

Research Article

Ship Accident Prediction Based on Improved Quantum-Behaved PSO-LSSVM

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Water transportation plays an important role in the comprehensive transportation system and regional logistics. The number of vessel accidents is an important indicator for evaluating vessel traffic safety and the efficiency of the maritime management strategy. The aim of this work is to provide an efficient way to predict the number of vessel accidents in China. Firstly, to weaken the randomness of the vessel accident number time series, the gray processing operation is adopted to generate a new sequence with exponential and approximate exponential rules. In addition, an extended least-squares support vector machine (LSSVM) model is applied in the forecasting of the new sequence, in which the parameters of the LSSVM are optimized by an improved quantum-behaved particle swarm (IQPSO). The proposed method is applied in the forecasting of the number of vessel accidents in China, and the efficiency is shown by comparing the prediction results with GM (1, 1), PSO-LSSVM, and QPSO-LSSVM.

1. Introduction

Marine transportation, which accounts for more than 90% of the global freight volume, plays a key role in international trade. The vessel navigation safety is the prerequisite for the normal operation of the marine transportation system. In recent years, with the steady increase of cargo throughput in Chinese ports, the number of vessels sailing along the coast of China is also gradually increasing. Taking the Taiwan Strait as an example, the number of 300 GT and above merchant vessels passing through the Taiwan Strait every day in the three years from 2015 to 2017 is as high as 483 [1]. The increase of vessel density and flow will inevitably lead to the increase of the maritime traffic accident probability, among which vessel collision accident ranks first among all kinds of accidents. Once a vessel collision accident occurs, it will cause casualties and heavy economic losses. However, the historical vessel collision accidents have the advantages of strong contingency, small sample size, and weak regularity, and the vessel collision conflicts have a replacement effect on vessel collision accidents, which can depict the

situation of maritime traffic safety. Therefore, it is of practical significance to carry out prediction research about vessel collision conflicts.

With the development of science and technology, the accident management and control of the vessel transportation system is transferred gradually from the vertical single data statistics, the logic analysis of deducing the accident mechanism, and formation model into the integrated analysis of the transverse composite data and the future crisis prevention, with the purpose of providing a basis to implement prediction and early warning [2–4].

Marine traffic engineering is complex system engineering, which has certain randomness and contingency due to the influence of the navigation environment, the hydrometeorology, the crew capacity, and the vessel undefined state. In view of this, vessel collision conflicts can be used as an important index to measure the traffic safety of the sea. Therefore, the analysis of the collision conflicts and the prediction of the future situation can provide data support for the further implementation of the maritime safety strategy of China.

The widely applied vessel accident prediction methods mainly include regression analysis method [5], fractal theory [6], gray system model [7–9], and Markov model [10, 11]. Regression analysis is a statistical inference method to study the relevant relation vessel between the phenomena (variables), and the advantage of the regression analysis method is to synthesize various factors of the vessel traffic system, but it requires a large amount of the system data. The gray system model takes the uncertain system characterized by incomplete information as the research object, and through the gray information processing technology, it seeks the law in the system evolution process and then reduces the uncertainty of the system internal information. Comparing with the regression analysis method, the gray system model can obtain high short-term prediction accuracy with less data, but it is only suitable to model the series data with exponential and approximate exponential rules and describes the monotonous changing process. The gray Markov prediction model has higher prediction accuracy for the nonstationary series with certain stochastic volatility and change trend, but the difficulty in application is to divide the vessel accident condition accurately.

In machine learning, support vector machines (SVMs) are supervised learning models with associated learning algorithms that analyze data used for the classification and regression analysis. SVM is a very effective approach and has been used widely for classification, regression, and pattern recognition [12]. SVM is based on the statistical learning theory (SLT) and the structural risk minimization (SRM) concepts, suits for small-sample, nonlinear problems, and can effectively avoid the dimension disaster [13]. In the case of much less data, the SVM can better describe the nonlinear and random characteristics of the vessel accidents. As a new type of the SVM, least-squares SVM (LSSVM) greatly improves the convergence speed by solving the function estimation problem with the quadratic programming method, which is more suitable for the research of vessel accident prediction [14]. The performance of the LSSVM depends on the choice of parameters, which are determined by the cross-validation method generally, but the limitations of the cross-validation method itself will affect the learning and generalization ability of the LSSVM. Genetic algorithm (GA) and particle swarm optimization (PSO) can be used as an optimization theme for indicating hyperparameters of the LSSVM [15]. Least-squares support vector machine was employed to predict rheology of the drilling fluid at wellbore conditions for different types of drilling fluids including oil-based muds, water-based muds, and gas aphrons. From the average absolute relative deviation, correlation coefficient, and mean square error, the proposed low-parameter model has an acceptable robustness, integrity, and reliability [16]. The new type of the support vector machine method was used for proposing the predictive model for specifying the efficiency of chemical flooding in oil reservoirs [17]. Quantum-behaved particle swarm optimization (QPSO) algorithm is a kind of intelligent optimization algorithm developed on particle swarm optimization and can be used to solve the nonlinear and complex optimization problems with the features of less control parameters, easily to set up, strong search capability, and good global search ability

[18, 19]. An extended least-squares support vector machine (LSSVM) model was applied in the forecasting of the new sequence, in which the parameters of the LSSVM were optimized by an improved quantum-behaved particle swarm (IQPSO) [20].

This study deals with the usability of the least-squares SVM paradigm, as a simplification of the conventional SVM, to predict the vessel accidents in China, where the hyperparameters of the LSSVM are optimized by an improved quantum-behaved particle swarm. The effectiveness of the proposed model is verified using the real data of the vessel accidents in China since 1990. The prediction result can, to some extent, provide a theoretical basis for the maritime department to develop an effective maritime management countermeasure.

2. Objectives and Contributions

Water transportation occupies a very important position in economic construction and plays an important role in the comprehensive transportation system and regional logistics. The number of vessel accidents is an important indicator to evaluate vessel traffic safety and measure the level of maritime management. The objective of this study is to predict the future state by analyzing the historical data of vessel accidents.

The contribution of this study lies in that it provides an efficient way to predict the number of vessel accidents in China, and it is helpful for the administrative department to develop a maritime management countermeasure to reduce the accidents.

3. Methodology

3.1. Least-Squares SVM. Least-squares SVM takes the regularization theory and structural risk minimization as the basis, greatly reduces the computational complexity by changing the quadratic programming problem in the standard SVM into solving the linear equations, and enjoys similar advantages as the SVM. At present, LSSVM is a very active artificial intelligence method and widely applied in the modeling and control problems.

The formulation of the LSSVM for nonlinear function estimation is expressed as follows: given a training set $S = \{(\mathbf{x}_i, y_i)\}_{i=1}^N$, where $\mathbf{x}_i \in \mathbb{R}^m$ is the input data in the input space and $y_i \in \mathbb{R}$ is the output value for a given value of the specific input variable, the formulation of the LSSVM model for function estimation becomes

$$y(\mathbf{x}) = \sum_{l=1}^N \alpha_l \cdot \text{Kernal}(\mathbf{x}, \mathbf{x}_l) + b. \quad (1)$$

The parameters $\alpha = [\alpha_1, \alpha_2, \dots, \alpha_N]^T$ and b satisfy

$$\begin{bmatrix} b \\ \alpha \end{bmatrix} = \begin{bmatrix} 0 & \mathbf{L}^T \\ \mathbf{L} & \Phi + \Delta \end{bmatrix} \begin{bmatrix} 1 \\ \mathbf{Y} \end{bmatrix}, \quad (2)$$

where $\mathbf{Y} = [y_1, y_2, \dots, y_N]^T$, $\mathbf{L} = [1, 1, \dots, 1]^T$, $\alpha = [\alpha_1, \alpha_2, \dots, \alpha_N]^T$, and $\Phi = (\Phi_{ij})_{n \times n}$ with general

element $\Phi_{ij} = \varphi(\mathbf{x}_i)^T \varphi(\mathbf{x}_j) = \text{Kernal}(\mathbf{x}_i, \mathbf{x}_j)$. Here, different weights γ_i are assigned for the i th data error; thus, Δ satisfies

$$\Delta_{ij} = \begin{cases} \gamma_i \triangleq \gamma_0 \exp((i/N)\varrho), & j = i, \\ 0, & j \neq i, \end{cases} \quad (3)$$

where, γ_0 and ϱ are two positive constants. The kernel function $\text{Kernal}(\cdot)$ is chosen RBF kernel function since the generalization ability of RBF is stronger.

In the literature, a number of comprehensive introductions to the LSSVM are available, and the theory of the LSSVM has also been described clearly [14, 16, 17]. So, for more details, refer to the aforementioned references.

3.2. Improved QPSO Algorithm. Quantum-behaved particle swarm optimization (QPSO) was proposed by Sun et al. inspired by the basic theory of quantum physics, which mainly adopted the expression characteristics of the superposition of quantum theory and probability features.

In the QPSO algorithm, the swarm updates the individuals' position according to the following way:

$$\mathbf{m}_{best}[t+1] = \left(\frac{1}{N} \sum_{i=1}^N \mathbf{p}_{besti1}[t], \dots, \frac{1}{N} \sum_{i=1}^N \mathbf{p}_{bestiD}[t] \right), \quad (4)$$

$$\mathbf{p}[t+1] = \varphi[t+1] \cdot \mathbf{p}_{best}[t] + (1 - \varphi[t+1]) \cdot \mathbf{g}_{best}[t],$$

$$\mathbf{x}[t+1] = \mathbf{p}[t+1] + \delta(u[t+1]) \cdot \ln\left((u[t+1])^{\beta[t+1] \cdot |\mathbf{m}_{best}[t+1] - \mathbf{x}[t]|} \right), \quad (5)$$

where $\varphi[t+1]$, $u[t+1]$ is a random number in $(0, 1)$ at the step $t+1$, N is the size of the swarm, D is the dimension of the particles, and $\mathbf{p}[t+1]$ is called a local attractor at the step $t+1$. The function $\delta(u[t])$ satisfies

$$\delta(u[t]) = \begin{cases} -1, & u[t] \leq 0.5, \\ 1, & u[t] > 0.5. \end{cases} \quad (6)$$

Note that $u[t]$ in equation (4) is a random number in $[0, 1]$ obeying uniform distribution, and $E(u[t]) = 0.5$, which indicates that when $u[t] = 0.5$, the position of the particle $\mathbf{x}[t]$ should be assigned at the local attractor $\mathbf{p}[t]$, but from equation (4), there is $\delta(0.5) = -1$, and thus, $\mathbf{x}[t]$ is not assigned to $\mathbf{p}[t]$ when $u[t] = 0.5$. Based on this consideration, a modification on equation (5) is made, i.e.,

$$\mathbf{x}[t+1] = \mathbf{p}[t+1] - \beta[t+1] \cdot |\mathbf{m}_{best}[t+1] - \mathbf{x}[t]| \ln(2u[t+1]). \quad (7)$$

In this work, a dynamically adjusting inertia weight $\beta[t+1]$ is adopted. Let FIT denote the fitness function in a minimization problem. Set $\chi[1] = \lambda[1] = 0$. For $t = 2, 3, \dots, t_{\max}$, define

$$\chi[t] \triangleq \frac{\text{FIT}(\mathbf{g}_{best}[t])}{\text{FIT}(\mathbf{g}_{best}[t-1])}, \quad (8)$$

$$\lambda[t] \triangleq \frac{\text{FIT}(\mathbf{g}_{best}[t-1])}{1/N \sum_{i=1}^N \text{FIT}(\mathbf{p}_{best}[t-1])}.$$

It is obvious that $0 \leq \chi[t], \lambda[t] \leq 1$, where $\chi[t]$ reflects the evolution speed of the quantum particle swarm and $\lambda[t]$ reflects all the particles' aggregation degree.

A dynamically adjusting inertia weight $\beta[t]$ is adapted, which takes the form

$$\beta[t] = \beta_0 - \beta_1 \chi[t] + \beta_2 \lambda[t], \quad (9)$$

where β_0 is the initial weight, and in general, $\beta_0 = 1$, and β_1, β_2 are the weights of $\chi[t]$ and $\lambda[t]$. Since $\chi[t]$ and $\lambda[t]$ are both dependent on the iteration times, $\beta[t]$ in equation (8) is also dependent on iteration times, but in an indirect way. As it was proved in [18] that, as long as $\beta[t] < 1.78$, the convergence of QPSO can be guaranteed, it is assumed that β_0, β_1 , and β_2 satisfy the constraints $\beta_1 < \beta_0$ and $\beta_0 + \beta_2 < 1.78$.

3.3. IQPSO-LSSVM Regression Model. When RBF is chosen as the kernel function,

$$\text{Kernal}(\mathbf{x}, \mathbf{x}') = \exp\left(\frac{-\|\mathbf{x} - \mathbf{x}'\|}{2\sigma^2} \right). \quad (10)$$

The parameters to be optimized are the regularization parameter γ_0 , ϱ in equation (3), and kernel parameter σ in equation (10).

The selection of the parameters has important effects on learning and generalization ability of the model. In this work, IQPSO is applied to optimize the parameters of the LSSVM. The flowchart of parameter adjustment based on IQPSO is depicted in Figure 1. The optimization procedure has been repeated several times as attempts to reach the most probable global optimum of the fitness function.

4. Data Collection and Preprocessing

4.1. Data of Vessel Accidents. The data used as the sample are the accident number per month from 1999 to 2014 [21], which are given in Table 1. The time series is shown in Figure 2.

4.2. Data Preprocessing

Step 1. Data gray preprocessing

For the time series $\mathbf{x}^{(0)} = \{\mathbf{x}^{(0)}(k)\}_{k=1}^T$ of vessel accidents ($T = 192$), let $\mathbf{x}^{(1)} = \{\mathbf{x}^{(1)}(k)\}_{k=1}^T$ denote the sequence generated by one accumulated generating operation (AGO), where $\mathbf{x}^{(1)}(k) = \sum_{i=1}^k \mathbf{x}^{(0)}(i)$, $k = 1, \dots, T$.

Step 2. Data phase space reconstruction

To sufficiently extract the useful information of the time series $\{\mathbf{x}^{(1)}(k)\}_{k=1}^T$, the commonly used method is the phase

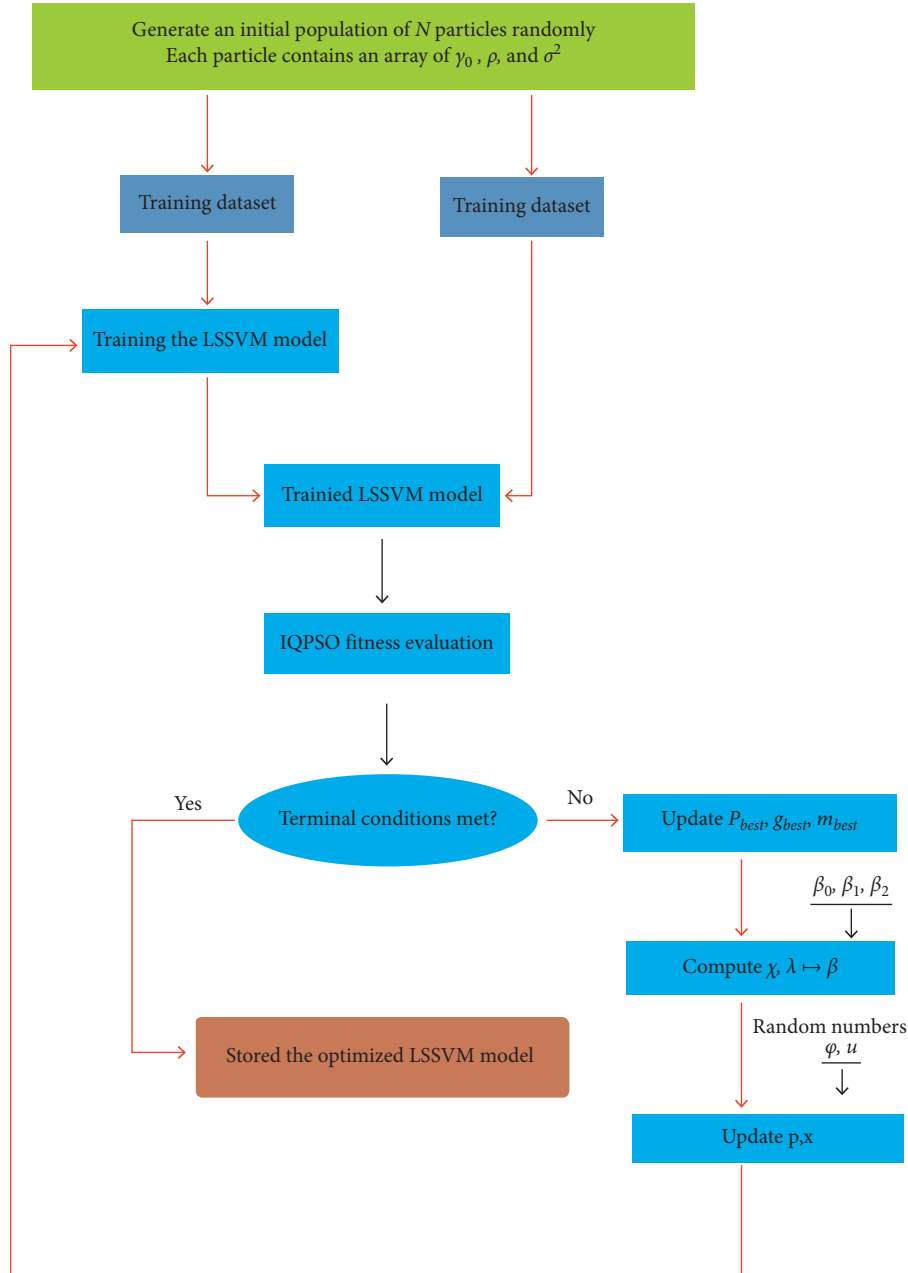


FIGURE 1: Flowchart of the parameters of the LSSVM model optimization by the IQPSO algorithm.

space reconstruction (PSR) in the delay coordinate proposed by Packard et al. [22]. According to Takens [23], a time series can sufficiently reconstruct an original dynamic system. From this procedure, the time series $\{\mathbf{x}^{(1)}(k)\}_{k=1}^T$ can be reconstructed in a multidimensional phase space as follows:

$$\begin{aligned} \mathbf{x}_i &= (\mathbf{x}^{(1)}(i), \dots, \mathbf{x}^{(1)}(i + (m - 1)\tau)), \\ y_i &= \mathbf{x}^{(1)}(i + m\tau), \quad i = 1, 2, \dots, T - m\tau, \end{aligned} \quad (11)$$

where τ is the delay parameter and m is the embedding dimension. It is very important to select a suitable pair of embedding dimension m and time delay τ when performing PSR [24–26]. Until now, there is still no exactly good way to determine τ and m . In [27], it is advised that τ should be

selected larger than needed to prevent ignoring system information. In the following discussion, embedding dimension m is set equal to 3 and 4 according to the studies of Brock et al. [28], which indicated that an appropriate embedding dimension m should be between 2 and 5; the time delay is assumed to be month to month, i.e., $\tau = 1$. The data from 1999 to 2012 are used as the training set, and the data in 2013 and 2014 are used as the test sample.

Step 3. Data prediction by IQPSO-LSSVM and representation

To improve the convergence rate of the model, a normalized operation on \mathbf{x}_i and y_i are taken, which are also denoted by \mathbf{x}_i and y_i . Use the data pair $\{(\mathbf{x}_i, y_i)\}_{i=1}^{T-m\tau}$ obtained in equation (11) to train IQPSO-LSSVM, and obtain

TABLE 1: Number per month of vessel accidents in China from 1999 to 2014.

	Jan.	Feb.	Mar.	Apr.	May	June
1999	38	38.5	49	65	59	51.5
2000	35	35	39	45	37	45
2001	34	30.5	74	62	37	44
2002	59	39	78.5	73	46.5	64
2003	43.5	45	74.5	51	48	49
2004	28	49	56.5	53	43.5	35
2005	46.5	33.5	44	64.5	42	44
2006	21	20	32	48	42	39
2007	31.5	23.5	40.5	33.5	35	30
2008	27	16	27.5	32	34.5	35
2009	8.5	27.5	25.5	31.5	30	40.5
2010	31.5	24	26	27.5	30.5	22
2011	31	14	22.5	24.5	28	18
2012	14.5	18	27	23	22.5	17.5
2013	22	13	22.5	27	24	32.5
2014	21	7.5	21	20	25	22
—	July	Aug.	Sep.	Oct.	Nov.	Dec.
1999	69.5	74	58	56	48.5	70
2000	52	63	68.5	53	48.5	62.5
2001	48	55	54.5	46.5	31	83.5
2002	65.5	76.5	67	37	59.5	69
2003	71	39.5	80	43.5	40	55
2004	47	54.5	40	42	42.5	71
2005	36.5	44	48	38	48.5	54.5
2006	37.5	39	34.5	38.5	37	47.5
2007	33	38.5	26.5	38	40	40
2008	26.5	32.5	25.5	23.5	36	26
2009	27	32	32	23.5	40.5	31
2010	23.5	27	17	23	25.5	54
2011	26	26.5	16	31.5	32	20
2012	28	34	13.5	56	16	24.5
2013	17.5	24	8	23.5	24	24
2014	23	25	25.5	23.5	40.5	25.5

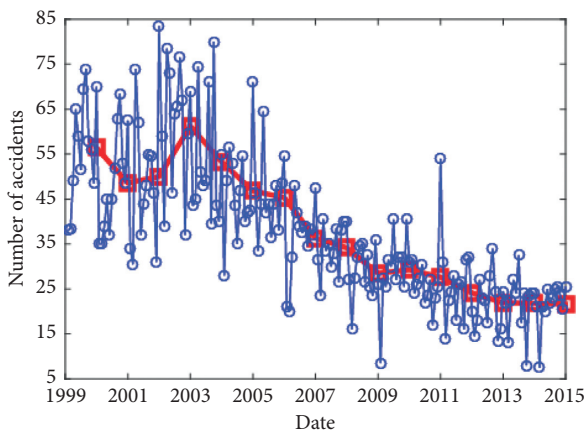


FIGURE 2: Time series of vessel accidents.

an optimal parameter pair $(\gamma_0, \varrho, \sigma^2)$, which is stored to optimize LSSVM as a prediction model, i.e.,

$$\mathbf{x}^{(1)}(T+1) = y_{T+1-m\tau} = \text{LSSVM}(\mathbf{x}_{T+1-m\tau}). \quad (12)$$

The final step is to reverse the predicted result $\mathbf{x}^{(1)}(T+1)$ of the new sequence by the inverse accumulated generating operation (I-AGO) and obtain that

$$\mathbf{x}^{(0)}(T+1) = \mathbf{x}^{(1)}(T+1) - \mathbf{x}^{(1)}(T). \quad (13)$$

5. Results and Discussion

In this study, root mean squared error (RMSE) and the mean relative error (MRE) were applied as criteria for assessing an estimation performance. The expressions to evaluate MSE and R2 are given as follows:

$$\text{RMSE} = \sqrt{\frac{1}{N_{\text{Pred}}} \sum_{i=1}^{N_{\text{Pred}}} (y_i^{\text{Actual}} - y_i^{\text{Pred}})^2}, \quad (14)$$

$$\text{MPE} = \frac{1}{N_{\text{Pred}}} \sum_{i=1}^{N_{\text{Pred}}} \left| \frac{y_i^{\text{Pred}} - y_i^{\text{Actual}}}{y_i^{\text{Actual}}} \right|.$$

5.1. The Prediction of the Gray Model. Gray model is easily built with model parameters $\alpha = 0.0057$ and $\beta = 62.7364$. The prediction result is presented in Figure 3. It can be observed that the prediction result is not quite desirable. The predicted accident numbers for all months are not quite different, and the number lies between 20 and 25, while the maximum prediction error 15 occurs at February 2014. The total accident prediction number in the first and second half year are, respectively, 143 and 138 in 2013 and 134 and 129 in 2014. The maximum cumulative error 17 occurs at the second half year of 2013 and the first half year of 2014.

5.2. The Prediction of PSO-LSSVM. To improve the prediction rate, the LSSVM with the radial basis kernel function is adapted, where the weight γ_0, ρ , and the kernel parameter σ^2 are optimized by the PSO algorithm and QPSO algorithm, respectively.

The size of the swarm is set to 10, and the maximum iteration is 50. To consider the existence of certain randomness in the optimization process, the algorithm is run 10 times, and the average value is taken as the predicted value.

The prediction results of PSO-LSSVM for $m=3$ and $m=4$ are presented in Figure 4. From Figure 4(a), it can be observed that the maximum prediction error 14 occurs at February 2014. The total accident prediction number in the first and second half year are, respectively, 117 and 118 in 2013 and 118 and 129 in 2014. The maximum cumulative error 24 occurs at the first half year of 2013. From Figure 4(b), it can be observed that the maximum prediction error 14 occurs at February 2014. The total accident prediction number in the first and second half year are, respectively, 119 and 122 in 2013 and 122 and 128 in 2014. The maximum cumulative error 22 occurs at the first half year of 2013.

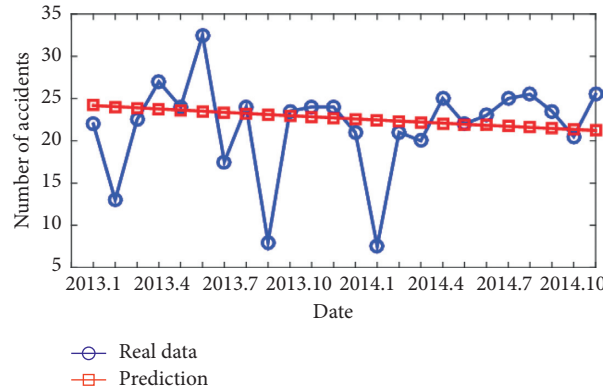


FIGURE 3: The comparison between the real data in 2013-2014 and the prediction result of GM (1, 1).

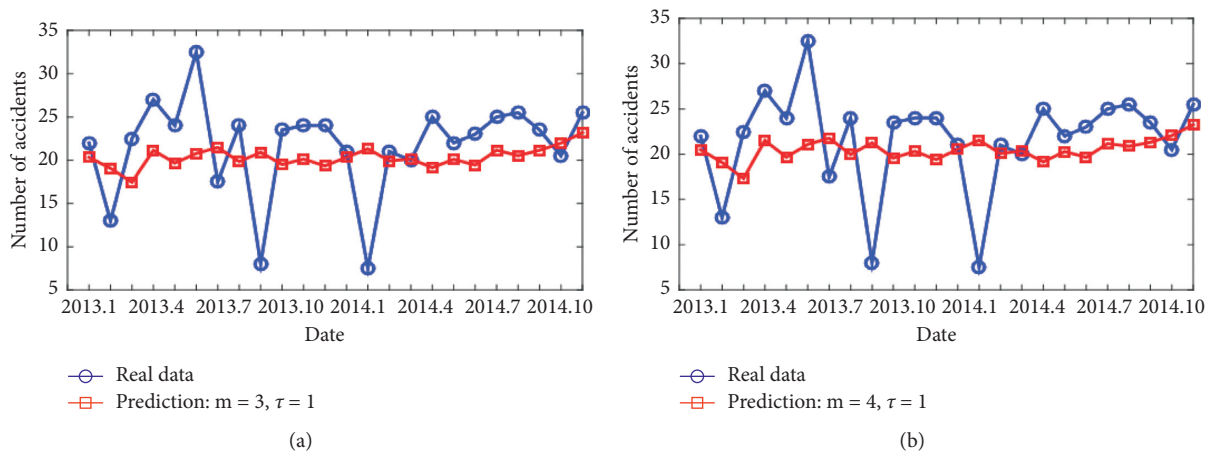


FIGURE 4: The comparison between the real data in 2013-2014 and the prediction result of the PSO-LSSVM model.

5.3. *The Prediction of QPSO-LSSVM.* The prediction of QPSO-LSSVM for $m = 3$ and $m = 4$ is presented in Figure 5. From Figure 5(a), it can be observed that the maximum prediction error 16 occurs at September 2013. The total accident prediction number in the first and second half year are, respectively, 124 and 111 in 2013 and 123 and 124 in 2014. The maximum cumulative error 19 occurs at the second half year of 2014. From Figure 5(b), it can be seen that the maximum prediction error 15 occurs at February 2014. The total accident prediction number in the first and second half year are, respectively, 126 and 113 in 2013 and 130 and 125 in 2014. The maximum cumulative error 18 occurs at the second half year of 2014.

5.4. *The Prediction of Gray-IQPSO-LSSVM.* The prediction of gray-IQPSO-ELSSVM for $m = 3$ is presented in Figure 6(a), and the maximum prediction error 18 occurs at September 2013. The total accident prediction number in the first and second half year are, respectively, 131 and 130 in 2013 and 122 and 135 in 2014. The maximum cumulative error 10 occurs at the first half year of 2013. And for $m = 4$, the prediction of QPSO-LSSVM is presented in Figure 6(b), and the maximum occurs at the second half year of 2014.

From Figure 6, it can be seen that the prediction of gray-IQPSO-ELSSVM for $m = 4$ is better than $m = 3$ and GM (1, 1), PSO-LSSVM, and QPSO-LSSVM, which can be used in the forecasting of the vessel accidents.

Table 2 shows the error comparison of different models, from which it can be seen that gray-IQPSO-LSSVM is better than other models.

To illustrate the impact of the time delay on gray-IQPSO-LSSVM, the prediction results for different time delays are shown in Figure 7, where the time delay is selected quarter to quarter, semiannual to semiannual, and year to year, i.e., $\tau = 3, 6, 12$. It can be observed that the prediction result for month to month is better than quarter to quarter, semiannual to semiannual, and year to year. For $\tau = 3$, the maximum prediction error 18 occurs at September 2013. The total accident prediction number in the first and second half year are, respectively, 137 and 132 in 2013 and 122 and 122 in 2014. For $\tau = 6$, the maximum prediction error 30 occurs at February 2013. The total accident prediction number in the first and second half year are, respectively, 154 and 120 in 2013 and 112 and 131 in 2014. For $\tau = 12$, the maximum prediction error 22 occurs at September 2014. The total accident prediction number in the first and second half year are, respectively, 151 and 127 in 2013 and 116 and 122 in

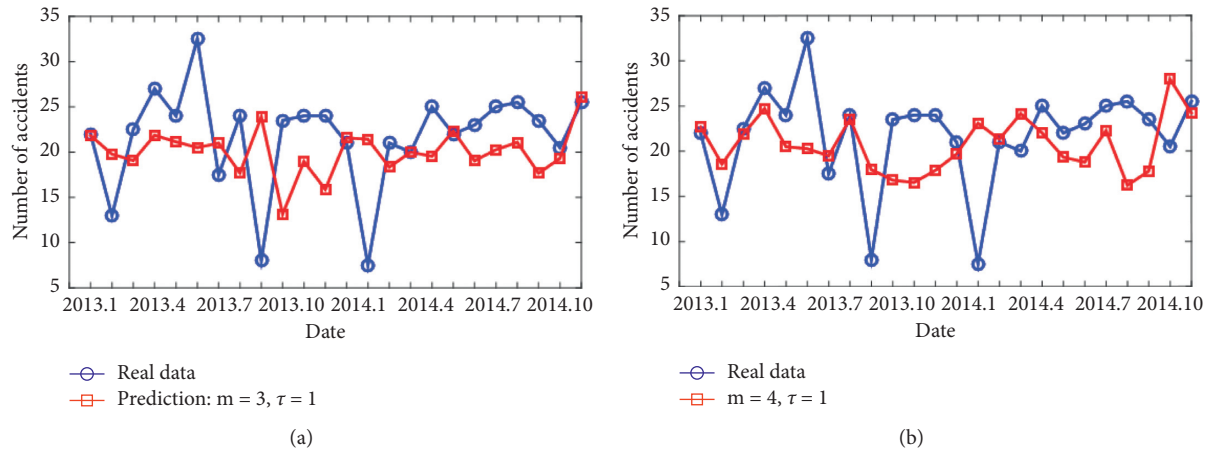


FIGURE 5: The comparison between the real data in 2013-2014 and the prediction result of the QPSO-LSSVM model.

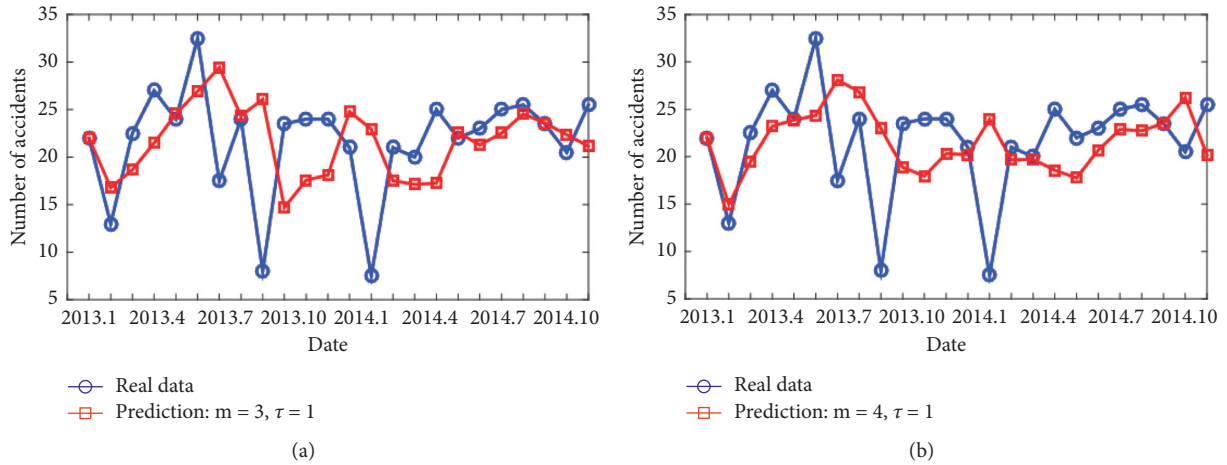


FIGURE 6: The comparison between the real data in 2013-2014 and the prediction result of the gray-IQPSP-ELSSVM model.

TABLE 2: The error comparison of different models.

Models	Errors	
	RMSE $m = 4$	MRE $m = 4$
GM (1, 1)	6.916	0.302
Lasso regression	6.904	0.292
Bayesian regression	6.864	0.289
PSO-LSSVM	6.787	0.288
QPSO-LSSVM	6.784	0.287
Gray-IQPSP-LSSVM	6.746	0.282

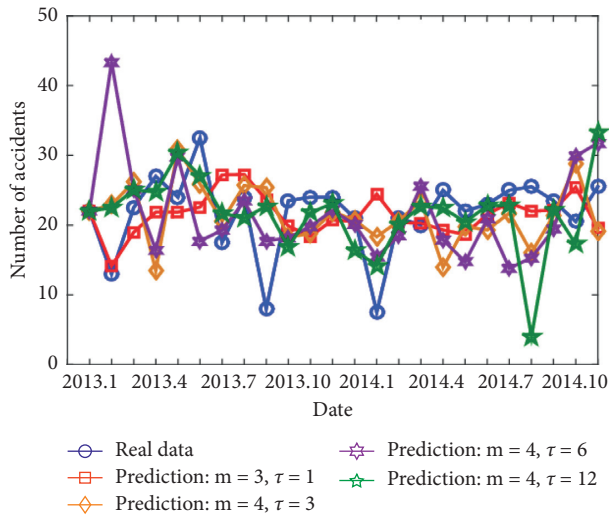


FIGURE 7: Comparison between the real data in 2013-2014 and the prediction result of the gray-IQPSO-LSSVM model.

2014. From 15, it can be observed that the prediction result for month to month is better than quarter to quarter, semiannual to semiannual, and year to year.

6. Conclusions

The number of vessel accidents is an important indicator to evaluate vessel traffic safety and measure the level of maritime management, and it has the vital significance for the maritime department to develop a maritime management countermeasure to reduce the accidents by analyzing the historical data of vessel accidents and predicting the future state. In this work, the problem of forecasting of the vessel accidents in China was discussed. To consider the advantages of the gray prediction model, LSSVM, and QPSO and make up the theoretical defect of the gray prediction model and the limitation of the LSSVM in the parameter solving, an integrated prediction model was proposed. Firstly, to weaken the randomness of the original sequence, the gray processing operations in the gray system theory are adopted to generate a new sequence with exponential and approximate exponential rules. And then, an extended least-squares support vector machine (LSSVM) model was applied in the forecasting of the new sequence, in which the parameters of the LSSVM are optimized by an improved quantum-behaved particle swarm (IQPSO). The prediction results show that the gray-IQPSO-LSSVM is an efficient algorithm and can be used in the forecasting of the vessel accidents.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare no conflicts of interest.

Acknowledgments

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