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A Cuckoo Search-Support Vector Machine Model for Predicting Dynamic Measurement Errors of Sensors

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ABSTRACT Sensors play a very important role in the Internet of Things. Error correction is of great significance to achieve sensor precision. Currently, accurately predicting the future dynamic measurement error is an effective way to improve sensor precision. Aiming to solve the problem of low model accuracy in traditional dynamic measurement error prediction, this paper employs the support vector machine (SVM) to predict the dynamic measurement error of sensors. However, the performance of the SVM depends on setting the appropriate parameters. Hence, the cuckoo search (CS) algorithm is adopted to optimize the key parameters to avoid the local minimum value which can occurs when using the traditional method of parameter optimization. To validate the predictive performance of the proposed CS-SVM model, the dynamic measurement error data for two sensors are applied to establish a predictive model. The root mean squared error and the mean absolute percentage error are employed to evaluate the models' performances. These results are also compared with those obtained from the SVM optimized by a grid search and the particle swarm optimization method. The experiments show that the SVM model based on the CS algorithm achieves more accurate prediction and is more effective in predicting dynamic measurement errors for sensors than the previous models.

INDEX TERMS Dynamic measurement errors, support vector machine, cuckoo search algorithm, sensors, prediction.

I. INTRODUCTION

With the development of modern measurement technologies, increasingly high accuracy is required in precision engineering [1], [2]. Inaccurate machine measurements can lead to the failure of entire systems and cause large economic losses. Real-time error correction of the instrument or sensor is an effective means to minimize error, and such corrections are critical for precision measurements because they not only enhance measurement stability but also improve the accuracy of the instrument. Building a model of dynamic measurement error to predict future error values based on existing error series is one of the basic methods to achieve dynamic measurement error correction. The effect of error correction in dynamic measurement depends on the accuracy of the model; therefore, prediction dynamic error modeling for sensors has become a topic of considerable importance in improving measurement accuracy [3], [4].

In recent years, several modeling methods for dynamic error prediction have been presented. These include time series analysis, gray theory and neural networks, and they have achieved certain results [5]–[9]. However, the modeling of time series analysis method is complex and the prediction accuracy is low. The gray theory method requires regular data; the neural network method has disadvantages such as overfitting and falls easily into extreme values, and so on. The support vector machine (SVM) is a learning technique based on the structural risk minimization principle as well as a new regression method with good generalization ability. It can better solve problems with few samples, nonlinear data, avoid local minima, and so on. However, the learning performance and generalization ability of SVM are dependent on appropriate parameter selection. The parameters directly impact the precision of the model predictions. Therefore, the grid search method, the particle swarm optimization algorithm, and the genetic algorithm have been adopted to optimize the SVM parameters [10]–[13]. However, the grid search method requires an exhaustive search over the hyper-parameter space, which is time consuming. The particle swarm optimization algorithm and the genetic algorithm fall into local extremes easily. The cuckoo search (cuckoo search CS) algorithm is a metaheuristic algorithm proposed in recent years [14]; it has the advantages of fewer parameters, strong global search ability, and a good search path, and it is powerful when solving multi-objective problems. In this study, a method of dynamic measurement error prediction for sensor based on a CS-optimized support vector machine is proposed.

The rest of the paper is organized as follows. In Section II, the support vector machine regression is described in detail. Section III introduces the optimization of SVM parameters based on the CS algorithm. Section IV reports on a simulation of the dynamic measurement error prediction model and provides the analysis results. Finally, Section V concludes the paper.

II. SUPPORT VECTOR MACHINE REGRESSION

A. SUPPORT VECTOR MACHINE REGRESSION THEORY

Assume (x_i, y_i), $i = 1, 2, \cdots, n$, $x_i \in R^d$, $y_i \in R$ are the training data sets, where X is the input vector, y_i is the output value, d is the dimension of sample space and n is the total number of the sample data. The basic idea of support vector machine regression is that the samples are mapped to a high dimensional feature space using nonlinear mapping Φ and then, SVM carries out the linear regression operations in this space. The regression function is expressed as follows:

$$f(x) = [\omega \cdot \Phi(x)] + b \quad \omega \in R^d,\ b \in R, \tag{1}$$

where ω is the weight vector and b is the threshold. Assuming that all training data can be fitted with a linear function without error, the optimization equation can be represented as follows:

$$\min_{\omega}\ \Phi(\omega) = \frac{1}{2}\|\omega\|^2$$
$$s.t.\ \begin{cases} y_i - \omega \cdot x - b \le \varepsilon \\ \omega \cdot x_i + b - y_i \le \varepsilon, \quad i = 1, 2, \cdots, n. \end{cases} \tag{2}$$

Considering there are errors in practice, the equation introduces slack variables and a punishment coefficient. According to the principle of construction risk minimization, Equation (2) can be rewritten as follows:

$$\min_{\omega,\xi}\ \Phi(\omega, \xi) = \frac{1}{2}\|\omega\|^2 + C\sum_{i=1}^{n}(\xi_i + \xi_i^*)$$
$$s.t.\ \begin{cases} y_i - \omega \cdot x_i - b \le \varepsilon + \xi_i \\ \omega \cdot x_i + b - y_i \le \varepsilon + \xi_i^* \\ \xi_i, \quad \xi_i^* \ge 0, \end{cases} \tag{3}$$

where ξ_i and ξ_i^* are slack variables, C is the punishment coefficient, and ε is a parameter of the insensitive loss function. The first term in equation (3) is a model complexity term and the second item is an empirical error term determined by the loss function. The punishment coefficient is used to adjust the balance of these two items.

Lagrange multipliers are introduced in equation (3). The corresponding dual problem can be expressed as follows:

$$\max \sum_{i=1}^{n} y_i(\alpha_i^* - \alpha_i) - \varepsilon\sum_{i=1}^{n}(\alpha_i + \alpha_i^*) - \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n}(\alpha_i - \alpha_i^*)(\alpha_j - \alpha_j^*)(x_i \cdot x_j)$$
$$s.t.\ \begin{cases} \sum_{i=1}^{n} y_i(\alpha_i - \alpha_i^*) = 0 \\ 0 \le \alpha_i, \quad \alpha_i^* \le C,\ i = 1, 2, \cdots, n, \end{cases} \tag{4}$$

where α_i and α_i^* are Lagrange multipliers. Finally, the linear function takes the following form:

$$f(x) = \sum_{i=1}^{n}(\alpha_i - \alpha_i^*)(x_i \cdot x) + b. \tag{5}$$

For the nonlinear regression, the dot product operation can be directly replaced by computing a so-called kernel function $K(x_i, x_j)$. When a $K(x_i, x_j)$ satisfies the Mercer condition, it corresponds to the inner product of a transform space according to functional theory. Therefore, the nonlinear regression function can be determined:

$$f(x) = \sum_{i=1}^{n}(\alpha_i - \alpha_i^*)K(x_i \cdot x_j) + b. \tag{6}$$

B. KERNEL FUNCTION AND PARAMETERS OF SVM

When dealing with nonlinear problems, SVM avoids computing an inner product in the high dimensional space by introducing a kernel function to solve the dimension disaster problem. According to SVM theory, the kernel function is the key technology in SVM. Selecting different kernel functions will construct different regression models. The common kernel functions are listed below:

1) POLYNOMIAL KERNEL FUNCTION

$$K(x_i, x_j) = ((x_i \cdot x_j) + 1)^q \tag{7}$$

2) SIGMOID KERNEL FUNCTION

$$K(x_i, x_j) = \tanh(\nu(x_i \cdot x_j) + t) \tag{8}$$

3) RBF KERNEL FUNCTION

$$K(x_i, x_j) = \exp\left\{-\frac{|x_i - x_j|^2}{2\sigma^2}\right\}, \tag{9}$$

where σ is the width coefficient of the kernel function. Compared with other kernel functions, the RBF kernel function has the advantages of fewer parameters, few numerical restrictions and good performance. Therefore, the RBF kernel function is used in this study.

The SVM parameters determine both its learning ability and generalization ability. Two major RBF parameters applied in SVM are C and σ. C controls the equilibrium between the complexity of the model and empirical error. If C is too large, the model's complexity will be increased and it may easily fall into the "over-fitting" phenomenon. Conversely, when C is too small, the model's complexity is too low and it may fall into the "under-fitting" problem. The parameter σ affects the complexity of the sample data distribution in the feature space. At present, most of the SVM parameters are determined through trial and error, or selected by an intelligent algorithm. Here, the CS algorithm is applied to find the optimal SVM parameters within specific limits.

III. SVM PARAMETER OPTIMIZATION BASED ON CS

A. THE CS ALGORITHM

Inspired by the special lifestyle of the cuckoo species and Levy flight, Xin-She Yang and Suash Deb proposed the CS algorithm in 2009 [14]. Cuckoos lay their eggs in other birds' nests when the host birds leave the nest unguarded. In the process, some of these eggs, which are similar to the host bird's eggs, hatch and grow into adult cuckoos. If the host birds discover the eggs are not their own, they will expel the alien eggs or abandon their nest and find another place to build a new nest. Each egg in a nest represents a solution, and a cuckoo egg represents a new solution. The aim of the CS algorithm is to use the new and potentially better solutions (cuckoos) to replace the not-so-good solutions in the nests. The CS algorithm has the following three rules [15], [16]:

1) Each cuckoo only lays one egg (one solution) at a time, and it places the eggs in a randomly chosen nest;
2) In these nests, the best nest, with high quality eggs, (solutions) will carry over to the next generation;
3) The total number of available host nests is fixed. A host bird can discover an alien egg with probability. In this case, the host bird may either expel the egg or leave and establish a new nest in a new location.

Based on the above three rules, the CS algorithm updates the bird nest locations. Its search path can be expressed as follows:

$$X_i^{t+1} = X_i^t + \alpha \oplus L, \tag{10}$$

where X_i^t represents the location of the ith nest at iteration t. The product $\oplus$ means entry-wise multiplication, and α is the step size, which is subject to a normal distribution. L is the Levy random search path, which can be expressed as follows:

$$L = 0.01 \times \frac{\mu}{|\nu|^{1/\beta}} \times (g_{best} - X_i^t), \tag{11}$$

where g_{best} represents the current best nest. When μ, ν is subject to a normal distribution, $\mu \sim N(0, \delta_\mu^2$, $\nu \sim N(0, \delta_\nu^2)$, and

$$\begin{cases} \delta_\mu = \left\{ \dfrac{\Gamma(1+\beta)\sin(\pi\beta/2)}{\Gamma[(1+\beta)/2]\beta 2^{(\beta-1)/2}} \right\}^{1/\beta} \\ \delta_\nu = 1, \end{cases} \tag{12}$$

where $\beta = 1.5$.

The CS algorithm has two advantages compared with other meta-heuristic algorithms [14]. The first is that the CS algorithm can more effectively maintain the balance between the local search strategy and the efficient exploration of the entire search space. The second is that the CS algorithm has only two parameters (population size, N, and the probability of egg detection, p_a). After N is fixed, p_a alone controls the balance between random and local search. Because the CS algorithm has fewer parameters, its universality is better [14].

B. SVM PARAMETER OPTIMIZATION BASED ON CS

The general procedure of CS-SVM is illustrated in the flowchart in Fig. 1. The CS algorithm is applied to optimize the SVM parameters C and σ as follows:

1) Initialize the cuckoo search algorithm and set the number of nests, N, the probability parameters, p_a, the maximum iterations, $t_{\max}$, and the ranges of C and σ.
2) Randomly generate nest positions using $q_i^0 = [x_1^0, x_2^0, \ldots, x_n^0]^T$. Each nest corresponds to a set of parameters (C, σ). The fitness evaluation function is defined as follows:

$$I = \sum_{i=1}^{n} (\hat{Y}_i - Y_i)^2/n, \tag{13}$$

where $Y(i)$ is the actual value and $\hat{Y}(i)$ is the prediction value of the model, and n is the number of training samples.
3) Evaluate the fitness value of each nest, discover the current best solution, and record the minimum fitness value and its corresponding position.
4) Keep the best solutions from the previous generation, and update the position of the other nests using Formula (10). Then, evaluate the fitness value of the new position.
5) Replace the best solution of the previous generation if the fitness value of the new generation is better than that of the previous generation, and record the position of the best nest.
6) Set a random number (*random*) as the probability of egg detection. Compare it with p_a. If $random > p_a$, change the position of the nest randomly to obtain a new set of positions.
7) Find the best nest position in Step 6). Stop searching when the maximum iteration limit is reached, and output the best position to achieve the optimal parameter value; otherwise, return to Step 3).

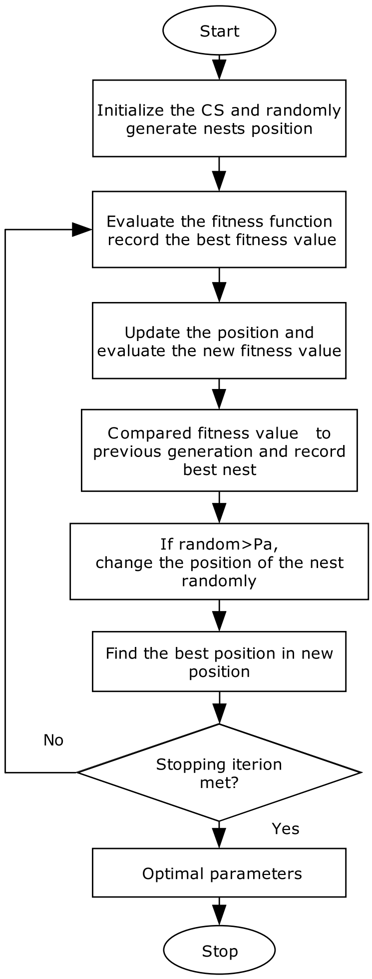

FIGURE 1. Flow chart of CS algorithm for SVM parameter selection.

IV. DYNAMIC MEASUREMENT ERROR PREDICTION MODEL

A. DATASET

To verify the validity of the method proposed in this study, the dynamic measurement error data of a goniometer (Case 1) and a diffraction grating encoder (Case 2) were used to evaluate the performance of the proposed CS-SVM model. The data for Case 1 is the measuring error of the goniometer with anticlockwise rotation (speed 2 r/min) based on standard value interpolation under room temperature; the error sequence contains a total of 240 samples. In Case 2, the resolution of the grating encoder is 20 μm and the sampling interval is 2 mm. The error sequence for the grating encoder contains a total of 77 samples. Because the two datasets are one-dimensional and restricted by unicity, to achieve better prediction results, we mine the relationship between them to obtain more information by transforming the one-dimensional forms into a multi-dimensional form. Let p be the dimension of the input vector. The reconstructed samples are shown in Table 1:

TABLE 1. Sample construction.

Samples	input vector	output vector
The first sample	$X(1), X(2), \cdots, X(p)$	$X(p+1)$
The second sample	$X(2), X(3), \cdots, X(p+1)$	$X(p+2)$
$\vdots$	$\vdots$	$\vdots$
The $(n-p)$-*th* sample	$X(n-p), X(n-p+1), \cdots, X(n-1)$	$X(n)$

B. MODEL PREDICTION

The steps of dynamic measurement error prediction based on CS optimized SVM are as follows:

1) Select the training data and testing data. After a series of experiments with different dimensions, the study employs the dimensions that can obtain good prediction results in the two Cases. In Case 1, based on the construction method shown in Table 1, the dimension is set to $p = 14$; therefore, the number of reconstructed samples is 226. We selected 126 samples as training data and 100 samples as testing data. In Case 2, the dimension is set to $p = 12$, and we selected 48 samples as training data and 20 samples as testing data. We preprocessed the sample data to normalize it.
2) Perform parameter optimization and train the model. We used the CS algorithm to determine the punishment coefficient, C, and the kernel width, σ, for SVM by selecting RBF as the kernel function. We trained the SVM model based on the training samples and using the optimized parameters in advance of prediction, so that it could achieve the highest accuracy.
3) Model prediction. After training, the testing samples were input to the trained model to obtain the predictive values.
4) The prediction data were re-normalized to obtain the actual dynamic measurement error prediction data.

C. RESULTS AND DISCUSSION

After using the above steps to establish the model, we obtained the prediction results from Case 1, as shown in Fig. 2. The parameters for CS were set as follows: number of nests: $N = 25$; nest discovery rate: $p_a = 0.25$; and the maximum number of iterations: $t_{\max} = 100$. To show the efficiency of the proposed method, the particle swarm optimization (PSO-SVM) and grid search (GS-SVM) models were also trained and implemented. The prediction results for these models are shown in Fig. 3 and Fig. 4. The predicted residuals of the three models were compared, and the comparison results are shown in Fig. 5. The parameters for PSO were set as follows: the initial population: $N = 25$; local search parameters: $C_1 = 1.5$; global search parameters: $C_2 = 1.7$; and the maximum number of iterations: $t_{\max} = 100$.

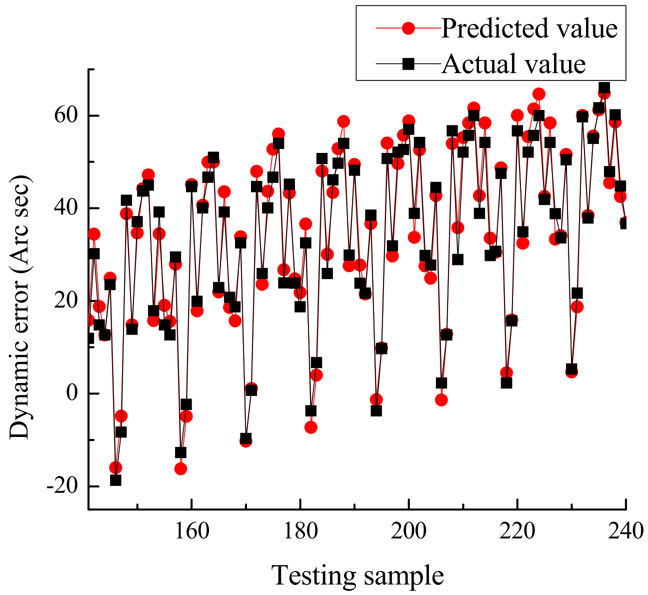

FIGURE 2. Prediction results of CS-SVM for Case 1.

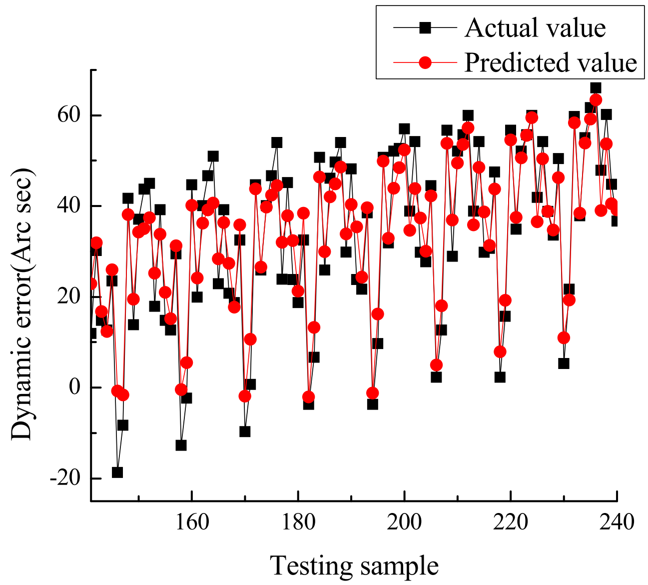

FIGURE 4. Prediction results of GS-SVM for Case 1.

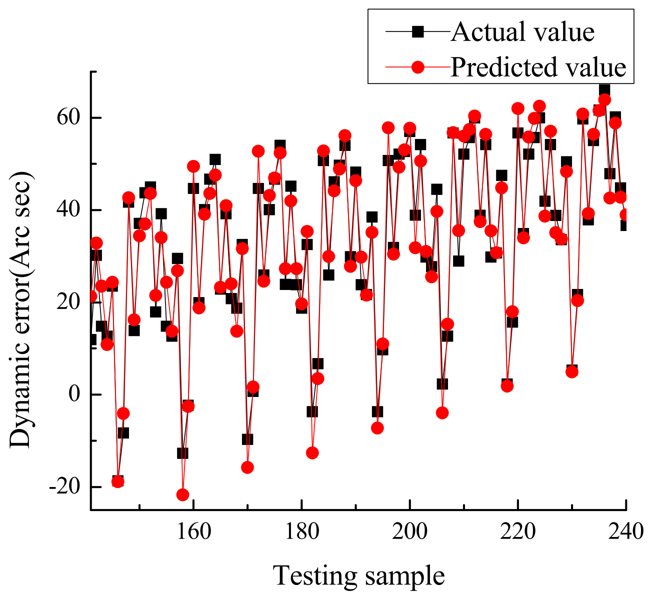

FIGURE 3. Prediction results of PSO-SVM for Case 1.

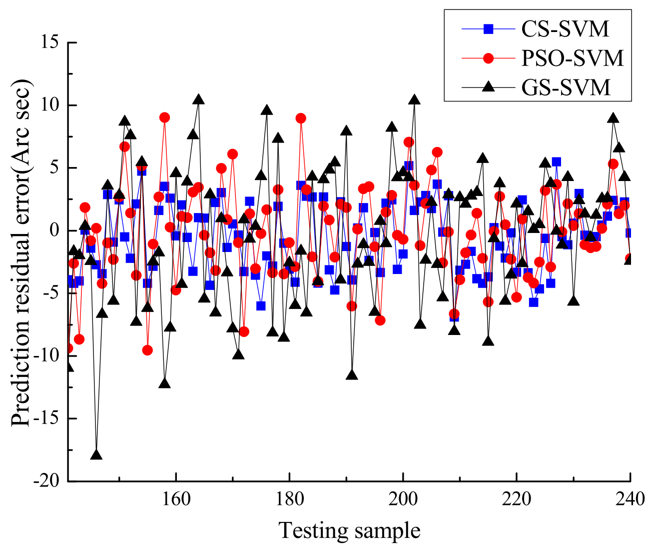

FIGURE 5. Comparison of the predicted residuals of the three models for Case 1.

Figs. 2–4, show that the CS-SVM model has the best prediction results among the three methods. Although the PSO-SVM model exhibits good prediction performance, the CS-SVM model prediction curve is closer to the real curve than the PSO-SVM prediction curve. The prediction curve of the GS-SVM model deviates greatly from the actual curve. From Fig. 5, the prediction residual curve for GS-SVM is large, ranging from −18 arc sec to approximately 12 arc sec. The prediction residual of PSO-SVM model is smaller than that of GS-SVM, but its curve is still relatively large, ranging from −9 arc sec to approximately 8 arc sec. The predicted residual curve of CS-SVM is gentler, ranging from −6 arc sec to approximately 5 arc sec. The overall results are that the dynamic measurement error prediction ability of the CS-SVM model is better than both the PSO-SVM and GS-SVM models, which indicates that the CS is an effective method for parameter optimization. To further evaluate the performance of CS-SVM the dynamic measurement error model, we use the mean absolute percent error (MAPE) and root mean square error (RMSE) measures as evaluation indices of model performance. Their definitions are as follows:

$$\mathrm{MAPE} = \frac{\sum_{i=1}^{n} \left| Y(i) - \hat{Y}(i) \right| / Y(i)}{n} \times 100\% \tag{14}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Y(i) - \hat{Y}(i))^2}, \tag{15}$$

where $\hat{Y}(i)$ is the modeling value, $Y(i)$ is the actual value, and n is number of testing samples. Table 2 lists the comparison results between the CS-SVM, PSO-SVM, and GS-SVM prediction models for these performance indices.

TABLE 2. Comparison of performance index among the three models in case 1.

Models	MAPE	RMSE
CS-SVM	0.1356	0.2867
PSO-SVM	0.1874	0.3710
GS-SVM	0.4041	0.5610

As shown in Table 2, the GS-SVM model predicts the dynamic measurement error with a MAPE of 0.4041 and an RMSE of 0.5610, whereas PSO-SVM results in a MAPE of 0.1874 and an RMSE of 0.3710. Compared with the GS-SVM model, the MAPE of the CS-SVM model is reduced by 0.2685, and the RMSE is reduced by 0.2743. Compared with the PSO-SVM model, the MAPE and RMSE of the CS-SVM model are reduced by 0.0518 and 0.0843, respectively.

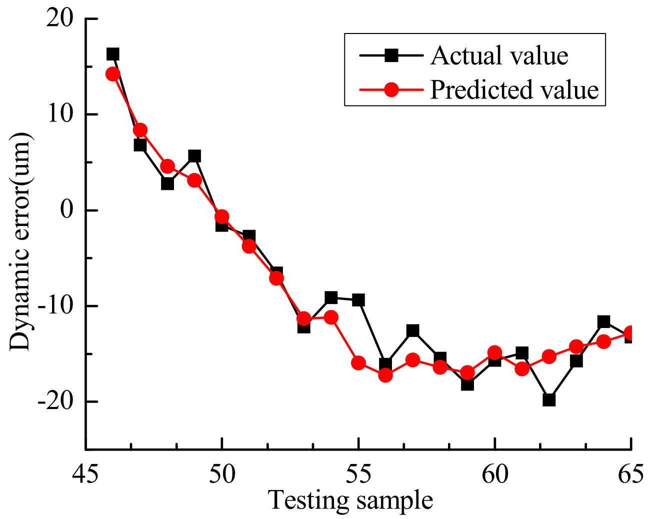

FIGURE 6. Predicted results by CS-SVM for Case 2.

Fig. 6 shows the prediction results of Case 2. A series of comparative experiments with other predictive models are also given. The parameters of each algorithm are the same as in Case 1. Fig. 7 and Fig. 8 present the prediction results for Case 2 for the PSO-SVM and GS-SVM methods, respectively. Fig. 9 presents the comparison of prediction residuals by CS-SVM, PSO-SVM and GS-SVM for Case 2. The assessments of the prediction results acquired by the three models of the dynamic measurement error are presented in Table 3.

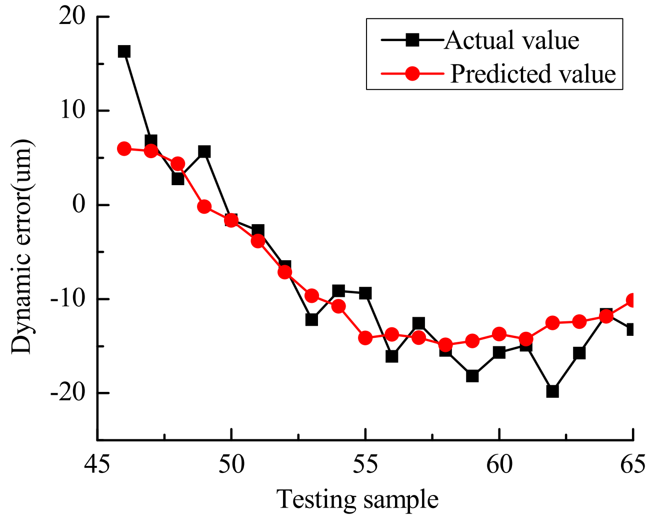

FIGURE 7. Prediction results of PSO-SVM for Case 2.

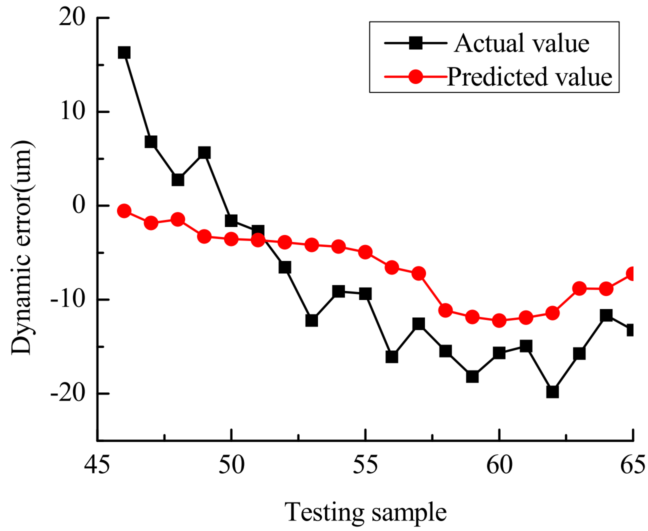

FIGURE 8. Predicted results by GS-SVM in case 2.

In Figs. 6–8, compared with GS-SVM and PSO-SVM, the simulation prediction results show that the CS-SVM prediction curve has is clearly superior. As Fig. 9 shows, the predicted residuals of GS-SVM range between $-10\ \mu$m $\sim$ 17 μm, while the PSO-SVM and CS-SVM predicted residuals are between $-7\ \mu$m $\sim$ 10 μm and $-5\ \mu$m $\sim$ 5 μm, respectively. As Table 3 shows, the GS-SVM model has the worst performance, while the PSO-SVM model has a good performance, acquiring MAPE and RMSE values of 0.2770 and 0.7942, respectively, reducing the MAPE and RMSE by 0.3483 and 0.7160, respectively, compared to GS-SVM. The CS-SVM model achieves an even better performance, outperforming the PSO-SVM model and reducing the MAPE and RMSE by 0.0451 and 0.2683, respectively, compared with PSO-SVM.

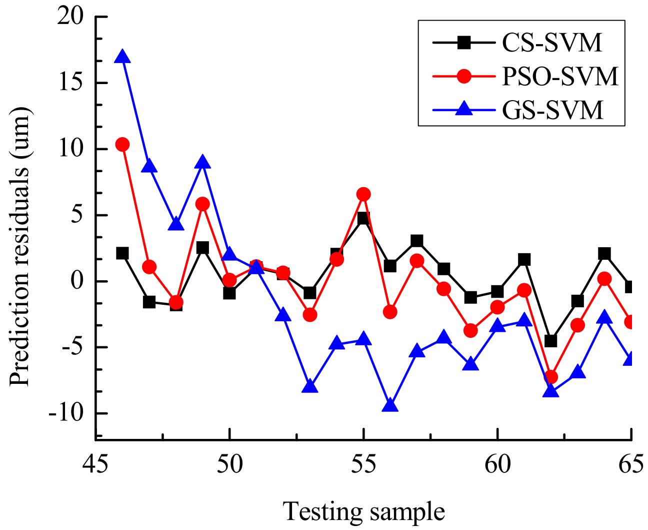

FIGURE 9. Comparison of the predicted residuals of the three models for Case 2.

TABLE 3. Comparison of performance index among the three models in case 2.

Models	MAPE	RMSE
CS-SVM	0.2319	0.5259
PSO-SVM	0.2770	0.7942
GS-SVM	0.6253	1.5102

The results of these two cases indicate that the proposed CS-SVM provides better prediction performance than the other two methods. This occurs because the CS method finds the global optimal solution for cases with large search intervals and small step distance. The adjustment of the position and velocity of the particles in the convergence of the PSO algorithm are excessively dependent on the current optimal particle, which leads to premature convergence and failure to find the global optimal solution. Because the CS algorithm introduces the Levy flight search mechanism, it can jump out of local optimal solutions to obtain the global optimal solution.

V. CONCLUSION

In this study, a method of dynamic measurement error prediction based on CS-optimized SVM parameters is proposed. The CS algorithm is employed to select the appropriate SVM parameters to effectively avoid the "overfitting" or "underfitting" phenomenon of SVM, thus enhancing the prediction accuracy. The simulation experiments show that the proposed model performs well in all tested cases. The results of the CS-SVM model were compared with those of the PSO-SVM and GS-SVM in terms of MAPE and RMSE, with the results that the CS-SVM has higher accuracy and a better effect than either GS-SVM or PSO-SVM. The proposed method may provide a new modeling method for dealing with dynamic measurement error and has definite value for application in error correction. However, the probability parameter in CS is fixed, which can affect the convergence of the algorithm. We will study the more effective method to improve the prediction results.

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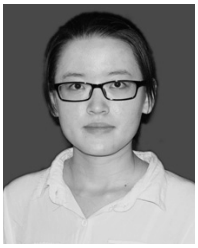

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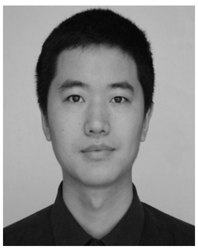

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