Water demand in watershed forecasting using a hybrid model based on autoregressive moving average and deep neural networks

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Water demand in watershed forecasting using a hybrid model based on autoregressive moving average and deep neural networks

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Highlights

- The ARMA-DNN model is constructed to predict water demand.
- Empirical studies show that the ARMA-DNN model has good performance in prediction
- The efficiency between economy and water demand is considered in the model.
- The food output of agricultural water sector, the economic output of industrial water sector and the satisfaction of domestic water sector are measured.

Ethics approval and consent to participate

The experimental scheme was formulated by the water resources allocation guidelines of Dujiangyan Management Committee and obtained personal written informed consent.

Consent for publication:

Not applicable

Declaration of competing interest：

All authors declare that no conflict of interest exists.

Author Contributions Statement：

Guangze Liu: Conceptualization, Methodology, Validation; Mingkang Yuan: Data curation, Conceptualization, Methodology, Software, Xiaokun Li: Validation, Data curation, Writing–original draft; Qingqing Jiang: Data curation, Supervision, Writing–review & editing. Xudong Chen: Conceptualization, Software.

Abstract

Water resource shortage is a realistic problem faced by water supply systems in river basins. Forecasting water demand is crucial for sustainable management of water supply systems. In this paper, the ARMA—DNN model is established to predict the water demand of the basin by combining the deep neural network (DNN) and the autoregressed-moving average (ARMA) mixed model. Taking the economic growth water demand and the actual social water demand as the main prediction targets, a mixed prediction model based on 14 statistical indicators is built. The model uses data from 2010 to 2020 to forecast water demand in the Minjiang River Basin. The results show that :(a) the model can accurately predict the future water consumption of the basin under the condition of actual water consumption changes; (b) The forecast of future water consumption has a significant impact on agricultural grain yield, industrial economic output value and domestic water satisfaction. In each region of the basin, agricultural grain yield and industrial economic output value and domestic water satisfaction are mutually restricted; (c) When climate conditions deteriorate and water shortages become severe, effective water demand forecasting can alleviate water demand contradictions to some extent. In a word, watershed managers need to make industrial water allocation schemes in different regions based on the forecast results of future water consumption, so as to balance the relationship among agricultural and food output, economic output value and domestic water satisfaction.

Key words: Deep neural network; Autoregressive moving average; prediction model, Annual water consumption; Water allocation

1. Introduction

Water resource is the basic resource for the survival and development of human society. However, in many countries and regions, limited water resources have become the bottleneck of regional economic and social development (Guo W et al.,2019; Sharma, S K, 2021). Therefore, scholars and engineers are committed to finding more effective strategies and methods to improve the utilization efficiency of water resources (Than N H, et al 2021; Tat P V, & Niu W J,2021). The premise of effective and reasonable utilization of water resources is accurate prediction of water demand (J Quilty et al, 2020; Swfab C, et al,2021).

Water demand forecasting can improve the emergency capacity of water resource management and provide technical support for water resource conservation or management (Fu J et al.,2019; Su et al., 2018). However, due to the nonlinear behavior of water consumption time series, water demand prediction is still a very difficult problem in the field of water resource management (Quilty J et al,2018). Over the past decades, scholars and managers have developed different water demand prediction models for different purposes, which mainly include two categories: data-driven models and physically-driven models (Sulaiman, Oleiwi S, Ravinesh C, et al.,2019; Sheffield J, et al,2014). Although water use processes in various sectors of a watershed can be expressed in physical models, measurement information and expert experience are often required to dynamically adjust the parameters and structure of the model. As for the data-driven model, it does not need to know the detailed water consumption process and mathematical information of water demand of each water consumption sector, so it can fully reflect the relatively complete forecast of water demand (Huang, Zhang, Peng, & Zhou, 2014). With the development of computer technology, some major data-driven models have been developed and applied to water resource demand prediction. He X et al. proposed a hybrid D-DNN model based on variational mode decomposition (VMD) and deep neural network (DNN) to predict daily runoff. Kumar R et al. built A

prediction model based on Extreme learning Machine (BBO-ELM) and deep Neural network (DNN) to predict future rainfall in various regions of India. Rl A et al. trained the neural network model by using terrain data and flood data (Rl A et al, 2021). Du et al. proposed a Markov modified auto-regression moving average (ARIMA) model based on the periodicity and randomness of daily water consumption data, and improved the progress of water demand prediction (Du et al, 2020). Jing et al. proposed the ARIMA model and the hybrid model combining wavelet neural network and genetic algorithm to predict river water quality, and the prediction result was significantly better than the single model (Jing et al, 2017). However, few studies have considered combining deep neural networks with autoregressive moving average models to predict water resources.

On the one hand, water managers desire regional economic development and equality (Van Campenhout et al., 2015; Hu et al, 2020). Therefore, the economic factors of the whole basin and the demand for water in various sectors must be considered. The supply of water resources in the whole basin brings the corresponding economic GDP growth of the cities in the basin. Agricultural water is mainly used for food production and animal husbandry, while industrial water is most commonly used for food, paper, chemicals and construction production, which has a significant impact on regional economic development (Zhou et al., 2015). At the same time, the proportion of water consumption can test the forecast of water consumption of various sectors to a certain extent. Lu et al. developed a hybrid model to predict monthly water demand in Austin, Texas, and found that demand was highly correlated with local population, monthly mean temperature, and monthly mean humidity; Li et al. used principal component analysis regression to study the annual water demand of Shanghai. Sun Y et al. Population and GROSS domestic product (GDP) have a significant impact on annual water demand.

On the other hand, equal distribution of water resources is closely related to social stability (D'Exelle et al., 2012). Water resource managers hope that the water resource

allocation plan can reasonably meet the actual social demand (Hu Z et al., 2016). The population, agricultural development, cultivated land area, industrial GDP and ecological environment of cities in the whole basin are all manifestations of the actual social demand. Sun et al. assessed the sustainable use of water resources in Beijing, China, taking into account economic, demographic, water supply and demand, land resources, water pollution and management factors. Tang et al. proposed an improved BP neural network model to predict water demand in Hubei Province, China, based on the characteristics of population, farmland irrigated area, GDP and industrial added value. Zhang et al. found that regional GDP, agricultural output value, industrial output value, year-end population, irrigated area and per capita disposable income were correlated with regional water demand. Therefore, the combination of economic development and social rationality can accurately predict water consumption.

The increasing uncertainty of water consumption and the instability of single deep neural network prediction model have intensified the demand of water resource managers for the accuracy of future water consumption prediction results. Therefore, it is necessary and important to integrate deep neural network and autoregressive moving average in water resource prediction model. This paper focuses on the above economic water use and social water demand, and its three main contributions are as follows:

(1) The ARMA-DNN model is constructed to predict water demand. The model combines deep neural network and autoregressive moving average mixed model. Empirical studies show that the ARMA-DNN model has good forecasting effect.

(2) Take economic growth water consumption and social actual water demand as the main forecast targets, and consider 14 statistical indicators, such as economic growth, social actual water demand and development level, to fully consider the actual water consumption to ensure the accuracy of the forecast results.

(3) The efficiency between economy and water demand is considered in the prediction model, and the food output of agricultural water sector, the economic output of industrial water sector and the satisfaction of domestic water sector are measured.

The rest of the paper is organized as follows: Section 2 introduces the research site, data sources and data processing; The mathematical model is described in section 3. In section 4, the developed model is applied to the Minjiang River Basin (southwest China) to obtain the predicted results of water consumption. The conclusion comes in part five.

2. Materials and methods

2.1. Study area

Minjiang River is an important tributary of Yangtze River (Fig. 1). Minjiang River flows through eight cities, namely Aba Prefecture, Chengdu, Zigong, Leshan, Meishan, Yibin, Ya 'an and Ziyang. In 2019, the Minjiang River Basin had a population of 18.751,000, a cultivated area of 2244.98 thousand hectares, and a total water consumption of 11.274 billion cubic meters. The Minjiang River basin supplies water to the domestic, agricultural, industrial and ecological sectors of eight cities. Chengdu agriculture, ecology and industrial water are at a higher level, the total water of Chengdu largest, which is mainly used for water management in agriculture crops for food, industrial water mainly supply all kinds of industrial companies, the ecological water use is mainly used for the protection of the ecological environment and various ecological demand, it is worth noting that the minimum ecological water, But ecological water should be satisfied first.

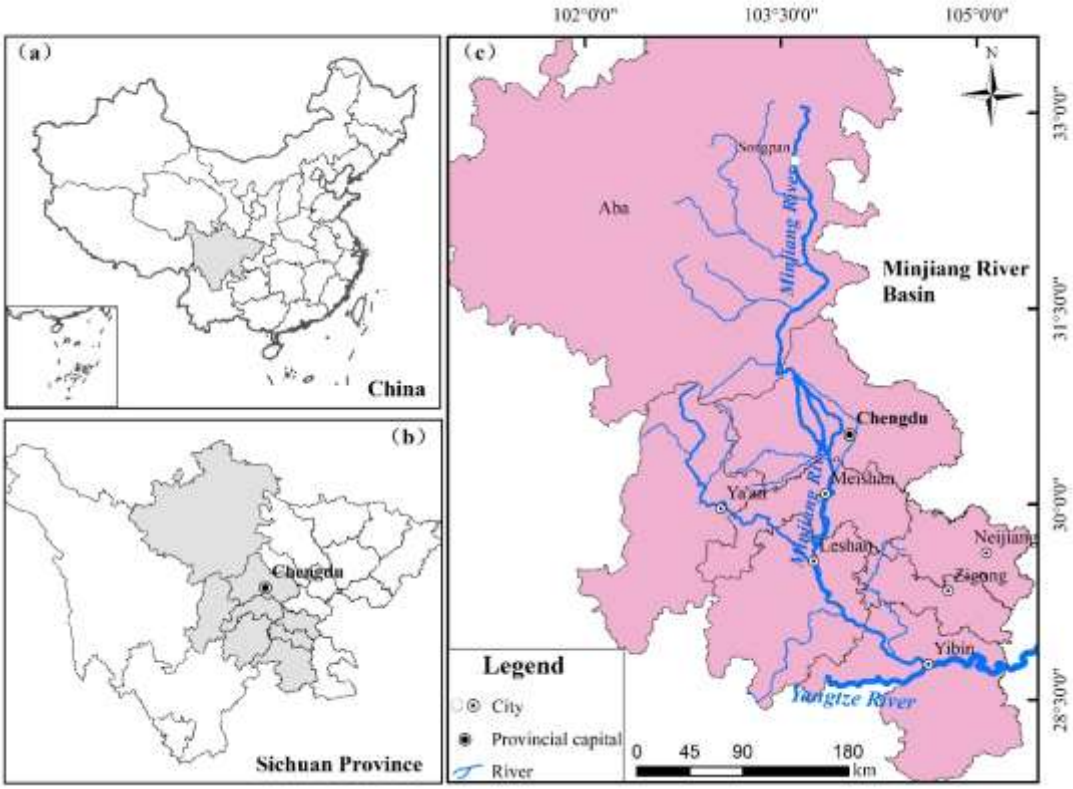

Fig 1. Geographical location of Minjiang River Basin

2.2. Data Sources

According to The Statistical Yearbook of Sichuan province from 2010 to 2020, the population, cultivated land area, tolal GDP and grain output of 8 municipalities in the Minjiang River Basin were statistically analyzed (the data in 2015 are shown in Table 1). Meanwhile, according to The Water Resources Bulletin of Sichuan Province from 2010 to 2020, a statistical analysis was conducted on the ecological water, agricultural water, industrial water, other water and the average annual water volume of Minjiang River in 8 municipalities directly under the Central Government in Minjiang River Basin (the data in 2015 are shown in Table 2).

Table 1. Basic data of Minjiang River Basin in 2015

Population (ten thousand)	Cultivated Area (Thousands of hectares)	Total GDP (100 million Yuan)	Grain output (ten thousand tons)
1465.75	421.54	10801.16	230.2
277.02	216.53	1143.11	132.6
326.05	272.89	1301.23	109.2

300.13	242.00	1029.86	168.5
449.00	487.69	1525.90	219.3
154.68	101.09	502.58	47.9
356.93	430.52	1270.38	227.7
93.01	83.76	265.04	16.7

Table 2. Water consumption data of Minjiang River Basin (2015)

Unilateral Water GDP(yuan /m^3)	Unilateral water grain yield(Ton /10,000 m^3)	Added value of agricultural output value of unilateral water(yuan/m^3)	Unilateral water industry value added(yuan/m^3)	Proportion of agricultural water(%)	Proportion of industrial water consumption(%)	proportion of ecological environment water consumption(%)
182.82	3.89	11.47	402.68	55.1	19.8	2.5
151.20	17.54	34.12	349.69	49.6	25.1	3.3
95.32	8.00	19.79	211.89	52.8	26.5	3.4
76.00	12.43	18.89	226.72	62.4	18.8	5.3
120.81	17.36	44.06	180.50	38.9	39	1
81.06	7.72	21.95	161.44	53.2	28.1	1.8
113.62	20.36	34.13	344.57	65.7	18.3	3.6
126.20	7.94	34.61	541.75	56.5	11.5	3.1

2.3. Data Processing

Through the processing and analysis of the collected data, the corresponding indicator system is constructed, which contains 3 first-level indicators and 14 second-level indicators. The data of each indicator can be obtained directly or indirectly through the data released by Sichuan Province (Table 3). At the same time, the values of each evaluation index are added to gaussian noise to generate a large number of simulated data, and then the actual data and simulated data are combined together as the input data of the model.

Table 3. Evaluation index system

Level indicators	Ssecondary indicators	Formula or definition.
Social rationality	Water-deficient ratio	(Water consumption - water supply)/water consumption
	Agricultural water consumption	Actual value of agricultural water use
	Industrial water consumption	Actual value of industrial water consumption

	Water consumption of ecological environment	Actual value of ecological water use
Economic rationality	GDP per square meter of water	GDP/ total water consumption
	Unilateral water grain yield	Grain constant/water consumption
	Added-value of agricultural output value of unilateral water	Agricultural output value/agricultural water consumption
	Unilateral water industry value-added	Industrial output value/industrial water consumption
	Proportion of agricultural water	Agricultural water consumption/total water consumption
	Industrial water ratio	Industrial water consumption/total water consumption
	Proportion of ecological environment water use	Water consumption of ecological environment/total water consumption
	Utilization ratio of river water resources	Actual water consumption/total amount of surface water in the city
	Annual equilibrium rate of water use	Per capita water consumption in this year/per capita water consumption in the previous year
	Annual equilibrium rate of water shortage	Water shortage rate of this year/water shortage rate of last year

3. Model building

3.1. Symbol Description

Table 4. Symbol description

Symbol	Instructions
L	Total number of layers of neural network
W	Hide the corresponding weight matrix between the layer and the output layer
b	Offset variable
x	Input value vector (evaluation index vector)
a^L	Output vector (predicted value of per capita water consumption)
y	Actual per capita water consumption
δ^l	The gradient of z^l at the l layer

ε	Iterative threshold
$\varphi_i(i=1,2,\mathrm{L}\ ,n)$	Autoregressive parameter
$\theta_j(j=1,2,\mathrm{L}\ ,m)$	Moving average parameter
N	Number of evaluation index sequences
$\{\alpha_t\}$	White-noise process
$\{SW_t\}$	Prediction evaluation index sequence
R_k	Evaluate the autocovariance function of index time series
AIC	Criterion function
$\sigma(z)$	Prediction function
$J(W,b,x,y)$	Loss function

3.2. Construction of the ARMA-DNN model

In this paper, the ARMA-DNN model is established to predict the future water demand of each region. Firstly, each index in Table 3 was taken as input and the water demand of each department as output to establish the DNN model. Then, to determine the future water demand, the ARMA model is used to predict each evaluation index of each region in the future. After obtaining the index values of each region in the future, the DNN model is finally used to complete the prediction of the water demand of each region and the water demand of each department.

3.2.1. Autoregressive moving average model

The autoregressive moving average model $ARMA(n,m)$ is established for the data series of each evaluation index as follows:

$$x_t=\sum_{i=1}^{n}\varphi_i x_{t-i}+\alpha_t-\sum_{j=1}^{m}\theta_j\alpha_{t-j} \tag{1}$$

Where $\varphi_i(i=1,2,...,n)$ is the autoregressive parameter; $\theta_j(j=1,2,...,m)$ is the moving average parameter; $\{\alpha_t\}$ is a normal white noise process with mean value 0

and variance σ_a^2. So it is $\alpha_t \in N(0,\sigma_a^2)$.

For each original evaluation index sequence, when its value is too large or too small, to ensure calculation accuracy, reduce rounding error and avoid overflow, the original evaluation index sequence can be standardized. $\{x_t^{'}\}$ is denoted as the original evaluation index sequence, and the data can be standardized as follows:

$$x_t = \frac{x_t^{'} - \mu_x}{\sigma_x} \tag{2}$$

In the formula, μ_x and σ_x^2 are respectively the estimation of the mean and variance of $\{x_t^{'}\}$, and their algorithms are as follows:

$$\mu_x = \frac{1}{N}\sum_{t=1}^{N} x_t^{'} \tag{3}$$

$$\sigma_x^2 = \frac{1}{N-1}\sum_{t=1}^{N}(x_t^{'} - \mu_x)^2 \tag{4}$$

In the above two formulae, N is the number of evaluation index sequences, which here is the number of years. The normalized sequence $\{x_t\}$ is modeled according to the autoregressive moving average model $ARMA(n,m)$, and the prediction evaluation index sequence $\{SW_t\}$ is obtained as follows:

$$SW_t = \sigma_x x_t + \mu_x \tag{5}$$

On this basis, we can predict the evaluation index value, and compare the distribution characteristics of the predicted evaluation index value and the measured evaluation index value, to demonstrate the feasibility of applying the time series model proposed in this paper to the prediction of water resources allocation evaluation index.

3.2.2. Deep neural network model

The input and output model of DNN is different from that of simple pairs. There will be a linear relationship between simple output and input, and the intermediate

output result will be:

$$z = \sum_{i=1}^{m} w_i x_i + b \tag{6}$$

It is activation function is:

$$sign(z) = \begin{cases} -1 & \mathrm{z}<0 \\ 1 & \mathrm{z} \geq 0 \end{cases} \tag{7}$$

The actual situation of DNN is composed of several input layers, several hidden layers and several output layers. It is fully connected between layers, and any neuron of layer I is connected with neuron of layer I +1. It has $z = \sum_{i=1}^{m} w_i x_i + b$ linear relationship, $z = \sum_{i=1}^{m} w_i x_i + b$ plus the activation function $\sigma(\mathrm{z})$. As the number of layers of DNN is larger, the number of coefficient W and offset B will also be larger. The following takes DNN of a hidden layer as an example to explain the working principle of DNN. The schematic diagram of DNN structure is shown in Figure 1.

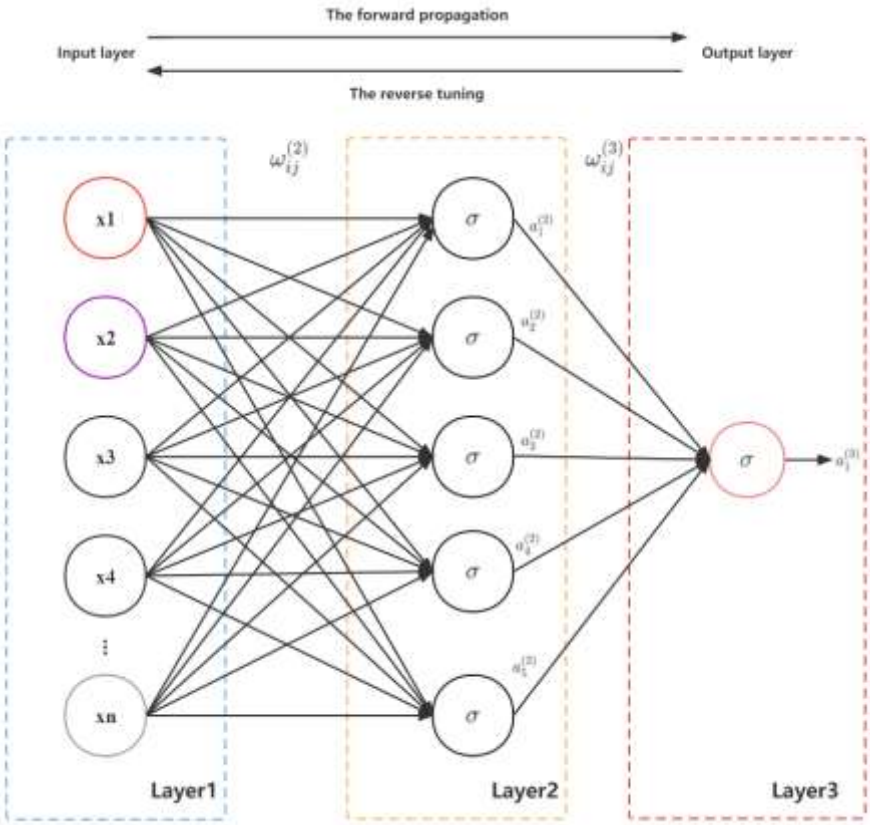

Fig 1. DNN structure diagram

(1) DNN forward propagation algorithm

It is not difficult to see that Layer1, Layer2 and Layer3 represent the input layer, hidden layer and output layer respectively. At this point, the output formula of Layer2 is:

$$a_1^{(2)} = \sigma(z_1^{(2)}) = \sigma(w_{11}{}^{(2)}x_1 + w_{12}{}^{(2)}x_2 + \mathrm{L} + w_{1m}{}^{(2)}x_m + b_1^{(2)}) \tag{8}$$

$$a_2^{(2)} = \sigma(z_2^{(2)}) = \sigma(w_{21}{}^{(2)}x_1 + w_{22}{}^{(2)}x_2 + \mathrm{L} + w_{2m}{}^{(2)}x_m + b_2^{(2)}) \tag{9}$$

$$a_3^{(2)} = \sigma(z_3^{(2)}) = \sigma(w_{31}{}^{(2)}x_1 + w_{32}{}^{(2)}x_2 + \mathrm{L} + w_{3m}{}^{(2)}x_m + b_3^{(2)}) \tag{10}$$

At this point, the output formula of Layer3 is:

$$a_1^{(3)} = \sigma(z_1^{(3)}) = \sigma(w_{11}{}^{(3)}x_1 + w_{12}{}^{(3)}x_2 + \mathrm{L} + w_{1m}{}^{(3)}x_m + b_1^{(3)}) \tag{11}$$

Induction can be obtained:

$$a_j^{(l)} = \sigma(z_j^{(l)}) = \sigma(\sum_{k=1}^{m} w_{jk}^{(l)} a_k^{(l-1)} + b_j^{(l)}) \tag{12}$$

(2) DNN backpropagation algorithm

DNN reverse algorithm involves loss function, and variance is commonly used to measure loss. For each sample, we expect to minimize the following formula:

$$J(w,b,x,y)=\frac{1}{2}\left\|a^{(L)}-y\right\|_2^2 \tag{13}$$

Where, a^L and y are edge dimension vectors, and $\|S\|_2$ is the L_2 norm of S.

At this point, the output layer L meets the following formula:

$$a^{(l)}=\sigma(z^{(l)})=\sigma(w^{(l)}a^{(l-1)}+b^{(l)}) \tag{14}$$

It is loss function is:

$$J(w,b,x,y)=\frac{1}{2}\left\|a^{(L)}-y\right\|_2^2=\frac{1}{2}\left\|\sigma(w^{(l)}a^{(l-1)}+b^{(l)})-y\right\|_2^2 \tag{15}$$

$$\frac{\partial J(w,b,x,y)}{\partial w^{(L)}}=\frac{\partial J(w,b,x,y)}{\partial z^{(L)}}\cdot\frac{\partial z^{(L)}}{\partial w^{(L)}}=(a^{(L)}-y)\cdot\sigma^{'}(z^{(L)})(a^{(L-1)})^T \tag{16}$$

$$\frac{\partial J(w,b,x,y)}{\partial b^{(L)}}=\frac{\partial J(w,b,x,y)}{\partial z^{(L)}}\cdot\frac{\partial z^{(L)}}{\partial b^{(L)}}=(a^{(L)}-y)\cdot\sigma^{'}(z^{(L)}) \tag{17}$$

$\odot$, which exists in the above formula, has the meaning of *Hadamard* product. At this point,

$$\delta^{(L)}=\frac{\partial J(w,b,x,y)}{\partial z^{(L)}}=(a^{(L)}-y)\cdot\sigma^{'}(z^{(L)}) \tag{18}$$

According to the recursive relationship, for layer l unactivated output z^l, its gradient can be expressed as:

$$\begin{aligned}\delta^L&=\frac{\partial J(w,b,x,y)}{\partial z^{(l)}}=\frac{\partial J(w,b,x,y)}{\partial z^{(L)}}\cdot\frac{\partial z^{(L)}}{\partial b^{(L-1)}}\cdot\frac{\partial z^{(L-1)}}{\partial b^{(L-2)}}\mathrm{L}\ \frac{\partial z^{(l+1)}}{\partial b^{(l)}}\\ z^{(l)}&=W^{(l)}a^{(l-1)}+b^{(l)}\end{aligned} \tag{19}$$

At this time, the gradient of W^l and b^l in the layer l is as follows:

$$\frac{\partial J(w,b,x,y)}{\partial W^{(l)}}=\frac{\partial J(w,b,x,y)}{\partial z^{(l)}}\cdot\frac{\partial z^{(l)}}{\partial W^{(l)}}=\delta^{(l)}(a^{(l-1)})^T \tag{20}$$

$$\frac{\partial J(W,b,x,y)}{\partial b^{(l)}}=\frac{\partial J(W,b,x,y)}{\partial z^{(l)}}\cdot\frac{\partial z^{(l)}}{\partial b^{(l)}}=\delta^{(l)} \tag{21}$$

By mathematical induction:

$$\delta^l=\frac{\partial J(W,b,x,y)}{\partial z^{(l)}}=\frac{\partial J(W,b,x,y)}{\partial z^{(l+1)}}\mathrm{g}\frac{\partial z^{(l+1)}}{\partial z^{(l)}}=\delta^{(l+1)}\mathrm{g}\frac{\partial z^{(l+1)}}{\partial z^{(l)}} \tag{22}$$

$$z^{(l+1)}=W^{(l+1)}a^{(l)}+b^{(l+1)}=W^{(l+1)}\sigma(z^{(l)})+b^{(l+1)} \tag{23}$$

$$\frac{\partial z^{(l+1)}}{\partial z^{(l)}} = W^{(l+1)}(\sigma^{'}(z^{(l)}),\mathrm{L}\ ,\sigma^{'}(z^{(l)})) \tag{24}$$

$$\delta^{(l)} = \delta^{(l+1)} \cdot \frac{\partial z^{(l+1)}}{\partial z^{(l)}} = (W^{(l+1)})^{T} \delta^{(l+1)} \cdot \sigma^{'}(z^{(l)}) \tag{25}$$

(3) Model evaluation indicators

In this paper, MSE, RMSE, MAE and R^2 are selected to evaluate the performance of the model. The four evaluation indicators are explained in Table 5.

Table 5. Model evaluation indicators

Model evaluation index	Formula	Meaning
MSE	$MSE = \frac{1}{m}\sum_{i=1}^{m}(y_i - \hat{y}_i)^2$	The smaller the mean square error, the better the prediction effect
RMSE	$RMSE = \sqrt{\frac{1}{m}\sum_{i=1}^{m}(y_i - \hat{y}_i)^2}$	The smaller the root mean square error, the better the prediction effect.
MAE	$MAE = \frac{1}{m}\sum_{i=1}^{m}\lvert y_i - \hat{y}_i \rvert$	The smaller the mean absolute error,, the better the prediction effect.
R^2	$R^2 = 1 - \frac{MSE(\hat{y}, y)}{Vary(y)}$	Determining coefficient, the closer the absolute value is to 1, the better the fitting effect is.

Note: m is the number of samples, y_i is known data, $\hat{y}_i$ is model predicted data, $MSE(\hat{y}, y)$ is the mean square error between predicted data and known data, $Var(y)$ is the sample variance of known data.

4. Results and discussion

In this paper, the deep neural network and auto-regression moving average model established above are applied to the Minjiang River Basin to verify the feasibility, effectiveness, and practicability of the model, and the water demand and economic

index values of the basin are predicted to depict the relationship between different water consumption sectors in the basin. The water consumption of three water consumption departments in eight sub-regions of Minjiang River Basin and the water demand distribution scheme among different departments are obtained. To verify the reliability of the model results, the water consumption and economic analysis of the basin will be described in the following two summaries.

4.1. Water demand prediction and configuration scheme analysis

4.1.1. Forecast analysis of water demand in the watershed

The data from 2010 to 2020 were used as DNN training data set, and the data set was set as 15 evaluation indexes, including water shortage rate, river water resource utilization rate, urban water resource utilization effect evaluation score, etc., to forecast the water consumption of water sector in Minjiang River Basin in 2021. The values of DNN's hyperparameters are shown in Table 6.

Table 6. Values of DNN hyperparameters

Hyper-parameter	Numerical
Percentage of test sets	0.3
learning rate	0.01
The number of steps that the learning rate drops	200
Rate of decline in learning rate	0.96
Hidden layers	3
The number of neurons corresponding to each hidden layer	64，128，256
Dropout value	0.5

Predicted results as shown in table 7 and figure 2, shows that the Minjiang river basin water consumption and water consumption forecasting, in which the difference in value between the two change in maximum, 58.66 minimum variation is 0.66, through comparison and analysis of results, the results show that the water in the actual situation changes, the model can forecast future water basin.

Table 7. Actual per capita water consumption and forecast per capita water consumption and their differences((2021, ten thousand m^3))

Actual per capita water consumption	Forecast per capita water consumption	Difference
225.782174	257.66168	-31.879506
272.904483	272.65012	0.254363
235.729387	249.27866	-13.549273
204.775023	203.45322	1.321803
212.987013	212.32153	0.665483
389.474406	369.42767	20.046736
451.471029	441.53235	9.938679
423.886800	402.52225	21.36455
312.536902	297.21277	15.324132
394.882120	368.08923	26.79289
218.550955	215.7801	2.770855
271.396896	247.53094	23.865956

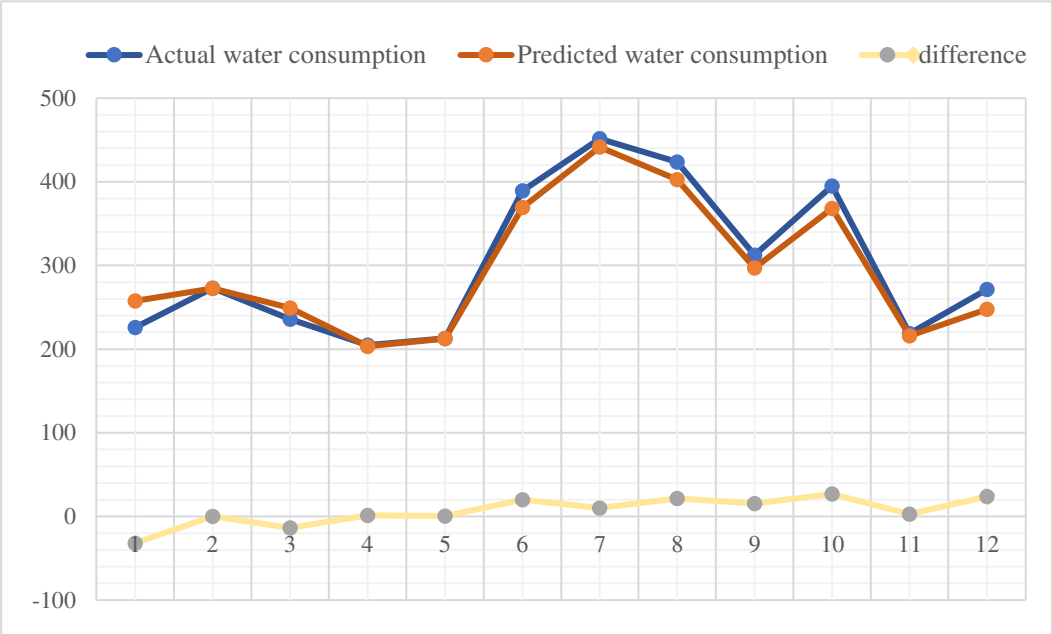

Fig 2 Actual water consumption and forecast per capita water consumption and their difference

It is worth noting that the MAE of the model is 5.14, R_2 is 0.78 (<1), and the error of mean square $RMSE$ is 17.53374 (as shown in Table 8), indicating that the model has A good prediction effect and can be used to predict the water consumption of various cities in the future. The model can be used to estimate future water consumption and provide guidance for watershed managers.

Table 8. Error index of the prediction model

Index	MSE	RMSE	R2	MAE
Numerical	32.38431	5.690721	0.78	5.137703

4.1.2. Analysis of water demand plan of the watershed water sector

The future water basin is one of the main factors influencing the river basin water resources management, which will affect the future of water resources allocation plan, through the water as the training data set in the first decade of 1 year for the future water demands of the different water department, formulate the corresponding water resources allocation, table 9 show the allocation of water resources of the river basin in the future one year, Among them, Chengdu has the largest total water supply of 41.678 billion cubic meters. Because of its huge economic volume, its GDP in 2021 will be 1991.698 billion yuan, exceeding the total GDP of the other seven cities in the Minjiang River Basin. At the same time, due to the differences of regional industrial structure and development level of Minjiang River, Minjiang river basin water consumption of water sector in different regions of the obvious difference, including Chengdu, water more, to 14.713 billion cubic meters, which is closely related to the economic development and population explosion of Chengdu, Meishan, Yibin, Zigong, Neijiang, Leshan, and zhu industrial water more, This shows that these six cities pay more attention to economic development, and aba uses more water for the ecological environment and domestic use, which is related to the rapid development of tourism in Aba, the increase of tourists and the protection of the ecological environment. The future water resources allocation plan should not only consider the water demand among different water consumption sectors in the region but also make water resources allocation predictions considering the actual development situation of each region.

Table 9. Future Water Resources Allocation plan of the Basin (2021, ten thousand m^3)

City	Total water supply	Agricultural	Industrial	Ecological	Domestic
Chengdu	416.79	204.64	56.27	8.75	147.13
Zigong	243.30	122.38	61.55	2.92	56.45
Neijiang	414.15	213.29	92.35	6.63	101.88
Leshan	357.13	235.35	61.78	30.00	30.00
Meishan	355.61	134.78	147.58	10.31	62.94
Yibin	211.44	106.36	38.27	4.44	62.38
Yaan	216.59	131.91	43.54	1.08	40.07

Aba	374.76	196.00	46.10	13.87	118.80

When considering different water departments of water resources allocation, should also consider the area change tendency of different water consumption departments, figure 3 shows the future one-year Minjiang river basin under the condition of different regions of the changing trend of water distribution, water department 8, figure 3 shows that Minjiang river in Leshan agricultural water most, the most meishan industrial water, water, most of Chengdu The water consumption of ecological environment in Minjiang River 8 cities is relatively balanced. In addition, agricultural water and domestic water in the eight cities of Minjiang River Basin have the same trend of change, while industrial water has a large range of change, which is caused by regional development differences in the basin, indicating that there are significant regional development differences in the basin. Therefore, the rationality and fairness of future water demand plans can be characterized by considering the variation trend of water consumption of different water consumption sectors in the basin in the future, and data support can be provided for the basin water resource managers in combination with the actual situation.

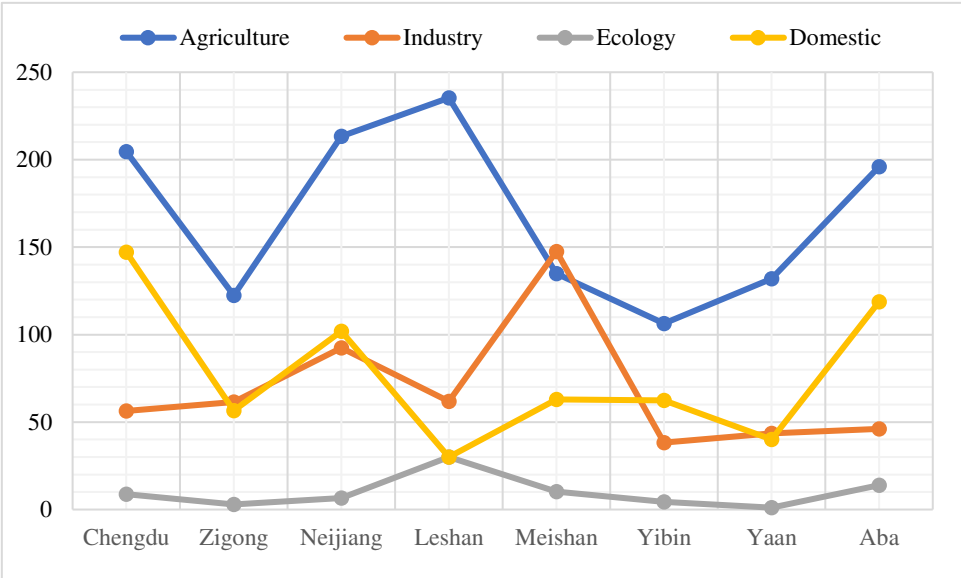

Fig. 3. Forecast water demand for different water sectors(2021)

4.2. Ideal yield forecast

4.2.1. Agricultural grain output

Water is mainly used for agricultural irrigation in agriculture and breeding livestock, agriculture occupies 92% of agricultural water, figure 4 shows the 2021 agricultural food production forecast, figure in the Minjiang river valley in neijiang is the most developed agriculture, food production reached 68911.32 tons, followed by, meishan, meishan, zigong, yibin, Leshan and aba, ya 'an Chengdu, The agricultural grain output of Chengdu and Aba is at the bottom with 4037.62 tons and 1886.26 tons respectively, which is due to the transformation of Chengdu's industrial structure and the reduction of agricultural land, which further reduces the agricultural grain output. Aba cannot produce too much grain due to its geographical location and soil conditions. It is worth noting that, Changes in agricultural water use in watersheds directly limit agricultural development, but regional development plans and missions should also be considered to make water allocation plans more consistent with future water use trends. Therefore, the prediction of agri-grain yield is consistent with the actual situation, and the model can predict the agri-grain yield under ideal conditions in the future, and provide a reference for the collaborative development of the basin.

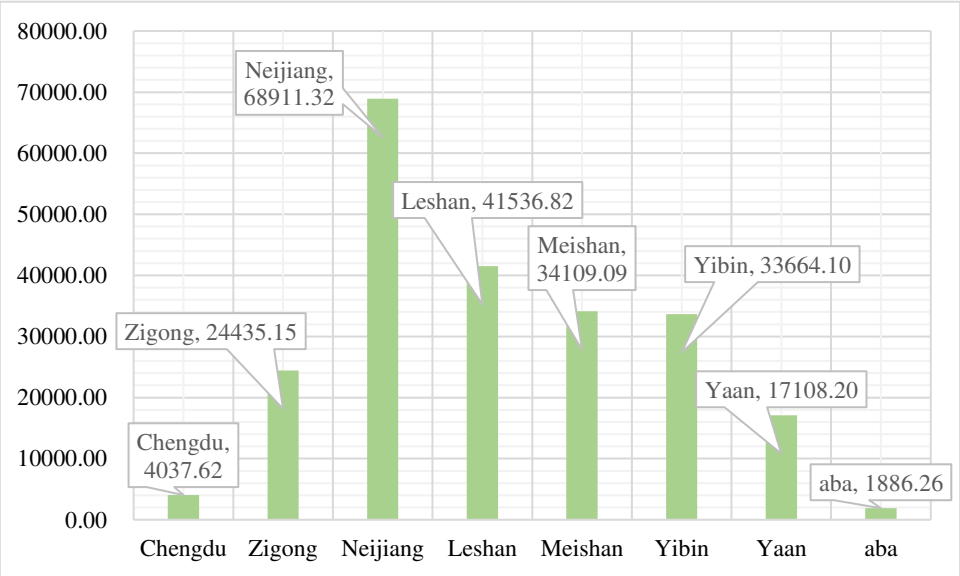

Fig 4. Forecast of agricultural water grain yield (2021, tons)

4.2.2. Industrial economic output

In river basin water consumption departments in different areas, the unilateral

water produced by the department of industrial water output is the largest, the future of the industrial water demand plan will seriously affect the development of urban economy, the industrial economic output prediction as shown in figure 5, indicating that the basin economy development difference obvious, the Chengdu industrial output, the largest of 1.5055924 billion yuan. The industrial economic output value of Ya 'an and Yibin is relatively low in Minjiang River Basin, which is 20186.12 yuan and 222.6392 yuan respectively. The industrial economic output value of Chengdu is in the first place, neijiang, Meishan, and Aba are in the second tier, and the industrial economic output value of Zigong is in the third tier, and Leshan, Ya 'an, and Aba are at the bottom. Compared with the actual situation, the change of industrial water demand plan will change the phenomenon that the economic output value of Chengdu city exceeds the other 7 cities in the basin, which is conducive to the coordinated and balanced development of the basin, and the prediction of the industrial economic output of cities in the basin will provide urban development assessment advice for water resources allocation and urban development in the later period.

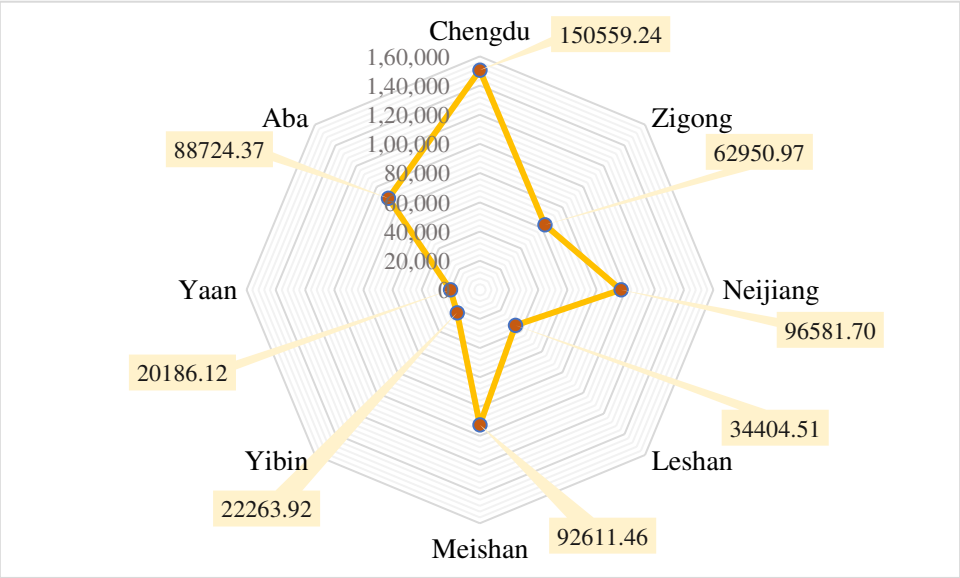

Fig 5. Forecast of Industrial economic Output value (2021, Ten thousand yuan)

4.2.3. Satisfaction with domestic water

Future water demand plan shall be the life should be a priority in water sector,

ensuring the basic life demand is the basic condition of water resources allocation, figure 6 shows that life satisfaction with water forecast in 2021, by using satisfaction for show the stand or fall of water allocation scheme, in which the satisfaction of Chengdu reached 102%, Already meet the demand of the residents living water, and have a rest of water resources to cope with population growth, the rest of the Minjiang river valley was 7, satisfaction are above 54%, basic meet the demand of the residents living water, neijiang, ya, aba and zigong city residents' satisfaction with water is relatively low, there are still about 40% did not meet, leshan and meishan and yibin water for life satisfaction is higher, Only 18% of water demands are not met, with the deterioration of climate conditions and the shortage of water resources situation, predict the future water can further provide the basis for water resources allocation plan, it is important to note that when the climate conditions of serious and shortage of water resources, effective water demand forecasting of a certain extent, can provide data support to relieve the contradictions of water demand, at the same time, In order to reduce the demand for water, water saving measures should be taken in each region of the basin.

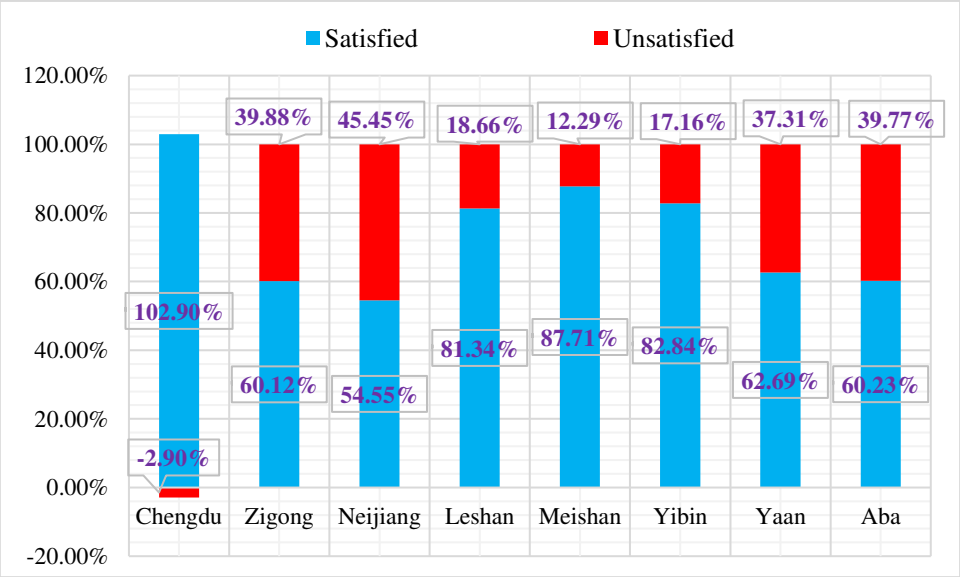

Fig. 6. Prediction of Domestic water satisfaction (2021)

5. Conclusion

In this paper, the depth of neural network and the combination of autoregressive moving average model, taking economic growth and social actual demand is given priority to with water to build index system, the basin water in future is forecasted, in addition, the total water consumption forecast, agriculture, industry, ecology, life water consumption is consistent with the actual situation, On this basis, the changes of agricultural grain yield, industrial economic output value, and domestic water satisfaction were explored. Taking Minjiang River Basin as an example, the rationality and practicability of the model are verified, and the following conclusions are drawn:

(1) Future water use forecasting is an effective way to deal with climate change and water shortage in the process of water resource allocation. Therefore, it is necessary and important to carry out water use forecasting. The future water resources allocation plan should not only consider the water demand among different water consumption sectors in the region but also make water resources allocation predictions considering the actual development situation of each region.

(2) considering the distribution of water resources in the different water departments, should consider the changing trend of water consumption in different regions of different departments in the future, by considering the water consumption change trend of the water basin in different departments, can depict the rationality of the allocation of water resources and fairness, provide data support for the river basin water resources management in combination with the actual situation.

(3) The forecast of future water consumption has a significant influence on agricultural grain yield, industrial economic output value, and domestic water satisfaction. The higher the predicted value of future water consumption is, the higher the agricultural grain yield, industrial economic output value, and domestic water satisfaction will be, the agricultural grain yield and industrial economic output value

and domestic water satisfaction will be mutually restricted in different regions of the basin. Therefore, according to the forecast results of future water consumption, watershed managers need to formulate corresponding distribution schemes according to different regional industrial plans to weigh the relationship among agricultural and grain output, economic output value, and domestic water satisfaction.

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