

Improved Hybrid Model Based on Support Vector Regression Machine for Monthly Precipitation Forecasting

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Abstract—In this paper, we study the time series techniques for the monthly precipitation forecasting. The techniques used in this study are moving average procedure, support vector regression machine, and seasonal autoregressive integrated moving average model and hybrid procedure. Firstly, the moving average procedure is employed to find the trend; secondly, the support vector regression machine is applied to forecast the trend; thirdly, the hybrid procedure is used for provide the last forecasting results based on the above models. For the coefficients, the optimization method we employed is the popular particle swarm optimization algorithm. Three time series are applied to test the proposed idea, which are the monthly precipitation data from Gansu Meteorological Bureau. The forecasting results show that our proposed model is an effective model for nonlinear time series forecasting.

Index Terms—monthly precipitation, forecasting, time series

I. INTRODUCTION

Currently, global changes have affected the all aspects of the living environment. Furthermore, global warming and spatial extent differences inevitably lead to changes in regional precipitation and temperature [1]. Therefore, short-term climate prediction is one important topic of meteorological science. It is useful for disaster reduction and prevention, so it is with important scientific and practical significance. Furthermore, the monthly precipitation and monthly mean temperature predictions are the two most important elements for short-term climate forecast system, where the monthly precipitation forecasting is the key. The accuracy is the soul of forecasting business. There are many random factors affect the climate prediction, so any method provides higher forecasting results is welcomed in this domain.

China has about 70 years history about short term

climate prediction, and there are four development stages: simple empirical statistical analysis, mathematical statistical analysis, physical statistic and dynamical and statistical approaches [2]. One of precipitation forecasting methods is based the impact signal combined the relationship between precipitation and external forcing [3]. With the sample number increasing, the factors and coefficients in the model should be changed. However, the factor features are unstable and it is hard to collect the data. Climate pattern for the short-term climate prediction is not very successful. Therefore, the forecasting precisions are not always good enough. General statistical techniques are the popular climate prediction methods, which achieve the optimal prediction results by combining many relevant factors analysis. One kind of statistical techniques is time series analysis. Therefore, this study develops a new model based on time series techniques for the monthly precipitation forecasting combined regional characteristics.

Gansu Province locates in China's northwestern region, whose precipitation is less than the southern region. From Fig.1, we can see that the average annual precipitation for Dunhuang and Jiuquan is less than 100mm, and it is between 100 mm and 200 mm for Minqin. For areas in Gansu with less rainfall, we model the monthly precipitation for improving the prediction precision which is tested by practical examples.

There are many methods for monthly precipitation, such as multimodel ensemble prediction techniques [4], downscaling method [5] and artificial Neural Networks [6]. The monthly precipitation has some trend and periodicity. In order to provide more accurate forecasting results, we firstly apply the moving average procedure [7] to determine the trend, secondly use the support vector machine (SVM)[8] to forecast the trend and finally apply the seasonal autoregressive integrated moving average model (SARIMA) [9] to model the difference series. The moving average procedure is a simple smoothing technique, and its basic idea is as follows. Basing on original time series, it computes the average value for a fixed length. Therefore, moving average technique can

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remove the cyclical and random fluctuations in the original series. The processed series reflects the long term trend. The original SVM algorithm was invented by Vladimir Vapnik and the current standard incarnation was proposed by Vapnik and Corinna Cortes in 1995[8]. SVM is a concept in statistical learning and machine learning

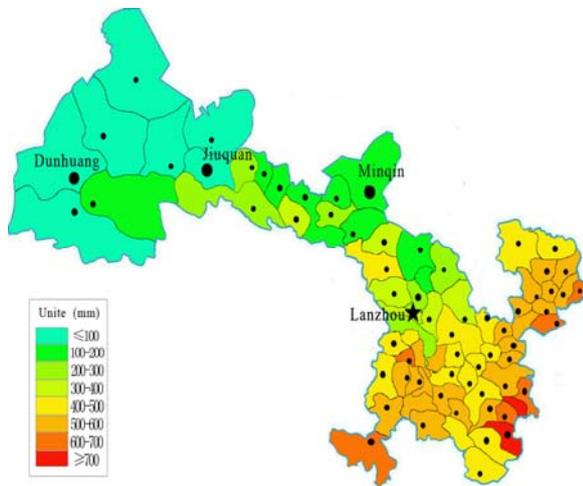


Figure 1. The average annual precipitation distribution between 1951 and 2010 for Gansu.

for a set of related supervised learning methods which is used for classification and regression analysis. The SVM is widely used in various domains, such as short-term wind speed prediction [10], electricity demand [7] and monthly stream flow forecasting [11]. For the difference data series, it has nonlinear or seasonal features. Therefore, we apply the seasonal autoregressive integrated moving average (SARIMA) model which is a generalization of an ARMA to forecast it. SARIMA is applied in some cases where data show evidence of non-stationary and seasonality, where an initial differencing procedure can be applied to remove the non-stationary. With global climate change, seasonality and trend for annual features have different affections on the short-term monthly precipitation forecasting, so they should have different weight coefficients. In order to get the rational predictive model with higher accuracy, we apply the weighted hybrid model to monthly precipitation forecasting [12]. Hybrid model is one kind of combining forecasting procedures. Combining forecasting model was firstly proposed by Bates and Granger and it makes full use of the individual models [13], which was widely studied by many researchers, such as Meade and Islam [14], Clemen [15], Higon [16], Armstrong [17], Winkler [18] and Makridakis [19].

Optimization technique is one method for finding the optimal solutions to various problems which is based on mathematics. Intelligent optimization algorithm is an important part of optimization techniques, which is an iterative algorithm as the other search algorithms. Particle swarm optimization is an artificial intelligence (AI) procedure that can be applied to search approximate solutions to extremely difficult numeric maximization and minimization problems. The coefficients of the weighted hybrid model are searched by particle swarm

optimization algorithm (PSO) [20]. The PSO is widely applied in various domains for its simplicity and effectiveness, such as MIG welding process [21], stock portfolio [22], multi-objective optimization [23] and multiple sequence alignment [24]. In this study, we apply an improved PSO for searching the weight coefficients of hybrid model.

The detailed procedures for our proposed procedure and case studies are as below:

- 1) Apply a first order moving average method to determine the trend data for the monthly precipitation series in which the moving average length is taken as 12 months for effectively eliminating the seasonal fluctuation
- 2) Forecast the trend series using SVM
- 3) Compute the difference data between actual data and forecasting trend data
- 4) Predict the difference series by SARIMA
- 5) Apply the hybrid model to fit the monthly precipitation, the weight coefficients searched by PSO
- 6) Apply the estimated hybrid model to forecast the monthly precipitation.
- 7) Case studies and forecasting ability analysis.

The outline of our paper is as follows. In Section II, we review forecasting techniques applied in this study including hybrid model, SVM, SARIMA and PSO. In Section III, we give detailed explanations for the training data. Concluding remarks are given in Section IV.

II. THE FORECASTING TECHNIQUES

A. Improved Hybrid Model

The hybrid model is one error correction technique which is welcomed in prediction domain. Generally speaking, there not exists one model is effective for any time series forecasting problems which suffers from trend and nonlinear features. Hybrid model is designed for linear and nonlinear forecasting series with higher precision compared with the individual model. Assume that $y_t (t = 1, 2, \dots, N)$ is the original data, N is the sample length, \hat{L}_t is the forecasting data at time t from one pre-specified model and $e_t = y_t - \hat{L}_t$ is the forecasting error or difference. The improved hybrid model can be described as [8]:

$$\hat{y}_t = \hat{a}\hat{L}_t + \hat{b}\hat{E}_t \tag{1}$$

where \hat{E}_t is the forecasting data for the difference series, the weights satisfy $\hat{a} + \hat{b} = 2$ and \hat{y}_t is the forecasting value obtained by the improved hybrid model. In the conventional hybrid model, the weight coefficients are $\hat{a} = \hat{b} = 1$. For one time series, the nonlinear and trend should have different weight coefficients for the forecasting results, so the weighted hybrid model is a rational method for time series forecasting and data analysis. In order to provide more effective forecasts and

rational hybrid technique, weight coefficients of the proposed hybrid model are relaxed to positive real data but with the constraint $\hat{a} + \hat{b} = 2$ which are searched by PSO.

B. Weighted Support Vector Machines Forecasting Model

Support vector machines (SVM) forecasting models [10] are popular techniques in data mining and statistical learning, and the weighted SVM is an improved SVM. Assume a training data set is consisted of N points $\{x_i, y_i\}_{i=1}^N$ in which $x_i \in R^n$ ($i = 1, 2, \dots, N$) is the input vector, $y_i \in R$ ($i = 1, 2, \dots, N$) is the output and N is the sample data length. The idea of SVM is to map the input space into a higher dimensional or possibly infinite-dimensional feature space A by nonlinearly mapping $\phi(x)$. The aim of SVM is to find $f(x)$ based on the training data set to approximate the unknown function or actual function $g(x)$. The form of approximation function $f(x)$ has the following format [25, 26]:

$$f(x) = \omega^T \phi(x) + b,$$

where $\phi(x)$ is the high dimensional feature space, which is nonlinearly mapped from the input space. In the higher dimensional feature space, $\phi: X \rightarrow A$, $b \in R$. The coefficients ω and b are estimated by minimizing

$$R_{SVM}(C) = C \sum_{i=1}^m L_{\varepsilon}(f(x_i), y_i) + \frac{1}{2} \|\omega\|^2 \tag{2}$$

$$L_{\varepsilon}(d_i, y_i) = \max\{0, |f(x) - y| - \varepsilon\} \tag{3}$$

where $L_{\varepsilon}(d_i, y_i)$ is ε loss function, $\|\omega\|^2$ denotes the inner product in the higher dimensional feature space and C is a positive constant which determines the trade-off between the empirical loss and the inner product.

In order to obtain the estimated values of ω and b , we can add two slack variables $\xi_i^+ \geq 0$ and $\xi_i^- \geq 0$ ($i = 1, 2, \dots, m$), and the (2) is transformed into one optimization problem defined as bellow:

$$\begin{aligned} &\text{minimize} \quad \frac{1}{2}(\omega, \omega) + C \sum_{i=1}^m (\xi_i^+ + \xi_i^-) \\ &\text{s.t.} \quad \begin{cases} y_i - \omega \phi(x_i) - b_i \leq \varepsilon + \xi_i^+ \\ \omega \phi(x_i) + b_i - y_i \leq \varepsilon + \xi_i^- \\ \xi_i^+, \xi_i^- \geq 0 \end{cases} \end{aligned} \tag{4}$$

The optimization equation can be transformed into a dual problem as described as below by introducing Lagrange multipliers α_i^* and α_i ,

maximize

$$\begin{aligned} W(\alpha, \alpha^*) &= -\frac{1}{2} \sum_{i=1}^m \sum_{j=1}^m (\alpha_i - \alpha_i^*) (\alpha_j - \alpha_j^*) k(x_i, x_j) \\ &+ \sum_{i=1}^m [\alpha_i (y_i - \varepsilon) - \alpha_i^* (y_i + \varepsilon)] \\ &\text{s.t.} \quad \begin{cases} \sum_{i=1}^m (\alpha_i - \alpha_i^*) = 0 \\ 0 \leq \alpha_i \leq C \\ 0 \leq \alpha_i^* \leq C \\ i = 1, 2, \dots, m \end{cases} \end{aligned} \tag{5}$$

The solution can be expressed in one form of

$$f(x) = \sum_{i=1}^m (\alpha_i - \alpha_i^*) K(x, x_i) + b \tag{6}$$

where $K(x, x_i)$ is kernel function, which performs the nonlinear mapping and satisfies the Mercer's condition, where $K(x_i, x_j) = \phi(x_i) \phi(x_j)$. The popular forms of kernel functions are Gaussian radial basis function (RBF), polynomial kernel, and a sigmoid function. Based on the advantages of Gaussian RBF demonstrated by Lessmann et.al [26], our SVM model applies the Gaussian RBF, which is defined as follows:

$$k(x, y) = \exp\left(-\frac{1}{\sigma^2}(x - y)^2\right) \tag{7}$$

Compared with the traditional SVM shown in (4), the weighted supported vector machines (W-SVM) model allows different weight allocation for different data samples and is more effective for monthly precipitation prediction for the following reasons: it provides forecasting results with higher prediction accuracy than original model and it allows different sample data to have different penalty, in other words, it allows the more recent data samples to be more important than the older data samples in the forecasting. Therefore, this paper employs the W-SVM model for the monthly precipitation prediction. The optimization problem for the W-SVM can be described as follows:

$$\min_{\omega, b, \xi} \frac{1}{2}(\omega, \omega) + C \sum_{i=1}^m s_i (\xi_i^+ + \xi_i^-) \tag{8}$$

where $s_i = \frac{1}{1 + \exp(r - 2ri/m)}$ ($i = 1, 2, \dots, m$) is the exponential weighted coefficients, here r is control parameter. The weighted SVM model shown in (8) has the same constraint formula as the traditional SVM model in (4).

C. Seasonal Autoregressive Integrated Moving Average

In statistics and econometrics, and in particular in time series analysis, an autoregressive integrated moving average (ARIMA) model is a widely applied method for data analysis. The seasonal autoregressive integrated moving average (SARIMA) was introduced by Box and Jenkins [27, 28] and has been widely used for various forecasting problems, which a generalization of an

autoregressive integrated moving average (ARIMA) model. These models are fitted to time series to better understand the data, finding the important information in the data series or to predict future data.

It is assumed that the time series $\{x_t | t = 1, 2, \dots, k\}$ has mean zero. A non-seasonal ARIMA of order (p, d, q) (denoted by ARIMA (p, d, q)) representing the time series can be expressed as [12, 29]:

$$x_t = \phi_1 x_{t-1} + \phi_2 x_{t-2} + \dots + \phi_p x_{t-p} + e_t - \theta_1 e_{t-1} - \dots - \theta_q e_{t-q}$$

or $\phi(B)\nabla^d x_t = \theta(B)e_t$ (9)

where x_t is the original data at the time t , e_t is the noise data, ϕ_t and θ_t are the coefficients, p is order for autoregressive, q is order for moving average polynomials, B is the backward shift operator, $\nabla^d = (1 - B)^d$ is the difference operator where d is the differences time, $\phi(B)$ and $\theta(B)$ are defined as $\phi(B) = 1 - \phi_1 B - \phi_2 B^2 - \dots - \phi_p B^p$ and $\theta(B) = 1 - \theta_1 B - \theta_2 B^2 - \dots - \theta_q B^q$ respectively. Particularly, assumed that e_t is independent and identically distributed as normal random variables with mean zero and variance σ^2 , and the roots of $\phi(x) = 0$ and $\theta(x) = 0$ all lie outside the unit circle. Similarly, a seasonal model can be written as follows:

$$\phi(B)\psi(B^s)\nabla^d(1 - B^s)^D x_t = \theta(B)\Theta(B^s)e_t$$

where $\psi(B^s) = 1 - \psi_1 B^s - \psi_2 B^{2s} - \dots - \psi_p B^{ps}$, $\theta(B^s) = 1 - \theta_1 B^s - \theta_2 B^{2s} - \dots - \theta_q B^{qs}$, D is the seasonal difference number, s is the period. If the time series is with mean $\mu \neq 0$, replace x_t with $x_t - \mu$.

D. Particle Swarm Optimization Algorithm

Inspired by the flocking behavior of the birds, Eberhart and Kennedy [20] firstly introduced particle swarm optimization (PSO) in 1995. Imagine a scenario: a group of birds randomly search one kind of food in one region. All birds do not know the location of the food, but the birds know the distance to the food. How to find the food? The simple and effective method is to search the region around the location of the bird which has shortest distance to the food. PSO is used to solve optimization problems inspired by this model. The PSO algorithm works by initializing a flock of birds randomly over the searching space, where every bird is called as a "particle" or random solution [20, 30]. All the particles have location and velocity update formula. The velocity update formulation determines the particles' flight direction and distance. After iterations, it can successfully search the optimal solution. The particles search the optimal solution followed the current optimal particle, one search is iteration. The particles renew position by tracking two "extreme values" which are called optimal values. The first is the individual extreme or optimal value (pbest).

Another is the current population extreme or optimal value (gbest) [31, 32].

In the D-dimensional space, each particle has a position vector $x_i = (x_{i1}, x_{i2}, \dots, x_{iD})$ and a velocity vector $v_i = (v_{i1}, v_{i2}, \dots, v_{iD})$, where n is the number of particles in the swarm. The best position visited by the total particle swarm (gbest) is denoted as vector $P_{gb} = (p_{g1}, p_{g2}, \dots, p_{gD})$ and the best position visited by the i -th particle (pbest) is denoted as $P_{ib} = (p_{i1}, p_{i2}, \dots, p_{iD})$. The PSO algorithm can be described as follows [12, 33]:

$$v_{id}(t+1) = v_{id}(t) + C_1 r_1 [p_{id}(t) - x_{id}(t)] + C_2 r_2 [p_{gd}(t) - x_{id}(t)]$$
 (10)

$$x_{id}(t+1) = x_{id}(t) + v_{id}(t+1), 1 \leq i \leq n, 1 \leq d \leq D$$
 (11)

where c_1 and c_2 are positive constants, which are commonly set to be $c_1 = c_2 = 2$, r_1 and r_2 are random numbers between zero and one.

E. Weights Determination

Let the weight coefficients of improved hybrid model be a particle which is the D-dimensional vector ($D=2$). The detailed steps of weights determination are as:

- Step 1. Randomly initialize position and velocity of particles.
- Step 2. Calculate the loss function or adaptive degree by $F_i = \frac{1}{n} \sum_{t=1}^n (y_t - \hat{y}_{it})^2$. Saving the current location $x_{i,d}(t)$ and F_i to pbest, and saving the best location and adaptive degree of pbest to gbest.
- Step 3. Generate new particles for the next generation. The new particles will be generated by (10) and (11).
- Step 4. Compare the loss function value for every particle with its experienced best position. If the new particle is better than the past one, it is saved as the current best position.
- Step 5. Compare the adaptive degree of all the current pbest and gbest, updating gbest.
- Step 6. Check whether the termination criterion is satisfied. If termination criterion (the maximum iteration number (500)) is reaching, continue to Step7. If the criterion is not satisfied, go back to Step 3.
- Step 7. Terminate the searching process and output the optimal particle position.

III. CASE STUDIES

A. Data Set and Accuracy Criterion

The monthly precipitation data are from Gansu Meteorological Bureau. Fig. 2 and Fig.3 show the actual data for the Minqin and Jiuquan, respectively. Two popular forecasting precision indexes mean absolute error (MAE) [34, 35] and mean square error (MSE) [36, 37]

are applied in this study and they are respectively defined as follows: $MAE = \frac{\sum_{t=1}^n |y_t - \hat{y}_t|}{n}$

$$MSE = \frac{1}{n} \sum_{t=1}^n (y_t - \hat{y}_t)^2$$

where y_t and \hat{y}_t respectively are the actual data and the forecasting value at time t , n is the data length.

The accuracy improvement (AI) is defined as [12]:

$$AI = \frac{S - S_h}{S} \times 100\%$$

where S_h is the mean absolute error for the hybrid model,

S represents the mean absolute error obtained from the single model SARIMA. It is clearly that if $AI > 0$, the hybrid model performs better and if $AI \leq 0$, the hybrid model does not overcome the deficiency of individual model.

Because the monthly precipitation is nonnegative real data, the fitting and forecasting data is negative are assigned to zeroes.

B. The Application of Hybrid Model

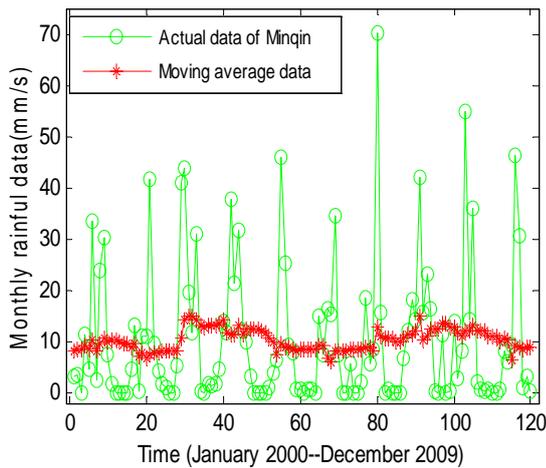


Figure 2. The actual data and moving average data for Minqin

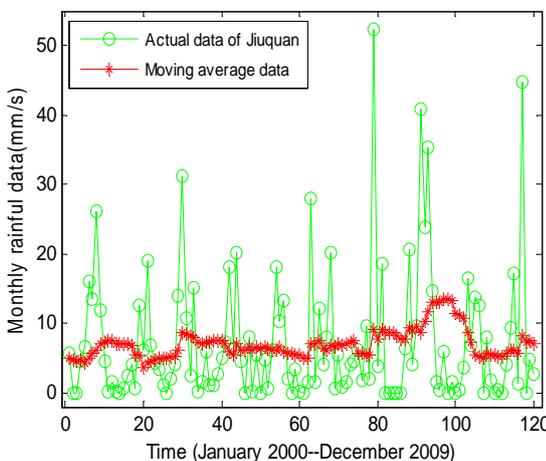


Figure 3. The actual data and moving average data for Jiuquan

The two monthly precipitation data series both show the seasonal and some trend features, so the moving average procedure is selected to find their trends. From Fig.2 and Fig.3, it can be seen that the trends from moving average procedure are flatter, and the W-SVM model is applied for the trend forecasting. The original data series has the fluctuations caused by different months, which is reflected by the difference series between original data and forecasted trend data. Therefore, the seasonal ARIMA (SARIMA) is selected to correct the forecasting residuals. The weights of the improved model are searched by PSO.

C. Results Analysis

Fig. 4 shows the fitting results of improved hybrid model and SARIMA for Minqin, and we can see that the hybrid model provides larger value than SARIMA for the data larger than 30, which is closer to the true data. However, the fitting data of hybrid model is also larger than SARIMA for the data smaller than 10, which is not good estimate for the actual data. Furthermore, the hybrid model is better from the overall fitting ability. For the Jiuquan, the hybrid model provides more accurate results than SARIMA for the data larger than 30 and smaller than 10. From the two data series, we can conclude that the hybrid model is better than SARIMA.

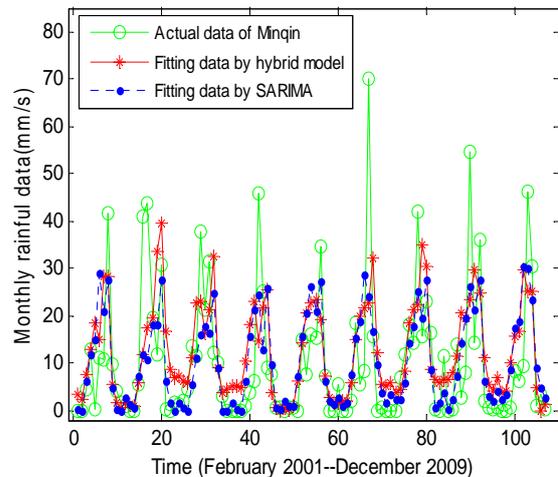


Figure 4. The actual data and fitting data for Minqin

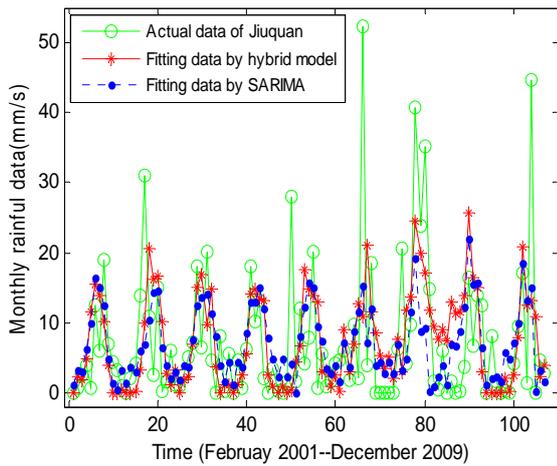


Figure 5. The actual data and fitting data for Jiuquan

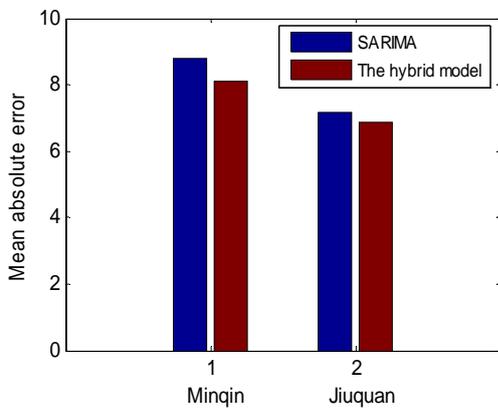


Figure 6. Mean absolute error for two models

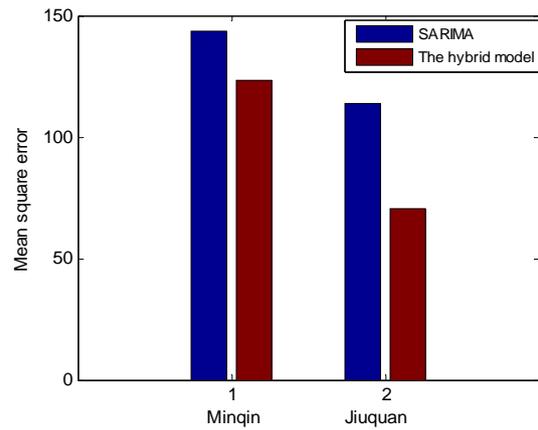


Figure 7. Mean square error for two models

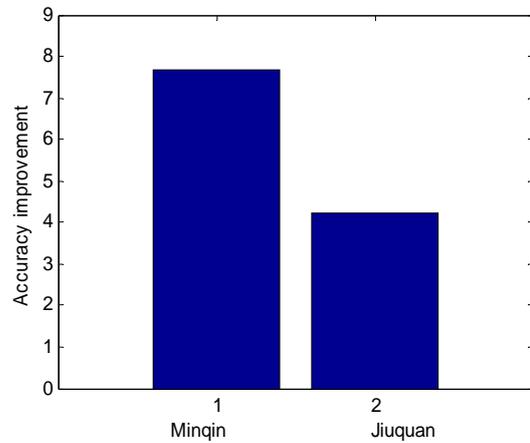


Figure 8. Accuracy improvements

The forecasting data are listed in Table I, and we can see that the hybrid model is better than SARIMA for the two series. Specifically, the MAE and MSE of hybrid model have different improvements over the SARIMA for the two series, see Fig.6 and Fig.7. The accuracy improvement is a more direct criterion for the model assessment see Fig.8, which shows that the hybrid model is more effective the SARIMA.

TABLE I.
THE FORECASTING RESULTS

Time	Minqin			Jiuquan			Yuzhong		
	Real Data	Forecasting Data		Real Data	Forecasting Data		Real Data	Forecasting Data	
		Hybrid	SARIMA		Hybrid	SARIMA		Hybrid	SARIMA
2010.1	0.4	3.2346	6.001027	1.6	4.1221	2.807411147	0.5	6.2666	8.272303
2010.2	5.2	0.8214	2.851602	2.4	1.8721	0.690624433	1.5	6.6116	8.356545
2010.3	3.1	1.6433	3.767225	16	6.806	4.548138997	8.1	10.4099	13.82017
2010.4	6.2	7.0336	9.476069	10.7	5.7255	3.120360304	27.8	16.2172	23.34757
2010.5	26.9	13.323	15.53433	14.8	8.6313	6.04464147	72.3	36.3825	47.93398
2010.6	6.2	14.8189	16.93972	11.3	13.9118	9.372549553	45.9	48.8828	65.64258
2010.7	1.7	26.038	30.45752	19.1	25.7594	18.08387061	28.6	38.8485	54.58813

Time	Minqin			Jiuquan			Yuzhong		
	Real Data	Forecasting Data		Real Data	Forecasting Data		Real Data	Forecasting Data	
2010.8	7.1	24.1855	27.13883	5	15.7676	11.13823318	59.8	57.8344	85.95288
2010.9	32.3	24.9276	28.66575	46.3	26.4085	16.87324375	62.2	42.2236	66.53639
2010.10	22.2	6.3691	9.27711	18.2	10.0602	4.817919361	23.4	20.9908	37.1675
2010.11	0	0.9775	3.70398	0	7.0137	1.829592428	1.7	0	10.10774
2010.12	0.5	0.7077	3.056007	3.1	7.0819	1.419530582	0.5	0	6.285697
AI	7.67%			4.24%			34.48%		

D. Results Analysis

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The forecasting data are listed in Table I, and we can see that the hybrid model is better than SARIMA for the two series. Specifically, the MAE and MSE of hybrid model have different improvements over the SARIMA for the two series, see Fig.6 and Fig.7. The accuracy improvement is a more direct criterion for the model assessment see Fig.8, which shows that the hybrid model is more effective than the SARIMA.

E. A new Test Case

In order to test the effectiveness of the proposed procedure, we apply it to the monthly precipitation prediction of Yuzhong. The forecasting results are listed in Table I. The AI of hybrid over the SARIMA is 34.48%. From this case study, we can see that the proposed model can be generalized to the other similar cases.

IV. CONCLUSION

In this study, we propose an improved hybrid model for monthly precipitation forecasting. The proposed model makes full use of the advantages of various models, which including the moving average procedure, support vector machines and seasonal autoregressive integrated moving average model. For the weight coefficients determination, the proposed model applies the popular artificial intelligence optimization algorithm, particle swarm optimization method. The fitting and forecasting results show that the proposed model is more effective than the conventional seasonal autoregressive integrated moving average model, which is as our expectation. There are two advantages of hybrid model. One is it can combine different models which means it can get much

information, another one is it assign different weights to the models according to the prediction precision.

There are many methods for precipitation forecasting, but no one can provide prediction results with higher precision for all problems. The world is changing! The forecasting problems are also changing! If we want to get better model for precipitation prediction, we must improve the existing models or establish new techniques. The proposed model can be used to solve the other forecasting problems. In order to provide more effective forecasting technique, we will study the adaptive hybrid model based on the artificial intelligence and learning techniques.

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