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SHIP MANOEUVRING MODEL PARAMETER IDENTIFICATION USING INTELLIGENT MACHINE LEARNING METHOD AND THE BEETLE ANTENNAE SEARCH ALGORITHM

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ABSTRACT

In order to identify more accurately and efficiently the unknown parameters of a ship motions model, a novel Nonlinear Least Squares Support Vector Machine (NLSSVM) algorithm, whose penalty factor and Radial Basis Function (RBF) kernel parameters are optimised by the Beetle Antennae Search algorithm (BAS), is proposed and investigated. Aiming at validating the accuracy and applicability of the proposed method, the method is employed to identify the linear and nonlinear parameters of the first-order nonlinear Nomoto model with training samples from numerical simulation and experimental data. Subsequently, the identified parameters are applied in predicting the ship motion. The predicted results illustrate that the new NLSSVM-BAS algorithm can be applied in identifying ship motion's model, and the effectiveness is verified. Compared among traditional identification approaches with the proposed method, the results display that the accuracy is improved. Moreover, the robust and stability of the NLSSVM-BAS are verified by adding noise in the training sample data.

Keywords: ship motions model; NLSSVM; BAS; parameter identification

1 INTRODUCTION

The mathematical manoeuvring model of a ship has a major influence on simulating the ship's motions and designing the ship's course controllers [1]. The ship response model, as a critical branch of the ship manoeuvring mathematical models, has been one of the most common models for assessing the ship's manoeuvreability and designing ship's motion controllers due to its simple structure and high accuracy [2]. For this purpose, an accurate identification of the ship motion model's linear and nonlinear parameters has become the key research issue in the fields of system identification and simulation [3].

Traditionally, common approaches including the least squares method (LS) [4], the maximum likelihood method (ML) [5], and the extended Kalman filter method (EKF) [6], have been successfully applied to identify the model parameters. Some disadvantages such as parameters drift, dependency on initial state, and ill-conditioned solutions are exposed in the conventional approaches. Then, the intelligent parameter estimation approaches such as the neural network (NN) method [7], are developed and considered to provide better results. The NN algorithm is able to achieve satisfactory performance for the black box identification, but the model needs to be trained with large sample data and long calculation time.

Therefore, this paper proposes a novel Nonlinear Least Squares Support Vector Machine (NLSSVM) algorithm to solve the problems of identifying the ship's motion models. Compared with the traditional and intelligent techniques using large sample data, the NLSSVM only depends on limited support vectors based on small samples. Moreover, the structure risk minimization theory instead of empirical risk

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minimization is adopted by NLSSVM to solve optimization problems. A global optimization result is obtained, and local optimization issues are avoided. In addition, to obtain the optimal penalty factor and RBF kernel parameters of the NLSSVM model, a new method based on the Beetle Antennae Search (BAS) algorithm is firstly investigated [8]. The BAS algorithm, due to simple structure and excellent optimization ability, can perform more accurately and faster to obtain the optimal parameters compared to other optimization approaches such as particle swarm optimization (PSO) method [9].

Based on the above analysis, the proposed NLSSVM-BAS is utilized to identify the ship motion model. Firstly, numerical simulation data and experimental data from 20-20 zigzag tests in a towing tank (SIMMAN 2014) are collected for parameter identification. Then, the optimized NLSSVM model by the BAS algorithm is applied to identify the linear and nonlinear parameters for the ship response model. Finally, the accuracy and validity of the NLSSVM-BAS are investigated by comparing the original data with predicted data.

2 NONLINEAR SHIP RESPONSE MODEL

To simplify the ship manoeuvring mathematical model, the forward speed $\boldsymbol{u}$ is assumed constant [10]. Thus, The steering mathematical model, accounting only for the sway and the yaw motions, is written as:

$$M\dot{v} + N(u)v = B\delta \tag{1}$$

where

$$M = \begin{bmatrix} m - Y_{\dot{v}} & mx_g - Y_{\dot{r}} \\ mx_G - N_{\dot{v}} & I_z - N_{\dot{r}} \end{bmatrix} \tag{2}$$

$$v = [v\ r]^T \tag{3}$$

$$N(u) = \begin{bmatrix} -Y_v & mu_0 - Y_r \\ -N_v & mx_g u_0 - N_r \end{bmatrix} \tag{4}$$

$$B = \begin{bmatrix} Y_\delta \\ N_\delta \end{bmatrix} \tag{5}$$

where m is the mass of ship, $Y_{\dot{v}}, Y_v, N_v$ are the hydrodynamic coefficients, u_0 is the surge speed, δ is the rudder angle, x_g is the coordinate of the center of gravity.

In the present paper only the yaw motion is considered and the manoeuvring model can be expressed as a first-order linear Nomoto model :

$$T\dot{r} + r = K\delta \tag{6}$$

with T the time constant and K the gain [10]. Including a static nonlinearity in the first-order linear Nomoto model, the following nonlinear form is obtained [11]:

$$T\dot{r} + r + ar^3 = K\delta \tag{7}$$

where a is the nonlinear constant.

3 PARAMETER ESTIMATION APPROACHES

3.1 Problem statement

Assuming that a parametric system in state-form is available as follows:

$$\frac{dX}{dt} = g(X, T, \theta) \tag{8}$$

where $X = [x_1, x_2, \dots, x_i]^T$ is the state variable, $\frac{dX}{dt} = \left[\frac{d}{dt}x_1, \frac{d}{dt}x_2, \dots, \frac{d}{dt}x_i\right]^T$ is the derivatives of the each state variable, $T = [t_1, t_2, \dots, t_i]^T$ is the time variable, $\theta = [\theta_1, \theta_2, \dots, \theta_i]^T$ is an unknown set of parameters.

For the parametric system, the main goal is to identify the unknown parameters θ from observed data $Y = [y_1, y_2, \dots, y_i]^T$ at time variable $T = [t_1, t_2, \dots, t_i]^T$.

$$e_i = Y(t_i) - X(t_i), i = 1,2 \cdots n \tag{9}$$

where $e_i = [e_1, e_2, \dots, e_i]^T$ is error between observed data Y and outputs of the estimate state variable X. The final goal is shifted to get the set of unknown parameters by minimizing the error e_i.

3.2 Identification procedure

Step 1: Obtain sample data

Obtain training samples data$\{(t_i, y_i), i = 1,2, \dots, n\}$, where t_i is the time series, and y_i is the numerical simulation data or experimental data [11].

Step 2: Approximate the state variable

Estimate the state variable $\hat{X} = [\hat{x}_1, \hat{x}_2, \dots, \hat{x}_i]^T$ based on numerical simulation or experimental data $\{(t_i, y_i), i = 1,2, \cdots n\}$. In the present study [12], the NLSSVM is adopted to approximate the state variable $\hat{X}$. For x_k of *k*-th state variable, which can be obtained by an approximation function in the form of:

$$\hat{x}_k(t) = w_k^T \varphi(t) + b_k \tag{10}$$

where t is the input data (time), $\hat{x}_k$ is the output data, w is the weights value, $\varphi(\cdot)$ is the nonlinear function, which maps the input data t to the Euclidean space, b_k is the bias [5].

To solve the convex optimization issue according to the minimization of structure risk theory, construct and solve the following cost function:

$$\min_{w,b,e} f(w, e) = \frac{1}{2} w^T w + \frac{1}{2}\gamma \|e_i\|_2^2 \tag{11}$$

subject to:

$$y_i = w^T \varphi(t_i) + b + e_i \tag{12}$$

where $i = 1,2, \cdots, \text{n}$, γ is penalty factor, e is the error.

The Lagrangian function is introduced to solve the optimization problem as follows:

$$\mathrm{L}(w,b,e,a) = \frac{1}{2}w^T w + \frac{1}{2}\gamma\|e_i\|_2^2 - \sum_{i=1}^{n} a_i[w^T\varphi(t_i) + b + e_i - y_i] \quad (13)$$

where the coefficients a_i are the Lagrange multipliers. The derivative matrix is obtained by partially differentiating Eq.(13) with respect to w, b, e, a:

$$\begin{bmatrix} K+\gamma^{-1}I_N & 1_N \\ 1_N^T & 0 \end{bmatrix}\begin{bmatrix} a^k \\ b^k \end{bmatrix} = \begin{bmatrix} y^k \\ 0 \end{bmatrix} \quad (14)$$

where $K(t_i,t_j) = \varphi(t_i)\varphi(t_j)$ is the kernel function, I_N is the identity matrix, $1_N = [1;1;\ldots;1]$, $\alpha^k = [a_1^k; a_2^k; \ldots; a_n^k]$.

The regression model is expressed as:

$$\hat{x}_k(t) = w_k^T\varphi(t) + b_k = \sum_{i=1}^{n}\alpha_i^k K(t_i,t) + b_k \quad (15)$$

Step 3: Approximate the derivative of state variables

Approximate the derivative of the state variable $\frac{d}{dt}\hat{X} = \left[\frac{d}{dt}\hat{x}_1, \frac{d}{dt}\hat{x}_2, \ldots, \frac{d}{dt}\hat{x}_n\right]$ by differentiating the approximated model with time [13].

Differentiate $\hat{x}_k(t)$ with respect to time, which yields:

$$\frac{d}{dt}\hat{x}_k(t) = w_k^T\dot{\varphi}(t) = \sum_{i=1}^{n}\alpha_i^k\ \varphi(t_i)^T\dot{\varphi}(t) \quad (16)$$

According to the Mercer Theorem [14], the derivatives of the kernel equal the derivatives of the feature map. Therefore, the derivatives of the kernel can be obtained as:

$$K_1(t_i,t) = \frac{\partial K(t_i,t)}{\partial t} = \varphi(t_i)^T\dot{\varphi}(t) \quad (17)$$

$$\frac{d}{dt}\hat{x}_k(t) = \sum_{i=1}^{n}\alpha_i^k K_1(t_i,t) \quad (18)$$

Step 4: Identification of unknown parameters, and model's prediction

$\hat{x}_k(t)$ and $\frac{d}{dt}\hat{x}_k(t)$ in Eq. (15) and Eq. (18) are the approximated values of the k-th state variable and its derivative. All the state variables $\hat{X}$ and their derivatives $\frac{d}{dt}\hat{X}$ can be obtained by using the above same procedure based on the NLS-SVM. After substituting $\hat{X}$ and $\frac{d}{dt}\hat{X}$ in the parameter system Eq. (8), the linear and nonlinear algebraic equations with unknown parameters are constructed.

Finally, unknown parameters can be obtained by solving the optimization problem:

$$\min_{\theta}\frac{1}{2}\sum_i^n\|e_i\|_2^2 \quad (19)$$

subject to:

$$e_i = \frac{d}{dt}\hat{X}(t_i) - g(\hat{X}(t_i), T, \theta), i = 1,2,\cdots n \quad (20)$$

3.3 BAS optimised NLSSVM algorithm

The BAS optimisation method is an efficient meta-heuristic optimisation algorithm which is similar to other intelligent optimisation algorithms such as Particle Swarm Optimisation (PSO) approach. The BAS algorithm, however, compared with other intelligent optimisation algorithms has some advantages such as: simpler structure, shorter computational time and superior optimisation ability with higher accuracy. Therefore, the BAS optimisation algorithm, as a recently proposed approach, is selected and applied to optimise the penalty parameter γ (see Eq. (11)) of the NLSSVM model as well as its kernel parameter σ.

In order to obtain optimal values for the penalty factor γ and the RBF kernel parameter σ in the NLSSVM model, an objective function is firstly defined as:

$$f(\mathrm{x}^t) = RMSE(r_{error}) \quad (21)$$

where $\mathrm{x}^t = [\gamma^t; \sigma^t]$ is the position matrix of the beetle at each penalty factor γ^t and RBF kernel parameter σ^t, the r_{error} is the error of the ship's yaw rate. The $f(\mathrm{x}^t)$ is the concentration of odor (fitness function), which is defined as the Root-Mean-Square Error (RMSE) of the ship yaw rate.

The goal is to obtain optimal penalty factor γ and RBF kernel parameter σ by minimizing RMSE (f_{best}) when $x_{best} = [\gamma_{best}; \sigma_{best}]$ is selected in the following form:

$$f_{best}(x_{best}) = \min RMSE(r_{error}) \quad (22)$$

When employing the BAS algorithm to optimise the NLSSVM model parameters, two different processes are defined: a). the parameters searching, and b). the parameters detecting according to the value of the fitness function. These steps are described in more detail in the following subsections (FIGURE 1).

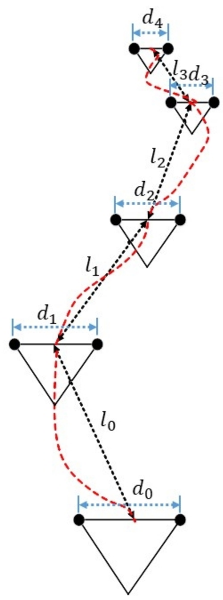


FIGURE 1 OPTIMISED PROCEDURES OF THE BAS ALGORITHM.

Firstly, Parameters searching

In the first process, the BAS algorithm parameters including the beetle's initial position $x_0 = [\gamma_0; \sigma_0]$, the distance between two antennae d_0 and the initial step length l_0 are initialized. At the beginning, a randomly generated initial position x_0 is regarded as the best position x_{best}, which is used to calculate the best fitness f_{best}. Additionally, the searching direction of the beetle is assumed to be random and expressed as:

$$\overrightarrow{Dir} = \frac{rands(n,1)}{\|rands(n,1)\|} \tag{23}$$

where $\overrightarrow{Dir}$ is the random searching direction, $rand(\cdot)$ represents the random function, and n denotes searching space dimensions.

Subsequently, the left antennae and the right antennae coordinates of the beetle are defined as x_l and x_r respectively. x^t is assigned as the beetle's centroid coordinate at time t. Then two antennae coordinates are calculated by the form of:

$$x_l = x^t + d^t\overrightarrow{Dir} \tag{24}$$

$$x_r = x^t - d^t\overrightarrow{Dir} \tag{25}$$

where d is the distance between two antennae corresponding to searching ability, whose value should be large enough to avoid local minimum values [15]. Then, the left and right antennae coordinates x_l and x_r are substituted in the fitness function as follows:

$$f_l = f(x_l) = RMSE_l(r_{error}) \tag{26}$$

$$f_r = f(x_r) = RMSE_r(r_{error}) \tag{27}$$

Secondly, Parameters detecting

In this part of the analysis, after the beetle searching parameters, the parameters detecting behaviour is formulated by setting an iterative system.

If $f_l \leq f_r$, the beetle will search toward the left direction with the step length l. The beetle's centroid coordinate is updated at time t as:

$$x^t = x^{t-1} + l^t\overrightarrow{Dir_l} \tag{28}$$

If $f_l \geq f_r$, the beetle will search toward the right direction with the step length l. The beetle's centroid coordinate is updated at time t as:

$$x^t = x^{t-1} - l^t\overrightarrow{Dir_r} \tag{29}$$

Therefore, according to the iterative model, the state variables (see Eq. 28 and 29) are rewritten as:

$$x^t = x^{t-1} + l^t\overrightarrow{Dir}\,\mathrm{sign}\big(f(x_l) - f(x_r)\big) \tag{30}$$

where $\mathrm{sign}(\cdot)$ is the sign function.

After the state variable x^t is updated, the fitness value $f(x^t)$ at time t is obtained. $f(x^t)$ is then compared with the memorized $f_{best}(x_{best})$ to update the best state variable x_{best} and minimum fitness value f_{best}.

$$\begin{cases} f_{best} = f(x^t) \\ x_{best} = x^t \end{cases}, f_{best} \geq f(x^t) \tag{31}$$

It is worth mentioning that the update rules of the searching parameters d and l have the following form:

$$l^t = c_1 l^{t-1} + l_0 \tag{32}$$

$$d^t = l^t / c_2 \tag{33}$$

where c_1 and c_2 are constants.

Finally, circularly parameters searching and parameters detecting processes are executed until ending iterations with minimum RMSE.

4 PARAMETER IDENTIFICATION

In this section, the novel NLSSVM-BAS approach is applied to identify the nonlinear ship response model. The identification processes are described in more detail in FIGURE 2 and TABLE 1.

TABLE 1 IDENTIFICATION PROCEDURES OF THE NLSSVM-BAS METHOD

NLSSVM model optimised by BAS algorithm
Input: Construct objective function, $f_{best}(x_{best}) = \min RMSE(r_{error})$; Initialize model's parameters $x_0 = [\gamma_0; \sigma_0]$, d_0 and l_0; Calculate initial fitness value $f(x_0)$, which is firstly stored as f_{best} at $x_{best} = x_0$;
For i=1:n (**Iterative mechanism**)
1. Randomly generate searching direction $\overrightarrow{Dir}$ according to Eq.(23);
2. Calculate the left antennae and right antennae coordinates x_l and x_r according to Eq.(24) and Eq.(25);
3. Calculate and compare $f(x_l)$ and $f(x_r)$ to update state variable x^t according to Eq.(26) and Eq.(27);
4. Calculate and compare $f(x^t)$ and f_{best} to update x_{best} and f_{best} according to Eq.(31);
5. Update rules of searching parameters d and l according to Eq.(32) and Eq.(33);
6. Execute parameters searching and parameters detecting procedures circularly
end
Output: $x_{best} = [\gamma_{best}; \sigma_{best}]$ and f_{best}.
Optimise NLSSVM model parameters

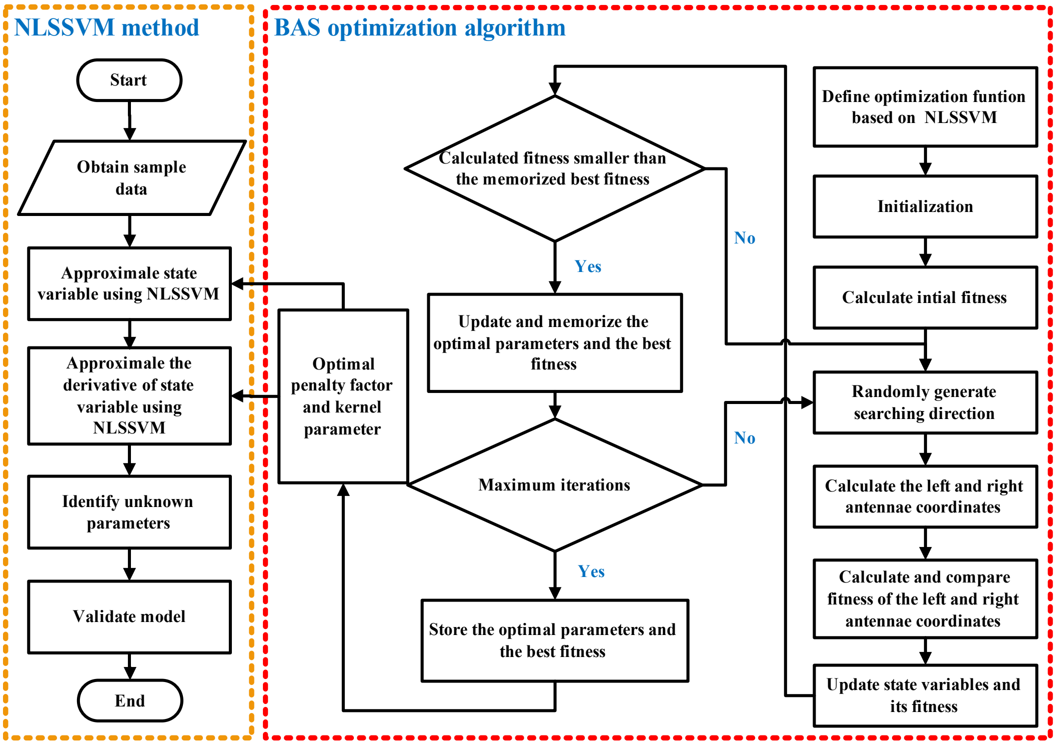


FIGURE 2 NLSSVM IDENTIFICATION MODEL OPTIMISED BY BAS ALGORITHM.

Aiming at verifying accuracy and applicability of the NLSSVM-BAS algorithm. Four case studies are carried out as follows:

Case1 Obtain optimal parameters of the NLSSVM model using the BAS method (4.1).

Case2 Investigate the effectiveness and accuracy of the NLSSVM-BAS model (4.2).

Case3 Analyse the characteristics of the NLSSVM-BAS model (4.3).

Case4 Study the robustness and stability of the proposed model (4.4).

4.1 BAS optimisation algorithm

In this section, the BAS optimisation algorithm is adopted to search for the optimal penalty factor and kernel parameter of the NLSSVM model. In the optimisation process, the RMSE of the ship yaw rate is assigned as the objective function. Then, global optimal parameters are found by the BAS optimisation algorithm [16].

FIGURE 3 and FIGURE 4 present the optimisation trajectories of the beetle searching in two-dimensional (2D) and three-dimensional (3D) space. It can be seen that the beetle gradually moves to the optimal parameters point and quickly converges to the optimal value. Moreover, the convergence curve is found in FIGURE 5, it can be seen that the convergence rate of the fitness (objective function) is very fast, and the minimum value of the objective function is obtained after around 40 iterations. The optimisation results illustrate that the BAS algorithm has excellent optimisation ability and can quickly provide optimal parameters for the NLSSVM model.

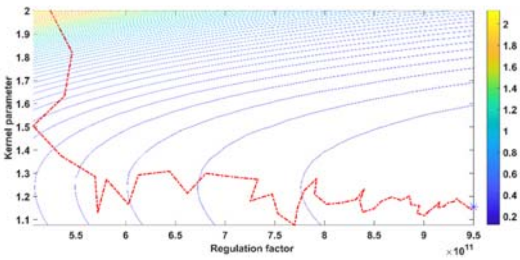


FIGURE 3 OPTIMISATION TRAJECTORIES OF THE BEETLE SEARCHING IN 2D SPACE.

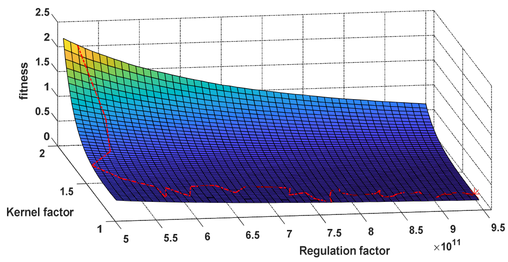


FIGURE 4 OPTIMISATION TRAJECTORIES OF THE BEETLE SEARCHING IN 3D SPACE.

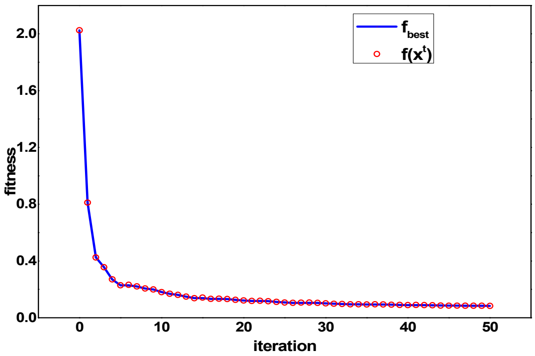


FIGURE 5 CONVERGENCE CURVE OF PARAMETRIC OPTIMISATION.

4.2 Effectiveness and accuracy of NLSSVM-BAS model

In this section, the first-order nonlinear Nomoto model Eq. (7) is selected as a case study. The validation process in detail is as follow:

The first step is to generate sample data and identify unknown parameters. The three parameters of the first-order nonlinear Nomoto model including time constant (T), gain (K) and nonlinear constant (a) are pre-defined as the known values. Then, a fourth-order Runge-Kutta algorithm is used to solve the Nomoto mathematical model, and training sample data are obtained. Subsequently, the NLSSVM-BAS is employed to identify the parameters of the Nomoto model. The results are displayed in TABLE 2. By comparing the pre-defined parameters with the identified parameters, small errors are observed with values of 0.6% for the time constant T, 0.1% for the gain K and 1.1% for the nonlinear constant a. It means that the proposed approach can successfully identify the nonlinear Nomoto model with high accuracy.

TABLE 2 PRE-DEFINED PARAMETERS AND IDENTIFIED PARAMETERS USING THE NLSSVM-BAS MODEL

Parameters	Known	Identified	Error (%)
T (s)	66.0	66.38	0.6
K (1/s)	0.10	0.10	0.1
a (s^2/deg^2)	1.00	0.99	1.1

Furthermore, for a better idea of the importance of the method, the identified parameters are applied to predict the ship yaw rates (FIGURE 6). It is easily seen that the predicted values of the ship yaw rate agree well with the actual values with only small deviations. It is worth noting that the maximum error between predicted data and actual data is around 0.01 °/s, which illustrates that the predicted results well match with the simulation results with high precision.

After qualitative and quantitative analysis, the effectiveness and accuracy of the NLSSVM-BAS model in identifying the ship response model are verified.

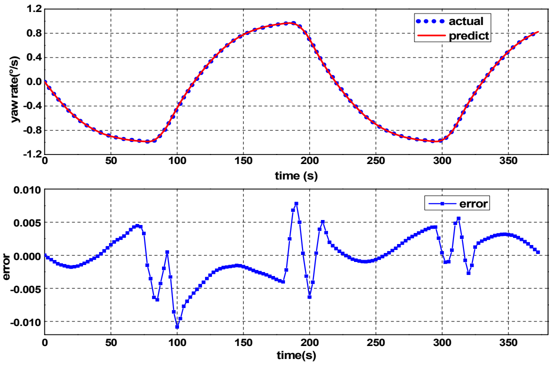


FIGURE 6 PREDICTED RESULTS AND ERRORS WITH PRE-DEFINED PARAMETERS USING SIMULATION DATA.

4.3 Comparison among different optimisation approaches

The aim of this section is to study the characteristics of the NLSSVM-BAS model by comparing the NLSSVM model optimised by other techniques such as CV (Cross Validation) and PSO [17]. The sample data are obtained from 20-20 zigzag tests on the 1/37.89 scale model of the KRISO Container Ship (KCS) in the MARIN towing tank (252 x 10.5 x 5.5 m, SIMMAN 2014) [18]. The main dimensions of the KCS are presented in TABLE 3.

TABLE 3 THE MAIN DIMENSIONS OF KCS SHIP MODEL

Parameters	Value
Length perpendiculars L_{pp}(m)	6.070
Breadth B_{wl} (m)	0.850
Draft D (m)	0.502
Displacement ∇ (m^3)	0.957
Block coefficient C_b	0.651

After setting the same simulation parameters and conditions of the NLSSVM model, three intelligent algorithms are adopted to optimise the parameters of the NLSSVM model, and their performances are compared and described in detail as follows:

For quantitative analysis, two characteristic indexes including the CPU time and the Root-Mean-Square Error (RMSE) of the ship yaw rate are selected for comparisons. The results including estimated parameters, the RMSE, the CPU time by three different optimised algorithms are listed in TABLE 4. From the TABLE 4, it can be found that there are similar results among the three optimisation methods, but there are differences for the estimated parameters and two characteristic indexes (RMSE and CPU time). Compared with other optimisation approaches, the BAS algorithm has the smallest RMSE (0.061°/s) and the shortest CPU time (6.2 s), which means the proposed model outperforms the other two algorithms.

TABLE 4 COMPARISON RESULTS AMONG DIFFERENT OPTIMISATION METHODS.

Parameters	CV	BAS	PSO
T (s)	61.75	62.38	62.27
K ($1/s$)	0.113	0.114	0.114
a (s^2/deg^2)	0.719	0.725	0.713
RMSE (°/s)	0.064	0.061	0.063
CPU Time (s)	7.5	6.2	15.4

For qualitative analysis, the identified parameters by the three methods are applied in predicting the ship yaw rates. The predicted results are showed in FIGURE 7. On one hand, the three identification algorithms perform similarly with small derivations compared to the measured data (red colour), but not significant. On the other hand, comparing the partial enlargement of the BAS, CV and PSO optimisation algorithms in FIGURE 7, it can be seen that the curve predicted by the BAS method (blue colour) is closer to the actual data curve compared to the CV and the PSO approaches.

Moreover, errors at each predicted points of three approaches are presented in FIGURE 8. Overall the trend of errors in the BAS algorithm is the lowest, and the maximum error of the BAS method is the smallest. As seen, the error curves illustrate that the NLSSVM model optimised by the BAS algorithm performs better than the other two approaches.

To summarize, the advantages of the NLSSVM-BAS approach are illustrated in detail by comparison with other optimisation methods.

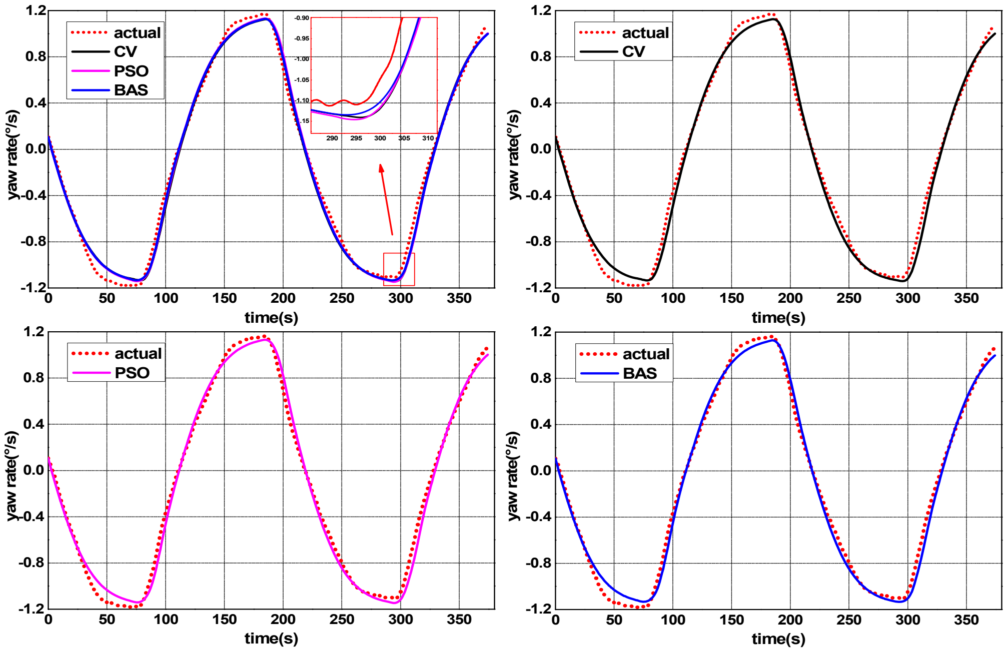


FIGURE 7 PREDICTED RESULTS OF THE NLSSVM MODEL OPTIMISED BY THE BAS, CV AND PSO.

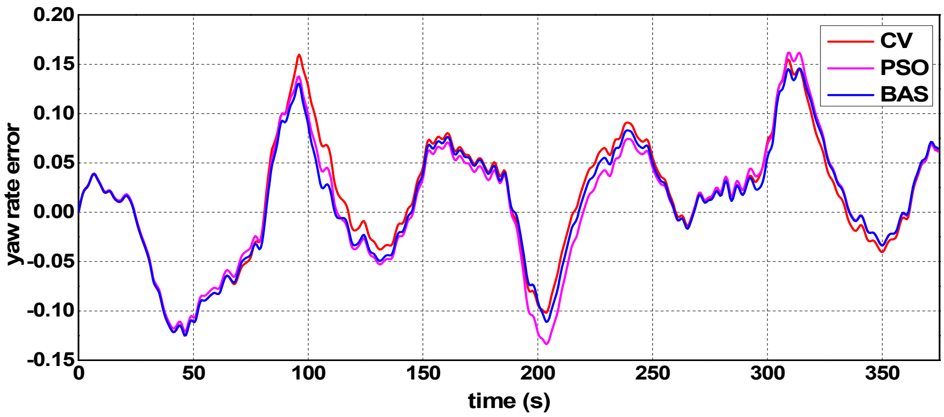


FIGURE 8 ERRORS OF THE NLSSVM MODEL OPTIMISED BY THE BAS, CV AND PSO.

TABLE 5 COMPARISON AMONG IDENTIFICATION RESULTS BY BAS METHOD AFTER ADDING DIFFERENT GAUSSIAN WHITE NOISES.

	T (*s*)			K (1/s)			a (s²/deg²)		
Noise	True	Estimate	Error (%)	True	Estimate	Error (%)	True	Estimate	Error (%)
0.000	66.00	66.38	0.57	0.10	0.10	0.10	1.00	0.99	1.13
0.001	66.00	66.54	0.82	0.10	0.10	0.35	1.00	0.98	1.63
0.003	66.00	66.62	0.94	0.10	0.10	0.58	1.00	0.98	1.85

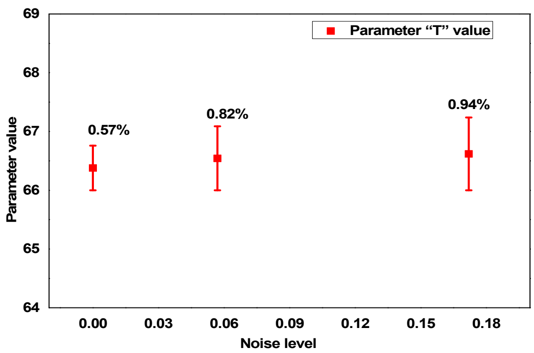
4.4 Robustness and stability analysis

In order to analyse the robustness and stability of the proposed model. Gaussian white noises are added in the original sample data. The noise level is defined as standard deviation of noises ranging from 0.057 °/s to 0.172 °/s.

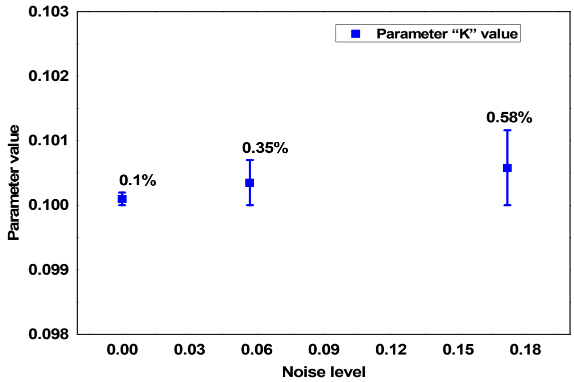
The identification results for different parameters and their relative errors in different noise levels are displayed in TABLE 5. To better illustrate the stability of the model, the comparison results are plotted in FIGURE 9(a), 9(b) and 9(c). From results in TABLE 5, the errors between pre-defined parameters and estimated parameters for the time constant T, gain constant K and nonlinear constant increase gradually with noise level rising. The relative errors get bigger as well.

Take time constant T as an example. The identified parameter value is around 66.38 s and its relative error is about 0.57% when there is no Gaussian white noise in the original sample data. Then, add Gaussian white noise with the levels of 0.057 °/s and 0.172 °/s to the sample data, the relative errors increase to around 0.82% and 0.94% respectively, and the identified parameters with small deviations, but not significant. Small errors mean that the identification results can be accepted and used to predict.

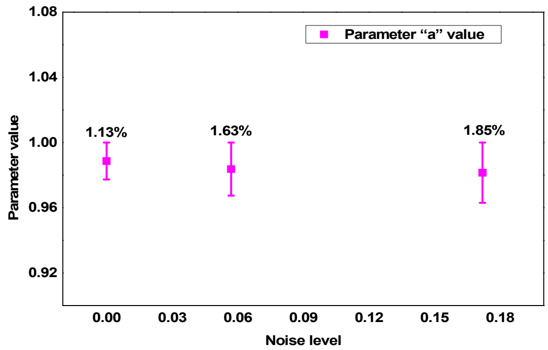
In conclusion, the proposed NLSSVM-BAS model can accurately identify model parameters with small Gaussian white noise. The robustness and stability of the proposed model are verified.



(a) TIME CONSTANT "T" AND ITS RELATIVE ERRORS.



(b) GAIN "K" AND ITS RELATIVE ERRORS.



(c) NONLINEAR CONSTANT "A" AND ITS RELATIVE ERRORS.

FIGURE 9 IDENTIFICATION RESULTS FOR DIFFERENT PARAMETERS AND THEIR RELATIVE ERRORS IN DIFFERENT NOISE LEVELS.

5 CONCLUSIONS

In this paper, a new NLSSVM-BAS method is proposed to improve the performance of parameters identification in the field of the ship motions model. Numerical simulation data and experimental data are used to identify the model and to predict the ship yaw motions. The comparison of the results demonstrates that the proposed model presents better performance. Compared the numerical simulation data with the predicted data by identified model, the good agreement and the high accuracy are observed, which illustrate that the developed model can be applied in estimating parameters of the ship motions model. Meanwhile, compared with CV and PSO, the NLSSVM approach, optimised by the BAS algorithm, outperforms and can improve the accuracy of parametric identification. In addition, comparisons among identified results disturbed by various Gaussian white noises, the stability and robustness are verified.

Future research will concentrate on developing the adaptive BAS optimisation algorithm to further enhance the performance of the NLSSVM model; besides, applying the identified ship motions model in a ship control system is another potential research direction.

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REFERENCES

[1] H. T. Xu, M. A. Hinostroza, and C. Guedes Soares, “Estimation of Hydrodynamic Coefficients of a Nonlinear Manoeuvring Mathematical Model with Free-Running Ship Model Tests,” *Int. J. Marit. Eng.*, vol. 160, no. A3, pp. 213–226, 2018.

[2] F. Xu, T. Xiao, X. Xing, and Z. Liu, “Identification of Nomoto models with integral sample structure for identification,” in *Proceedings of the 33rd Chinese Control Conference*, 2014, pp. 6721–6725.

[3] X. K. Zhang, Q. Zhang, H. X. Ren, and G. P. Yang, “Linear reduction of backstepping algorithm based on nonlinear decoration for ship course-keeping control system,” *Ocean Eng.*, vol. 147, pp. 1–8, 2018.

[4] T. W. Liu, H. B. Wang, Y. Dang, and S. R. Yang, “A Ships Parameter Identification Arithmetic Based on Improved Ant Colony Algorithm,” *Appl. Mech. Mater.*, vol. 347–350, no. 1662–7482, pp. 3450–3455, 2013.

[5] C. Jian *et al.*, “Parametric estimation of ship maneuvering motion with integral sample structure for identification,” *Appl. Ocean Res.*, vol. 52, pp. 212–221, 2015.

[6] L. P. Perera, P. Oliveira, and C. Guedes Soares, “System Identification of Nonlinear Vessel Steering,” *J. Offshore Mech. Arct. Eng.*, vol. 137, no. 3, pp. 1–7, 2015.

[7] G. Rajesh, G. G. Rajasekhar, and S. K. Bhattacharyya, “System Identification for Nonlinear Maneuvering of Ships Using Neural Network,” *J. Sh. Res.*, vol. 54, no. 1, pp. 1–14, 2010.

[8] X. Jiang and S. Li, “BAS: Beetle Antennae Search Algorithm for Optimization Problems,” *Int. J. Robot. Control*, vol. 1, no. 1, pp. 1–5, 2018.

[9] M. Tomera, “Swarm intelligence applied to identification of nonlinear ship steering model,” in *2nd IEEE International Conference on Cybernetics (CYBCONF 2015)*, 2015, pp. 133–139.

[10] T. I. Fossen, *Handbook of Marine Craft Hydrodynamics and Motion Control*. United Kingdom: John Wiley & Sons Ltd, 2011.

[11] X. R. Hou, Z. J. Zou, and C. Liu, “Nonparametric identification of nonlinear ship roll motion by using the motion response in irregular waves,” *Appl. Ocean Res.*, vol. 73, pp. 88–99, 2018.

[12] X. R. Hou and Z. J. Zou, “SVR-based identification of nonlinear roll motion equation for FPSOs in regular waves,” *Ocean Eng.*, vol. 109, pp. 531–538, 2015.

[13] S. Mehrkanoon, T. Falck, and J. A. K. Suykens, “Parameter estimation for time varying dynamical systems using least squares support vector machines,” *IFAC Proc. Vol.*, vol. 45, no. 16, pp. 1300–1305, 2012.

[14] I. Steinwart and C. Scovel, “Mercer’s Theorem on General Domains: On the Interaction between Measures, Kernels, and RKHSs,” *Constr. Approx.*, vol. 35, no. 3, pp. 363–417, 2012.

[15] S. Liangshan and H. Ruida, “Beetle antenna search flower pollination algorithm,” *Comput. Eng. Appl.*, vol. 54, no. 18, pp. 188–194, 2018.

[16] W. Tian-tian and L. Qiang, “The assessment of storm surge disaster loss based on BAS-BP model,” *Mar. Environ. Sci.*, vol. 37, no. 3, pp. 457–463, 2018.

[17] O. Hegazy, O. S. Soliman, and M. A. Salam, “Comparative Study between FPA, BA, MCS, ABC, and PSO Algorithms in Training and Optimizing of LS-SVM for Stock Market Prediction,” *Int. J. Adv. Comput. Res.*, vol. 5, no. 18, pp. 35–45, 2015.

[18] SIMMAN, 2014, The workshop on benchmark the capabilities of different ship manoeuvring simulation methods. Lyngby, Denmark, 2014, (https://simman2014.dk/).

