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IDENTIFICATION OF CONTINUOUS ROTARY MOTOR BASED ON IMPROVED PARTICLE SWARM OPTIMIZING SUPPORT VECTOR MACHINE MODEL

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Abstract. *Due to high nonlinearity, friction, leakage and other external factors existing in the flight simulator with continuous rotary electro-hydraulic servo motor, it is difficult to establish the accurate system model. In order to solve it, an identification method was proposed based on the improved particle swarm optimizing (IPSO) the parameters of support vector machine regression (SVR) model. The non-linear auto-regressive model of continuous rotary electro-hydraulic servo motor was established by adopting the time-series analysis method, and then a group of motor input and output data of low-speed performance experiment on continuous rotary motor were adopted. The non-linear auto-regressive model of electro-hydraulic servo system was identified by applying the heuristic improved particle swarm optimizing (IPSO) the parameters of support vector machine regression (SVR) model under empirical risk minimization. According to computing the mean square error (MSE) between the identified model's and experimental output, and furthermore comparing with least squares (LS) identified result, the introduced identification method is proved to have higher precision and practical value.*

Keywords: Continuous rotary motor, Time-series analysis method, Empirical risk minimization, Improved particle swarm optimizing (IPSO), Support vector machine regression (SVR) model

1. Introduction.

The hydraulic simulating turntable is used to imitate the gesture angle and angular velocity's changing of the aircrafts in laboratory, whose important equipment is continuous rotary electro-hydraulic servo motor. It is requested that continuous rotary electro-hydraulic servo motor should have perfect low-speed performance, high precision and frequency response, but actually there are unpredictable factors such as noise in the external environment, which can result in electro-hydraulic servo system nonlinearity, friction interferences and other uncertainties and time variations. So in order to solve this problem, there are two ways, on the one hand, selecting an identification method with high precision and fitting degree to identify the system and establish the identification model, on the other hand, adopting the transfer functions to establish the system mathematics model and designing the controller by using an intelligent control strategy to improve the system performance.

As far as the identified model was concerned, Gauss-Newton optimizing prediction error was adopted to identify mathematical model of continuous rotary electro-hydraulic servo system, and then QFT (Qualifitative Feedback Theory) robust controller with two freedom degree was designed, and finally the experiment confirmed that QFT controller improved the systemic stability under low-speed [1]. In order to solve the difficulties

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of online detecting the part surface roughness, the identification model was established and could detect the surface roughness, and eventually the rationality of identification model was proved by experiment [2]. In [3], an improved multi-innovation extended Kalman filtering was proposed to improve the accuracy of parameter model on vessel autonomous navigation, this method's convergence was analyzed, and finally the accuracy of the presented methods was verified by the comparative experiments. Of all above literature, when establishing the system model, usually the gray box identification theory was adopted to identify the parameters of system mathematical model, but the real-time nonlinearities and instabilities of system were neglected, so that the mathematical model is not accurate.

Support vector machine regression (SVR) based on the VC (Vapnik-Chervonenkis) dimension and empirical risk minimization principle, can be turned into a convex quadratic programming by adopting a nonlinear mapping to identify the system mathematical model, so that the global optimization of the network structure is automatically generated by solving the convex quadratic programming. Compared with neural network identification, SVR can avoid the phenomenon of over learning effectively and has higher generalization ability as well as stronger extension [4,5]. For example, in [6], aiming to the nonlinearity and time variation properties of aero engine, the aero engine's identification model applying SVR identification method was established, and the research results show that this method has higher identification precision.

Particle swarm optimizing algorithm (PSO) is a stochastic heuristic optimization algorithm, and this algorithm can be calculated by velocity-position search formula. And PSO has advantages of not only simple operation, low computations compared with the general heuristic algorithm, but also high ability of global search and optimal characteristics. Based on PSO algorithm, the improved particle swarm optimizing algorithm to which the elastic variable δ^k is added was designed, which changes the searching way. And the precision of SVR identification model is determined by the width of kernel σ and penalty coefficient C. So IPSO is adopted to optimize two parameters of SVR model, it can make two parameters of SVM model convergent to the global minimum effectively, for the structure of IPSO can avoid the solution falling into local minimum and reduce the calculation time greatly, so that higher identification accuracy of the regression model can be obtained [7].

Therefore, the nonlinear factors were considered in this paper, and the time series analysis method was put forward to describe continuous rotary electro-hydraulic servo system, so a nonlinear SVR model of continuous rotary motor was established. The experiment data of continuous rotary motor was collected and pre-processed, then IPSO was adopted to optimize two parameters of SVR model, namely the width of kernel σ and penalty coefficient C, so as to get the optimal regression model of continuous rotary motor [8,9]. As the contrastive model, the least squares (LS) identification model of continuous rotary motor was established. And it can be proved that the established parameter model of electro-hydraulic servo system based on the identification strategy proposed in this paper is closer to the original system model than the least squares (LS) identification model by contrastive simulation. Meanwhile, the rationality and validity of the identification strategy are verified.

2. **The Establishment of Nonlinear Autoregressive Time Series Model.** Generally, AR (Auto Regression model), MA (Moving Average model), and ARMA (Auto Regressive and Moving Average model) are expressed by linear limiting, all of which just only are applied to linear system. However, in practice, there are varieties of factors such as the external friction, leakage, external load change, pressure pulse of oil source,

the pressure-current nonlinear properties of servo valve and others in continuous rotary electro-hydraulic servo system, which leads to model's inaccuracy. Thus, the ideal system model cannot be obtained.

Theorem 2.1. *Therefore, it is necessary to establish a general nonlinear auto regression (GNAR) model, and regard it as identification model of continuous rotary electro-hydraulic servo motor, so the GNAR is expressed by the following [10-13]:*

$$y(k) = f[y(k-1), y(k-2), \ldots, y(k-n_y), x(k-1), x(k-2), \ldots, x(k-m_x)] + x(k) + e(k) \quad (1)$$

where the input $x(k)$, and the output $y(k)$ can be expressed as,

$$\begin{aligned} x(k) &= [x_1(k), x_2(k), \ldots, x_m(k)]^T \\ y(k) &= [y_1(k), y_2(k), \ldots, y_n(k)]^T \end{aligned} \quad (2)$$

It is assumed that the phase lag of continuous rotary electro-hydraulic servo system is 0, input order is m, output order is n, and the current number of sampling step is k, $e(k)$ is the random error of zero mean and the $f(\cdot)$ is the continuous nonlinear function.

Corollary 2.1. *According to the Weierstrass theory of function approximation, a continuous function defined in a closed interval can be expressed as polynomial. Thus, nonlinear function $f(\cdot)$ is expressed as follows in a closed interval [14]:*

$$y(k) = \eta_1 y(k-1) + \eta_2 y(k-2) + \cdots + \lambda_1 x(k-1) + \lambda_2 x(k-2) + \cdots + e(k) \quad (3)$$

Since a related stationary time series $\{y_i\}$ can be replaced by a linear combination of the present and past values of an unrelated stationary time series $\{x_i\}$,

$$y_i = \sum_{j=0}^{n} G_j x_{i-j} \quad (4)$$

where G_j is Green function.

Based on Equation (4), GNAR model of continuous rotary electro-hydraulic servo motor can be obtained, as follows:

$$Y(x) = G_n^T \cdot \Phi(x) + E \quad (5)$$

Meanwhile, the objective function of least square (LS) based on GNAR model of continuous rotary electro-hydraulic servo motor is described by

$$\arg\min \left\| Y(k) - G_n^T \Phi(k-1) \right\| \quad (6)$$

Then the estimated coefficients of the model are defined as follows,

$$\hat{G}_{wls} = \left(\Phi^T \Phi\right)^{-1} \Phi^T Y \quad (7)$$

3. **Identification Based on Support Vector Machine Parameter Model.** Generally, the linear SVR is adopted to identify the parameters of nonlinear model, the basic idea of which makes the data x_i map to high dimensional feature space (Hilbert space) with nonlinear kernel function K and then linear regression is done in high dimensional feature space. So the linear regression of high dimensional feature space can correspond to the nonlinear regression function of low dimensional space.

Corollary 3.1. *According to Equation (4), the nonlinear auto regression model of continuous rotary electro-hydraulic servo motor can be shown as,*

$$\theta(u) = \sum_{i=1}^{n} g_i * u_i + b \quad (8)$$

where u_i is input signal of electro-hydraulic servo system, $\theta(u)$ is the output oil pressure of electro-hydraulic servo motor, and b is constant.

It is assumed that the sample is n dimensions vector, so the expression of l samples is,

$$(u_1, \theta_1), (u_2, \theta_2), \ldots, (u_l, \theta_l) \in R^n \times R \tag{9}$$

Introducing the slack variable ξ_i and ξ_i^*, then according to the parameters of model under the principle of empirical risk minimization, the identification issue of SVR is equal to optimizing quadratic programming, so the programming objective function can be obtained:

$$\min \frac{1}{2} \|g\|^2 + C \sum_{i=1}^{n} (\xi_i - \xi_i^*) \tag{10}$$

where the inequality constraints are shown as Equation (11).

$$S.t. \quad \begin{array}{l} \theta_i - g * u_i - b \le \varepsilon + \xi_i \\ g * u_i + b - \theta_i \le \varepsilon + \xi_i^* \\ \xi_i, \xi_i^* \ge 0 \end{array} \tag{11}$$

The key of realizing the linear regression of high dimensional feature space to the non-linear regression function of low dimensional space is kernel function. As the function approximation theory demonstrates, the function satisfying Mercer conditions can be regarded as kernel function. In [15], it was proved that the total performance of radial basis kernel function (RBF) was the best by comparing the influences of different kernel functions on the identification system's accuracy. Therefore, this paper selects the RBF as the kernel function, and the expression is defined as

$$k(u_i, u) = \exp\left\{-|u - u_i|^2 / 2\sigma^2\right\} \tag{12}$$

Meanwhile, the ε-insensitivity function is shown as follows,

$$e(\theta(u) - \theta) = \max(0, |\theta(u) - \theta| - \varepsilon) \tag{13}$$

Therefore, the nonlinear SVR identified model $\theta(u)$ is regarded as the following equation

$$\theta(u) = \sum_{i=1}^{l} (\alpha_i - \alpha_i^*) k(u_i, u) + b \tag{14}$$

In Equation (14), when $\alpha_i - \alpha_i^*$ is not equal to zero, the sample data corresponding to $\alpha_i - \alpha_i^*$ is the identification model's support vectors as well as the parameters of the linear system [16-18].

The complexity and precision of SVR model are determined by the width of kernel σ and penalty coefficient C. The penalty coefficient C is used to adjust the complexity of model and training error, and the complexity of high dimensions space's distribution is determined by the width of kernel σ. At present, in order to obtain appropriate parameters, the optimizing methods of SVR model's parameters are usually studied, such as the mesh method, gradient descent method and intelligent search algorithm [19].

Grid method means that the global optimal solution can be found just when the optimal range is large enough and the step distance is small enough, but all the parameters within the grid should be calculated, which not only wastes time but also has low accuracy. The gradient descent method is a local optimization algorithm and cannot get the global optimal solution. And the intelligent search algorithms, generally the genetic algorithm, can obtain the global optimal solution in the solution space, but the algorithm is complex and the amount of calculation is large. Due to the advantages of simple operation, low computation and higher identified accuracy, IPSO algorithm is proposed to identify the parameters of SVR model on continuous rotary motor in this article, which not only can solve the global optimal solution, but also change the search step so that it can improve the optimal solution accuracy without increasing the computation.

4. **Model Identification of Improved Particle Swarm Optimization.** Particle swarm optimization (PSO) is an intelligent algorithm based on group optimization, with the properties of group intelligent, such as the simple structure, fast convergence and others, so every particle represents for a possible optimized value. In the SVR model, every particle is expressed as 2 dimensions space, and composed of the kernel width σ and penalty coefficient C. So the objective function of optimizing problem is defined as the least MSE between the electro-hydraulic servo system model output which is calculated by the improved particle swarm optimizing (IPSO) the parameters of support vector machine regression (SVR) and experiment's original output, so as to get the global optimal kernel width σ and penalty coefficient C [20,21].

4.1. **Improved particle swarm optimization.** The intelligent optimization algorithm of particle swarm is adopted to optimize the two parameters in the support vector machine model, that is the nuclear width σ and the penalty coefficient C, and the non-sensitive loss parameter ε is 0.01. Because there are a great deal of experiment data of continuous rotary motor, the speed of operating data is low, and consequently an improved particle swarm optimization (IPSO) is put forward. The process of optimization adopts the ideological variable-step with long search steps in the prophase of algorithm and short in the anaphase, which can improve the ability of global searching efficiently [22].

Assumption: there are m particles in the D dimensions, and $1 \leq i \leq m$.

The position of particle i (at the moment of k) is:

$$X_i = (X_{i1}, X_{i2}, \ldots, X_{iD}) \tag{15}$$

The velocity of particle i (at the moment of k) is:

$$V_i = (V_{i1}, V_{i2}, \ldots, V_{iD}) \tag{16}$$

The best position of particle i is:

$$P_i = (P_{i1}, P_{i2}, \ldots, P_{iD}) \tag{17}$$

Their own best positions of all the particles in the group are as follows.

$$P_g = (P_{g1}, P_{g2}, \ldots, P_{gD}) \tag{18}$$

The iterative formula of the position and velocity with the IPSO (usually the position and velocity of particle are all in real space) can be written as the following equations.

$$\begin{aligned} V_{iD}^{k+1} &= \omega V_{iD}^{k} + c_1 r_1 \left(P_{iD}^{k} - X_{iD}^{k}\right) + c_2 r_2 \left(P_{gD}^{k} - X_{iD}^{k}\right) \\ X_{iD}^{k+1} &= X_{iD}^{k} + \delta^{k+1} V_{iD}^{k+1} \\ \delta^{k+1} &= 0.95\delta^{k} \end{aligned} \tag{19}$$

where ω is inertial weight coefficient, and the value is less than 1; c_1, c_2 are learning factors and usually are positive number; r_1, r_2 are the random numbers obeying uniform distribution, and the range is $[0, 1]$, δ^1 is elastic variable, equal to 1.

According to Equation (19), the vector analytic space of improved particle swarm algorithm (IPSO) is shown as Figure 1. The current position of the particle is supposed as point A; the current velocity of the particle is vector a; vector b is the difference between the best position of one particle and current position of the particle, $P_{iD}^{k} - X_{iD}^{k}$. Vector c represents the difference between the best position of group particles and the current position of one particle, $P_{gD}^{k} - X_{iD}^{k}$, therefore, it can be deduced from Equation (17), and the next step position is the linear combination of vectors a, b and c.

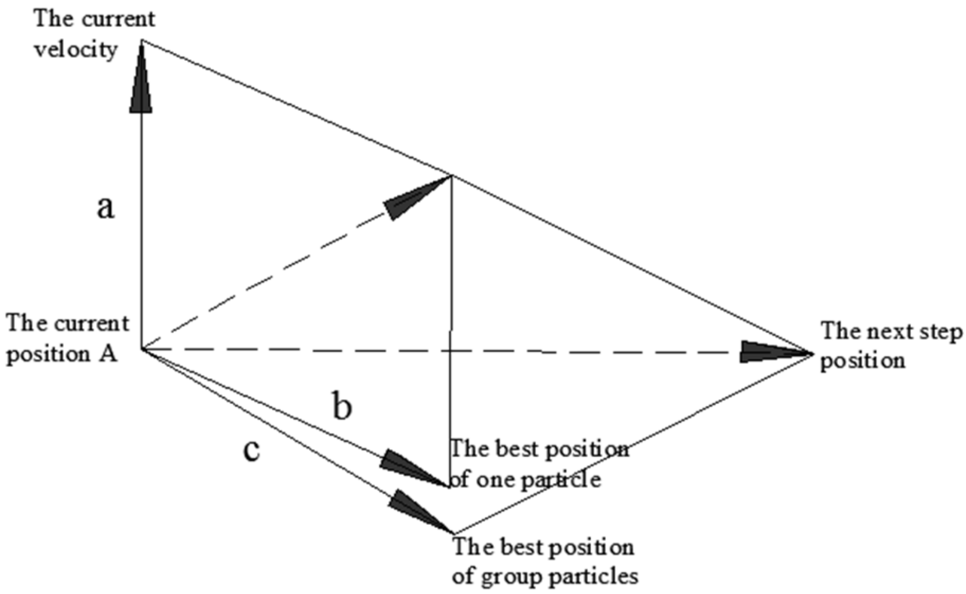


FIGURE 1. The vector construct of IPSO

4.2. **The convergence of improved particle swarm algorithm.** When judging the convergence of the improved particle swarm algorithm (IPSO), Equation (19) can be written as Equation (20)

$$\begin{aligned} X_{iD}^{k+1} = & \left(1 + 0.95\delta^k \omega - 0.95\delta^k c_1 r_1 - 0.95\delta^k c_2 r_2\right) X_{iD}^k \\ & - 0.95\delta^k \omega X_{iD}^{k-1} + 0.95\delta^k \left(c_1 r_1 P_{iD}^k + c_2 r_2 P_{gD}^k\right) \end{aligned} \tag{20}$$

where

$$\begin{aligned} & 0.95\delta^k \omega = \phi \\ & 0.95\delta^k c_1 r_1 = \phi_1 \\ & 0.95\delta^k c_2 r_2 = \phi_2 \end{aligned} \tag{21}$$

Thus,

$$X_{iD}^{k+1} = (1 + \phi - \phi_1 - \phi_2) X_{iD}^k - \phi X_{iD}^{k-1} + \phi_1 P_{iD}^k + \phi_2 P_{gD}^k \tag{22}$$

The equation also can be expressed in another way, as Equation (23) shows.

$$\begin{pmatrix} X_{iD}^{k+1} \\ X_{iD}^k \\ 1 \end{pmatrix} = \begin{pmatrix} 1 + \phi - \phi_1 - \phi_2 & -\phi & \phi_1 P_{iD}^k + \phi_2 P_{gD}^k \\ 1 & 0 & 0 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} X_{iD}^k \\ X_{iD}^{k-1} \\ 1 \end{pmatrix} \tag{23}$$

Equation (23) is transformed into $X^{k+1} = AX^k$.

[23] illustrated that in order to make the equation $X^{k+1} = AX^k$ be convergent, the equation should satisfy two necessary and sufficient conditions, as follows,

(1) Spectral radius $\rho(A) < 1$

(2) There is a matrix subordinate norm $\| \bullet \|$, and $\|A\| < 1$.

Therefore, by computing the characteristic polynomial of the matrix coefficient A, $(\lambda - 1)\left(\lambda^2 - (1 + \phi - \phi_1 - \phi_2)\lambda + \phi\right)$, and the characteristic roots are as follows.

$$\begin{aligned} & \lambda_1 = 1 \\ & \lambda_2 = \frac{1 + \phi - \phi_1 - \phi_2 - \gamma}{2} \\ & \lambda_3 = \frac{1 + \phi - \phi_1 - \phi_2 + \gamma}{2} \end{aligned} \tag{24}$$

where $\gamma = \sqrt{(1+\phi-\phi_1-\phi_2)^2-4\phi}$.

So if the characteristic roots satisfy the formula $\lambda_1\lambda_2\lambda_3 \leq 1$, the algorithm iterative direction will be convergent.

It can be assumed when the algorithm is closing to be convergent gradually, the present position X_{iD}^k approaches to the global best position X_{gD}^k infinitely. Therefore, Equation (23) can be deduced:

$$\begin{aligned} V_{iD}^{k+1} &= \omega \cdot 0.95\delta^k \cdot V_{iD}^k \\ X_{iD}^{k+1} &= X_{iD}^k + 0.95\delta^k\omega \cdot V_{iD}^k \end{aligned} \tag{25}$$

So the position updating formula can be obtained.

$$X_{iD}^{k+1} = \left(1+0.95\delta^k\omega\right)X_{iD}^k - 0.95\delta^k\omega X_{iD}^{k-1} \tag{26}$$

Equation (26) can be expressed as Equation (27) in another way.

$$\begin{pmatrix} X_{iD}^{k+1} \\ X_{iD}^k \end{pmatrix} = \begin{pmatrix} 1+\phi & -\phi \\ 1 & 0 \end{pmatrix}\begin{pmatrix} X_{iD}^k \\ X_{iD}^{k-1} \end{pmatrix} \tag{27}$$

So transforming Equation (27) to $X^{k+1} = BX^k$, the characteristic polynomial of matrix coefficient B is $\lambda(\lambda-1-\phi)+\phi$, and the characteristic roots are as Equation (28) shows.

$$\begin{aligned} \lambda_1 &= 1 \\ \lambda_2 &= \phi = 0.95\delta^k\omega \end{aligned} \tag{28}$$

Because the step factor δ and the weight factor ω are less than 1, the algorithm will be convergent to the global minimum finally.

4.3. **The parameters optimization of support vector machine.** Through continuous rotary electro-hydraulic servo motor experiment, the input signal and output oil pressure are collected. The oil source pressure is 12MPa, and the inertia load is 42.97kg·m^2. Selecting the sine swept signal as excitation signal, the input peak value of swept signal is 0.2°, the initial frequency is 0.2Hz, and the frequency of excitation signal increases 0.2Hz every 4 periods. Apply AK-4 pressure sensor to obtaining the inlet and outlet hydraulic pressure of continuous rotary motor.

Collecting 20000 sample data as the original data of SVR parameter identification, regression model of continuous rotary motor $\theta(u)$ is applied to taking the system identification as shown in Equation (14), and then Equation (29) is selected as the fitness function of the improved particle swarm optimizing support vector machine, where $\tilde{\theta}(u)$ is the experiment data. So the minimum value corresponds to the optimal SVR identification model, including the optimal kernel width σ and penalty coefficient C.

$$\min MSE = \frac{1}{n} \cdot \left|\theta(u) - \tilde{\theta}(u)\right|^2 \tag{29}$$

The optimal steps of the improved particle swarm optimization (IPSO) algorithm are shown as follows.

Step 1: Initialize the particle swarm whose scale is 100, and every particle is two-dimensional vector.

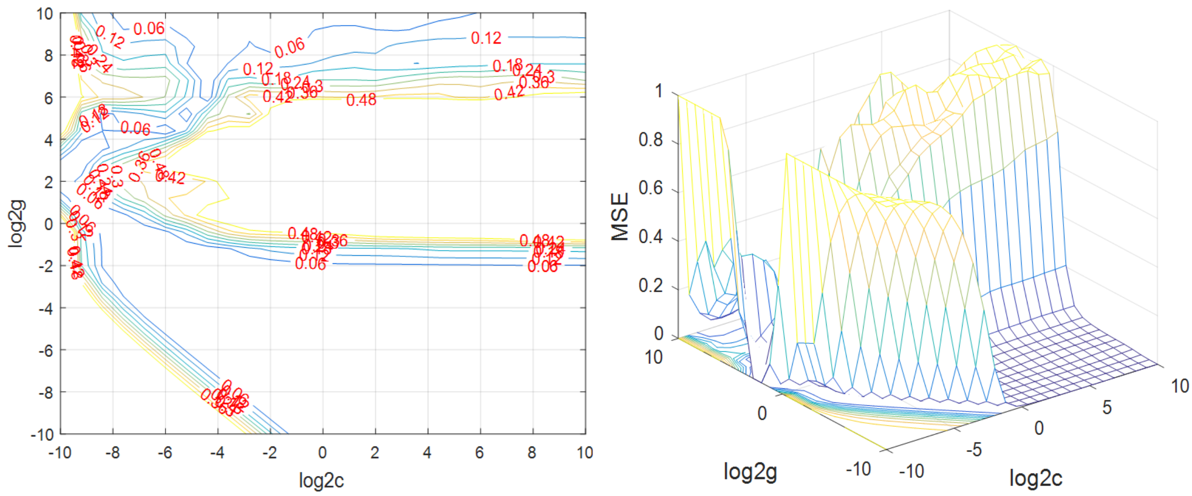
Step 2: Set up the initial position and velocity, then calculating the fitness value.

Step 3: Comparing the fitness value of one particle best position and the global best position, if the former is better than latter, regard it as the global best position.

Step 4: According to Equations (19) and (22), update the position and velocity.

Step 5: If the terminal condition is satisfied, the optimization is ended up, if not, back to Step 2.

The particle swarm's scale is 100 and the iterative number is 100 to optimize the kernel width σ and penalty coefficient C of the SVR model, and the value of fitness function is small and changes smoothly, as Figure 2 shows the variation trend of optimizing SVR model's parameters. Generally the learning factor is $c_1 = c_2 = 2$, and the insensitive loss parameter ε is 0.01. The initial velocity and position are randomly generated in the continuous function space.



(a) The contour map of parameters optimizing (b) The 3D map of parameters optimizing

FIGURE 2. The parameters optimizing of SVR

The kernel width σ and penalty coefficient C of SVR model can be obtained from Figure 2, by using the above optimized parameters and 20000 sample data to identify the identification model, and then the 4640 support vectors are generated. The result of optimizing is shown as Table 1.

TABLE 1. The parameters' optimization of SVR

Parameter	σ	C	MSE	The number of SVM
Optimizing result	1.3195	0.0029604	0.005779	4640

5. **Simulations.** In order to verify the validity of the identified nonlinear auto regression model in Chapter 4.3, it is necessary to sample a group of experiment data of continuous rotary motor. There are 50000 couples of experimental sample data including the input and output of system, and the first 20000 sample data is regarded as the training sample (output oil pressure of the front 40s) of SVR identification model, and the next 30000 as the testing sample (output oil pressure of the post 60s).

5.1. **SVM identification.** Figure 3 shows the experiment input signal of continuous rotary electro-hydraulic servo system, namely the swept signal. Figure 4(a) shows the comparison of the experimental output and training output in the process of training, the curve 1 is the experimental output, and the curve 2 is the training output of the identifying process. Figure 4(b) shows the testing output of the experimental output and identified model output in the course of testing.

It can be concluded that the identified model of continuous rotary motor has the higher fitting degree and better generalization ability from the comparison experimental output

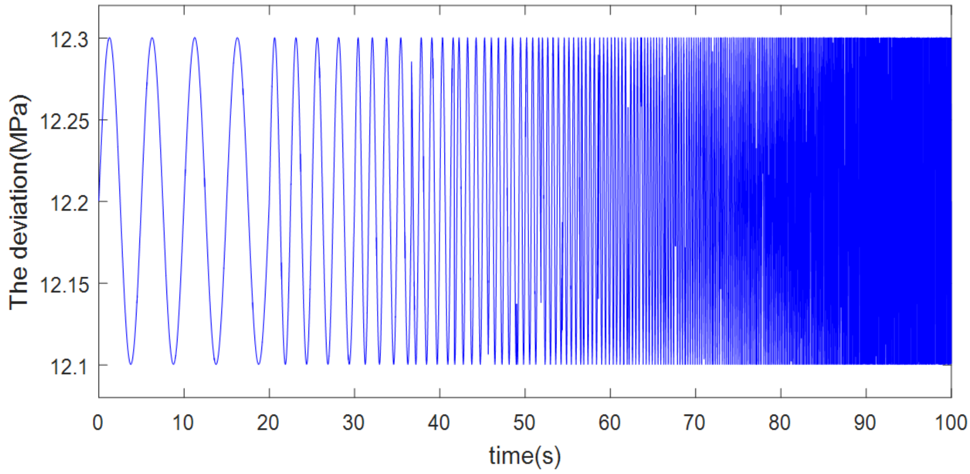
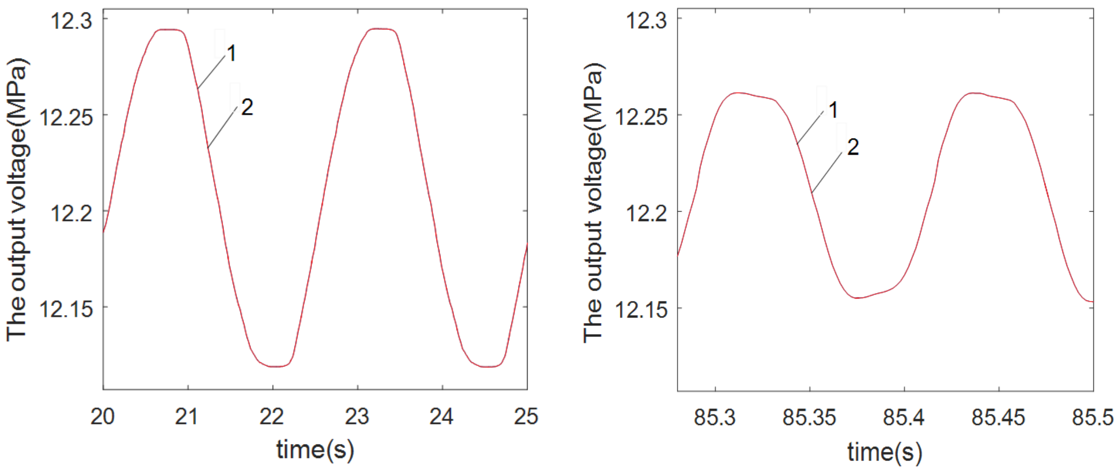


FIGURE 3. The experimental input signal



(a) The comparison of training (b) The comparison of testing

FIGURE 4. The identified output of SVR model

and the identified output under the circumstance of the training and testing of SVR identification model in Figure 4.

As Figure 5 shows that the identified model output of continuous rotary motor has the better ability to trace the experimental output.

As Figure 5 shows that, the solid curve is the identified model output within 100s and the dotted curve is the experimental output. It can be concluded from the simulation comparison that the identified model has a smaller error, which testifies the identified model has bigger fitting degree and ability of generalization. Figure 6 shows the error between identified and experimental output.

Figure 7(a) describes the local enlarged curve of identification in the course of training, and Figure 7(b) in the course of testing. And the curve 1 is the output of identification model, and the curve 2 is the experimental output.

As Figure 7 shows the identified model has a stronger ability to trace the experimental output, so it can simulate continuous rotary electro-hydraulic servo system greatly.

Table 2 demonstrates the identified models mean square error (MSE) and correlation coefficient under the circumstance of training and testing.

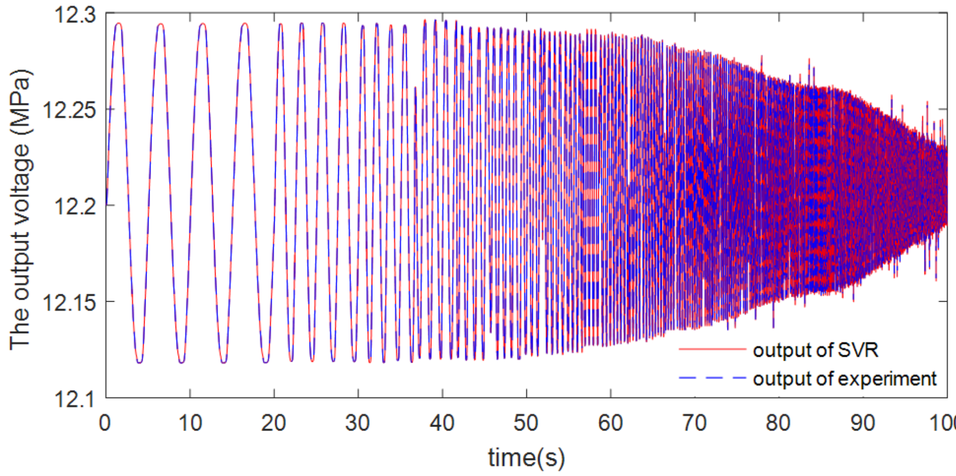


FIGURE 5. The identification output

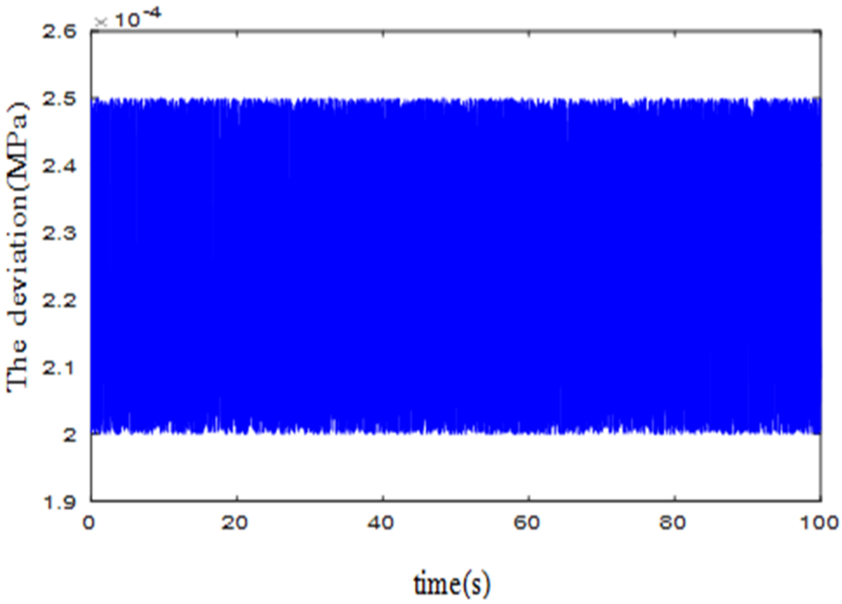
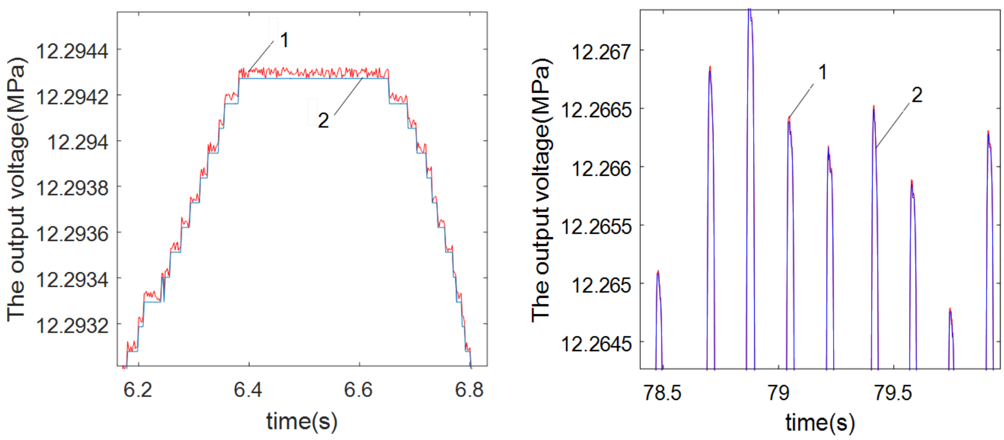


FIGURE 6. The identification error



(a) The local effect of tracing (b) The local effect of testing

FIGURE 7. The identified effect

TABLE 2. The identified result of SVR

Identified Type	Mean Square Error	Correlation Coefficient
Training Effect	0.00569502	0.959398
Testing Effect	0.00575504	0.958913
Identified Output	0.01145006	0.959156

5.2. **The identification of least squares.** In order to prove the identification effect of SVR has a better tracing ability, the least squares (LS) identification method is adopted to make a contrastive simulation. The nonlinear auto regression model of continuous rotary electro-hydraulic servo motor can be established by using the time-series analysis method so the real-time output of motor's model is determined by the past moment's input and output, so the output is defined as Equation (30).

$$y(k+2) = a_1 * y(k+1) + a_2 * y(k) + b_1 x(k+1) + b_2 x(k) + e(k) \tag{30}$$

In Equation (30), $y(k+2)$ is the identified output of least squares (LS) method at the moment of $k+2$, and $x(k)$ is the input at the moment of k, similarly $y(k+1)$, $y(k)$ and $x(k+1)$; $e(k)$ is the zero mean random error of identifying system and a_1, a_2, b_1, b_2 are the parameters of the least squares identified model.

The parameters of identifying model are obtained by using the data acquired from the continuous rotary motor experiment, and the identified result is shown in Table 3.

TABLE 3. The parameters of identified model

Parameters	a_1	a_2	b_1	b_2	MSE
The identified value	-1.55570561	0.57235483	-0.05541893	0.07207815	0.8912

Comparing the least squares identified model output with the experimental output, the mean square error (MSE) is 0.8912 that is bigger than MSE of the SVR identified model, so it can be concluded that the accuracy of SVR identified model is higher than the least squares (LS).

Figure 8 shows the contrastive effect of the least squares identification and the experimental output, where the solid curve is the experiment and the dotted curve is the output of least squares identification. Figure 9 describes the deviation between them, so it shows

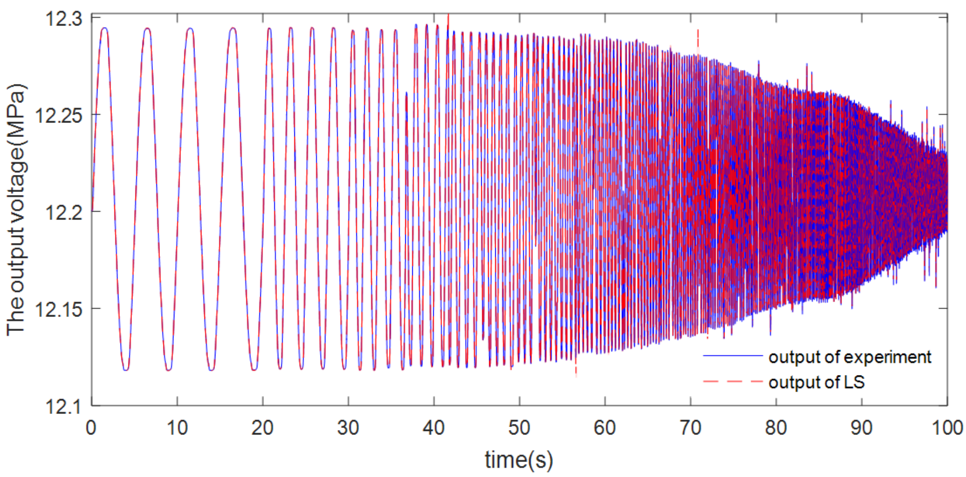


FIGURE 8. The output of LS identification

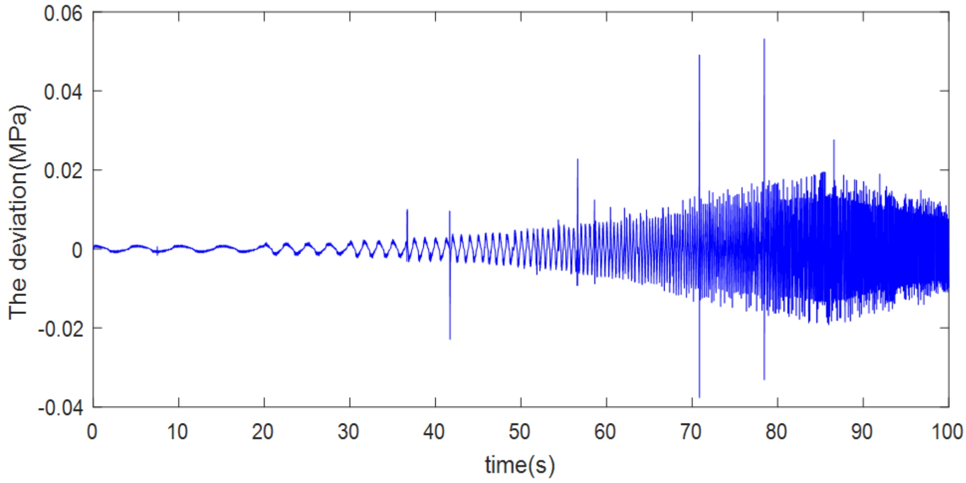
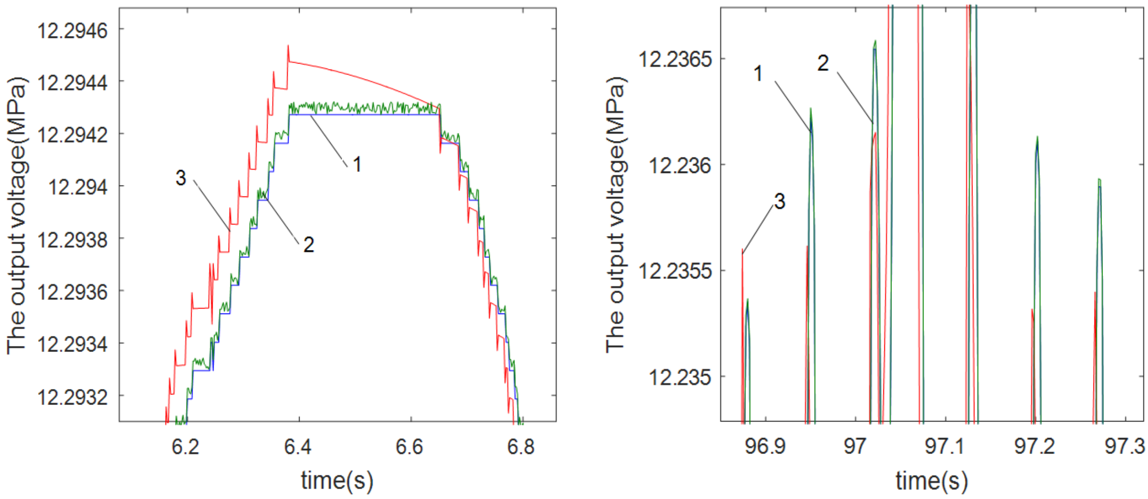


FIGURE 9. The error of LS identification



(a) The local contrastive effect of training (b) The local contrastive effect of testing

FIGURE 10. The contrastive effect of LS and SVR

that with the simulating going on, the error is bigger and bigger, and the identified effect is worse than the SVR identification model.

Figure 10 shows the local contrastive effect of the least squares (LS) and the SVR identification model, where the curve 1 is the experimental output, the curve 2 is the least squares model output and the curve 3 is the SVR identified output. So it can be concluded from Figure 10 the SVR model has higher accuracy and better identifying effect.

6. **Conclusions.** Due to the uncertainties and high nonlinearity caused by friction, leakage and other external factors existing in the flight simulator with continuous rotary electro-hydraulic servo motor, the nonlinear auto regression model of continuous rotary motor has been established, and the model identification method based on the improving particle swarm optimizing (IPSO) the parameters of support vector machine regression (SVR) model has been proposed. The optimized kernel width σ and penalty coefficient C of the support vector machine regression (SVR) model have been obtained by the improving particle swarm (IPSO) algorithm, and then the identification model of continuous

rotary electro-hydraulic servo motor is obtained by using the optimized SVR model, which effectively prevents SVR model from falling into the local optimal solution on parameters optimization. According to the simulation results, the correlation coefficient between the output of identification model and continuous rotary motor experimental output is 95.9%, which can prove that identification model is close to continuous rotary motor's actual model, that is, the identified model based on improved particle swarm optimizing support vector machine theory can overcome the weakness that the accurate mathematical model of system cannot be established due to the leakage, friction, noise and other uncertain factors in the process of building traditional mathematical model. Meanwhile the time series model with good fitting ability to continuous rotary motor is selected and the time series model's parameters are identified by least square (LS) method. By the comparative simulation, the results show that SVR identification method can approximate the complex nonlinear model greatly and has better identification effect than the least squares (LS).

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