Forecasting Model of the Cultural Heritage Displacements Based on Verhuslt Radial Basis Function Neural Network

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***Abstract* — Based on the displacement monitoring sequence of cultural heritage, the stability of relics could be judged effectively by forecasting the displacement in the future. Through analyzing advantages and disadvantages of grey forecasting methods and neural network respectively , a new forecasting model of verhuslt radial basis function neural network was proposed. First, in this study,by use of the time series analysis theory ,the accumulation of the displacement sequences were generated, then the result sequence were predicated by the model of verhulst radial basis function neural network, at the same time, the ant colony clustering algorithm was used to optimize the parameters of new model. The new model not only developed the advantages of accumulation generation of the grey forecasting method, weakened the effect of stochastic-disturbing factors in original sequence and strengthened the regularity of data, but also used the quickly solving speed and the excellent characteristics of radial basis function neural network for nonlinear relationship and avoided the theoretical defects existing in the grey forecasting model.At last, one example is given to testify the effectiveness of the verhuslt radial basis function neural network method to forecast displacements of Tianlu stone carving of Tangshun tomb in China. The results show that the new model has higher precision.**

Keywords - Displacement forecasting; Grey system;Radial basis function neural network; Ant colony clustering algorithm

I. INTRODUCTION

Due to historical reasons,there are lots of non continuous structures in the stone relics,including joints and fractures,coupled with many external factors influences such as groundwater, rainfall and human activities and so on ,displacement changes have the characteristics of non uniformity, uncertainty and complicated nonlinear[1]. Therefore ,it is difficult to forecast the stability of relics by the traditional numerical methods[2].

Displacement is one of the most important disease information of cultural relic historical evolution process. Modeling the monitoring displacement can predict the future evolution and development trend to effectively judge relics health state . Currently many methods have been used for displacement prediction , mainly including the time series model [3], grey model [4] ,support vector machine [5],neural network model [6], and a variety of the combination model [7,8] etc.. The core of these methods is to establish the corresponding prediction model . However ,because of the stone relics of displacement time series with the characteristics of complex nonlinear and fuzzy , it is difficult to establish the system perfect prediction model. In addition, cultural relic disease development is a uncertain chaotic system, the pursuit of long term prediction in displacement evolution is difficult . Considering the characteristics of the displacement sequences , the advantage of Grey model and neural network ,In this paper, an intelligent method combining Verhulst Grey Model and radial basis function (RBF) Neural Network was proposed.

The remainder of this paper is organized as follows: Section 3 describes the methodology of the model of displacement forecasting. Section 4 presents experiments to evaluate the performance of the model, including the results, analysis, and discussion. Section 5 summarizes the conclusions.

II. STATE OF ART

Displacement of relics is caused by some factors including groundwater exploitation, rain, structure and others. Therefore, displacement data has the characteristics of nonlinear, complex and multi-modal, as the result ,there are many difficulties in displacement prediction.

Displacement prediction can be considered as a grey system because part of the information is known and part of the information are unknown , so many scholars using the grey system theory to predict the displacement, and achieved some results.The traditional grey model is mainly used in a monotone increasing or monotone decreasing exponential time series, but the actual displacement sequence is much more complex, which makes the prediction results appear larger errors. At the same time, there are also some theoretical defects of solving algorithm for the model parameters . On the other hand,many scholars have studied using BP artificial neural network, wavelet analysis to study displacement forecasting. Zhen-de Zhu[9] designed a forecasting model ,named as PSO-SVM (Particle Swarm Optimization-Support Vector Machine) model, which is based on particle swarm optimization to optimize the kernel function and model parameters. P.Caamaño [10] described and tested an approach to improve the temporal processing capabilities of the neuroevolution of augmenting topologies (NEAT) algorithm that was able to generate artificial neural networks (ANNs) with trainable time delayed synapses in addition to its previous capacities. Vassallo [11]defined the relations between displacement and environments, design the evolutionary modeling technique EPRMOGA, based on a genetic algorithm. PENG Ling [11]built the displacement prediction model, which used the kernel principal component analysis (KPCA)to extract main features from influential factors data, and SVM model parameters of which was optimized by the particle swarm optimization(PSO)algorithm. Most displacement forecasting models are only suitable for short-term forecasting, and the length and accuracy of long-term forecasting is not well.

Displacement data belongs to "small sample" data typically because of monitoring [12].Verhulst model is a special model of grey system, mainly describing the saturated process, which called "S" type process. And it has been widely used in population projects, predicting the time of landslide, forecasting stone deformation and other numerous research fields.

Verhulst model equation uses the accumulated data to weaken the randomness of data . However, it is difficult to describe the approximate complex nonlinear data because the grey coefficient and development coefficient will not change in time. RBF [15] network (Radial Basis Function Neural Networks) has advantages in data simulation , local optimization, learning speed and robustness based on regularization theory. Thus, based on the premise and reliability of the model, the key issue is how to improve the forecasting ability of the model.

In view of these, this paper combines the advantages in overall trend forecasting of Verhulst model and RBF neural network ,designs the prediction model of verhulst RBF netural network with the advantage in the forecasting accuracy of local optimization.

III. METHODOLOGY

The Hydraulic (H-) and Mechanical (M- or structural) FEM equations without stochastic analysis are:This paper presented a forecasting model based on Verhulst-ACC-RBF network, which includes two main steps. The first step is to use Verhulst grey model to forecast displacement processed by smoothing filtering, which weakened the effect of stochastic-disturbing factors in original sequence and strengthened the regularity of data . The second step is the forecasting of RBF neural network based on the ant colony clustering logarithm . The center of RBF is calculated by ant colony clustering,which can reduce the run time of RBF neural network. The forecasting displacement is output of the RBF neural network, which is shown in Fig. 1.

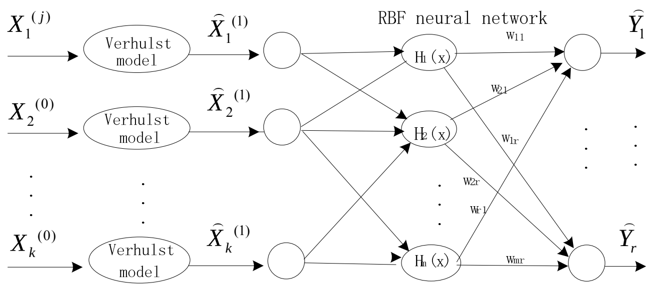

Figure 1. Verhulst-ACC-RBF combination forecasting model

This paper makes use of Verhulst grey neural network combination model of relics.At first, the original sequences are expressed as follows:

$$X^{0)}{}_i = (x^{(0)}{}_i(1), x^{(0)}{}_i(2),..., x^{(0)}{}_i(n)), i = 1,2,...,k$$

And then, they were input into verhulst model and get the forecasting sequence vector ,which are expressed as follows:

$$X^{(1)}{}_i = (x^{(1)}{}_i(1), x^{(1)}{}_i(2),..., x^{(1)}{}_i(n)), i = 1,2,...,k \,.$$

After that, RBF basic funciton in neural netword are choosed to train $\hat{x}^{(1)}$,and the ant colony clustering algorithm(ACC)was used to create and optimize the center of basic function. At last,$\hat{y}^{(1)}$was gained as the result of RBF neural network model,the vector are expressed as follows:

$$\hat{Y}^{(1)}{}_i = (\hat{y}^{(1)}{}_i(1), \hat{y}^{(1)}{}_i(2),..., \hat{y}^{(1)}{}_i(n)), i = 1,2,...,k$$

This model uses small samples to forecast the displacement trend using Verhulst grey model. Then, enter the preliminary forecasting result into RBF neural network to optimize and correct . This model not only can effectively avoid the over fit question of BP neural network, also can avoid the low-precision problems in multi-step. The following text will describe the key aspects about grey model and ant colony clustering RBF neural network of the new conmbination forecasting model.

Verhulst model is differential equation of single variable to fit the saturated data. Firstly, the original sequence is as follows: $X^{(0)} = (x^{(0)}(1), x^{(0)}(2), ..., x^{(0)}(n))$,and its 1-IAGO(1-Inverse Accumulating Generation Operator)sequence is as follows: $X^{(1)} = (x^{(1)}(1), x^{(1)}(2), ..., x^{(1)}(n))$,where $x^{(1)}(k) = \sum_{i=1}^{k} x^{(0)}(i), k = 1,2,...,n.$

Suppose $Z^{(1)} = (z^{(1)}(1), z^{(1)}(2), ..., z^{(1)}(n))$ is the internal points of consecutive neighbor sequence of $X^{(1)}$, and $z^{(1)}(k) = 0.5x^{(1)}(k) + 0.5x^{(1)}(k-1)$ .Establish the Verhulst grey model differential equation of $Z^{(1)}$ is $x^{(1)}(k) + az^{(1)}(k) = b(z^{(1)}(k))^2$,Where a is development coefficient, and b is grey coefficient. The solve of the differential equation is expressed as follows:

$$\hat{x}^{(1)}(k+1) = \frac{a\hat{x}^{(0)}(0)}{b\hat{x}^{(1)}(0) + (a - b\hat{x}^{(1)}(0))e^{ak}} \tag{1}$$

And the development coefficient *a* and grey coefficient *b* is defined by least square method, as follows:

$$\hat{a} = (a,b)^T = (B^T B)^{-1} B^T Y \tag{2}$$

where $Y = \begin{bmatrix} x^{(0)}(2) \\ x^{(0)}(3) \\ ... \\ x^{(0)}(n) \end{bmatrix}, B = \begin{bmatrix} -z^{(1)}(2)(z^{(1)}(2))^2 \\ -z^{(1)}(3)(z^{(1)}(3))^2 \\ ... \\ -z^{(1)}(n)(z^{(1)}(n))^2 \end{bmatrix}$.

Then, after inverse accumulating generation operation of $\hat{X}^{(0)}$,in which $\hat{x}^{(0)}(k+1) = \hat{x}^{(1)}(k+1) - \hat{x}^{(1)}(k)$, $k = 1,2,..n$ .The obtain the estimation sequence of original numeric is: . $\hat{X}^{(0)} = (\hat{x}^{(0)}(1), \hat{x}^{(0)}(2), ..., \hat{x}^{(0)}(n))$

Compared with BP network, RBF network has not only faster calculation capacity, but also good generalization ability, avoiding the defects in multi-calculation and learning. RBF neural network is a three-layer forward network, called input layer, hidden layer and output layer. In the ant colony clustering RBF neural network, the input of RBF neural network is the sequence $\hat{X}^{(0)}$ which is the output of Verhulst model[16].

Supposed $\hat{X}_i^{(1)} = (\hat{x}_i^{(1)}(1), \hat{x}_i^{(1)}(2), ..., \hat{X}_i^{(1)})), i = 1,2,...k$,and $\hat{Y}^{(1)}{}_j = (\hat{y}^{(1)}{}_j(1), \hat{y}^{(1)}{}_j(2), ..., \hat{y}^{(1)}{}_j(n)), j = 1,2,...,r$ is output of $\hat{X}_i^{(1)}$ .There are some key question to build the RBF model based on Ant Colony clustering.as follows:

In hidden layer, each node uses the nonlinear function $\Phi(\bullet)$ as the radial basis function, which transform the data of input layer to hidden layer by non-linear. Radial basis function normally has many forms, including Gaussian basis functions, Reflected Sigmoid function, Multiquadrics function. Compared with other radial basis function, Gaussian function is monotonic decreasing from the center to both sides, and local optimization.Therefore, we choose Gaussian function as the radial basis function , which is : $H_j(x) = \psi(\frac{\|x - c_j\|}{\sigma_j}) = \exp(-\|x - c_j\|^2 / 2\sigma^2{}_j)$,

where c_j is the central point of basis function, σ_j is spread constant.

K-means clustering algorithm is sensitive to the initial cluster centers. It produced choose different results for different initial cluster centers . Traditional K-means causes more iterated times. Ant colony algorithm is a heuristic swarm intelligence algorithm. We use the global optimization capabilities of ant colony algorithm to solve the sensitive problem K-means algorithm.

Therefore, this paper adopts ant colony clustering algorithm to initialize the centers of RBF neural network. The sample set $X = \{x_1, x_2, ..., x_n\}$ is divided into k modes: $C = \{C_1, C_2, ..., C_k\}$,and $\cup_{j=1}^{k} C_j = X, C_i \cap C_j = \Phi, (i \neq j)$.

The amount of ant is m, the maximum evolution generation is N , the leaving pheromone of ant is $\tau(x_i, m_j)$. m_j is the initial value of sample center in ant colony algorithm ,and takes it as the center of C_j , which is defined as follows :

$$m_j = \frac{1}{\mathrm{c}_j} \sum_{xi \in C_j} x_i \tag{3}$$

Calculate the Euclidean distance from each sample to the center of each mode, which is $d(x_i, m_j)$ and x_i heuristic $\eta = 1/d(x_i, m_j)$ function.Constitute clustering results of sample points that each ant crawled as a solution. When ant randomly selects pattern sample , calculate the attribution probability about that to cluster center, which is defined as follows:

$$p(x_i, m_j) = \frac{|\tau(x_i, m_j)|^\alpha \times |\eta(x_i, m_j)|^\beta}{\sum_t^k |\tau(x_i, m_j)|^\alpha \times |\eta(x_i, m_j)|^\beta} \tag{4}$$

Ants classified all the samples into k modes, constituting a solution. The update method of maximum and minimum ant colony algorithm, that is, only increases clustering pheromone for m ants that are optimal for the target, and additional pheromone attenuates. Wherein the increases method of pheromone $\tau(x_i, m_j)$ is: $\tau(x_i, m_j) = \rho\tau(x_i, m_j) + \Delta\tau(x_i, m_j)$, $\Delta\tau(x_i, m_j) = \begin{cases} Q / lmb, x_j \in C_i \\ 0, others \end{cases}$, ρ is evaporation parameter of pheromone. From the objective function value of m solution for m ants' clustering ,choose k optimal solution.

Make the sum of dispersion minimum, then F is defined as follows:

$$F = \min \sum_{j=1}^{k} \sum_{x_j \in C_i} d(x_i, m_j) \tag{5}$$

The linear mapping from hidden layer to output layer is $H_j(x) \to y$ .And it could get the weighted value of each $H_j(x)$, which is defined as follows:

$$y_i = w\mathrm{H}_j(x) = \sum_{j=1}^{m} \omega_{ij} H_j(x), i = 1,2,...,r \tag{6}$$

The study process of RBF could divide into two sections: the central point of hidden layer and studying spread parameter, and the study of output weight[17].

The optimization of the center $\vec{c}_i$ for hidden layer unit, which is defined as follows:

$$\vec{c}_i(t+1) = \vec{c}_i(t) - \eta_2 \cdot \frac{\partial E(t)}{\partial \vec{c}_i(t)}, i = 1,2,...,m \tag{7}$$

For the width σ_i of hidden layer unit(it could calculate the derivative of E to σ_i^{-1} for convience), which is defined as follows:

$$\sigma_i^{-1}(t+1) = \sigma_i^{-1}(t) - \eta_3 \cdot \frac{\partial E(t)}{\partial \sigma_i^{-1}(t)}, i \in [1, m] \tag{8}$$

The study method of connection weight of RBF neural network is gradient descent method , that is as follows:

$$\omega_{ij}(k+1) = \omega_{ij}(k) + \beta \frac{[\hat{y}_i(k) - y_i^{\,d}]H_j(x)}{H(x)^T H_j(x)} \tag{9}$$

where β is the rate of study. In order to make sure the convergence for study ,set the value as $0 < \beta < 2$.

IV. PREDICTION AND DISCUSSION

As an example, an displacement of relics is predicted. The data comes from a relic named Tangshun tomb in China from the year 2012 to 2014, which is displacement monitoring data. It is as follows:

X_0=(9.733188529,9.701449821,9.792826087,9.7628248, 9.702826544,9.703878971,9.740710147,9.732185704,9.689748162,9.670865714,9.696605985,9.703257368,9.7143392, 9.702730073,9.708051029,9.681779925,9.672811778,9.634812353,9.680314961,9.718799037,9.76962562,9.792629769,9.803763852,9.79867406,9.819359113,9.79712353).

The data from strain gauge often superimposed noise for various reason, resulting in the characteristic information of time series drowned in the noise. In order to restore the true displacement signal, it need to do filtering and such pre-process. In this paper, we adopt three five-point smoothing filtering to do filtering[18], and its formula as follows:

$$\begin{cases} y_1 = [69x_1 + 4(x_2 + x_4) - 6x_3 - x_5]/70 \\ y_2 = [2(x_1 + x_5) + 27x_2 + 12x_3 - x_4]/35 \\ y_i = [-3(x_{i-2} + x_{i+2}) + 12(x_{i-1} + x_{i+1}) + 17x_i]/35 \\ y_{m-1} = [2(x_{i-4} + x_m) + 12x_{m-2} - 8x_{m-3} - 12x_{m-1}]/35 \\ y_m = [-x_{i-4}(x_{m-3} + x_{m-1}) - 6x_{m-2} + 69x_m]/70 \end{cases} \tag{10}$$

where $i \in [3, m-2]$.

Suppose

$X_1 = (x_1, x_2, ..., x_{20}), X_2 = (x_3, x_4, ..., x_{22})$,

$X_3 = (x_5, x_6, ..., x_{24})$ are the three sequence of original sequence with the same length as the input sequences of verhulst model.Three Verhulst model formulas are the follows respectively:

$$\hat{x}_1^{(1)}(k+1) = \frac{-0.0280\hat{x}_1^{(1)}(0)}{-0.0001\hat{x}_1^{(1)}(0) + (-0.0280 + 0.0001\hat{x}_1^{(1)}(0))e^{-0.0280k}} \tag{11}$$

$$\hat{x}_2^{(1)}(k+1) = \frac{0.01079\hat{x}_2^{(1)}(0)}{-0.00003x_2^{(1)}(0) + (0.01079 - 0.00003\hat{x}_2^{(1)}(0))e^{0.01079k}} \tag{12}$$

$$\hat{x}_3^{(1)}(k+1) = \frac{-0.000944\hat{x}_3^{(1)}(0)}{-0.00002\hat{x}_3^{(1)}(0) + (-0.000944 - 0.00002\hat{x}_3^{(1)}(0))e^{-0.000944k}} \tag{13}$$

And the forecasted value of three set *x6-x28* is: $\hat{X}_i^{(1)} = (\hat{x}_i^{(1)}(6), \hat{x}_i^{(1)}(7), ..., \hat{x}_i^{(1)}(25))), i = 1,2,3$

The improved K-means algorithm based on ant colony algorithm obtains eight centers by ant colony clustering algorithm.

Before the training for RBF, do normalization for all data ,in order to increase the accuracy of forecasting. Proposed x is the output of Verhulst, and the minimum and maximum value of resultis represented as min and max respectively[19]. It could normalize and inversely normalize between displacement data and the value in [0.1,0.9] by formula (14) and formula(15) [20].

$$y = 0.1 + \frac{x - \min}{\max - \min} \times (0.9 - 0.1) \tag{14}$$

$$x = \frac{(y - 0.1)(\max - \min)}{0.9 - 0.1} + \min \tag{15}$$

The results of the three sequences $\hat{X}_i^{(1)}(i = 1,2,3)$ by Verhulst after normalization, which are input into RBF neural network to learn and train. Make sure the center and spread of RBF network expansion, and use the gradient descent method to train, the fitting sequence that is $\hat{Y} = (\hat{y}(6), \hat{y}(7), ..., \hat{y}(25))$.

Compared with Verhulst grey model and RBF neural network respectively,the final fitting and training values of the new model are shown in Table 1 and Fig. 2.

As shown in Fig. 2, the forecasting and fitting of Verhulst model mainly forecast the overall trend, showing a monotonous curve on the trend. The rate of change decreases, the curve towards easing. To some extent, it couldn't well reflect the complexity and repetition of the displacement data. For details of the time series, forecasting and fitting is not good, which is decided by theoretical basis of grey model. Compared with Verhulst model, the fitting error of RBF neural network and Verhulst-ACC-RBF neural network model is lower.

TABLE I. RBF FITTING TRAINING RESULT OF DISPLACEMENT DATA

No.	Original value	Verhulst prediction	RBF prediction	Ver-RBF prediction
y6	9.7 4071	8.984223	9.315776	9.317013
y7	9.732186	8.995008	9.376056	9.35397
y8	9.689748	9.007438	9.431486	9.356665
y9	9.670866	9.021709	9.232339	9.26424
y10	9.696606	9.038025	9.108733	9.145663
y11	9.703257	9.056582	9.108835	9.113624
y12	9.714339	9.077566	9.153096	9.163811
y13	9.70273	9.101128	9.34547	9.324879
y14	9.708051	9.127371	9.327344	9.329089
y15	9.68178	9.156327	9.396759	9.399577
y16	9.672812	9.187923	9.312696	9.307269
y17	9.634812	9.221959	9.36007	9.354288
y18	9.680315	9.258072	9.480854	9.489449
y19	9.718799	9.295715	9.500873	9.48757
y20	9.769626	9.334138	9.641929	9.666416
y21	9.79263	9.372389	9.5222	9.510339
y22	9.803764	9.409329	9.520868	9.51385
y23	9.798674	9.443683	9.596701	9.612009
y24	9.819359	9.474107	9.514075	9.502633
y25	9.797132	9.499288	9.540911	9.549925

In order to evaluate and compare the forecasting results, adopt respectively MAE (mean absolute error) and MAPE (mean absolute error rate) to evaluate the fitting error of Verhulst-ACC-RBF. The evaluation results are shown in table 2.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|\hat{y}_i(k) - y_i(k)\right| \tag{16}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{\left|\hat{y}_i(k) - y_i(k)\right|}{y_i(k)} \times 100\% \tag{17}$$

TABLE II. TRAINING ERROR FOR FORECASTING MODELS

Error standard	Verhulst model	RBF	Verhulst-RBF model
MAE(mm)	0.523311	0.337056	0.338296
MAPE	5.384%	3.4676%	3.4804%

And from Table 2 we can see, the forecasting result of Verhulst-ACC-RBF neural network forecasting algorithm is closest to true value, the RBF neural network algorithm followed. In the fitting process, it could well fit curve detail changes. As shown in Table 2, MAE is 0.338296mm, MAPE reaches 3.4804% in the forecasting. Compared with0.523311 and 5.384% of Verhulst's, the error is reduced greatly.

In this paper,Verhulst-ACC-RBF combination model predicted the displacement data, and the results are $\hat{Y} = (\hat{y}(29), \hat{y}(30), ..., \hat{y}(34))$
$= (9.4606, 9.3250, 9.3570, 9.3545, 9.3757, 9.4671)$

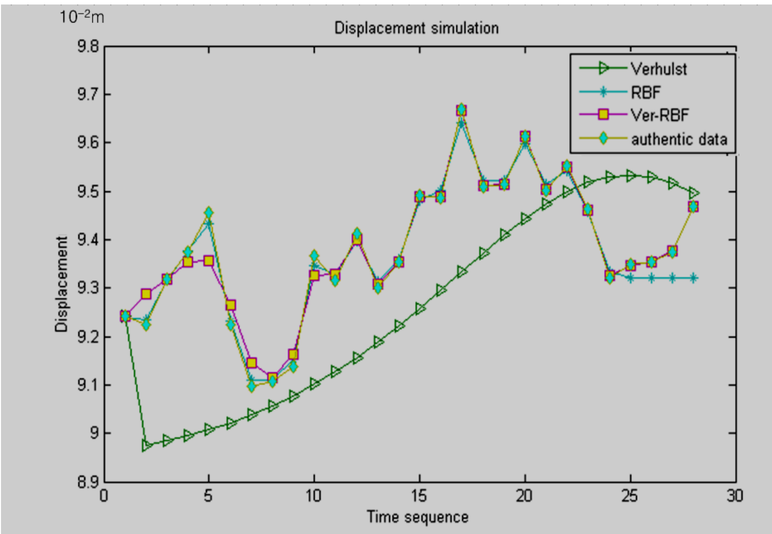

Figure 2. Training process of Verhulst-ACC-RBF.

Adopt GM-BP neural network combination forecasting model in Literature [21]. Where in the grey GM (1,1) model uses the method of least squares equation to determine grey coefficient and development coefficient, the grey equation and whitening equation showed in formula (18) and (19).

$$x^{(0)}(k+1) = 0.2499e^{-0.0590k} \text{ ,where } k = 2,3,...,32 \tag{15}$$

$$x^{(0)}(k) - 0.0590z^{(1)}(k) = 0.2499, \text{ where } k = 2,3,...,34 \tag{16}$$

The numbers of cells of input layer and hidden layer in BP neural network are six. The input vector is output sequence of grey forecasting as follows:

$$X_1=(x_1,x_2,...,x_{23}),X_2=(x_3,x_4,...,x_{24}),X_3=(x_5,x_6,...,x_{25}),$$
$$X_4=(x_4,x_5,...,x_{26}),X_5=(x_5,x_6,...,x_{27}),X_6=(x_6,x_7,...,x_{28})$$

The transfer function of neural network is Sigmoid, the output layer's transfer function is Purelin, learning rate is 0.02, the maximum numbers of iterations is 100. The forecasting result and error analysis are shown in table 3 and table 4.

TABLE III. FORECASTING RESULT OF MODELS

Original value (10^{-2}m)	Verhulst F orecast (10^{-2}m)	RBF Forecast (10^{-2}m)	GM-BP model (10^{-2}m)	Verhulst-ACC-RBF model (10^{-2}m)
9.9023	9.5180	9.4584	9.4606	9.5337
9.9846	9.5295	9.3329	9.3250	9.5523
9.9692	9.5329	9.3210	9.3470	9.5715
9.9405	9.5283	9.3209	9.3545	9.5913
9.8702	9.5157	9.3209	9.3757	9.6116
9.8431	9.4960	9.3209	9.4671	9.6326

As shown in table 4, forecasting error of Verhulst-AAC-RBF neural network is 0.3362, improving 30% than GM-RBF neural network combination forecasting in accuracy

TABLE IV. FORECASTING ERROR OF MODELS

Evaluate index	Verhuls t	RBF	GM-BP	Verhulst-ACC-RBF
error	0.3843	0.4439	0.4418	0.3687
	0.4551	0.6517	0.6596	0.4323
	0.4363	0.6482	0.6222	0.3977
	0.4122	0.6196	0.5860	0.3492
	0.3544	0.5493	0.4944	0.2585
	0.3471	0.5222	0.3760	0.2105
MAE	0.3982	0.5725	0.5300	0.3362
MAPE	4.01%	5.77%	5.34 %	3.39%

As shown in Fig. 3, Verhulst-ACC-RBF model, GM-BP model and Verhuslt model have better forecasting accuracy than RBF model. Verhulst-ACC-RBF model can better forecast dynamic changes of data compared to GM-BP model in literature[21]. Verhulst-ACC-RBF model not only retains the advantages of grey model in easy establishing, but also eliminates the disadvantage of RBF in fitting precision and limited forecasting accuracy. Therefore, the choice of Verhulst-ACC-RBF combination model to forecast displacement is feasible and effective.

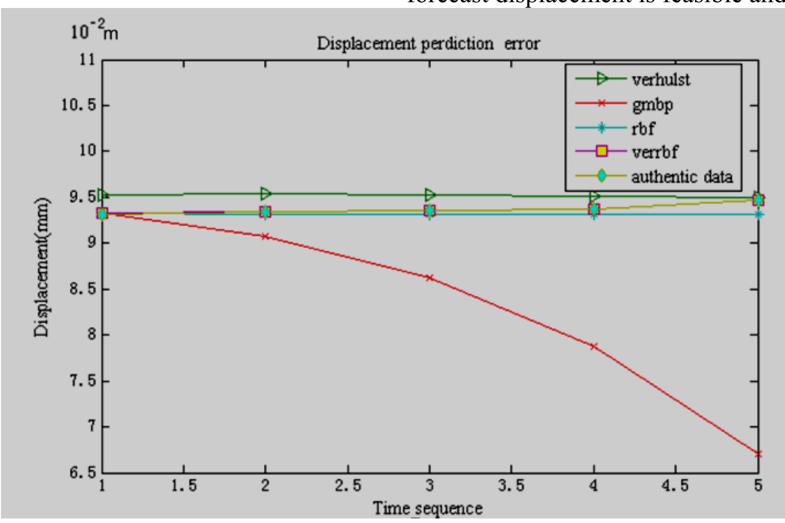

Figure 3. Forecasting results of four models

V. CONCLUSION

Based on the nonlinear characteristics of the displacement data, forecasting model for the relics displacement named Verhulst-ACC-RBF combination model was established, which combined grey system and RBF neural network. In this model, the displacement sequences after smoothing filtering were inputted into Verhulst grey model to get the tendency, and then were forecasted by radial basis function (RBF)neural network. The results show that the MAPE of Ver-ACC-RBF forecasting model is 3.39%, significantly better than single Verhulst or RBF neural network or GM-BP forecasting model. Meanwhile, the effect of the new forecasting model is analyzed. The main conclusions of this paper are presented below.

The model using smoothing filtering method reduced the noise interference of the original displacement data effectively, and enhanced the accuracy of the forecasting model .

The forecasting model weakened the effect of stochastic-disturbing factors in the displacement original sequence and strengthened the regularity of data,which is fit to forecast the data with the characteristics of non uniformity, uncertainty and complicated nonlinear.

The model used the quickly solving speed and the excellent characteristics of radial basis function neural network for nonlinear relationship and avoided the theoretical defects existing in the grey forecasting model.

The proposed model decreased the error of forecasting with low computation ,and provided a simple, practical and efficient new method for the prediction of displacement.

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