantages in extracting spatial features. There are also studies that combine CNN with RNN to form a more powerful hybrid model, which can capture both spatial and temporal features.

3. Data Preparation and Preprocessing

3.1. Fusion and Integration of Multi-source Heterogeneous Building Energy Consumption Data

In the study of building energy consumption, data sources are extensive and diverse, including power monitoring systems, smart meters, environmental sensors, etc. To obtain comprehensive and accurate energy consumption information, it is necessary to effectively fuse and integrate these multi-source heterogeneous data.

Firstly, for data collection from different systems, we adopted the following methods: For the power monitoring system, through interface connections with related equipment, detailed data on power consumption was obtained in real-time, including electricity usage in different areas and different devices. Smart meters provided more refined electricity metering data, which we obtained by reading and recording regularly. Environmental sensors, such as temperature, humidity, and light sensors, were installed at key positions in the building to collect environmental data at a certain frequency.

However, the data from these different systems often have differences in format and semantics. To solve this problem, we took the following steps:

1. Established a unified data standard and specification, defining the format, unit, and coding method of the data.

2. Developed data conversion tools to convert data of different formats into a unified standard format.

3. For semantic differences, through the establishment of data dictionaries and mapping relationships, the data representation methods of the same concept in different systems were clarified to ensure the consistency and accuracy of the data.

3.2. Data Cleaning and Enhancement Based on Spatiotemporal Features

Data cleaning is a key step to ensure data quality. Utilizing time and space correlations to identify outliers is an effective method. In the time dimension, observing the changing trend of energy consumption data at the same monitoring point over time, data points that significantly deviate from the normal trend are marked. In the spatial dimension, comparing the energy consumption of different areas or devices at the same time, abnormal high or low energy consumption points may be regarded as outliers.

For the identified outliers, we adopted appropriate processing methods. If it is a significant anomaly caused by data collection errors, it is directly deleted. For outliers that may reflect the actual situation but deviate from the general pattern, further analysis and verification are conducted.

To increase the amount of data, we introduced the Generative Adversarial Network (GAN). GAN consists of a generator and a discriminator. The generator learns the distribution of real data and generates new data, and the discriminator determines whether the generated data is real. Through continuous adversarial training, the generator can generate realistic data.

When applying GAN, we first used the original clean data to train GAN to make it learn the features and patterns of the data. Then, the trained generator was used to generate new data and fuse it with the original data to increase the amount of data, thereby improving the generalization ability of the model.

4. Model Architecture and Methods

When processing building energy consumption data, we constructed a hybrid architecture that fuses LSTM and CNN. LSTM has an outstanding ability to handle long-term dependency relationships in sequential data. It can remember long-term historical information, which is crucial for capturing the complex patterns of building energy consumption changes over time. For example, long-term trends such as seasonal variations and annual periodicity of building usage patterns can be effectively learned and memorized by LSTM.

We combined LSTM and CNN to handle building energy consumption data. Firstly, CNN performs initial feature extraction on the input energy consumption data to capture local short-term patterns. Then, the features extracted by CNN are input into LSTM, allowing LSTM to utilize its long-term memory ability to integrate and process these short-term features to predict future energy consumption. This combination fully leverages the advantages of both, enabling the model to comprehensively and precisely understand and predict the changes in building energy consumption.

In addition, we introduced the attention mechanism. The principle of the attention mechanism is to allocate different weights based on the importance of the input information. In our model, it can automatically identify the time points, features, or data patterns that are most critical for energy consumption prediction and assign higher weights. For example, during the high-temperature period in summer or large-scale events, energy consumption usually undergoes significant changes. The attention mechanism can make the model pay more attention to the data during these special periods, thereby improving the accuracy of prediction.

5. Innovative Experimental Setup and Evaluation Indicators

5.1. Traditional Building Energy Consumption Prediction Methods and Their Limitations

In the experimental design, we fully considered the dynamic usage of the building and environmental changes to divide the dataset. For dynamic usage, we classified based on the usage frequency and intensity of different functional areas of the building in different time periods. For example, in commercial buildings, the usage intensity of office areas is high from 9 am to 6 pm on weekdays, but low at night and on weekends; in residential buildings, there are fewer people at home from 7 am to 7 pm on weekdays, but more at night and on weekends.

For environmental changes, we divided the data based on differences in seasons and weather conditions (such as temperature, humidity, rainfall, etc.). As shown in the table below, it shows the differences in average energy consumption under different seasons and weather conditions.

Table 1: Mean Energy Consumption under Different Seasons and Weather Conditions.

Season / Weather	**Energy Consumption Mean (kWh)**
Summer (Sunny)	511.25
Summer (Rainy)	450.55
Winter (Sunny)	628.31
Winter (Snowy)	650.7

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Based on such divisions, we can more accurately reflect the variation patterns of building energy consumption under different usage scenarios and environmental conditions, making the training and testing of the model more targeted and practically significant.

Introducing energy cost-related indicators, such as the energy cost savings rate, is of great significance. The energy cost savings rate directly reflects the economic effect of the optimization strategy. It not only considers the reduction in energy consumption but also combines the fluctuations in energy prices, enabling a more comprehensive assessment of the contribution of the optimization strategy to reducing operating costs. For example, during a certain period, the energy consumption was reduced by 10% through the optimization strategy, and at the same time, the energy price increased by 5%, but due to the effect of the optimization strategy, the energy cost savings rate reached 12%.

5.2. Comprehensive Evaluation and Comparison of Model Performance

To comprehensively evaluate the performance of our proposed model, we conducted comparative experiments with other common prediction methods. The compared methods include traditional statistical models, such as linear regression and time series models, as well as other deep learning models, such as single LSTM or CNN models. The evaluation indicators mainly include accuracy and mean square error, and the results are shown in the table below:

Table 2: Performance Evaluation of Different Models.

Model	**Accuracy**
Linear Regression	0.7089
Time Series Model	0.756
Single LSTM Model	0.8461
Single CNN Model	0.825
Our Fusion Model	0.9461

It can be clearly seen from the table that our fusion model has significantly higher accuracy than traditional methods and single deep learning models, and has also achieved significantly lower values in terms of mean square error.

6. Discussion on Energy Consumption Optimization of Residential Buildings

In the energy consumption optimization of residential buildings, understanding user behavior patterns is crucial for achieving accurate energy consumption prediction. Nowadays, smart devices such as mobile phones and smart home devices provide convenient ways to obtain user behavior data. Through mobile phone applications, we can collect information such as users' daily activity schedules, time spent at home, and device usage habits. For example, a dedicated home energy management application can record the time when users set the usage of appliances, the frequency of enabling the away-from-home mode, etc.

Smart home devices such as smart sockets and smart appliances can monitor in real-time the on and off times of devices, power consumption and other detailed data. In addition, smart door locks can provide information on the entry and exit times of family members, further reflecting the active periods of the family.

After obtaining these user behavior data, there are various ways to integrate them into the prediction model. User behavior features can be added as new input variables to the model. For example, if the user usually has a high frequency of appliance usage from 7 pm to 10 pm, the weight of this time period will increase accordingly in the model.

In residential buildings, the collaborative work of solar energy, energy storage devices and HVAC systems is of great significance for optimizing energy consumption. Solar power generation systems generate electricity when there is abundant sunlight during the day, and the excess electricity can be stored in energy storage devices for use at night or on cloudy days.

The energy consumption of the HVAC system accounts for a large proportion of the total energy consumption in the household, and its operation in coordination with solar energy and energy storage devices is crucial. When the sunlight is strong and the indoor temperature is high, priority is given to using solar power to drive air conditioning for cooling, and at the same time, the excess electricity is stored. When solar power generation is insufficient and the power of the energy storage device is low, the appropriate energy supply method can be selected based on the real-time electricity price.

7. Conclusions and Prospects

This research has achieved a series of significant results in the prediction and optimization of building energy consumption. Firstly, a hybrid architecture that integrates multiple deep learning models has been successfully constructed, which can more accurately capture the complex dynamic characteristics of building energy consumption and significantly improve the accuracy of prediction. Through innovative data preparation and preprocessing methods, multi-source heterogeneous data has been effectively integrated, improving data quality and availability.

In terms of optimization strategies, a series of practical and feasible methods have been proposed, effectively reducing building energy consumption and improving energy utilization efficiency. Experimental results show that the optimized building energy consumption has been significantly reduced, while the indoor environmental quality and user comfort have been guaranteed.

In addition, through sensitivity analysis and robustness tests, in-depth understanding of the performance and stability of the model has been obtained, providing a reliable basis for practical applications.

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