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Daily Water Demand Prediction Driven by Multi-source Data

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Abstract

The best scheduling of water distribution systems may be supported by accurate and trustworthy water demand forecasts, which is a positive assurance for the development of smart cities and smart water services. This paper studies a new multivariate time-series prediction model that is based on the Convolution Neural Network (CNN) and Gate Recurrent Unit(GRU), taking into account the limitations of the prediction of multivariate time series using a single model. According to the regularity of water use during the time period, the characteristics of water users are clustered and classified to form two types of users: tidal type and irregular type. The factors that affect the daily water consumption such as user type, week, water consumption of the day of the previous three weeks, major events, etc. are used as input vectors, and the 2018-2021 resident daily water consumption time series data of a domestic water company is used as the training sample , respectively establish CNN-GRU models.CNN-GRU approach is checked using the root mean square error(RMSE),mean absolute error(MAE),and mean percentage absolute error(MAPE).The results are compared with Long-Short Term Memory (LSTM),CNN and GRU.Results show that CNN-GRU improves water demand prediction. The CNN-GRU model's RMSE dropped by around 0.648, 0.82, 0.82 when compared to the LSTM, CNN, and GRU models.the MAE decreased by about 0.418,0.47,0.462;and the MAPE decreased by about 0.722,0.649,0.712.

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Keywords: Water consumption; CNN; GRU; machine learning; prediction

1. Introduction

With the improvement of smart water affairs, it has turned into a pattern use big data and artificial intelligence to forecast water consumption. Accurate water consumption prediction is an important part of smart water utilities, and is an effective way to increase the water supply system's efficiency, dependability, and safety, which has significant positive economic and social effects.

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In recent years, hardware collection technology has been used extensively in smart cities, and water consumption prediction methods based on data have turned into a research hotspot. Many scholars have proposed countless forecast models to further develop the critical thinking skill of water demand. The majority of study has been carried out using statistical and machine learning techniques. The traditional typical models are autoregressive integrated moving average (ARIMA) [1], and Zhao Ling et al [2] established ARIMA model in the application of ARIMA-based multiplicative seasonal model in urban water supply forecasting, using the water supply from 2005 to February 2010 as the base data, and the model was able to fit better in 2010 water supply in Chengdu city. Yalcintas M et al. [3] used bi-seasonal ARIMA to construct a prediction model using only historical data as variables for a one-day water demand prediction for an area, and the fit was good by comparing the residential water meter readings with the predicted values, but external influences were ignored because the change in water demand is related to many factors, such as: weather information, historical consumption data, seasons, population, etc. For dealing with complex nonlinear time series data, classical statistical model-based forecasting methods may not be accurate enough to predict water demand series of stochastic nature [4-6]. To improve time series prediction algorithms, breakthroughs in model complexity and sequence feature representation have been attempted, and deep learning algorithms represented by neural networks are gradually utilized in multivariate time series models [7,8]. Capturing complex time-series patterns and inter-variate dependencies is the focus of multivariate time series forecasting research and the key to achieving accurate forecasting models. [9,10]Kozłowski et al. [11] used improved time series forecasting methods and artificial intelligence (AI) algorithms for short-term water forecast using weather conditions, maximum temperature, minimum temperature and whether it is a holiday as the main influencing factors for predicting the day. Mou Tianwei et al. [12] built a wavelet deep belief network (SW-DBN) time series model based on a deep learning framework and applied the model to forecast daily urban water consumption. Li Weite et al [13] proposed an artificial swarm optimization multivariate gated recurrent unit model (WD-ABC-MGRU) based on wavelet decomposition, which can effectively capture multivariate multi-scale time series features and thus significantly improve the model's ability to handle complex patterns. Han Hongquan et al [14] established a kernel-based extreme learning machine (KELM) model with a residual correction module (Fourier series, FS) based on the theory of Fourier series to form a combined prediction model (KELM+FS) without significantly increasing the prediction time. improving the accuracy of the KELM prediction model. Li Shuping [15] suggested a method for estimating the urban hourly water demand according to a comprehensive weighting factor, which completely accounts for the weights of the factors influencing water demand. For the study of influencing factors, Yao Junliang et al [16] proposed an improved method by introducing the previous day's water consumption and the previous 8 h water consumption as influencing factors, which was verified to obtain good accuracy. For short-term water demand prediction,Bata M H et al. [17] employed two nonlinear autoregressive artificial neural networks and a linear model with a specified topology to produce good results.

According to the studies in recent years, they have indicated that the single prediction model for water supply exists limitations. [18,19] In order to form the complementation between the models, the researchers proposed the combined model to improve the prediction accuracy and complexity. Zhao Jiandong et al. [20] use CNN-GRU model to predict the classification of bus passenger flow which has achieved great results. The water level of many stations in the Yangtze River Basin is predicted by Pan et al. [21] using a CNN-GRU combination model, and this forecast accuracy is superior to the ARIMA models, WANN models, and LSTM models. Muhammad et al. [22] use CNN-GRU combined model to predict short-term residential load, which can effectively replace previous combined models in terms of computational complexity and prediction accuracy. Tao et al. [23] proposed a deep learning model based on one-dimensional convolution neural network and bidirectional GRU neural network to predict air pollution. Zhang et al. [24] proposed a method combining CNN and bidirectional GRU neural network for time series classification. As mentioned above, a variety of machine learning models and hybrid methods have been applied in many relevant research [25], which also indicates that the combination of CNN and GRU has a wider application scope.

There are relatively few studies on short-term water consumption prediction between CNN and GRU applications. To accurately predict the daily water consumption situation, this study suggests a daily water consumption prediction model based on CNN-GRU. According to time series, a two-dimensional matrix of historical water demand, holiday, day of the week, user type, and other characteristics as input. Use CNN's strong feature extraction capabilities to identify the natural connections between water consumption data, therefore simplifying the complexity of the original data. The collected feature vectors are fed into the GRU neural network, which completes the daily water consumption forecast by learning the patterns of dynamic changes in the water consumption data.

2. CNN-GRU model structure

Take tidal users as an example, define the user data sequence X as $X=(X_1,X_2, X_3,X_4, \cdots X_a)$, Input matrix X' is $X'=(X,C_1,C_2,C_3,C_4,C_5,C_6,C_7,C_8)^T$. Where $X_1\sim X_a$ are the waterconsumption data of the 1st~a time interval. Where $C_1\sim C_8$ are the user type, season, highest temperature of the day, lowest temperature of the day, holiday, day of the week, water consumption of the previous day, and water consumption of the day of the week in the previous three weeks. In order to fully explore the potential connections between these features, In this paper, a convolutional neural network and a gated recurrent unit neural network are combined to construct a daily water consumption prediction model based on CNN-GRU. The basic structure is shown in Fig. 1.

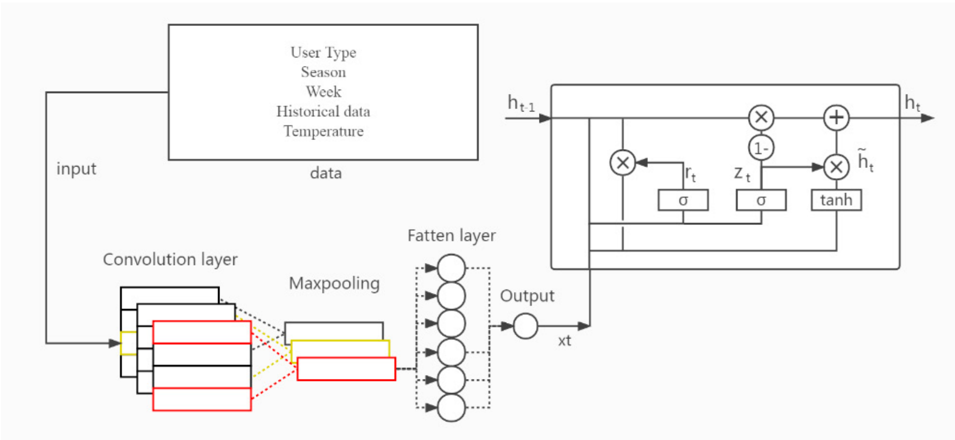


Fig. 1. basic structure diagram of CNN-GRU.

The formulas involved in CNN-GRU are as follows:

$$C = f(X \otimes W + b) \tag{1}$$

C is the output feature map of the convolution layer; X is the input dataset; f(·) is the nonlinear activation function; ⊗ is the convolution operation; W is the weight vector of the convolution kernel and b is the bias term.

$$P = \text{pool}(C) \tag{2}$$

P is the output feature map of the pooling layer; pool(·) is the pooling rule(Average pooling)
The formula involved in GRU is as follows:

$$r_t = \sigma(w_t[h_{t-1}, x_t]) \tag{3}$$

$$z_t = \sigma(w_z[h_{t-1}, x_t]) \tag{4}$$

$$\tilde{h_t} = \tanh(w_{\tilde{h}}[r_t h_{t-1}, x_t]) \tag{5}$$

$$h_t = (1 - z_t)h_{t-1} + z_t\tilde{h_t} \tag{6}$$

x_t is the input,r_t is the reset gate,z_t is the update gate,w_t is the reset gate weight matrix,w_t is the update gate weight matrix，$w_{\tilde{h}}$ is the candidate hidden state weight matrix,h_t is the hidden layer output,σ( ) is the sigmoid activation function,tanh( ) is the hyperbolic tangent activation function.

The specific steps of the CNN-GRU combined model are as follows:

Step 1: The time step and eigenvector are connected in series to form a new time series eigenvector. The input matrix required by cnn-gru combined model is normalized and put into the input layer.

Step 2: The CNN layer is designed with four convolution layers according to the temporal and spatial characteristics in the historical sequence.The number of convolution kernels is 8, 8, 16, and 16 in turn, and the ReLU activation function is selected for activation. Considering that when different convolution kernels are used for convolution operation, the structure of the model will be more complicated, which is not conducive to the training of the model. Therefore, the convolution kernel of 3*3 size is used in the convolution process in this paper. In order not to discard the information of the input data as much as possible, padding with 0 is used to keep the size consistent, and the pool size is 2. Finally, through the Flatten operation, the extracted deep-level abstract features are converted into global feature vectors as the input of GRU.

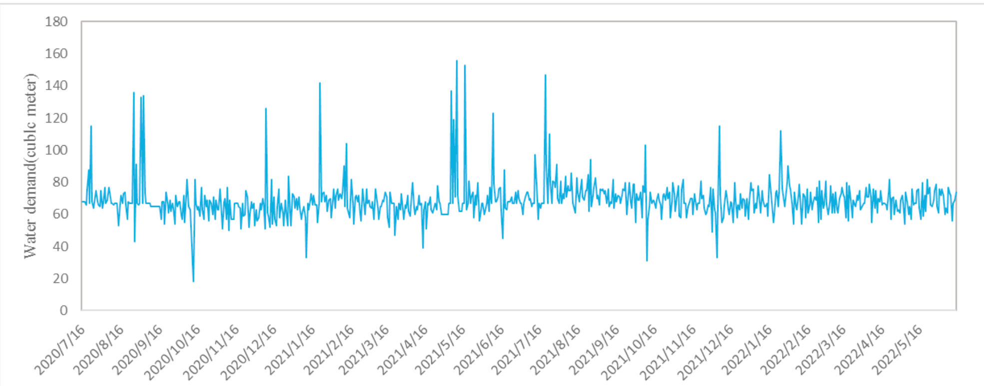
Step 3: Feed these short sequences of CNN features into the GRU neural network. The GRU unit continuously adjusts its own parameters in a large number of training, and builds a 2-layer GRU structure to achieve the prediction effect. The activation function adopts the ReLU activation function, and the number of neurons is 64 and 128 respectively. Finally, the output of the fully connected layer is denormalized to obtain the predicted value of the next day.In order to use gradient descent method to train the model, this paper adopts the mean square error (MSE) function as the target loss function.

3. CNN-GRU model training

Multi-factors such as user classification and water consumption on the day of the first three weeks are introduced into the input features, and the CNN model, the GRU model, and the CNN-GRU model are constructed respectively, and the three models are compared.

3.1. Data sources and pretreatment

This study uses data from one area of a domestic water utility company. The water supply area in this area is about 3.67 square kilometers and the water supply residents are about 50,000. As the city's smart water construction pilot, all smart metering water meters were installed in 2018, with a total of 13 metering sites. This paper selects a measurement point, there are 361 households. A total of 252339 pieces of data were collected from July 16, 2020 to June 16, 2022. The weather and temperature data came from the National Meteorological Science Data Center. The emergencies were mainly water outage notices, which were announced on the official website of the water company. The daily water demand data collected is shown in Fig. 2(a). Daily maximum temperature and minimum temperature is shown in Fig. 2(b).Divide the obtained sample data according to the ratio of 4:1, of which 80 percent of the data is utilized as a training set to train the model, and 20 percent of the data is used as a testing dataset to assess the model's specific performance.



(a) Date

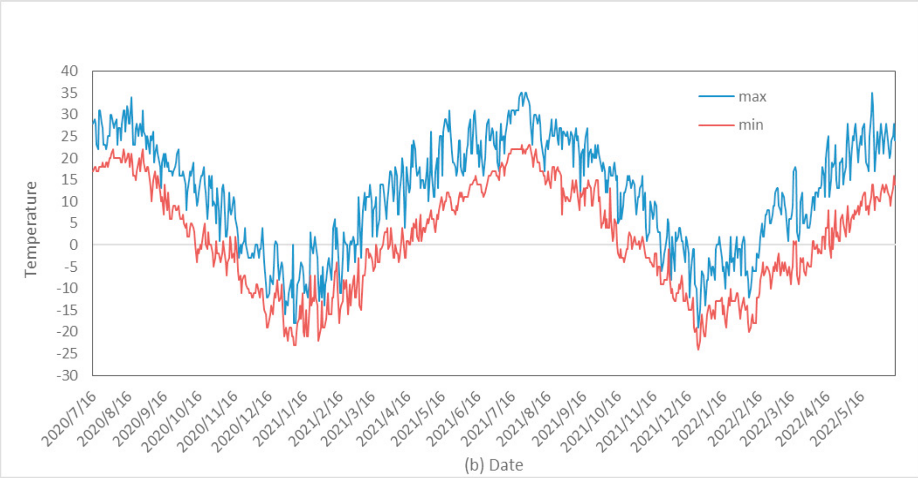


Fig. 2. (a) Raw data of daily water demand;(b) Daily maximum temperature and minimum temperature

Due to factors such as the quality of network transmission, equipment failures, etc., data abnormality and data loss may occur during the data collection process of smart water meters. The interpolation method is used to complete the data abnormality, and the influence factors and target variables are normalized.

3.2. Model training

This experiment uses Python as the development language, selects the data from July 16, 2020 to December 31, 2021 as the training set, and uses TensorFlow and Keras to build an experimental model framework for training. The number of hidden layers of the benchmark deep learning model is 2, the number of neurons is 64, the loss function is MSE, the optimizer is Adam, the activation function is Relu, the number of iterations is set to 200, and the rest of the parameters are default.

4. Test results and analysis

Several widely used neural network models are chosen as comparison models in order to assess the performance of the CNN-GRU model, such as CNN, GRU, and LSTM.Obtain CNN, GRU, LSTM, CNN-GRU model parameters by learning the training dataset, and input the test data to the four prediction models. The strengths and weaknesses of the prediction models are feedback through three evaluation metrics: RMSE,MAE,MAPE.

Take the trained model and select the data from February 1st to June 14th, 2022 as the prediction sample, and the model prediction result is shown in Fig. 3.

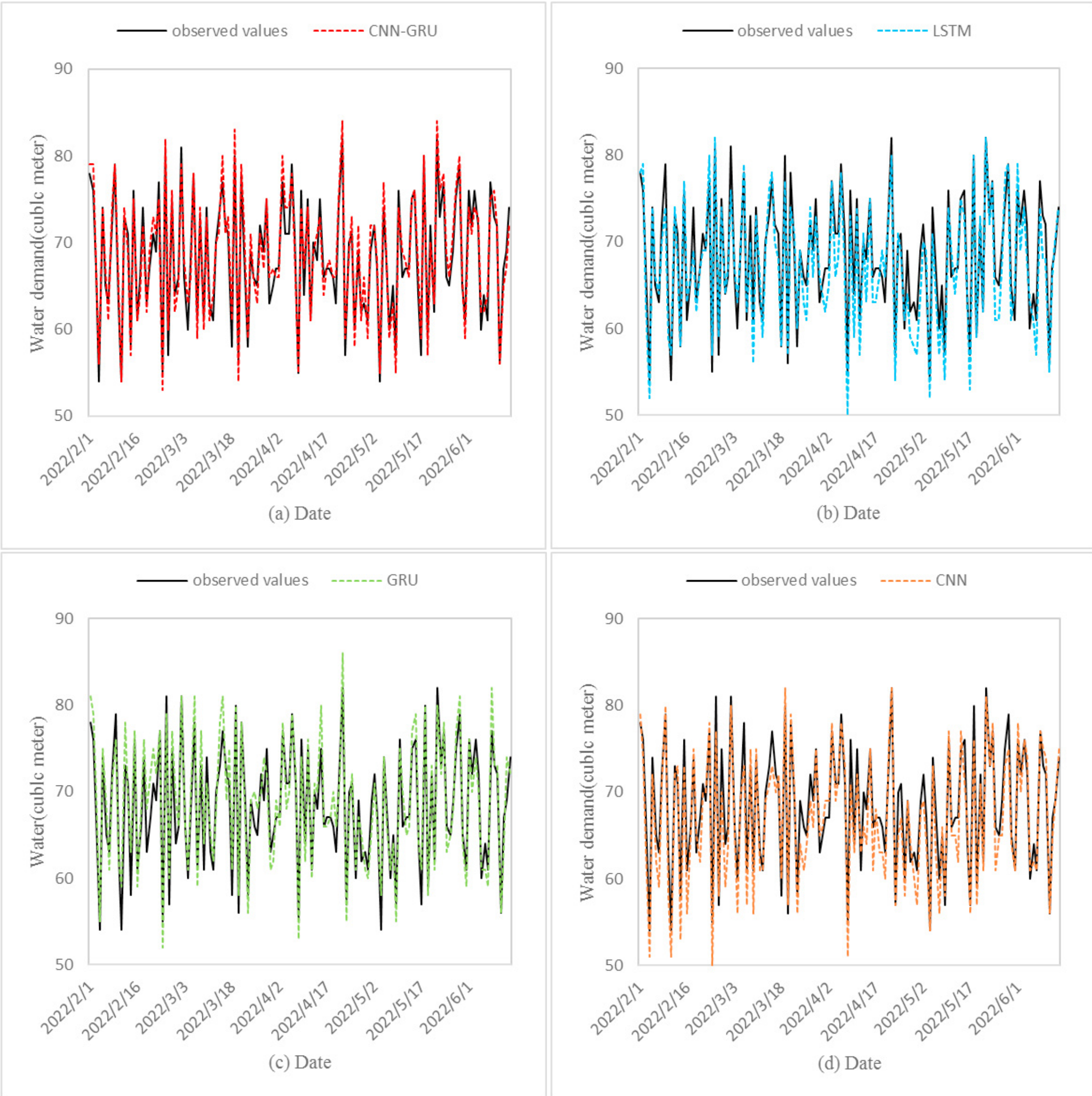


Fig.3.The prediction result of the CNN-GRU.(a) CNN-GRU. (b) LSTM. (c) GRU. (d) CNN

Comparing the three single models, it can be found that the expectation impact of the CNN model is superior to the other two. Comparing GRU, CNN and CNN-GRU model, the prediction curve of CNN-GRU model is closer to the real curve, indicating that the combined model is more conducive to mining the implicit relationship between data and improving the prediction accuracy of the model. In order to more clearly reflect the superiority of the model, the root mean square error, mean absolute error, and mean absolute percentage error indicators of the four models are analyzed, and the analysis results are shown in Table 1. RMSE error、MEA error and MAPE error for CNN-GRU models compared with the LSTM models is 23.6%、18.9%、21.4% less, compared with the CNN models is 23.0%、20.7%、19.7% less and compared with the GRU models is 25.8%、20.5%、21.2% less.

Table 1. Evaluation indicators.

Model	Evaluation indicators		
	RMSE	MAE	MAPE/%
LSTM	2.735	2.209	3.361
CNN	2.712	2.261	3.288
GRU	2.813	2.253	3.351
CNN-GRU	2.087	1.791	2.639

5. Conclusion

Based on the relevant theory of machine learning, a CNN-GRU hybrid model is suggested. The proposed model is trained and predicted through historical data and multiple factors. The conclusions are as follows:

1. As for the input factors of the prediction model for water consumption, besides daily factors such as weather, day of the week and season, the author introduces another two, the type of user and the water consumption on the same day of the week in the previous three weeks, thereby increasing the prediction model's accuracy by 1.4 percent.
2. Taking the data of a domestic water company as an example, CNN-GRU was established and compared with three single models of GRU, CNN, and LSTM. The three evaluation indicators were the lowest, with high prediction accuracy and good applicability.
3. The daily water consumption forecast in this paper can provide data support for the optimal scheduling of the water supply system.

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