A OPTIMIZATION TUNED ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM FOR DAM DEFORMATION PREDICTION

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ABSTRACT:

The performance and stability of Adaptive Neuro-Fuzzy Inference System (ANFIS) depend on its network structure and preset parameter selection, and Particle Swarm Optimization-ANFIS (PSO-ANFIS) easily falls into the local optimum and is imprecise. A novel ANFIS algorithm tuned by Chaotic Particle Swarm Optimization (CPSO-ANFIS) is proposed to solve these problems. A chaotic ergodic algorithm is first used to improve the PSO and obtain a CPSO algorithm, and then the CPSO is used to optimize the parameters of ANFIS to avoid falling into the local optimum and improve the performance of ANFIS. Based on the deformation data from the Xiaolangdi Dam in China, three neural network algorithms, ANFIS, PSO-ANFIS, and CPSO-ANFIS, are used to establish the dam deformation prediction models after data preparation and selection of influencing factors for the dam deformation. The results are compared using evaluation indicators that show that CPSO-ANFIS is more accurate and stable than ANFIS and PSO-ANFIS both in predictive ability and in predicted results.

1. INTRODUCTION

Dams are hydraulic constructions with the function of controlling water flow for the development and utilization of river water resources. Monitoring dam safety to predict dam deformation is important for ensuring dam safety. Dam deformation prediction models based on the neural network algorithm have been widely used and rapidly developed, in which the approximation capability of artificial neural network (ANN) models have been used to fit the complex function relationship between the monitoring effect of dam deformation and related influential factors, to predict the function and effect of the factors on the deformation. Compared with traditional models, although the fitting prediction accuracy and performance have been improved, the neural network has low generalization ability and easily falls to the local minimum.

In order to solve these problems, optimized combination models, such as the optimized combination model of the Adaptive Neuro-Fuzzy Inference System (ANFIS) (Wu et al., 2017) and the Particle Swarm Optimization (PSO) algorithm (Gu et al., 2016), were introduced. ANFIS has been widely used in landslide spatial modeling, estimation of elastic constant of rocks, and prediction of swell potential of clay soils (Chen et al., 2017, Tatar et al., 2016, Singh et al., 2012, Yilmaz, Kaynar, 2011, Liu et al., 2015). However, ANFIS is still prone to falling into the local minimum and selecting the preset parameters is difficult. The PSO algorithm and its improved algorithm are widely used in classification, electric power system-related issues, and job-shop scheduling problems (Xue et al., 2014, Jordehi et al., 2015, Nouiri et al., 2018). However, the PSO algorithm still easily falls into the local optimum and has poor accuracy.

Several reports showed that the optimized combination model can be applied to solve practical problems and can work well. The Particle Swarm Optimization-ANFIS (PSO-ANFIS) algorithm was used by (Zahmatkesh et al., 2017) to predict the physical properties of rocks, and effectively improved the estimation accuracy. An adaptive ANFIS and different meta-heuristic algorithms were combined by (Razavi et al., 2018)to map the ship flood disaster in Yarrow, Fars, and the results showed that the model based on PSO-ANFIS was the most practical. ANFIS and its improved algorithm were employed by (Rezakazemi et al., 2017) to evaluate the performance of hydrogen-selective mixed matrix membranes (MMMs) in various operational conditions. Although the PSO algorithm improves upon the convergence rate of the optimized combination model, such as PSO-ANFIS, the optimized combination model still easily falls into the local optimum and has poor accuracy due to the defects in the PSO algorithm itself.

In order to overcome the defects of the PSO algorithm or the optimized combination of the ANFIS and PSO algorithms, chaos theory can be used to improve PSO performance. The application of chaotic sequences instead of random sequences in PSO is a powerful strategy to diversify the population of particles and improve the PSO performance in preventing premature convergence to the local minimum (Gao, Liu, 2016, Liu et al., 2005, Coelho, Mariani, 2009, Rad et al., 2015, Hu et al., 2013, Hong, 2009). In this contribution, we first propose a novel chaotic PSO (CPSO) algorithm that uses a chaotic ergodic algorithm to improve PSO. We then use the proposed CPSO algorithm to optimize the ANFIS parameters. A novel CPSO-tuned ANFIS (CPSO-ANFIS) algorithm is proposed and applied to a dam deformation prediction example.

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2. ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM

ANFIS applies adaptive fuzzy reasoning. ANFIS operates by constructing a fuzzy inference system based on a given set of input and output data. It determines the fuzzy membership function and fuzzy rules of the dataset by learning a large amount of input data. The algorithm combines least squares and error inversion to adjust the parameters of the membership function and finally determines the fuzzy rules. ANFIS essentially maps from fuzzy sets to constant sets or linear sets.

In order to create an ANFIS model, we needed to adjust two parameter sets, premise and consequent parameters. To determine the above parameters, we needed both a forward pass and a backward pass in the hybrid training algorithm. For the forward pass of this hybrid algorithm, the least squares approach was applied to optimize the consequent parameters on layer 4, by considering fixed parameters set in layer 1. Once the optimal parameters for the corresponding parameters were found, the output of the ANFIS was calculated in the backward pass, whereas the errors were back propagated and the premise parameters were modified by using the back propagation method while the set parameters of layer 4 were fixed (Zahmatkesh et al., 2017).

Due to the large number of ANFIS parameters, large computational complexity, and complicated calculation process, an efficient search method for finding global optimal parameters is important for the selection of ANFIS parameters. Relevant studies (Rezakazemi et al., 2017) have shown that, in most cases, PSO-ANN-based hybrid methods provide more reliable and accurate predictive capabilities than least-squares methods and standard back-propagation algorithms, so PSO and Improved PSO can be introduced into ANFIS to optimize the algorithm.

3. CHAOTIC PARTICLE SWARM OPTIMIZATION ALGORITHM

3.1 Particle Swarm Optimization

Assume that in a D-dimensional search space, there are m particles that make up a particle swarm, where the position of the ith particle in the D-dimensional search space is expressed as a vector $x_i = (x_{i1}, x_{i2}, \ldots, x_{iD})^T$ and the velocity is expressed as $v_i = (v_{i1}, v_{i2}, \ldots, v_{iD})^T$, $i = 1, 2, \ldots, m$. The optimal position that the ith particle has searched so far is P_i, called the individual extremum. The individual optimal fitness value is P_{ibest}. The best position searched by the entire particle swarm so far is P_g, which is called global extremum. The global optimal fitness value is P_{gbest}. Each particle is iterated according to Equations (1) and (2), updating its own speed and position (Nouiri et al., 2018):

$$v_{id}^{n+1} = wv_{id}^n + c_1 r_1^n \left(p_{id}^n - x_{id}^n \right) + c_2 r_2^n \left(p_{gd}^n - x_{id}^n \right) \tag{1}$$

$$x_{id}^{n+1} = x_{id}^n + v_{id}^{n+1} \tag{2}$$

where v_{id}^k = the velocity of the dth dimension in the kth iteration of particle
         x_{id}^k = the position of the dth dimension in the kth iteration of particle
         d = the dth variable in the D-dimensional search space
         c_1, c_2 = non-negative acceleration constants
         r_1, r_2 = random numbers between [0, 1]

n = the number of iterations
w = a non-negative number

3.2 Chaotic Particle Swarm Optimization Algorithm

In the PSO implementation process, PSO cannot ensure the particles are evenly distributed in the entire solution space when the solution space is too large, and the algorithm is prone to falling into a local optimum. In contrast, chaos (Hao et al., 2017) is a random state of motion obtained by a deterministic equation. The traversal characteristics of chaotic motion enable chaotic variables to traverse all states in a certain range according to their "law" without repetition. Therefore, in this paper, we introduce chaos traversal into the PSO algorithm and propose a novel chaotic particle swarm optimization (CPSO) algorithm so that the PSO algorithm can jump out of the local optimum for improved performance. The chaotic optimization steps of CPSO are as follows:

1. Chaotic search for the selected particles, and ensure that the range of particles is [0, 1].
2. Obtain the chaotic variable.
3. Transform chaotic variables into the allowable solution space of optimization problem.
4. Perform iterated search with chaotic variables.

The following Equations (3) and (4) are used in Step 2 and Step 4, respectively:

$$x_{k+1} = \lambda x_k \left(1 - x_k \right), x_k \in \left[0, 1 \right] \tag{3}$$

where λ = he control parameter valued between 0 and 4

$$x_{i,k}^{'} = o_i + s_i x_i, \quad (i = 1, 2, \ldots, n) \tag{4}$$

where s_i = the value range of the ith independent variable
         o_i = the ith variable value endpoint

3.3 CPSO Tuned ANFIS Algorithm

The proposed CPSO-ANFIS integrates the chaotic particle swarm optimization algorithm into ANFIS. With the help of the efficient global search capability of the CPSO algorithm, the relevant parameters of ANFIS are optimized. In CPSO-ANFIS, each particle in the particle swarm represents a possible solution and the goal is to obtain a minimum fitness value. When CPSO-ANFIS is running, the training data are input first, and the fuzzy C-means clustering algorithm is selected to determine the antecedent membership function based on Sugeno's reasoning. After constructing the neural network, the particle swarm is generated according to CPSO and the particles in the particle group are sequentially assigned to the relevant parameters of the membership function of ANFIS, which is the optimization of the prior parameters. Then, we used the least squares method to determine the consequent parameters. When the program continued to run, the corresponding performance index of those parameters was obtained, which was passed back to the particle swarm as the fitness value of each particle. Finally, if meeting the stop criteria, the particle swarm algorithm jumps out after several iterations, which means the ANFIS parameters have been optimized. Otherwise, iterations continue.

The optimization procedures for ANFIS parameters using CPSO are as follows, where the root mean squared error ($RMSE_i^n$) is selected as the performance index in this study:

1. Randomly initialize particle swarms in the sample space.
2. Assign the position vector X_{id}^n to the premise parameter of the membership function.
3. Calculate the firing strength of each fuzzy rule.
4. Normalize the fitness of each rule.
5. Randomly generate the subsequent parameters p, q, and r in the first iteration.
6. Calculate the actual output Y using the ANFIS algorithm.
7. Based on actual output and target output, use the least squares method to identify and update the conclusion parameters p, q, and r.
8. Calculate $RMSE_i^n$ of the actual output and the target output as the performance index.
9. Compare $RMSE_i^n$ with P_{ibest}. If $RMSE_i^n < P_{ibest}$ then $P_{ibest} = RMSE_i^n$, $P_i = X_d^n$.
10. Compare P_{gbest} with P_{ibest}. If $P_{ibest} < P_{gbest}$, then $P_{gbest} = P_{ibest}$, $P_g = P_i$.
11. Update the velocity and position of the particles, and return to Step 2 to execute the next iteration. When all particles complete iteration, execute the next Step l.
12. Select 20% of the optimal particles (i.e., the top 20% of P_{gbest} particles) as data for the chaotic search and convert them to the range of [0, 1]. Then obtain the chaotic variables based on the logistic map.
13. Transform chaotic variables into the allowable solution space of the optimization problem.
14. Execute Steps 2–11 to implement the iterative search of chaotic variables.
15. If P_{gbest} remains unchanged after multiple searches or reaches a maximum number of iterations, the search terminates. Continue to Step 16.
16. To maintain the diversity of the particles, the remaining 80% of the particles are randomly generated in the dynamic contraction region.
17. Randomly generate the remaining 80% of the particles and to execute Steps 2–11 .
18. If P_{gbest} remains unchanged or reaches a maximum number of iterations after multiple searches, end search.
19. Generate and obtain the optimal P_{gbest}, the smallest $RMSE$ value, and the optimal parameter set of the optimization procedures.

The following dynamic contraction equations are used in Step 16:

$$m_{\min,j} = \max\{x_{\min,j}, x_{gj} - r \cdot (x_{\max,j} - x_{\min,j})\}, \quad 0 < r < 1 \quad (5)$$

$$x_{\max,j} = \min\{x_{\min,j}, x_{gj} + r \cdot (x_{\max,j} - x_{\min,j})\}, \quad 0 < r < 1 \quad (6)$$

where x_{gj} = the value of the current P_g in the jth dimension
$x_{min,j}$ = the minimum
$x_{max,j}$ = the maximum

Accordingly, the main implementation steps of CPSO-ANFIS are as follows:
1. Data collection and standardization. Due to the different dimensions, the input influence factor values need to be normalized. After normalization, the range of all the data are in the range of [−1, 1].
2. Divide the original data into a training subset and a test subset.
3. Create an initial Fuzzy Inference System (FIS) using the fuzzy C-means (FCM) cluster. The clustering method divides the data into sub-regions. Each sub-region

corresponds to a fuzzy rule. According to the structural characteristics of each sub-region, the method learns and extracts the membership functions of the linguistic variables in each piece of fuzzy rules. Then the firing strength is calculated.
4. Optimize ANFIS parameters by CPSO, as described in the above Steps 1–19.
5. Results output. The output of the results is displayed with mean-square error (*MSE*), root-mean-square error (*RMSE*), average error *(Error Mean)*, standard deviation *(Error Std)*, and correlation analysis index (R^2) as indicators.

The following normalized equation is used in Step 1:

$$\hat{x} = 2 \times \frac{x - x_{\max}}{x_{\max} - x_{\min}} - 1 \quad (7)$$

where $\hat{x}$ = the normalized sample data
x = the original sample data
x_{max} = the maximum values of the influence factor
x_{min} = the minimum values of the influence factor

4. DAM DEFORMATION PREDICTION

4.1 Data and Influential Factors

In this paper, we aimed to perform horizontal displacement monitoring, which is one type of deformation monitoring. Combined with the characteristics and actual conditions of the Xiaolangdi Dam, the horizontal displacement monitoring along the water flow direction uses the collimation line method and the horizontal displacement monitoring along the axis direction of the dam uses the distance measurement method. In order to verify the performance of the proposed CPSO-ANFIS algorithm, the horizontal displacement of the Y-axis of a survey point of the dam crest was used as a research example. The deformation amount is shown in Table 1, where Cyc is the number of observations and Dis means a corresponding displacement.

Cyc	Dis	Cyc	Dis	Cyc	Dis	Cyc	Dis
1	1.56	14	−1.138	27	0.785	40	1.99
2	0.869	15	0.245	28	0.54	41	1.873
3	1.683	16	1.187	29	0.044	42	1.382
4	2.536	17	0.83	30	−0.915	43	0.468
5	0.412	18	1.388	31	−1.439	44	0.785
6	−0.859	19	1.666	32	−1.924	45	−1.11
7	−0.185	20	1.873	33	−1.461	46	−1.656
8	−0.842	21	1.644	34	−1.333	47	−1.032
9	−0.932	22	1.36	35	−0.948	48	−0.748
10	−1.132	23	0.903	36	−0.859	49	−0.67
11	−1.339	24	1.315	37	0.261	50	1.705
12	−1.478	25	0.975	38	1.07	51	1.984
13	−1.216	26	1.326	39	1.839		

Table 1. The displacement of a certain point along the Y-axis at the top of the dam (dm)

The original observational factors are shown in the following Table 2, where Cyc is the number of observations, t is the interval days of observations, H is the water level of the observe day, T_0 is the temperature of the observe day, and T_5 is the temperature five days ahead of the observation day.

Cyc	t	H	T_0	T_5
1	0	240.9	18.8	18.1
2	15	237.45	19	17.8

3	18	243.26	19.4	18.6
4	15	234.24	19.6	19.1
5	14	238.5	20	19.8
6	35	237.2	21.8	18.8
7	22	243.2	23	19
8	28	240.96	24.4	19.4
9	40	239.3	25.3	19.6
10	17	240.45	25.5	20
11	15	240.2	25.6	21.8
12	17	240.1	25	23
13	14	240.06	24.5	24.4
14	16	239.85	24	25.3
15	14	241.1	23.2	25.5
16	19	242.03	22.3	25.6
17	21	239.7	21.6	25
18	25	239.36	20.2	24.5
19	13	238.16	19.3	24
20	11	239.16	19	23.2
21	24	239.3	19.6	22.3
22	14	239.2	20.3	21.6
23	13	238.2	20.8	20.2
24	13	240.5	21.4	19.3
25	22	241.1	22	19
26	14	242.4	22.4	19.6
27	14	241.42	23	20.3
28	19	242.1	23.5	20.8
29	16	240.56	24.1	21.4
30	13	240.6	24.6	22
31	15	238.5	25.2	22.4
32	20	238.8	25.7	23
33	17	239.6	25.8	23.5
34	14	240.2	25.4	24.1
35	13	240.7	25	24.6
36	15	239.8	24.4	25.2
37	13	240.5	23.6	25.7
38	27	239.95	21.9	25.8
39	29	240.3	20.3	25.4
40	33	240.8	19.6	25
41	32	239.7	20	24.4
42	31	239.3	21.2	23.6
43	31	239.5	22.7	21.9
44	32	243.15	24.2	20.3
45	31	238.5	25.1	19.6
46	39	239.1	25.8	20
47	27	241	25.6	21.2
48	22	240.35	25	22.7
49	28	239.56	23.8	24.2
50	36	242.2	21.4	25.1
51	26	241.25	20.3	25.8

Table 2. The original observational factors

The factors influencing dam deformation selected in this paper were H^1, H^2, H^3, T_0, T_5, and θ, where H^1, H^2 and H^3 represent the power of every water level, T_0 and T_5 represent the temperature component influencing factors, and θ represents the aging factor. The function mapping relationship between the six factors and the displacement value δ can be established by an ANFIS model. The values of the influencing factors θ, H^2, and H^3, selected in this paper can be calculated from the data in Table 2 and used as input samples for the ANFIS network.

4.2 Model Establishment

To compare our proposed CPSO-ANFIS prediction model, we established other two models, an ANFIS model and a PSO-ANFIS model. The three models used the same training and test data sets as control variables, and their model parameters were

set to the same values as much as possible. In particular, the neural network parameters for PSO-ANFIS and CPSO-ANFIS were set the same as those for ANFIS. From above, the input samples included H^1, H^2, H^3, T_0, T_5, and θ—six impact factors. The output samples were the horizontal displacement values or components of the dam. Therefore, the number of input neurons in the network was six and the number of output neurons was one. The specific parameters for the three models are provided in Tables 3–5, respectively.

Parameter	Description
Fuzzy structure	Sugeno-type
Initial FIS	Genfis3
Number of clusters	Automatic
Number of inputs	6
Number of outputs	1
Optimization method	Hybrid (least squares and back propagation techniques)
Fuzzy rule number	Automatic
Maximum number of training	1000
Initial step size	0.01
Step reduction rate	0.9
Step increase rate	1.1

Table 3. Parameters for ANFIS

Parameter	Description
Maximum number of iterations	1000
Number of particles	25
Initial inertia weight	1
Inertia weight damping ratio	0.99
Acceleration constant	1
Acceleration constant	2

Table 4. Parameters for PSO-ANFIS

Parameter	Description
Maximum number of iterations	1000
Number of particles	25
Initial inertia weight	1
Inertia weight damping ratio	0.99
Acceleration constant	1
Acceleration constant	2
Maximum number of steps in chaotic search	15

Table 5. Parameters for CPSO-ANFIS

4.3 Results and Analysis

In this example, there are 52 sets of sample data. All three models used the first 70% as input and output sample data for training (the first 35 periods of data), and the last 30% was used for testing (after 17 periods of data). In the proposed CPSO-ANFIS model, the chaotic optimization used only the first 20% of particles, which were the best particles, and the remaining 80% particles were randomly generated.

In order to compare different estimation models, mean-square error (*MSE*), root-mean-square error (*RMSE*), average error (*Error Mean*), standard deviation (*Error Std*), and correlation analysis index (R^2) between model output and measured data were used as performance criteria, for which the equations are:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(x^{\exp} - x^{sim}\right)^2 \qquad (8)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(x^{\exp} - x^{sim}\right)^2} \qquad (9)$$

$$ErrorMean = \frac{1}{n}\sum_{i=1}^{n}\left(x^{\exp} - x^{sim}\right) \quad (10)$$

$$ErrorStd = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(x^{sim} - x^{m}\right)^2}, x^{m} = \frac{\sum_{i=1}^{n} x^{sim}}{n} \quad (11)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left[x^{sim} - x^{\exp}\right]}{\sum_{i=1}^{n}\left[x^{sim} - x^{m}\right]}, x_m = \frac{\sum_{i=1}^{n} x_{sim}}{n} \quad (12)$$

where x^{exp} = the target value
             x^{sim} = the model output
             n = the number of experimental data

A predictive model with high-accuracy is desired when *MSE*, *RMSE*, *Error Mean*, and *Error Std* are near to 0 and R^2 is 1. Figures 3–5 exhibit the running results of the ANFIS, PSO-ANFIS, and CPSO-ANFIS, respectively. Each result is divided into two parts: training result and test result. From Figures 3–5, the fitting degree between the output value and the target was higher and the error was smaller in the training part of the three models. Among them, the fitting degree of CPSO-ANFIS was the best, followed by PSO-ANFIS, then ANFIS. In contrast, the error value for CPSO-ANFIS was the smallest, followed by PSO-ANFIS and ANFIS.

Among the three models, although the fitting degree in the prediction part was smaller than that in the training part, and the error in the prediction part was larger than in the training part, this is in line with scientific logic. Notably, the results of the prediction part were the same as those of the training part. The fitting degree from good to bad was CPSO-ANFIS, PSO-ANFIS, and ANFIS, and error from small to large was CPSO-ANFIS, PSO-ANFIS, and ANFIS.

The comprehensive results of the training part error and the prediction part error are shown in Table 6. From Table 6, ANFIS had the highest *MSE*, *RMSE*, *Error Mean*, and *Error Std* values, followed by PSO-ANFIS and CPSO-ANFIS, which indicates that the CPSO-ANFIS error was the smallest among the three models. Moreover, the correlation coefficients of the three models were very high, all over 90%, and the R^2 value for CPSO-ANFIS was the highest among the three models, which means CPSO-ANFIS has the highest reliability. Regarding the experimental results, CPSO-ANFIS outperformed the other two models in terms of reliability and lowest estimation error. The chaotic ergodic algorithm can be used for improving the search accuracy and performance of the PSO-ANFIS model. Therefore, the proposed CPSO-ANFIS model can be used to predict dam deformation.
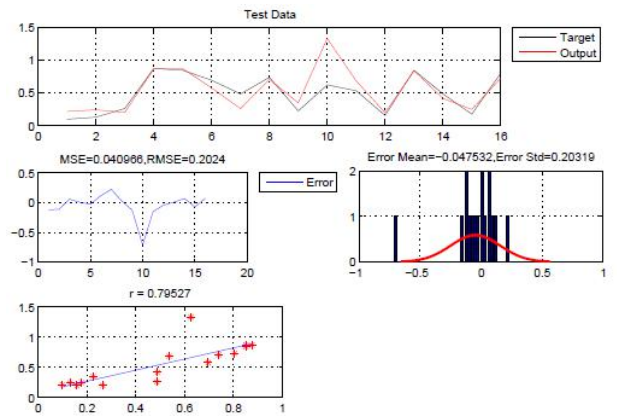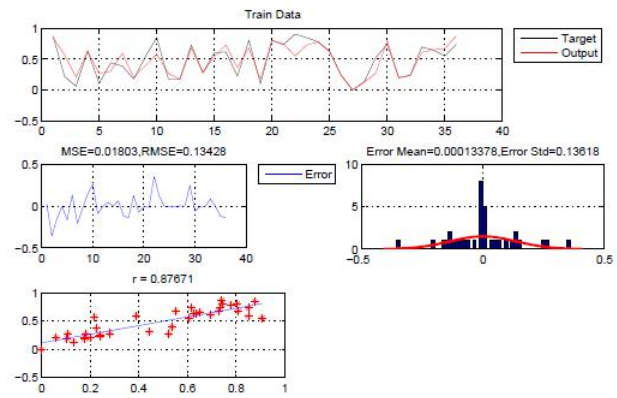

Figure 3. *Top*: The training results of ANFIS. *Bottom*: The test results of ANFIS
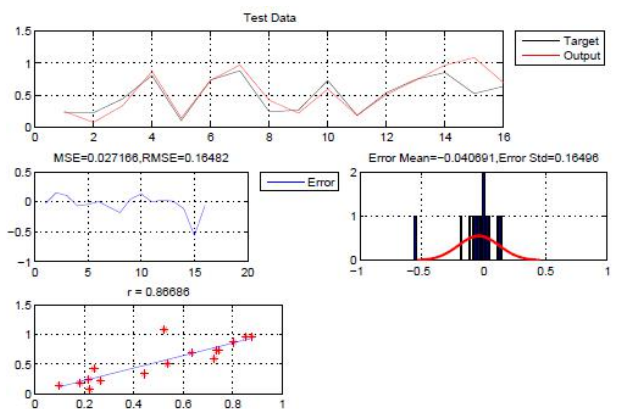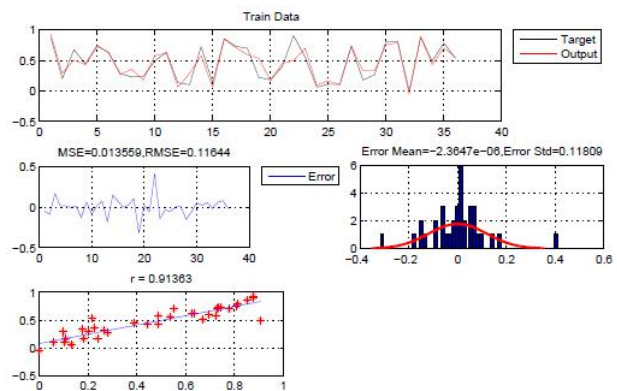

Figure 4. *Top*: The training results of PSO-ANFIS. *Bottom*: The test results of PSO-ANFIS
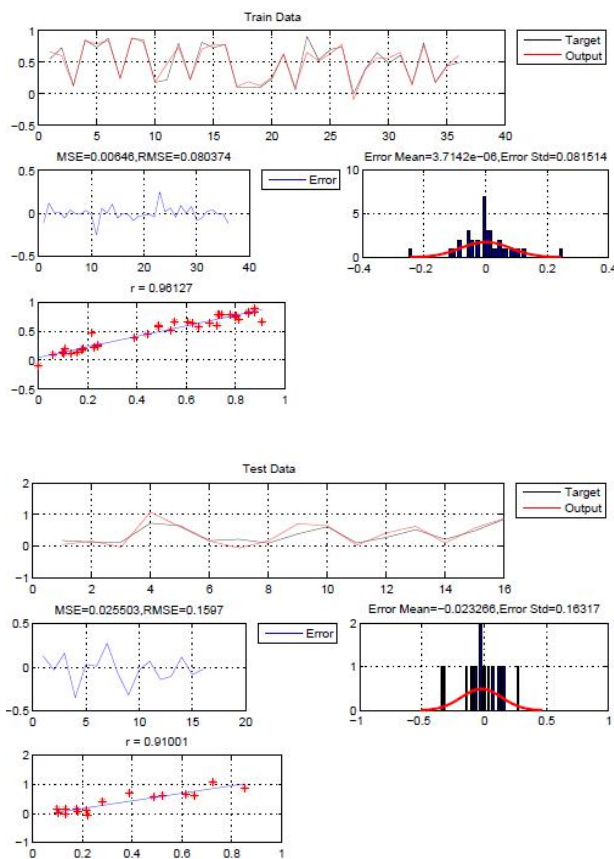
Figure 5. *Top*: The training results of CPSO-ANFIS. *Bottom*: The test results of CPSO-ANFIS

criteria	ANFIS	PSO-ANFIS	CPSO-ANFIS
MSE	0.158189	0.102088	0.081455
RMSE	0.375647	0.311966	0.283229
Error Mean	0.06351	−0.05759	−0.02124
Error Std	0.371678	0.304236	0.286796
R^2	0.9495	0.970489	0.971135

Table 6. The training and prediction results of the three models (mm)

5. CONCLUSIONS

In this study, we aimed to investigate how to improve PSO and PSO-ANFIS. The solution we adopted used a chaotic ergodic algorithm in PSO to propose a novel CPSO algorithm, and then, by combining CPSO rather than POS with ANFIS, we proposed and constructed a novel CPSO-ANFIS algorithm. In CPSO-ANFIS, the chaotic ergodic algorithm allows the particles to jump out of the local optimum and distribute evenly throughout the solution space, so a more complex spatial search was implemented and more accurate parameters were obtained. Because the parameters of CPSO-ANFIS are updated iteratively until the optimal results are obtained, the performance of the algorithm and the precision of search were considerably improved. We applied CPSO-ANFIS to a dam deformation prediction example, which evaluation indicators such as *MSE*, *RMSE*, *Error Mean*, *Error Std,* and R^2 showed that CPSO-ANFIS is more accurate and stable than ANFIS and PSO-ANFIS, both in predictive ability and predicted results. This we foresee as the next area for researchers with an interest in applying CPSO-ANFIS to other studies, or introducing chaos ergodic algorithm into other algorithms, such as the ant colony algorithm or monkey colony algorithm, and forming some new hybrid algorithms through combinations with neural network algorithms.

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