Research on Annual Runoff Forecast of Shaanxi Section of Hanjiang River based on Multi-model

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Abstract: Because of its strong non-stationary and nonlinear characteristics, the runoff series bring serious challenges to the accurate and reasonable prediction of runoff. In the past, the research direction of runoff prediction is mainly the improvement of a single model or mixed model prediction, which often ignores the model's applicability to the actual situation. From the perspective of multiple models, based on the runoff series data of Yangxian Station in Shaanxi Section of Han River, this paper adopts the ARIMA model, the MGF model, the Grey dynamic model and the DenseNet model to forecast the annual runoff of Yangxian Station. The prediction results are compared and analyzed to select the model most suitable for Yangxian Station among the four models. The results show that the DenseNet model is the most suitable for the runoff prediction activities of the selected watershed. Through the applicability analysis of runoff prediction model, a scientific and reliable runoff prediction can be obtained, which provides a scientific basis for water resources management and allocation, water resources development and utilization.

1 INTRODUCTION

In recent years, human activities have led to significant climate change, changes in precipitation forms, and changes in natural watershed environment, which makes the change of runoff more complex (Lei et al., 2003). The prediction of runoff series becomes more and more difficult. Under the conditions of existing station network, instruments and equipment and observation technology, the temporal and spatial changes of various information are difficult to reflect. In addition, affected by objective conditions such as natural factors, it is bound to cause measurement errors of various information. There are many research results of the existing runoff prediction models, but different models have their own applicability (Liang et al., 2020). When predicting the runoff of the basin, the most appropriate model is selected from different models to obtain higher runoff prediction accuracy, which has important practical significance for accurately predicting the runoff and is also a problem to be solved in Hydrological Prediction.

There are many uncertainties and complexities in runoff time series. At present, people mostly realize runoff prediction through various hydrological model methods, including time series prediction model, nonlinear model and prediction model based on intelligent algorithm (Labat et al., 2004; Li J et al., 2008). Time series analysis (Hsu et al., 1995; Dutta et al., 2012) is an earlier and more mature analysis method. It studies the change law of prediction with time and establishes a time series prediction model to predict. For example, ARIMA model proposed by box and Jenkins (Du & Ma, 2018; Liu, 2011; Sun et al., 2013). The mean generating function model proposed by Wei Fengying et al (Wei & Cao, 1990). Because the runoff variation characteristics often show highly nonlinear characteristics, nonlinear models appear, such as the Grey prediction model based on Grey system theory (Liu & Yang, 2015; Deng, 1982a; Deng, 1982b). With the development of computer technology and mathematical theory, intelligent algorithms have also been applied to runoff prediction, such as machine learning, data mining and so on. For example, DenseNet model, a machine learning model based on neural network

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theory (Gu, 2008).

There are many models for runoff prediction, but the characteristics and emphases of different prediction models are different, and the applicable conditions are different. There is no best model for watershed runoff prediction, only suitable models. In addition, the prediction results of a single prediction model are lack of comparison, so it is difficult to obtain accurate and satisfactory results. Therefore, in the runoff prediction of the basin, it is necessary to comprehensively compare the prediction results of different models in order to select a more appropriate prediction model. From the perspective of multi model, taking Yangxian station in Shaanxi section of Hanjiang River as the representative station, this study uses ARIMA model, MGF model, Grey dynamic model and DenseNet model to predict the annual runoff. The results are compared, in order to select the most suitable runoff prediction model for Shaanxi section of Hanjiang River.

2 STUDY AREA AND DATA

The Han River is the largest tributary of the Yangtze River, also known as the Hanshui, originating from Panzhong Mountain in Ningqiang County, Shaanxi Province. The main stream of the Han River is 1,577 km in length, with a drainage area of 159,000 km². The section from the source of the upper reaches of the Han River to the Baihe River belongs to Shaanxi Province, with a total length of 652 km and a catchment area of 59,100 km², accounting for about 33% of the total area of Shaanxi Province. The water volume of this area accounts for about 66.7% of the entire Shaanxi province, and the river narrow here, the water level drop is large and the water energy resources are abundant (Xiong & Chen, 1987). Yangxian Station on Shaanxi section of Han River at Daqiaotou, Chengguan Town, Yangxian County, is an important national control station with a catchment area of 14,484 km² and a distance of 1,316 km from the estuary (Figure 1).

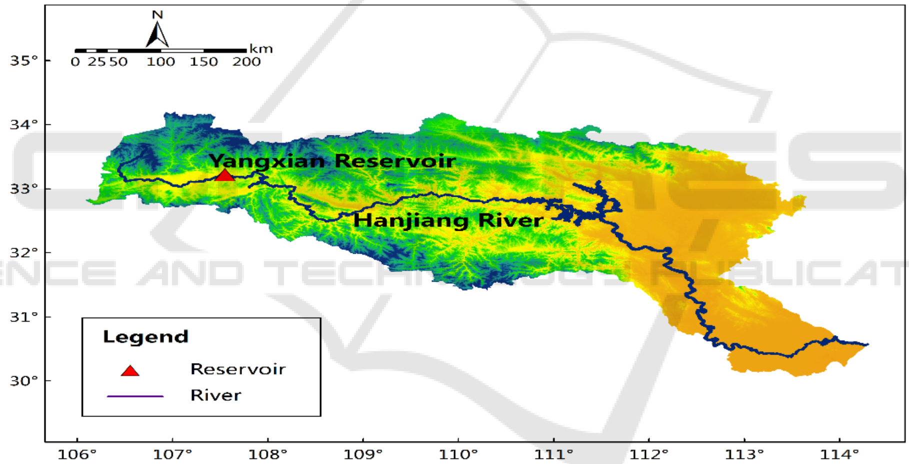


Figure 1: location of Yangxian station in Shaanxi section of Hanjiang River.

Due to the strong and ever-changing role of human activities, the natural law of hydrology is changing anytime and anywhere, so that the observed hydrometeorological data are not representative enough, and some data may be "polluted". These factors will produce errors and affect the accuracy of prediction results. Therefore, a long enough hydrological series is needed to reduce the prediction error. This study mainly collects the annual runoff data of Yangxian station in Shaanxi section of Hanjiang River from 1967 to 2014, and forecasts and analyzes the annual runoff of Yangxian station based on the 48-year annual runoff data.

3 RESEARCH METHOD

3.1 ARIMA Model

The ARIMA model is also known as the summation autoregressive moving average model and is widely used in time series forecasting. The basic idea of the model is to treat a given time sequence as a non-random sequence, and use the past sequence value to make predictions by analyzing the information of the sequence for model identification, ordering and determining the model (Sun, 2012; Liu et al., 2006; Schreider et al., 1997). The general structure of the ARIMA model is:

$$\begin{cases} \Phi(B)(1-B)^d x_t = \Theta(B)\varepsilon_t \\ E(\varepsilon_t)=0, Var(\varepsilon_t)=\sigma_\varepsilon{}^2, E(\varepsilon_t\varepsilon_s)=0\,(s\neq t) \\ E(\varepsilon_t\varepsilon_s)=0(\forall s<t) \end{cases} \quad (1)$$

Where $\Phi(B)=1-\phi_1 B-\cdots-\phi_p B^p, \phi_p \neq 0$;

$$\Theta(B)=1-\theta_1 B-\cdots-\theta_q B^q, \theta_q \neq 0;$$

$\{\varepsilon_t\}$is the white noise sequence.

Where p is the AR term, which represents the autoregressive order of the model; q is the MA term, which represents the moving average order of the model; d is the Integrated term, which represents the number of differences between the model and the time series.

3.2 MGF Model

The MGF model is a time series forecasting method. The model is based on the time series memory idea and constructs an extended series for forecasting. The advantage of this model is that multi-step prediction may be performed, and the sequence of extrema has a good predictive result (Sun, 2012).

The basic steps of the model establishment are: Firstly, the maximum number of mean generation functions of MGF model is calculated according to the length data of time series and the actual situation; Then, the values of each mean generating function are obtained and the L-order mean generating triangular matrix is constructed; Then, according to the periodic extension formula, the constructed triangular matrix is extended to obtain the extension matrix with length N, forming l prediction factor sequences; Finally, several factors closely related to the prediction object are selected through cross-correlation analysis, or all factors are considered, and the factors are selected through stepwise regression to establish a multiple regression model for prediction (Cui & Ye, 2009). After the model is established, the significance of the established model needs to be tested, and the tested model can be used for prediction.

The basic principle of the model is: assuming that there is a time series $X=(x_1,x_2,x_3,\cdots,x_n)$, construct a mean generating function for the series according to the following formula:

$$\bar{X}_l(i)=\frac{1}{n_l}\sum_{j=0}^{n_l-1}X(i+lj) \quad (2)$$

where $n_l=\max\{n_l \leq \left[\frac{N}{l}\right]\}$; $l \leq \left[\frac{N}{2}\right]$; $i=1,2,3,\cdots,l$; [] is the rounding symbol; N is the sequence length. After each mean generating function is obtained, an *L-order* mean generating matrix can be constructed. When constructing the *L-order* mean generating matrix, each element requires at least two original time series values to calculate the mean value, $L=l_{max}=\left[\frac{N}{2}\right]$. The constructed mean generation function is periodically extended according to the following formula:

$$f_l(t)=\bar{X}_l\left[t-l\bullet Int\left(\frac{t-1}{l}\right)\right] \; (l=1,2,\cdots,L; t=1,2,\cdots,N) \quad (3)$$

By extending each mean generating function in equation (3), the extension matrix in the form of the following formula can be obtained:

$$\bar{F}=\begin{bmatrix} \bar{X}_1(1) & \bar{X}_1(1) & \bar{X}_1(1) & \bar{X}_1(1) & \bar{X}_1(1) & \cdots & \bar{X}_1(1) \\ \bar{X}_2(1) & \bar{X}_2(2) & \bar{X}_2(1) & \bar{X}_2(2) & \bar{X}_2(1) & \cdots & \bar{X}_2(i_2) \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ \bar{X}_L(1) & \bar{X}_L(2) & \cdots & \bar{X}_L(L) & \bar{X}_L(1) & \cdots & \bar{X}_L(i_L) \end{bmatrix}$$

In matrix $\overline{X_L}(i_L)$ means taking $\overline{X_L}(1)$, $\overline{X_L}(2)$, …, $\overline{X_L}(L)$ in sequence. Put $f_L(t)$ is regarded as L basis function as the predictor of the original time series. Finally, a model is established for prediction.

3.3 Grey Dynamic Model

The gray dynamic model is based on the gray theory system. The model does not focus on the mathematical statistics of the time series, but converts the chaotic time series into a time series with a certain law, and then builds the model (Zheng & Shi, 2010).

The basic idea of gray dynamic model establishment is to transform the sequence in a differential equation, and then establish a dynamic model of its change, expressed as Grey dynamic model, generally denoted as the GM model (Xia & Ye, 1995; Xu et al., 2005), the established the $GM(h,n)$ model is differential the time continuous function of the equation:

$$\frac{d^n(X_1^{(1)})}{dt^n}+a_1\frac{d^{n-1}(X_1^{(1)})}{dt^{n-1}}+\cdots+a_nX^{(1)}(1)=b_1X_2^{(1)}+b_2X_3^{(1)}+\cdots+b_{n-1}X_n^{(1)} \tag{4}$$

where H is the order of the above differential equation; N is the number of variables.

The coefficient vector a of the above equation is expressed in matrix form as follows: $a=[a_1,a_2,\cdots,a_n \vdots b_1,b_2,\cdots,b_{n-1}]^T$;The coefficient vector a can be solved by the least square method: $a=[(A\vdots B)^T(A\vdots B)]^{-1}(A\vdots B)^TY_n$,($Y_n=[X_1^{(0)}(2)X_1^{(0)}(3)\cdots X_1^{(0)}(n)]^T$).

For $GM(h,n)$ model, the larger the order h of differential equation, the more complex the model calculation is, but the prediction effect is not necessarily the better, so h is generally less than order 3. For single sequence, the Grey dynamic prediction model $GM(1,n)$ is generally a commonly used state analysis model, which is called the first-order dynamic Grey model of n sequences (Zeng & Lin, 2010).

In the $GM(1,n)$ model, the original data are expressed as follows:

$$X_1^{(0)}=\left\{x_1^{(0)}(1),x_1^{(0)}(2),\cdots,x_1^{(0)}(\mathrm{m})\right\} \tag{5}$$

The rest of the factor sequences are expressed in the same form. Then, the original sequence, that is, the prediction object sequence and each factor sequence are accumulated once to obtain the corresponding 1-AGO sequence. Then establish the differential equation of the following formula:

$$\frac{dX_1^{(1)}}{dt}+aX_1^{(1)}=b_1X_2^{(1)}+b_2X_3^{(1)}+\cdots+b_{n-1}X_N^{(1)} \tag{6}$$

Where a is called development coefficient; $b_1b_2,\cdots,b_{N-1}$ are called driving coefficients; $b_{i-1}X_1^{(1)}(i=2,3,\cdots,N)$ is called the driver; The corresponding time function of the model is obtained by solving the differential equation as follows:

$$\widehat{X}_1^{(1)}(t+1)=\left[X_1^{(0)}(1)-\sum_{i=2}^{n}\frac{b_{i-1}}{a}X_i^{(1)}(t+1)\right]e^{-at}+\sum_{i=2}^{n}\frac{b_{i-1}}{a}X_i^{(1)}(t+1) \tag{7}$$

Where $t=1,2,\cdots,m$; The cumulative sequence value of the original sequence is calculated by the above formula, which needs to be restored to obtain the predicted value. The restoration formula is as follows:

$$\widehat{X}_1^{(0)}(t)=\widehat{X}_1^{(1)}(t+1)-\widehat{X}_1^{(1)}(t)\quad(t=1,2,\cdots,m) \tag{8}$$

The above formula is the prediction model of Grey dynamic prediction model $GM(1,n)$.

3.4 DenseNet Model

The DenseNet model is also called dense convolutional neural network, which is a neural network model developed in recent years. The whole structure of the DenseNet model includes dense blocks and transition layers, while the hidden layers are located in dense blocks. Dense blocks are connected through convolution layer and pooling layer. The convolution layer extracts the features of input information of the upper layer, and the pooling layer performs dimensionality reduction processing. The input of a certain layer in the model is the output of all previous layers, forming L(L+1)/2 connections (Schreider et al., 1997).

The DenseNet model uses a single-step prediction model. The principle assumes that there is a time series $X=(x_1,x_2,x_3,\cdots,x_n)$. First, input n historical data before time t in the input layer, and the predicted value of time t is obtained in the output layer. When the model is calculated, the eigenvector is first input at the input level, and convolution and pooling operations are carried out at the transition level. The obtained eigenvalue is transferred to the next level until the output value is obtained. In the convolution layer, the commonly used activation functions are as follows:

(1) Logarithmic S-shaped Sigmoid function:

$$f(x)=\frac{1}{1+e^{-x}} \tag{9}$$

(2) Tanh function:

$$f(x)=\frac{1-e^{-2x}}{1+e^{-2x}} \tag{10}$$

(3) Relu linear correction unit:

$$f(x)=\max(x,0) \tag{11}$$

4 EXAMPLE APPLICATION

4.1 ARIMA Model Prediction

The annual runoff sequence of Yangxian Station in the section of Han River in Shaanxi was selected for ARIMA model prediction. Firstly, the stationarity and pure randomness of the annual runoff sequence of the Yangxian Station were analyzed by drawing the time series diagram and autocorrelation diagram of the annual runoff sequence. After judgment, the station runoff time sequence is a non-stationary sequence and a non-white noise sequence. Therefore, it is necessary to carry out differential treatment to the annual runoff series. In order to avoid the phenomenon of over-differential, the annual runoff sequence of Yangxian station is processed by first-order difference (Figure 2), and the time series graph after the difference and the autocorrelation graph and partial autocorrelation graph are drawn, as shown in Figure 3.

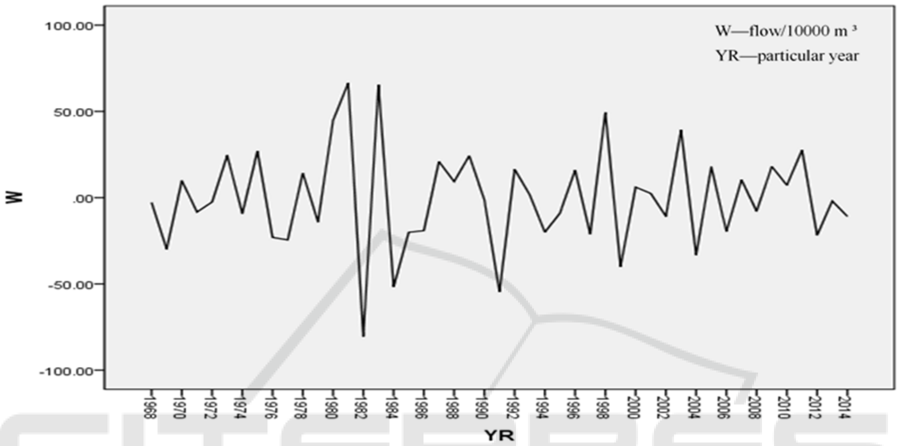
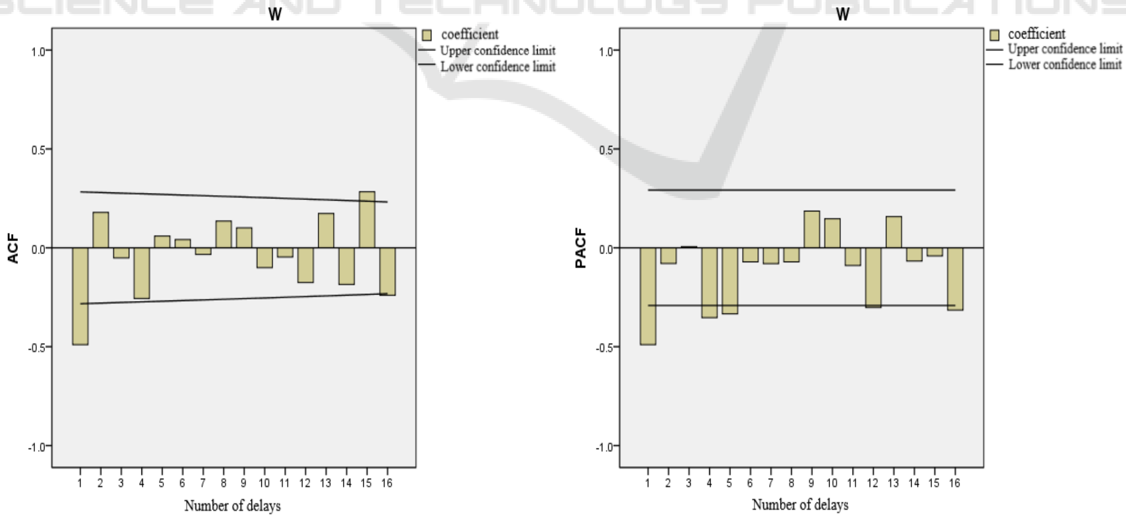


Figure 2: First order differential time sequence diagram of annual runoff sequence.



(a) Autocorrelation diagram (b) Partial autocorrelation diagram

Figure 3: First order differential autocorrelation and partial autocorrelation of runoff series.

It can be seen from (a) and (b) in Figure 3 that the sequence has basically been a zero mean stationary sequence after the first-order difference, and the autocorrelation diagram is basically within the confidence interval after the first-order lag time. It can be judged that the autocorrelation function is a first-order tail, and the partial autocorrelation diagram decays rapidly to zero from the lag time of 2, which can be preliminarily judged as truncated. In order to ensure the accuracy of prediction, partial autocorrelation is used as truncation and tailing, and the model is established to select the optimal model. Four models are determined through parameter trial calculation: ARIMA (5,1,1), ARIMA (6,1,1), ARIMA (5,1,0) and ARIMA (6,1,0). The four models are tested and optimized. The statistics of each model are shown in Table 1.

Table 1: Model parameter comparison.

Model	LB Statistics			BIC Value
	Sequence Value	DF	Sig.b	
ARIMA (5,1,1)	23.065	12	0.322	7.017
ARIMA (6,1,1)	22.120	11	0.169	7.103
ARIMA (5,1,0)	23.321	13	0.310	6.923
ARIMA (6,1,0)	23.809	12	0.242	7.022

It can be seen from Table 1 that the Q statistic P value (Sig.b) of the residual sequences of the four models are all greater than 0.05, indicating that the residual sequences of the four models are all white noise sequences. All four models are effective in extracting the original sequence information sufficiently. The optimal model is selected by the BIC criterion. The smaller the BIC value, the better the model. Therefore, the ARIMA (5,1,0) model with the smallest BIC value is selected as the final model. The model is used to predict the annual runoff sequence of Yangxian Station, and the fitting curve between the predicted value and the measured value is shown in Figure 4. It can be seen that the predicted value of ARIMA model does not fit well with the measured value. Although the predicted sequence can basically fit the trend of the measured sequence, when the measured sequence rises and falls sharply, the predicted sequence does not have the same change law, and the predicted value also differs greatly from the measured value, so the prediction effect of ARIMA is poor.

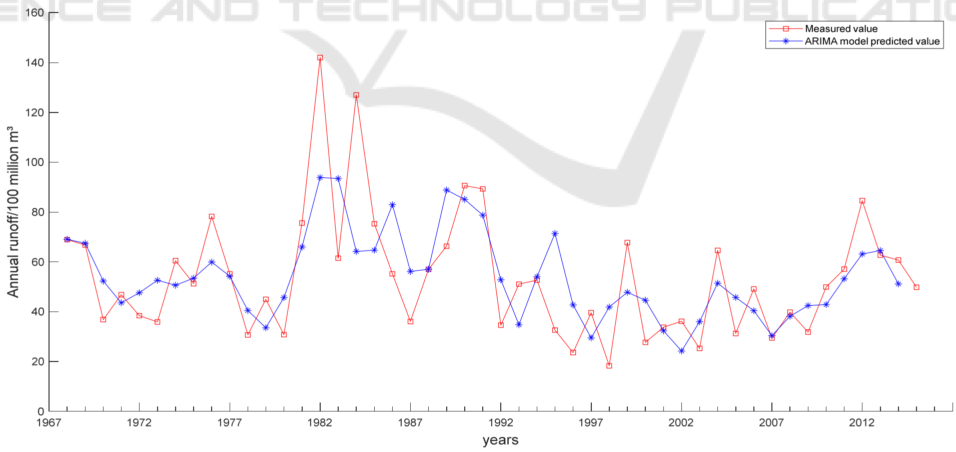


Figure 4: Fitting diagram of the ARIMA Model forecasted and measured values.

4.2 Prediction of Mean-generating Function

According to the basic principle of the mean generating function model and formula (2), the mean generating function is constructed based on the annual runoff time series data of Yangxian station, and the L-order mean generating matrix is obtained. Then carry out periodic epitaxy according to formula (3), and finally obtain the epitaxy matrix as follows:

$$F = \begin{bmatrix} 53.67 & 53.67 & 53.67 & 53.67 & \cdots & 53.67 & 53.67 \\ 56.62 & 50.73 & 56.62 & 50.73 & \cdots & 56.62 & 50.73 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 52.06 & 58.93 & \cdots & 69.56 & 52.06 & \cdots & 69.56 \end{bmatrix} \tag{12}$$

Thus, 24 predictors of the original annual runoff series are obtained, conduct cross-correlation analysis between each prediction factor and annual runoff series, select the factors with good correlation with the original series for multiple linear regression, or consider all prediction factors for stepwise regression. When modeling the mean generation function, this paper considers the multiple regression model, treats the selected factors equally, does not distinguish the importance of each factor, and ignores the independence of each factor. Therefore, the model is established by stepwise regression of all predictors, and then the 8 predictors most closely related to the original sequence are selected according to correlation analysis, and then the final model is established by stepwise regression method for prediction. First calculate the AIC value and BIC value of the model, and the serial numbers of predictors selected through correlation analysis are 15, 17, 18, 20, 21, 22, 23 and 24 respectively.

The final model is established by stepwise regression method for prediction, and the parameters and test statistics of the model are shown in Table 2. It can be seen that only factor 22, factor 23, factor 17 and factor 15 are left after stepwise regression; The p value (SIG) in F test is less than 0.05, indicating that the overall linear regression of the model is significant; The p value (SIG) in the t-test is also less than 0.05, indicating that the regression coefficient of the model passes the significance test, that is, the remaining four factors (factors 22, 23, 17 and 15) have a significant relationship with the annual runoff series, and the model is effective. Therefore, the final model is:

$$y = -25.773 + 0.481x_{22} + 0.349x_{23} + 0.319x_{17} + 0.323x_{15} \tag{13}$$

Table 2: MGF model correlation coefficient and test statistics.

Forecasting factors	regression coefficient		F test		t test	
			F	Sig	t	Sig
constant	b_0	-25.773			-2.989	0.005
Factor 22	b_1	0.481			3.199	0.003
Factor 23	b_2	0.349	25.425	0	2.134	0.039
Factor 17	b_3	0.319			2.560	0.014
Factor 15	b_4	0.323			2.047	0.047

The model is used to predict the annual runoff series of Yangxian station, and the fitting curve between the predicted value and the measured value is obtained, as shown in Figure 5. It can be seen that the prediction effect of the mean generation function model is significantly better than the ARIMA model. The prediction sequence of the mean generation function model has the same change law as the measured sequence. From 1967 to 1992, the difference between the predicted value of the model and the measured value is small, and the predicted sequence and the measured sequence have a good fitting effect, while from 1992 to 2007, the difference between the predicted value and the measured value becomes larger. The fitting degree between the predicted sequence and the measured sequence is general. Generally speaking, the prediction effect of mean generation function model is general.

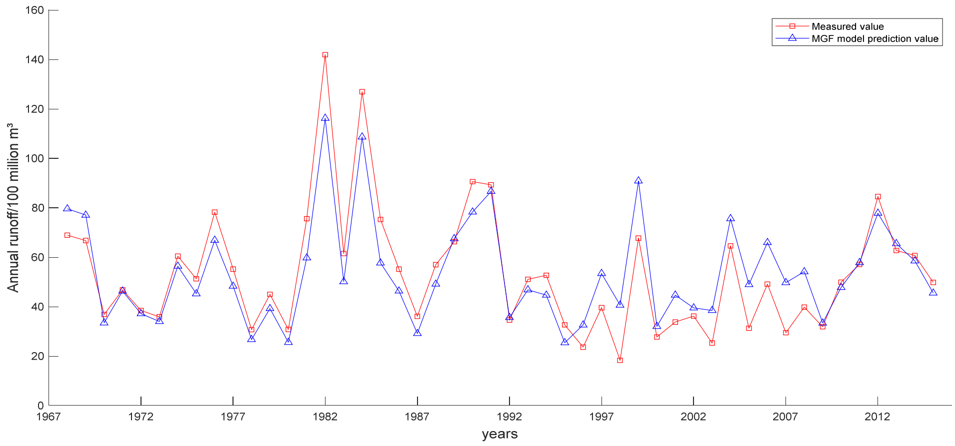


Figure 5: Fitting diagram of MGF model forecast and measured values.

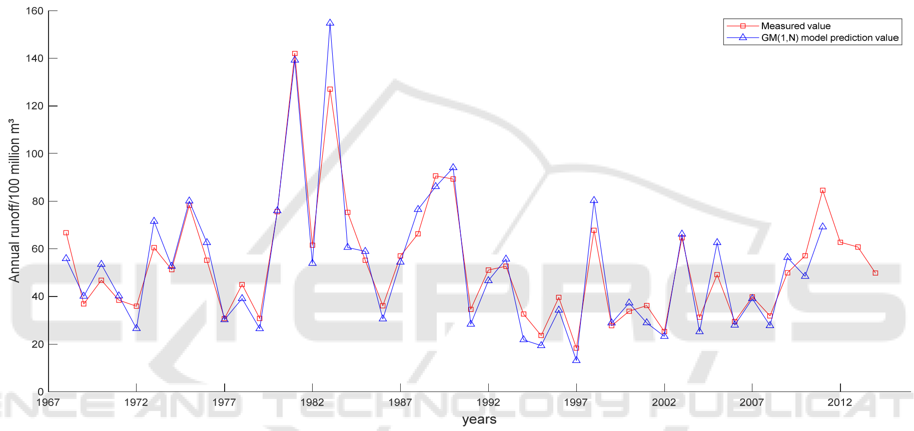


Figure 6: Fitting diagram of predicted values and measured values of GM (1, N) model.

4.3 Gray Dynamic Model Prediction

In this study, the annual runoff time series of Yangxian station from 1967 to 2011 is taken as the original data, that is, the prediction object. The monthly average flow of this series from May to October each year is taken as six prediction factor series, and the GM (1, n) Grey dynamic prediction model is established. Based on the established model, the annual runoff of each year is predicted and tested with the annual runoff from 2012 to 2014.

According to the basic principle of the model, the 1 - AGO series of each series can be calculated based on the six series data of the monthly average flow. These data are from May to October of the annual runoff series of Yangxian Station. The calculation results is the accumulation series, and then the accumulation matrix B is obtained.The coefficient vector a is obtained by using the least square method. The parameters of the $GM(1,N)$ model is calculated as shown in Table 3.

Table 3: Annual runoff GM (1, N) model parameter calibration results.

Name of parameter	Development coefficient a	Driving coefficient					
		b_1	b_2	b_3	b_4	b_5	b_6
Constant Value	1.408426	0.004813	0.000698	0.000590	0.001919	0.000517	0.002650

In the above table, a is the development coefficient and the six driving coefficients are the Grey action quantity of the model. Bring the model parameters into formula (7) to obtain the time response function of Grey dynamic model $GM\ (1, n)$, and then restore according to formula (8) to obtain the predicted value of annual runoff series of Yangxian station. The fitting curve between the predicted value and the measured value of the Grey dynamic prediction model is shown in Figure 6. It can be seen that the Grey dynamic model has a good prediction effect on the annual runoff prediction of Yangxian station. The prediction sequence has the same change law as the measured sequence. The predicted value of the model is close to the measured value, and the predicted sequence has a good fit with the measured sequence

4.4 DenseNet Model Building

This paper starts from the traffic data of Yangxian Station on January 21, 1967, predicts the average daily traffic of the previous nine days, takes the daily traffic data of Yangxian Station on January 21, 1967 solstice on May 29, 2005 as the training data to train the model, and the remaining data from 2006 to 2014 as the verification data. In order to train the model effectively to improve the prediction accuracy and make the model have better performance and convergence speed, it is necessary to transform the basic data in advance. The transformation formula is: $z = a\log_{10}(x_i + b)$ (where Z is the value after transformation; a is an arbitrary constant; x_i is the measured value, and b is generally 1). Then, the predicted sequence obtained from the transformed sequence is reduced according to the formula: $x_i = 10^{z/a} - b$. In order to determine the model structure, the partial autocorrelation diagram of the original time series is also required, as shown in Figure 7.

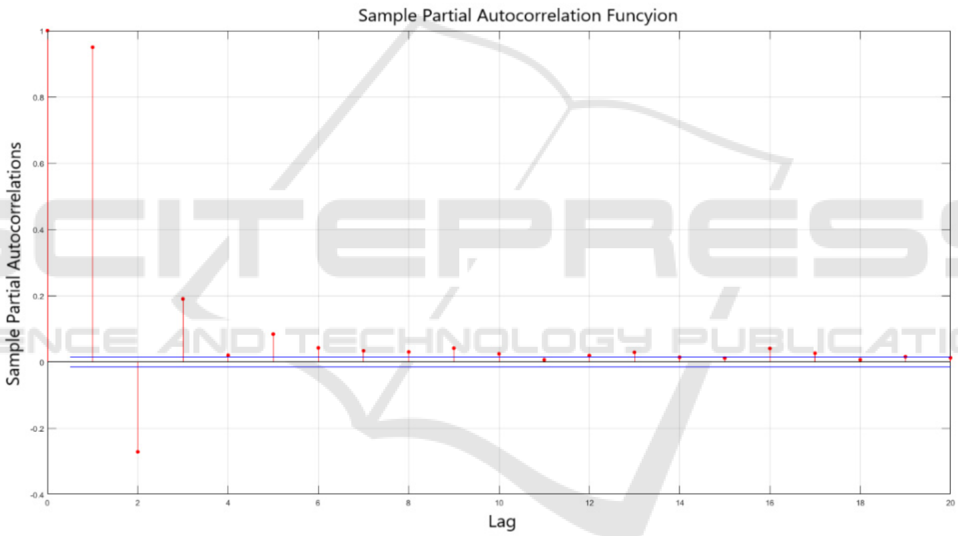


Figure 7: Partial correlation diagram of original sequence.

As can be seen from Figure 7, the lag time is set to 20, and after the lag time is 9, the partial correlation coefficient basically remains stable and oscillates in the upper and lower interval. Therefore, the input layer of the model is set as nine neurons in this paper. Through the trial algorithm, the number of hidden layers is determined as three layers, and each layer contains 30 neurons. The output layer is set to the day forecast. Thus, the DenseNet model structure was finally determined as 9-30-30-30-1.

After determining the model, first all the original daily flow data are transformed, and then the training set data are input into the model for training. Then, the data of the validation set are used for verification, and the prediction results of the training set and the validation set are obtained. The predicted daily average flow is restored, and the predicted annual runoff of each year is finally accumulated and calculated. The fitting curve between the predicted value and the actual value of the DenseNet model is shown in Figure 8. It can be seen that DenseNet model has a good prediction effect on the annual runoff prediction of Yangxian station. The prediction sequence has the same change law of steep rise and fall as the measured sequence. The difference between the predicted value of the model and the measured value is very small, and the predicted sequence has a good fit with the measured sequence.

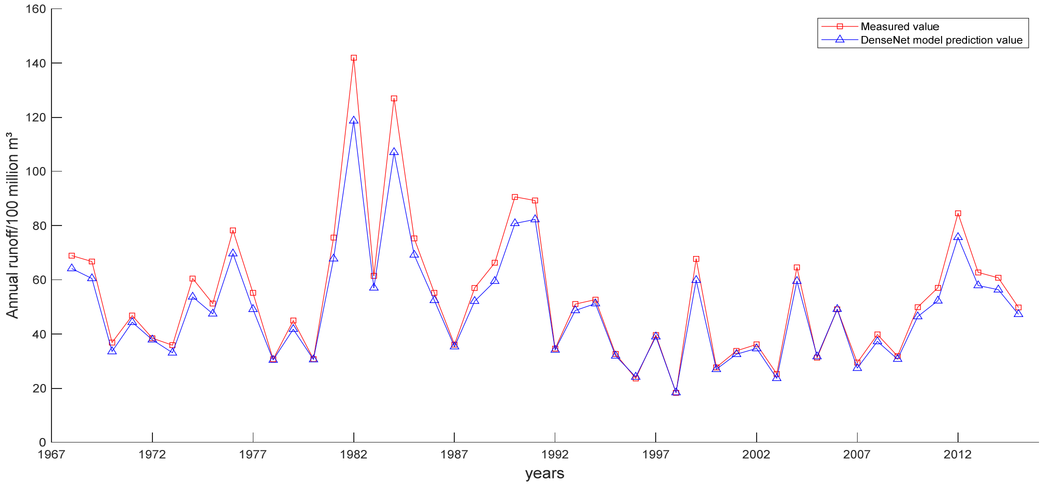


Figure 8: Fitting diagram of the predicted value of the DensetNet model and the measured.

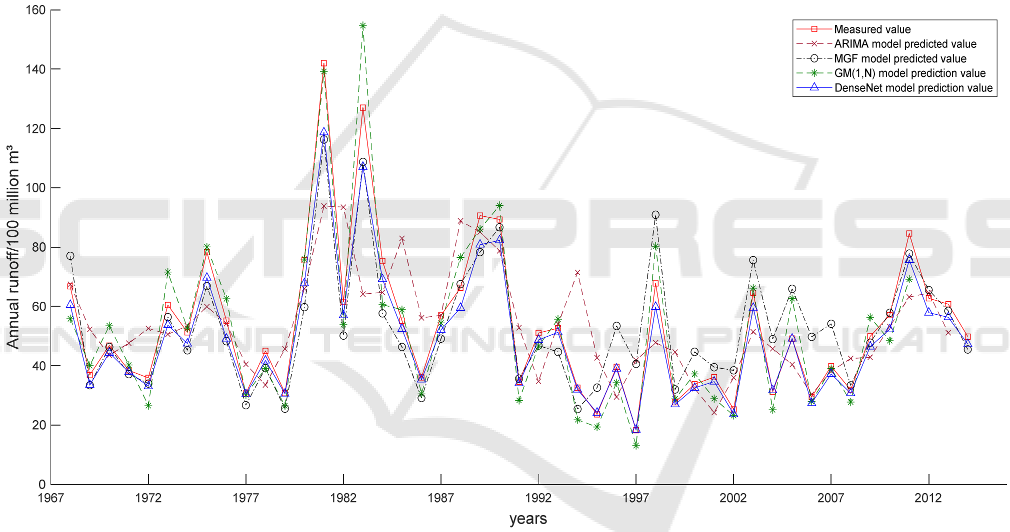


Figure 9: Fitting Diagram of Predicted Values and Measured Values of Multiple Models.

5 COMPARATIVE ANALYSIS OF MULTI-MODEL PREDICTION RESULTS

The model is used to predict the annual runoff series. The reliability of the model prediction result needs to be tested after obtaining the prediction sequence value. According to the Hydrological Prediction specification, it is considered that the relative error of one prediction is within plus or minus 20%, and the qualified rate of prediction is calculated (Ministry of Water Resources of the People's Republic of China, 2000), The average relative error MAPE, root mean square error RMSE and certainty coefficient DC are used to analyze the coincidence degree between the predicted sequence and the measured sequence (Sun, 2012; Huang, 2015). The DC coefficient represents the degree of coincidence between the predicted sequence and the measured sequence. It and the predicted qualified rate are maximized indicators, and the greater its value, the better. MAPE and RMSE are minimization type indicators. The smaller the value, the better. The calculation results of the above four indicators are shown in Table 4. The fitting diagram between the predicted value of each model and the measured value of annual runoff of Yangxian station is shown in Figure 9.

Table 4: Multi-model annual runoff forecast accuracy evaluation.

Model	Qualification rate (%)	MAPE (%)	RMSE	DC
ARIMA model	51.1	33.89	22.06	0.203
MGF model	72.9	19.47	13.40	0.801
Grey dynamic model	86.4	12.40	8.09	0.893
DenseNet model	100	6.39	6.18	0.937

According to the order of ARIMA model, MGF model, $GM\ (1,n)$ model and DenseNet model, it can be seen from table 4 and Figure 9 that the predicted qualified rate and DC coefficient are getting larger and larger, the values of MAPE and RMSE are getting smaller and smaller, and the fitting degree between the predicted value series and the measured value series is getting better and better. Therefore, among the four models, ARIMA model has the worst prediction effect. However, it can basically show the trend of runoff series with large error. The prediction effect of mean MGF model is general. The prediction effect of Grey Dynamic prediction model is better, and the prediction effect of DenseNet model is the best. The prediction qualified rate and DC coefficient of the prediction results of DenseNet model are the largest, and MAPE and RMSE are the smallest, showing obvious advantages in all aspects. Therefore, for the annual runoff prediction of Shaanxi section of Hanjiang River, DenseNet model is the most suitable for the annual runoff prediction of this area.

6 CONCLUSION

In this study, ARIMA, MGF model, Grey dynamic prediction model and DenseNet model are used to predict the annual runoff of Shaanxi section of Hanjiang River. Through analysis and comparison, the runoff prediction model most suitable for Shaanxi section of Hanjiang River among the four models is selected, which can improve the accuracy of prediction results.

(1) Comprehensive comparative analysis of the prediction results of the four models shows that compared with ARIMA model, MGF model and Grey Dynamic model, DenseNet model has the highest prediction qualification rate, up to 100%, the average relative error and root mean square are the smallest, and the fitting effect is the best. It is most suitable for the research of runoff prediction in Shaanxi section of Hanjiang River.

(2) DenseNet model is the most suitable runoff prediction model for the Shaanxi section of Hanjiang River in this study. It is a runoff prediction model based on neural network theory. In recent years, some new theories have emerged in the field of neural networks, such as Meshk (Huang, 2015) theory. Densenet model can be used as a simple template for creating neural network runoff prediction model, and provide a reference for future research.

(3) Appropriate runoff prediction models for different regions can improve the accuracy and rationality of runoff prediction, and provide scientific and reasonable runoff prediction for solving water problems such as water shortage, water pollution, frequent flood disasters and urban waterlogging. At the same time, it can also provide basis for water conservancy departments to carry out water regulation and rational allocation of water resources, and provide guidance for reservoir operation management and prevention Put forward guidance on flood and drought relief, water conservancy and power generation, agricultural irrigation, etc.

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