IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received 17 October 2023, accepted 12 December 2023, date of publication 19 December 2023,
date of current version 26 December 2023.

Digital Object Identifier 10.1109/ACCESS.2023.3345029

RESEARCH ARTICLE

Urban Water Supply Forecasting Based on CNN-LSTM-AM Spatiotemporal Deep Learning Model

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This work was supported in part by the Hunan Provincial Natural Science Foundation of China under Grant 2020JJ4151, in part by the Scientific Research Fund of Hunan Provincial Education Department under Grant 20B077, and in part by the Science Foundation of Hengyang Normal University under Grant 2020QD21.

ABSTRACT Accurate and efficient forecasting of urban water supply is of great significance for urban water supply management. In this paper, a spatiotemporal deep learning model that integrates convolutional neural network (CNN), long short-term memory (LSTM), and attention mechanism (AM) is proposed for predicting the urban daily water supply. First, a one-dimensional CNN is used to identify the potential pattern structure in the water supply system and automatically extract the spatial features of the water supply data. Second, the feature vector output from the CNN is constructed into time series form and used as input to the LSTM network, and the parameters of the LSTM network are searched and optimized using the Bayesian algorithm. Then, the AM is introduced into the LSTM network, and the weighted sum is obtained by assigning the weights to the hidden layers of the LSTM network. Finally, the constructed CNN-LSTM-AM model captures the spatiotemporal information of the water supply data and makes an accurate prediction. Results show that the proposed CNN-LSTM-AM model reduces the mean absolute error, mean square error, and root mean square error values for two different sets of water supply data compared with the traditional LSTM, CNN-LSTM, and LSTM-AM models. The model has high forecasting accuracy and robustness, which are attributed to the excellent spatiotemporal feature extraction.

INDEX TERMS Attention mechanism, Bayesian optimization, convolutional neural network, long short-term memory network, urban water supply forecasting.

I. INTRODUCTION

Urban water supply networks are an important part of urban infrastructure and play a pivotal role in the protection of people's daily life and the urban development process. The urban population has increased substantially with the rapid development of the national economy, and the demand for water resources is also constantly growing. According to the China Urban and Rural Construction Statistical Yearbook 2021 published by the Ministry of Housing and Construction [1], the urban water supply has shown a trend of gradual increase in recent years, as shown in Table 1.

The urban water supply situation is affected by many factors, such as environmental climate, policy management, economic development, population size, and living habit [2], and its actual change is a combination of linear and nonlinear, showing regularity and randomness. Therefore, the feature extraction and nonlinear mapping of water supply forecasting are challenging. Urban water supply forecasting is not only the basis for relevant departments to carry out water resources planning and realize the rational allocation of water resources, it is also an important part of the urban water supply system that optimizes the quality of supply and management to achieve a balance between the supply and demand of urban water production and water use. Efficient and accurate forecasting of urban water supply is the link to

The associate editor coordinating the review of this manuscript and approving it for publication was Zijian Zhang.

TABLE 1. Statistics of total water supply in China from 2012 to 2021.

Serial number	Year	Total Quantity of Water Supply (10,000m³)
1	2012	5230326
2	2013	5373022
3	2014	5466613
4	2015	5604728
5	2016	5806911
6	2017	5937591
7	2018	6146244
8	2019	6283010
9	2020	6295420
10	2021	6733442

the optimal allocation of water resources and urban planning and construction [3].

The research on urban water supply forecasting at home and abroad started in the early 1970s. Many scholars have carried out substantial beneficial research and explorations on water supply forecast problems using different methods and achieved some valuable results [4], [5], [6]. The statistical theory method is the earliest forecasting method. The urban water supply forecast models based on this method mainly includes time series analysis [7], regression analysis [8], and autoregressive integrated moving average [9]. With the rapid advancement of computer technology, the forecast models with various artificial intelligence algorithms have continuously emerged, such as artificial neural network [10], support vector machine [11], random forest [12], recurrent neural network (RNN) and its variant long short-term memory (LSTM) [13]. Among them, the LSTM network is currently the most important time series forecasting model. Given that the unit state is added in the hidden layer to save the preserved information of the historical time, the temporal characteristics of the data can be fully considered [14], [15]. The LSTM-based model can extract important features at a deeper level, thus solving more complex forecast problems than the traditional statistical theory.

Chen et al. [16] proposed a method for forecasting short-term water demand on the basis of a one-dimensional convolutional gated recurrent unit. Convolutional neural network (CNN) was integrated into the gated recurrent unit to fully exhume the spatial feature information of the data. This model exhibited better forecasting accuracy and data feature extraction adaptability than the other models in the literature. CNN [17] is a kind of deep neural network with convolutional structures and has good robustness and generalization ability. In the field of prediction, CNN can automatically extract the spatial features of data and complete model fitting. If the spatial features extracted by the CNN are used as input to the LSTM model as training data, both the structure and characteristics of the spatial distribution of the water supply system can be considered, and the time series dependence of the water supply data's change process can be adequately extracted.

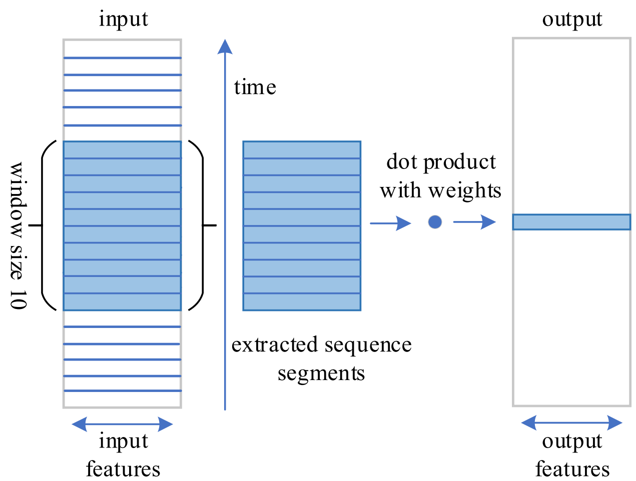

FIGURE 1. Schematic of one layer convolution of a 1D CNN.

A single LSTM model cannot simultaneously obtain the inherent spatial and temporal feature information in the data, making the high forecasting accuracy and wide generalization requirements difficult to meet [18]. In view of this, an urban water supply forecast model based on CNN-LSTM-attention mechanism (AM) is proposed in this paper. First, spatial features are efficiently extracted from the water supply data using CNN. Second, the Bayesian algorithm is utilized to optimize the LSTM network parameters, and the AM is introduced to implement weighted summation of the hidden layer information of the LSTM network. Next, LSTM is used to fully explore the temporal dependencies in the spatial feature sequences extracted from the CNN. Finally, the predictive effectiveness of the CNN-LSTM-AM model is examined and compared with that of the LSTM, CNN-LSTM, and LSTM-AM models, and the water supply data from two waterworks of different sizes in Zhuzhou City, Hunan Province, China are verified to ensure the superiority of the methodology outlined in this paper.

II. METHODOLOGIES

A. CONVOLUTIONAL NEURAL NETWORK

Convolutional neural networks [19], [20] are neurons with learnable weights and bias constants, and are composed of one or more convolution, pooling, and fully connected layers. CNN is characterized by local connection, weight sharing, pooling operation, and a multi-level structure. It can extract the local features of data, reduce the difficulty of network training, realize data dimensionality reduction, and combine low-level local features into higher-level features. CNN is widely used in computer vision, image processing, and time series forecasting [21].

The convolution layer is the core of CNN, and its idea is mainly to extract the important part of local features through a convolution operation. The convolution filter moves along all the dimensions of the input data, calculates the weights and dot products of the inputs, and then outputs it as part of a

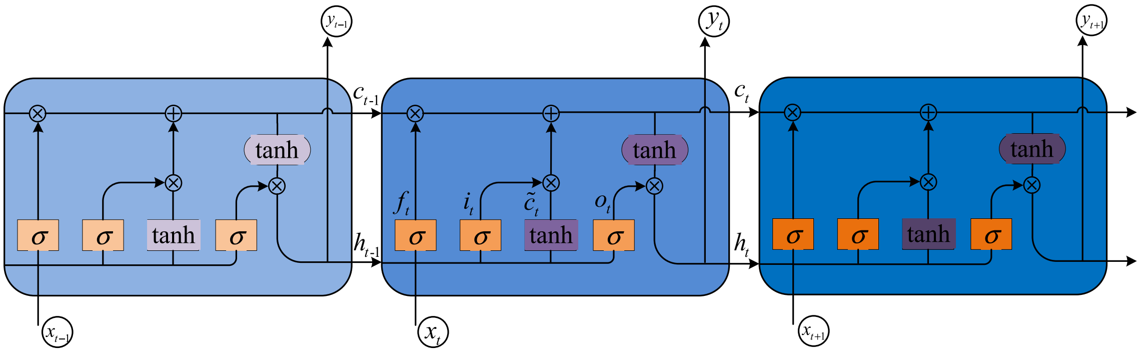

FIGURE 2. Information flow in inner structure of LSTM at three consecutive time steps: t-1, t, and t+1.

new sequence. Take a time window of size 10 as an example, as shown in Figure 1.

The number of convolution kernels directly affects the abstraction of feature extraction, but excessive convolution kernels will lead to a waste of resources. The pooling layer primarily involves the subsampling of the convolutional learned feature map through maximum (Max) or average (AVG) pooling. The former outputs the maximum value of the window, while the latter outputs the average value of the window. The significance of pooling layer [22] lies in its ability to decrease the input dimension of the subsequent network layer, decrease the model's size, enhance the calculation speed, and improve the feature map's robustness to prevent over-fitting.

B. LONG SHORT-TERM MEMORY

The LSTM network is a temporal convolutional neural network derived from RNN and was first proposed by Hochreiter and Schmidhuber [23]. LSTM has been broadly used in the field [24] of time series forecasting due to its outstanding advantages in dealing with long-distance dependency problems and reducing the learning difficulty of RNN.

The LSTM network is a special type of RNN, and its main structure is illustrated in Figure 2. To solve the problems of gradient vanishing and explosion, memory cell and three gate structures [25], including the input, forgetting, and output gates are introduced into LSTM. The gate structures are composed of the sigmoid activation function and the element-by-element multiplication operation for deleting, updating, and generating data. The LSTM network calculates the mapping from the input sequence to the output sequence, as shown in Eq. (1).

$$\begin{cases} f_t = \sigma(w_f x_t + u_f h_{t-1} + b_f) \\ i_t = \sigma(w_i x_t + u_i h_{t-1} + b_i) \\ o_t = \sigma(w_o x_t + u_o h_{t-1} + b_o) \\ \tilde{c}_t = \tanh(w_c x_t + u_c h_{t-1} + b_c) \\ c_t = f_t \odot c_{t-1} + i_t \odot \tilde{c}_{t-1} \\ h_t = o_t \odot \tanh(c_t) \end{cases} \tag{1}$$

where w_f, w_i, w_o, and w_c denote the weight vectors of the input gate to the input gate, forgetting gate, output gate, and cell state, respectively. u_f, u_i, u_o, and u_c denote the weight vectors of the hidden layer to the input gate, forgetting gate, output gate, and cell state, respectively. b_f, b_i, b_o, and b_c denote the bias vectors of the input, forgetting, and output gates and the cell state, respectively. σ denotes the sigmoid activation function that maps real numbers to intervals (0, 1). tanh denotes the hyperbolic tangent activation function, and $\odot$ represents the multiplication of vector elements.

C. ATTENTION MECHANISM

During neural network learning, adding model parameters can enhance the model's expressiveness and store more information. However, this approach will also lead to information overload. The AM [26] essentially realizes the assessment and trade-off of the importance of information. In the training process, the importance of different time nodes and the characteristics of time series data are easily ignored by the LSTM network. AM is added to the LSTM network, so that LSTM can be focused on information that is critical to the current task among the numerous input information, reducing the attention to other non-important information, and even filtering out irrelevant information. This approach not only solves the problem of information overload but also realizes the spatiotemporal interpretability of CNN-LSTM, thereby improving the accuracy and generalization ability of forecasting [27]. The formulas are shown in Equations (2) to (4).

$$s_i = \tanh(w^T h_i + b_i) \tag{2}$$

$$\alpha_i = soft\max(s_i) = \frac{\exp(s_i^T s_0)}{\sum_{i=1}^{t} \exp(s_i^T s_0)} \tag{3}$$

$$c_i = \sum_{i=1}^{t} \alpha_i h_i \tag{4}$$

where s_i indicates the degree of correlation between h_i and c_i. α_i is the attention weight, which is usually expressed as a softmax function.

D. STRUCTURE OF THE CONSTRUCTED CNN-LSTM-AM MODEL

A spatiotemporal deep learning forecast model based on the combination of LSTM, CNN, and AM is proposed. The basic

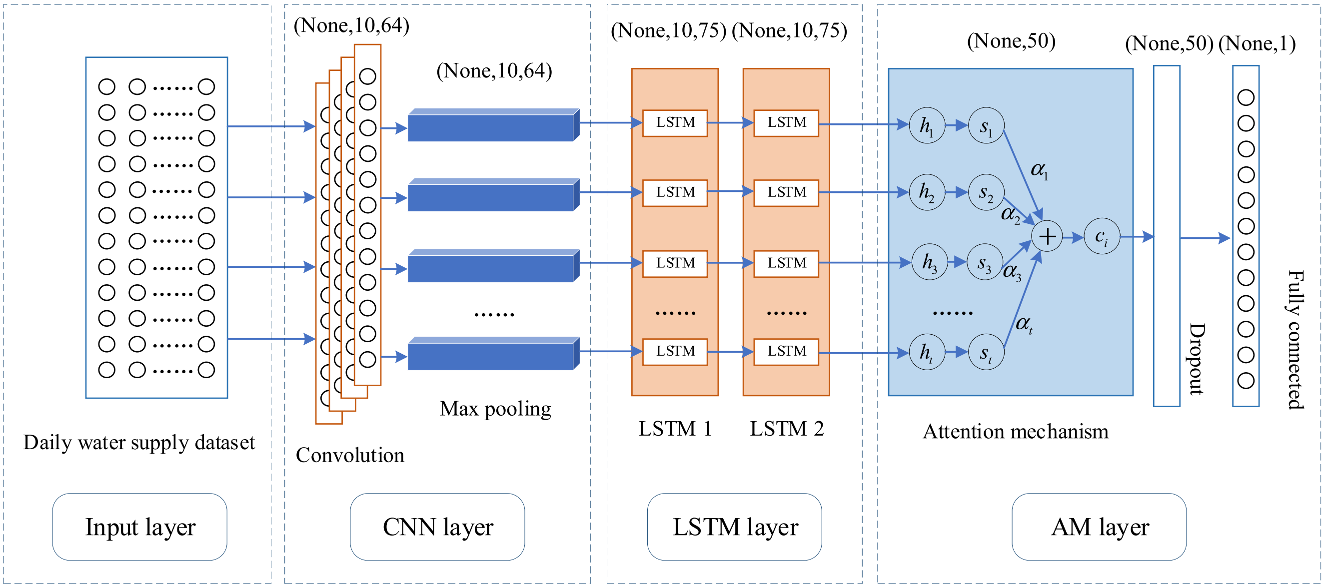

FIGURE 3. **CNN-LSTM-AM forecast modeling network architecture framework.**

structural framework of the CNN-LSTM-AM model is shown in Figure 3.

a) The first layer is the input layer. The historical operation data of urban water supply is analyzed, and the input format is specified by the input layer. The data is in turn fed into the CNN layer.

b) The second layer is the CNN layer. The CNN layer mainly includes convolution and pooling operations. The water supply sample data is divided into a three-column data matrix, and the input data takes the form of a sliding window of 10 water supply time series data at a time, forming a 10 × 3 vector. The 10 × 3 vector is transformed a data characteristic graph, and then the convolution operation is carried out. The convolution is composed of a group of filters. The depth of the filter is determined by the depth of the input sample data, and different granularity features can be extracted. The feature vectors of the convolution layer output are reduced by pooling, which reduces the spatial size of the data and improves the robustness of spatial feature extraction.

c) The third layer is the LSTM layer. The feature vectors of the CNN layer are taken as input after the Reshape operation and passed to the LSTM layer. The LSTM network has a memory function for extracting the nonlinear time-order change of the water supply data. By learning and processing the special structure of its hidden layer, the transmission of historical water supply information is controlled, and the temporal variation law is excavated.

d) The fourth layer is the AM layer. On the one hand, AM employs the probability weighting mechanism to facilitate the LSTM network's extraction of information, concentrating on the most significant time series for the forecast task, and ultimately enhancing the forecast accuracy. On the other hand, feature synthesis and dimension transformation are carried out through the fully connected layer. The water supply data is learned through a series of model training, and the forecasted values are finally output.

TABLE 2. **Water supply data for waterworks.**

Datasets	Time	Daily Water Supply Time Series
Waterworks A	January 1, 2007–June 22, 2012	2000 data
Waterworks B	January 1, 2007–December 5, 2016	3627data

The CNN-LSTM-AM spatiotemporal deep learning model utilizes CNN to extract spatial connections between different feature values in water supply data, thereby compensating for the shortcoming of LSTM in capturing the spatial components of the data. The AM enables the LSTM network to distinguish the impact of different water supply timing points on future water supply forecasting, increase the weight proportion of key information, and reduce the weight of non-important information. The model can mine the implicit features present in a vast amount of historical water supply data, learn and model these nonlinear relationships, effectively handle the spatiotemporal relationship between long-term dependence and short-term change, and capture the complexity of internal factors in water supply.

III. CASE STUDY

A. EXPERIMENTAL DATA

The research examples were selected from the daily water supply of two different waterworks in Zhuzhou City, Hunan

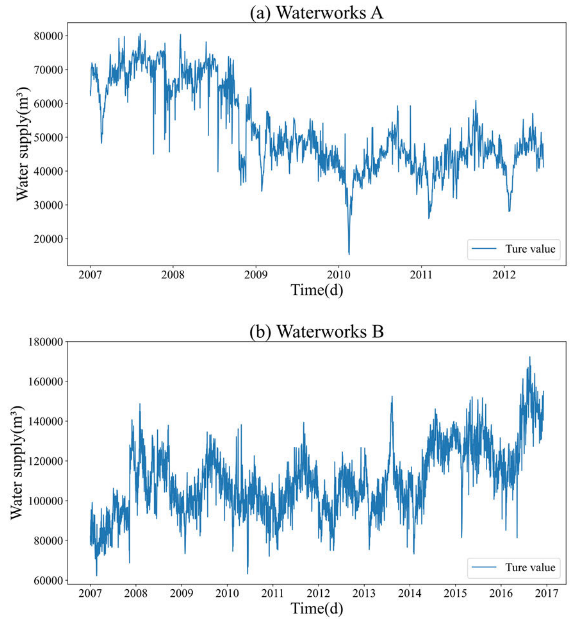

FIGURE 4. Curve plot of water supply data.

Province, China (other influencing factors are not considered), namely, the total readings from the outflow meters of Waterworks A and B, respectively. A total of 2000 samples with water supply data from January 1, 2007 to June 22, 2012 were collected from Waterworks A, and 3627 samples with water supply data from January 1, 2007 to December 5, 2016 were collected from Waterworks B, as shown in Table 2.

As shown in Figure 4, the daily water supply sequence shows a certain change rule over time. Given that the New Year holiday in China is from February to March every year, the lowest point of water supply usually occurs in this period. In summer, from June to September, the water consumption in China is expected to increase significantly, resulting in a corresponding increase in water supply demand. A certain degree of volatility and randomness exists in the relative regularity due to the occurrence of various emergencies.

B. DATA PREPROCESSING

The water supply data is monitored daily at different time steps. During the detection process, some water supply data may be lost or abnormal due to unexpected circumstances, such as human record error, deviation, or damaged measuring instrument. Missing or abnormal data will affect the accuracy and generalization ability of the model in the later prediction process, so missing or abnormal data must be preprocessed.

First, the original data was cleaned to eliminate missing or abnormal samples. Second, the water supply data was smoothed and denoised by Savitzky-Golay (S-G) filtering. Subsequently, to reduce the computational complexity and accelerate model training, the max-min normalization method was employed to standardize the data set. The experimental results should be evaluated at follow-up, requiring the denormalization of the forecasted data. The normalization formula is shown in Eq. (5), and the inverse normalization formula is shown in Eq. (6).

$$\hat{x}_t = \frac{x_t - \min(x_t)}{\max(x_t) - \min(x_t)} \tag{5}$$

$$x_t = \hat{x}_t(\max(x_t) - \min(x_t)) + \min(x_t) \tag{6}$$

where x_t is the original value. $\max(x_t)$ and $\min(x_t)$ are the maximum and minimum values of x_t, respectively. $\hat{x}_t$ indicates the normalized value.

C. EVALUATION INDEXES

In this study, the mean absolute error (MAE), the mean square error (MSE), the root mean square error (RMSE), and the coefficient of determination (R^2) were considered as the evaluation indexes to quantitatively validate the forecast effect of the model. The MAE responds to the average of the forecast error, the MSE indicates the average of the square sum of the difference between the forecasted and true values, and the RMSE measures the deviation of the forecasted value from the true value. The smaller the values of the three errors are, the more accurate the forecast results are. The value of R^2 is in [0, 1]. Generally, the closer the R^2 value is to 1, the better the model fitting will be. The formulas are shown in Eq. (7).

$$\begin{cases} \mathrm{MAE} = \frac{1}{\mathrm{n}} \sum_{i=1}^{n} \left| y - y_{pre} \right| \\ \mathrm{MSE} = \frac{1}{\mathrm{n}} \sum_{i=1}^{n} (y - y_{pre})^2 \\ \mathrm{RMSE} = \sqrt{\frac{1}{\mathrm{n}} \sum_{i=1}^{n} (y - y_{pre})^2} \\ R^2 = 1 - \frac{\sum_{i=1}^{n} (y_{pre} - y)^2}{\sum_{i=1}^{n} (\bar{y} - y)^2} \end{cases} \tag{7}$$

where y is the true value, y_{pre} is the forecasted value, $\bar{y}$ is the average of the true values, and n denotes the sample size.

D. EXPERIMENTAL PROCESS

In this paper, we proposed a spatiotemporal feature extraction model based on CNN-LSTM-AM for urban water supply forecasting. The flow diagram is shown in Figure 5, and the specific steps are as follows.

(1) The water supply data was acquired as shown in Section III-A, and two sets of data were selected for this experiment.

(2) After preprocessing the data Section III-B, it was divided into training and test sets at an 8:2 ratio. In this case, 1600 data in Waterworks A were used as training samples,

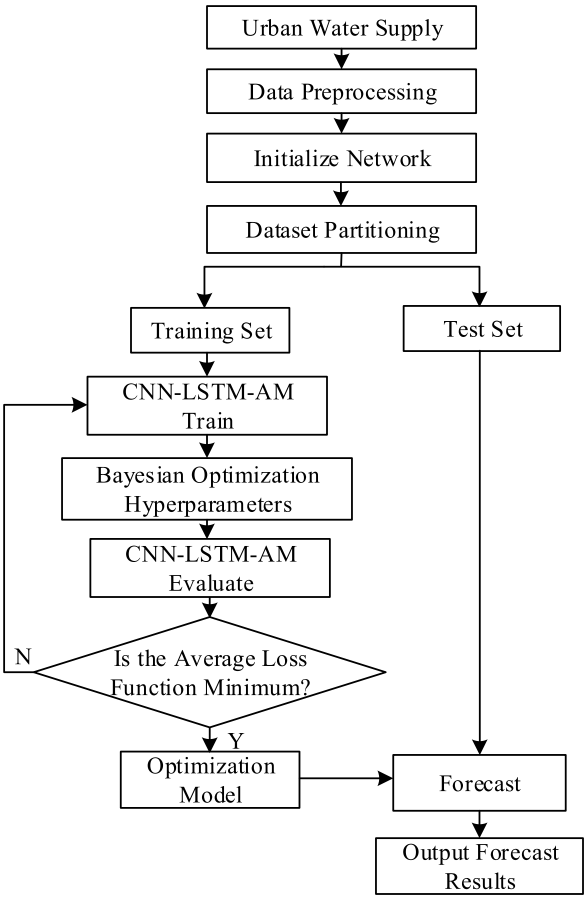

FIGURE 5. Flowchart of this research.

and the remaining 400 data were used as test samples. Then, 2901 data in Waterworks B were used as training samples, and the remaining 726 data were used as test samples. The data in the training set was selected for training and learning, and the data in the test set was used to check the forecast accuracy of the model.

(3) The water supply data from the training set was fed to the constructed CNN-LSTM-AM model to be trained and learned to optimize the model, and the specific process was shown in Section II-D.

(4) The optimal hyper-parameters of the LSTM network could be searched using the Bayesian optimization algorithm, and each set of hyper-parameters was evaluated using K-fold cross validation.

(5) The average loss function value was calculated for each set of hyper-parameters after training, and the set of hyper-parameters with the smallest average loss function value was selected as the optimal hyper-parameters of the LSTM network in this model to obtain the optimal forecast model.

(6) The test set data was used as input to the trained CNN-LSTM-AM model for forecasting, and the final forecasted values were output. The evaluation indexes of the forecast results were calculated based on the forecasted and true values.

E. PARAMETER SETTINGS

The predictive performance and generalization ability of the model are directly proportional to the number of network layers. Generally, increasing the number of network layers can increase the model's capacity and expressive ability and improve the fit of the training data. In addition, excessive network layers can easily lead to over-fitting, which deteriorates the model performance on the test set, decreases the generalization ability, and takes up considerable computing resources. Given that the historical water supply was selected as an input variable in this study, one layer was adopted for each network layer of the model. A single-layer CNN network was used to extract the spatial features of the data. A single-layer LSTM network was used to extract the temporal features of the data. A single-layer AM network was used for weight assignment.

In this model, the number of convolution cores in the convolution layer was set to 64, and the size of the convolutional kernel was set to 2*2. The filling method was set to same, and Relu was utilized as the activation function to accelerate the training process while ensuring the effectiveness of the training. The window size of the maximum pooling layer was 3. In the LSTM layer, the Bayesian optimization algorithm was utilized to determine the most appropriate value of its hyper-parameters, such as the LSTM unit, the dropout, the optimizer, and the activation function. The batch size was set to 32; the number of epochs was set to 100; the number of neurons in the AM was set to 50 to allocate the weight proportion of the LSTM hidden layer output, and the number of neurons in the fully connected layer was 1, realizing the dimensional transformation of data and generating the forecast results of the model.

F. INSTANCE VERIFICATION

To illustrate the effectiveness of the proposed algorithm, the proposed CNN-LSTM-AM model is compared with the traditional LSTM model and the combined CNN-LSTM and LSTM-AM models. The forecast results of Waterworks A in different models are compared in Figure 6(a), and the scatter plot of the forecasted and true values of Waterworks A in the CNN-LSTM-AM model is shown in Figure 6(b). The forecast results of the Waterworks B in different models are compared in Figure 7(a), and the scatter plot of the forecasted and true values of Waterworks B in the CNN-LSTM-AM model is shown in Figure 7(b).

The forecast effect of the proposed CNN-LSTM-AM model is compared with that of other traditional forecast models, as depicted in Figures 6(a) and 7(a). All four models have good predictive performance, and the forecast curves can respond well to the changing trend of the true curve. Nevertheless, when sudden changes in water supply occur, such as the peaks and corners in Figures 6(a) and 7(a), the single LSTM model cannot accurately and timely follow the changes in the true value of the water supply to make adjustments, resulting in a large forecast error. The CNN-LSTM

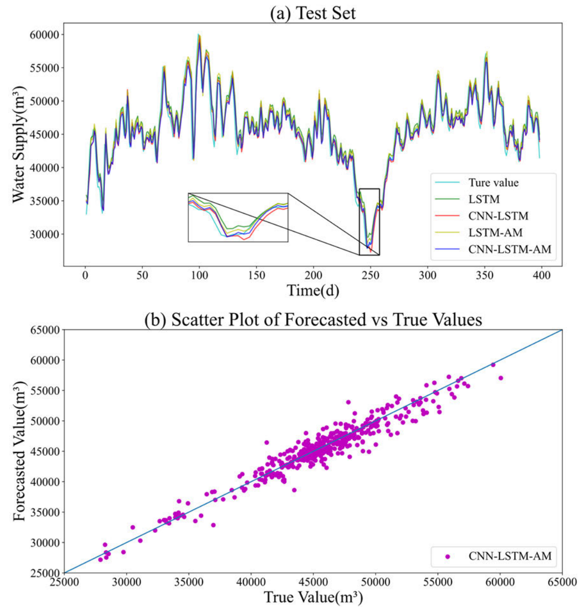

FIGURE 6. Forecast results and scatter plot for test set of the waterworks A.

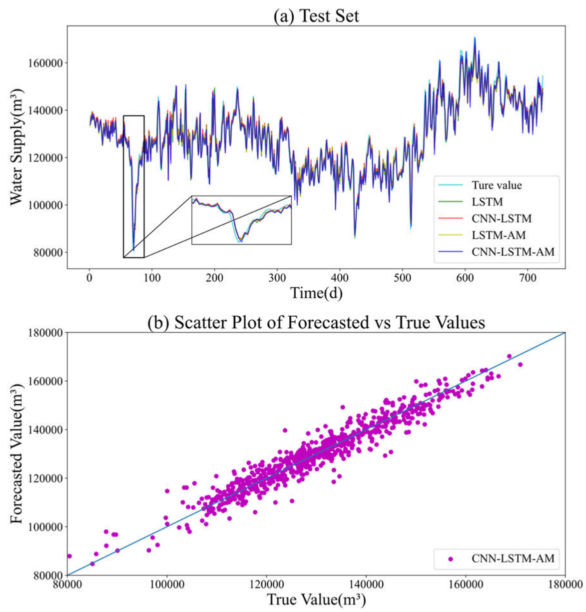

FIGURE 7. Forecast results and scatter plot for test set of the waterworks B.

and LSTM-AM models can follow the changes in the true value of water supply better than a single LSTM model, reflecting less bias. However, the CNN-LSTM-AM model more accurately forecasted the changes in the true value of water supply with a better fit at some points with large fluctuations, especially at peaks and corners. The forecasted curve of the model basically coincides with the true curve, accurately capturing the small changes in the values. The scatter plots in Figures 6(b) and 7(b) illustrate the correlation between the forecasted and true values. From the scatter plots, it can be noticed that the forecasted values are generally

TABLE 3. Comparison of forecast results of different models (Waterworks A).

Model	MAE	MSE	RMSE	R^2
LSTM	0.00059	0.02832	0.02011	0.89643
CNN-LSTM	0.00050	0.02269	0.01700	0.92622
LSTM-AM	0.00052	0.02274	0.01737	0.92537
CNN-LSTM-AM	0.00048	0.02194	0.01687	0.93050

TABLE 4. Comparison of forecast results of different models (Waterworks B).

Model	MAE	MSE	RMSE	R^2
LSTM	0.00150	0.03875	0.02972	0.91557
CNN-LSTM	0.00132	0.03642	0.02797	0.92543
LSTM-AM	0.00111	0.03332	0.02542	0.93758
CNN-LSTM-AM	0.00106	0.03257	0.02459	0.94036

consistent with the true values, and the scatter points are concentrated and distributed near the straight line. The proposed CNN-LSTM-AM model, which has great learning and forecasting capabilities, is visually verified by Figures 6 and 7. In summary, the forecast results of the CNN-LSTM-AM model illustrate that the ability of the LSTM model to extract information and process long time series and the CNN and the AM play an extremely important role in improving the effectiveness of water supply forecasting.

The forecast results of the four models were determined on the two test sets using the MAE, MSE, RMSE, and R^2 evaluation indexes. The results of the evaluation indexes in Tables 3 and 4 are provided using Waterworks A and B. The final value of each index was determined by taking the average of 10 run.

The MAE, MSE, RMSE, and R^2 values of Waterworks A and B in different models are presented in Tables 3 and 4, respectively. The proposed CNN-LSTM-AM model was calculated and analyzed with the other three models in terms of the specific values of the evaluation indexes. Specifically, in Waterworks A, the proposed model was compared with the LSTM, CNN-LSTM, and LSTM-AM models. The MAE was reduced by 18.6%, 4%, and 7.6%, respectively; the MSE was reduced by 22.5%, 3.3%, and 3.5%, respectively; the RMSE was reduced by 16.1%, 0.7%, and 2.8%, respectively; and the R^2 was improved by 3.8%, 0.4%, and 0.5%, respectively. In Waterworks B, the MAE was reduced by 29.3%, 19.6%, and 4.5%, respectively; the MSE was reduced by 15.9%, 10.5%, and 2.2%, respectively; the RMSE was reduced by 17.2%, 12.0%, and 3.2%, respectively; and the R^2 was improved by 2.7%, 1.6%, and 0.2%, respectively. Tables 3 and 4 confirm that the forecast error of this model is smaller than that of the other three models, which is confirmed by the values of the MAE, MSE, RMSE, and R^2 indexes. The historical water supply data is implicitly affected by temperature, humidity, holidays, and other relevant factors and has a certain degree of complexity and uncertainty. The

CNN-LSTM-AM model can mine the implicit features in the historical data, capture the change rule of the data, and obtain forecast results in the forecast process of the complex urban water supply better than the other models.

IV. CONCLUSION

In this paper, through the in-depth analysis and research of existing urban water supply forecast methods, a spatiotemporal deep learning model based on CNN-LSTM-AM was proposed for urban water supply forecasting. First, the historical water supply data from two waterworks were preprocessed and fed into the CNN network as feature variables, and CNN could effectively extract the spatial characteristics of the water supply sequence. Second, the Bayesian algorithm and AM were introduced to the LSTM network to realize the automatic selection of LSTM network parameters and the autonomous assignment of weights to the time series data to highlight the influence of important information. Finally, the model realized automatic spatial and temporal feature extraction, deeply mining relevant water supply information and obtaining high-precision forecast results. The experimental results demonstrated that the proposed CNN-LSTM-AM model not only strengthened the capture and representation of time series correlation information in LSTM networks but also improved the training speed and accuracy of the model. Although the research results mainly focus on the forecast of water supply, this method can also be applied to other forecast problems in water resources and hydrological research.

The performance of the proposed CNN-LSTM-AM model was comprehensively analyzed in this study, but some aspects deserve further investigation. For example, when analyzing the impact of input variables on the model's forecast performance, the interactions between variables should be considered in addition to the effects of a single variable on the model prediction performance. Therefore, we will consider the interactions between multiple variables and the effects of multivariate inputs on model forecasting in future research to improve and refine the forecast model.

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