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Research Journal of Applied Sciences, Engineering and Technology 4(23): 5251-5260, 2012
ISSN: 2040-7467
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Submitted: May 04, 2012 Accepted: June 08, 2012 Published: December 01, 2012

New Intelligent Method of Forecasting Control for Fishing Boat Security in the Coastal Area of Fujian

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Abstract: To ensure the fishing boat security in the coastal area of Fujian, it is imperative to develop efficient forecasting control system to manage the boats operation in a safe and orderly process. The core issue of establishing the forecasting control system is to predict the relationship of the real time traffic flow and the boat security condition. However, literature review shows that limited reports have addressed on this problem. Hence, a new intelligent forecasting control method base on the Chaos-Particle Swarm Optimization (PSO) and Fuzzy Neural Network (FNN) is proposed for the short time traffic flow prediction in this paper. The Empirical Mode Decomposition (EMD) was first used to denoise the original ship traffic flow observation and then the Chaos-PSO-FNN was applied to the forecasting of the ship traffic flow and hence established the relationship of the real time traffic flow and the boat security condition. The advantage of the proposed approach is that the Chaos-PSO is employed to optimize the FNN parameters to overcome the premature problem of the FNN. As a result, the forecasting control performance is enhanced greatly. In the experiment analysis, the fishing boat traffic information provided by the Fujian marine bureau has been used to evaluate the newly proposed method. The analysis results demonstrate that the proposed Chaos-PSO-FNN method can extract distinct features of the traffic data and the prediction rate is beyond 93.7%. In addition, it found that the fishing boats is supposed to be safe when their travel time avoids the rush time of the traffic flow. This result agrees well with the real data. Thus, the new intelligent forecasting control method for fishing boat security can be used in practice.

Keywords: Chaos-PSO, fishing boat security, forecasting control, fuzzy neural network, traffic flow prediction

INTRODUCTION

Fujian coastal fishing industry in China is the important development base, which plays a key role in pushing the Chinese shipbuilding industry. With the rapid development of the west coast of the Taiwan Strait, the sea trade increases significantly between Fujian and Taiwan and the Fujian fishing and shipping industry obtains fast development. Nowadays, the ship traffic flow exceeds 5000 every day. The large traffic flow poses new requirements and challenges on the maritime navigation safety. According to the official report (Feng and Shen, 2003), Maritime traffic accidents have already threatened the development of the Fujian coastal shipping. In China's "eleventh five-year plan" period, there are 109 maritime traffic accidents and 80% of which happened on fishing boats, leading to 89 people dead or missing and 109,38 million RMB economic losses. Form other analysis (Jin *et al*., 2002; Jin and Thunberg, 2005; Shih *et al*., 2010; Wang *et al*., 2005), it shows a real safety problem in the fishing vessel industry. Hence, it is critical to establish forecasting control system to prevent traffic accidents.

To date, although the Vessel Monitoring Systems (VMSs) have been installed on the fishing boats, this precaution measurement is insufficient for the fishing boat safety. Further development for improved monitoring and management of fishing boats is urgent needed. Figure 1 shows the maritime traffic accident statistics in the coastal area of Fujian from 1994 to 2003. It can be seen from Fig. 1 that the crash accounted for 35% of all the accidents. This statistics value increased to 40% in 2008. That is to say, when the ship traffic flow is heavy, the crash accident is readily to happen. Hence, it is important to figure out the influence of the ship traffic flow on the probability

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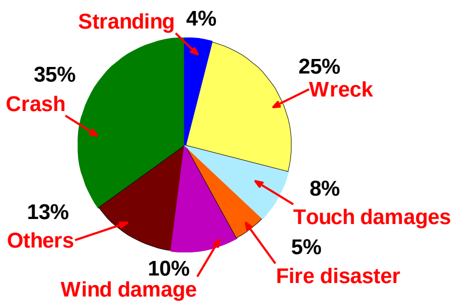

Fig. 1: Maritime traffic accident statistics in the coastal area of Fujian from 1994 to 2003

of maritime traffic accident. To deal with this problem, it should firstly predict the maritime traffic flow to control the fishing boat dispatch and help them be out of damage and accident. Accurate and on-line maritime traffic flow prediction is the key issue for forecasting control of fishing boats. Maritime traffic flow prediction can also make it easy to find the inner relationship between the traffic flow and the ship security, realize the dynamic route guidance and relieve the traffic congestion (Feng and Shen, 2003).

Many effective traffic flow prediction methods have been proposed for the land transportation prediction. However, for the water transportation, the outcomes of some popular prediction models need to be further evaluated, such as the Artificial Neural Network (ANN) based intelligent methods and the nonlinear theory based approaches. Due to the complex of the maritime traffic flow, the prediction performance of the existing methods is not satisfactory when used independently (Li *et al*., 2011a, 2012a; Nejad *et al*., 2009; Park *et al*., 2003; Wen and Lee, 2005; Zhao *et al*., 2008; Zahra *et al*., 2010). There is a strong evident that the integration of different analysis techniques can enhance the traffic flow prediction rate. Hence, this paper presents a new intelligent method for the maritime traffic flow prediction based on Empirical Mode Decomposition (EMD) and Fuzzy Neural Network (FNN). This method is marked by the powerful nonlinear signal process ability and intelligent learning ability of the EMD-FNN.

On the other hand, improper parameters of FNN may reduce the prediction precision. To tackle this problem, the Chaos-Particle Swarm Optimization (PSO) algorithm has been employed to optimize the FNN via its powerful global search capability (Chang and Ramakrishna, 2002; Huang *et al*., 2010; Li *et al*., 2010, 2011b, 2011c, 2012b; Xiong and Wang, 2009; Zhang and Yang, 2005). This optimization procedure has used the chaotic technology to improve PSO optimization process and avoid the PSO's local minimum problem. The generalization of the optimized FNN can be promoted by doing so. Based on the accurate maritime traffic flow prediction, the guide and control of the fishing boats can be realized. The experiment analysis has been carried out on the fishing boat traffic data provided by the Fujian marine bureau. The experimental results show that the new method can predict maritime traffic flow efficiently and thus the potential security protection strategies can be provided to prevent impending incidents.

DESCRIPTION OF THE PROPOSED PREDICTION MODEL

Due to the noise disturbation, the maritime traffic flow data presents nonlinearity. The maritime traffic flow contains signal components with different characteristics. The uncertainty of the flow data makes the actual maritime traffic flow fluctuate nearby the general trend. In order to eliminate the noise, the preprocessing is needed. As the Empirical Mode Decomposition (EMD) is good at dealing with non-stationary signal, it has been applied to preprocess the original data. Given that the fluctuation characteristics are often independent, the original flow signal is decomposed step-by-step into several Intrinsic Mode Functions (IMFs) by EMD. Each IMF indicates specific component in the flow signal and the sole property of every IMF makes the IMFs suitable for the accurate forecasting of the traffic flow (Huang *et al*., 1998, 2003; Luo *et al*., 2010).

In the maritime traffic flow prediction, the EMD is firstly used to remove the disturbance components in the maritime traffic flow. Followed, the prediction mode for the chosen IMFs is established using FNN and the Chaos-PSO is used to optimize the models. Lastly, the predicted flow is obtained by sum the output of each FNN models.

Empirical Mode Decomposition (EMD) : Empirical Mode Decomposition (EMD) (Huang *et al*., 1998, 2003) is an effective nonlinear signal processing technique. EMD has the ability to decompose a signal into a number of IMFs (Huang *et al*., 1998). IMFs are regarded as the simple oscillatory modes embedded in the signal (Huang *et al*., 2003). In the IMF decomposition, the number of extrema and the number of zero-crossings of the dataset must either equal or differ at most by one and at any point the mean value of the envelope defined by local maxima and the envelope defined by the local minima is zero.

In the EMD decomposition, it firstly identifies all the local extrema of the original signal *x*. Then the upper envelope and lower envelope are obtained by a cubic spline line. Hence, the mean of upper and lower envelope can be extracted obtain i_1. If i_1 satisfies the IMF conditions, it is an IMF, otherwise find the upper and lower envelopes of i_1 and the process is repeated till the first IMF is got. Subtract i_1 from *x* and extract the second IMF. Keep continuing the process till no more IMF can be found. Thus, at the end of the EMD decomposition we obtain (Parey and Tandon, 2007):

$$x = \sum_{i=1}^{N} i_i + r \quad (1)$$

where, *r* is the final residue and i_i (i = 1, 2, …, N) is the i^{th} IMF.

Chaos-PSO: Particle Swarm Optimization (PSO), proposed by (Kennedy and Eberhart, 1995), aims to find extreme values by the social behavior of bird flocks. Its advantages are simply and efficient in the search processing. However, PSO may suffer from premature (Mendes *et al*., 2003; Richards and Ventura, 2003; Vesterstroem *et al*., 2002). The weak particle diversity in the offspring may be the causing (Riget and Vesterstroem, 2002). Hence, to avoid the local minima, Chaos search is adopted to enrich PSO's particle diversity. The Chaos search can search all the space and provide the optimal solution to maintain particle diversity (Dong *et al*., 2010). Thus the PSO premature can be prevented.

PSO adjusts the flight according to flying experience of the particles (Xiong and Wang, 2009). The best position experienced by the particles is the optimal solution. The PSO algorithm for updating speed υ and position P is:

$$\begin{aligned} \upsilon_i(k+1) &= \omega_i \upsilon_i(k) + c_1 r_1 [P_a - P_i(k)] \\ &+ c_2 r_2 [P_g - P_i(k)] \end{aligned} \quad (2)$$

$$P_i(k+1) = P_i(k) + \upsilon_i(k+1) \quad (3)$$

where,

P_a = The individual extremum
P_g = The global extremum experienced
ω_i = The inertial weights
r_1 and r_2 = The random coefficients among [0, 1]
c_1 and c_2 = The speeding constants

To diverse the PSO offspring, the chaotic search is used to optimize the PSO flying processing. The Logistic mapping based Chaos algorithm can be expressed as (Wang and Meng, 2007):

$$P_i(k+1) = \eta P_i(k)(1 - P_i(k)) \quad (4)$$

where, η is the control constant. The Chaos optimization process is as follows. To optimize the PSO flying, the flying position P is mapped to chaos variables in [0 1] by the carrier:

$$C_i(k) = (P_i(k) - a_i) / b_i \quad (5)$$

where, a_i and b_i are constant. Then Eq. (4) is adopted to calculate the chaos updating to get:

$$C_i(k+1) = \mu C_i(k)(1 - C_i(k)) \quad (6)$$

After some iterative, the optimal value C_i can be found. Then the flying position is mapped back to its original space by:

$$P_i(k) = a_i + b_i C_i(k) \quad (7)$$

By doing so, proper P_g can be obtained and the PSO can jump out of local optimal solution.

Improved fuzzy neural network : Fuzzy logic is used to deal with analog variables that take on continuous values between 0 and 1 to imitate the human thinking. In contrast to digital logic, the fuzzy values are not disserted in the form of true/false. Fuzzy concept cannot be expressed as "true" or "false" but rather as "partially true" in terms that is close to human understanding. Thus, Fuzzy method has been widely used in various applications, such as the control engineering, signal processing and pattern recognition, etc. However, the membership functions and rules are often decided using human knowledge and experiences, which deteriorates the adaptation of the fuzzy approach (Lee and Heinbuch, 2001; Russell and Norvig, 2003; Kohonen, 1997; Sin *et al*., 2002). To solve this shortcoming, the Artificial Neural Network (ANN) has been incorporated in the fuzzy logic and the Fuzzy-ANN (FNN) can provide more powerful learning ability (Huang *et al*., 2010). The FNN structure is shown in Fig. 2.

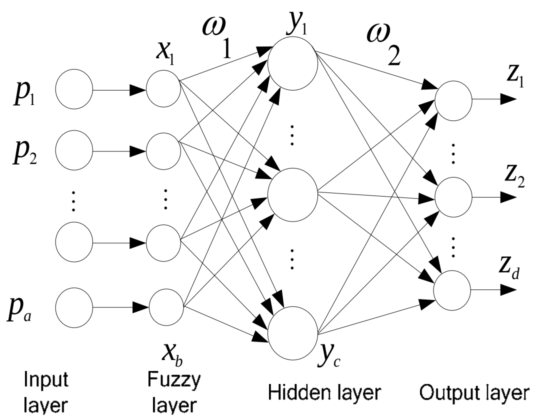

Fig. 2: Structure of FNN

The FNN has four layer, including input layer, fuzzy layer, hidden layer and output layer. The input layer connects with input feature vector $F=[f_1, f_2, ..., f_a]^T$. The fuzzy layer is used to fuzz the input F to get the fuzzy membership $x_b = \mu_{Aab}(p_a) = [q_{1b}, q_{2b}, ..., q_{ab}]^T$. The Gaussian function was adopted as the fuzzy membership function:

$$\mu_{Aab}(p_a) = \exp[-(\frac{p_a - \alpha}{\beta})^2] \qquad (8)$$

where, α denotes the center of membership function and β denotes the width of the function. Hence, the output of the fuzzy layer is $X=[x_1, x_2, ..., x_b]$. In the hidden layer, for the c neuron nodes, the weights ω_2 were used as the fuzzy relation matrix to perform fuzzy inference rules. Then the output of the cth fuzzy rule is:

$$y_c(x_b) = \omega_2 x_b \qquad (9)$$

The fourth layer outputs the fuzzy decision. One can note that FNN adopts the ANN coefficients to realize the Fuzzy inference. The traditional Back Propagation (BP) learning is usually applied to the training of FNN. However, the BP algorithm suffers from local optimal solution, leading to low FNN performance. To overcome this problem, the Chaos-PSO has been used to optimize the training of the FNN due to its global robust searching. The neuron number of the hidden layer and the coefficients of the Gaussian function are the optimization objectives of the Chaos-PSO. The proposed forecasting processing is given as follows:

Step 1: Standardize the data format of the original maritime traffic flow data.

Step 2: Extract IMFs from the original traffic data and eliminate disturbed ones.

Step 3: Establish the prediction model for the selected IMFs using the Chaos-PSO-FNN and train the model using practical data.

Step 4: Test the intelligent prediction model and further analysis the prediction to relate it with the fishing boat security.

Forecasting control of fishing boat security: This study aims to instigate the relationship between the maritime traffic flow and the fishing boat security. The intelligent flow prediction model is developed in order to manage the fishing boat behavior so as to contribute possible insights into the forecasting control. A flow chart of the proposed forecasting control method for fishing boat is illustrated in Fig. 3.

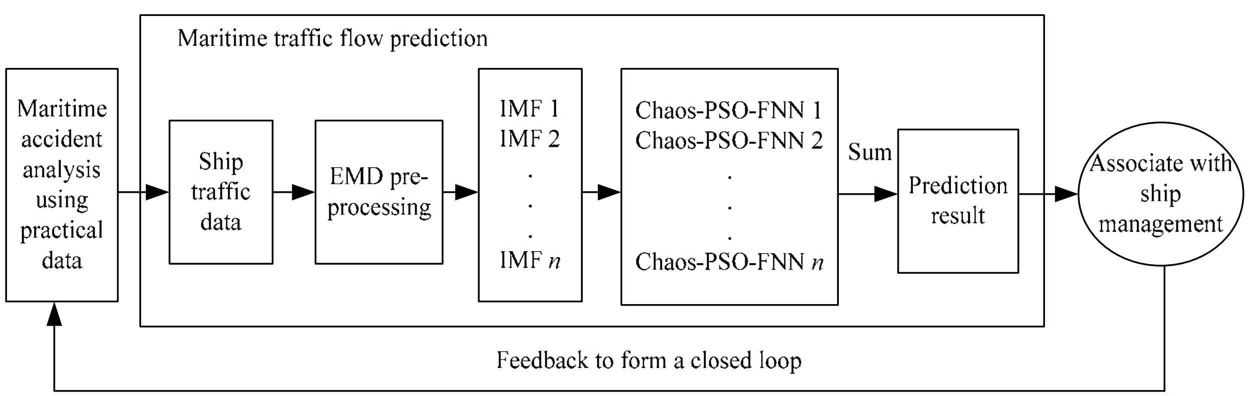

Fig. 3: Intelligent forecasting control for fishing boat traffic flow prediction

EXPERIMENTAL ANALYSIS

In order to realize the forecasting control of the fishing boats, the fishing boat traffic information provided by the Fujian marine bureau has been used to evaluate the newly proposed method. The traffic information is recorded for 10 year, i.e., 2001-2011 by the Fujian marine bureau. The ship traffic flow data and marine accident data have been used in this study to investigate the relationship of them. By doing so, some effect prevention and maintenance strategies can be obtained.

Analysis of the original data: To relate the ship traffic flow and marine accidents, it need firstly discuss the characteristics of the original data. As shown in Fig. 1 that the crash is the most common but most dangerous accident type. This kind of accident is caused frequently by the illegal operation. Moreover, the working time and ship traffic flow contribute a large amount of responsibility on the accidents. Hence, the relationship of the shipping time and the crash accidents has been investigated, as well as the relationship of the ship traffic flow and the crash accidents. Figure 4 shows the relationship of the shipping time and the crash accidents and Fig. 5 shows the relationship of the shipping time and the traffic flow. It can be seen from Fig. 4 that the crash accidents mainly happen during the time interval of [04:00 07:00], [12:00 14:00], [17:00 18:00] and [22:00 24:00]. For the time period of [12:00 14:00] and [17:00 18:00], it is the rush traffic hours because it is time to have meals for the boatmen and it is the time for the fishing boats to return. For the time slot of [12:00 14:00] and [17:00 18:00], the traffic flow is very heavy. This means that the fishing boat is more likely to crash in rush hours. Thus, it suggests that the fishing boat should avoid the high traffic flow time for the safe purpose.

Traffic flow prediction for forecasting control: As mentioned above, if the ship traffic flow can be predicted precisely, the proper management of the shipping activities can be made and thus the marine accident can be reduced. This is why the Chaos-PSO-FNN method is proposed. By the used of the intelligent prediction model, it can provide a possibility of forecasting control of the fishing boat to prevent marine accidents.

In the experimental analysis, one week ship traffic flow data has been used for the flow prediction. The measurement of ship traffic flow has been conduct every half an hour. Hence, there are 336 data sets in total. 288 sample data of the first 6 days have been applied to the training procedure and the reminder has used for testing. Figure 6 shows the traffic flow of the first six days. One can note from Fig. 6 that although the traffic flow presents a certain degree of randomness, the traffic flow trend is presented every 24 h. This statistic of the traffic flow allows the data mining of useful information to forecast the future traffic flow.

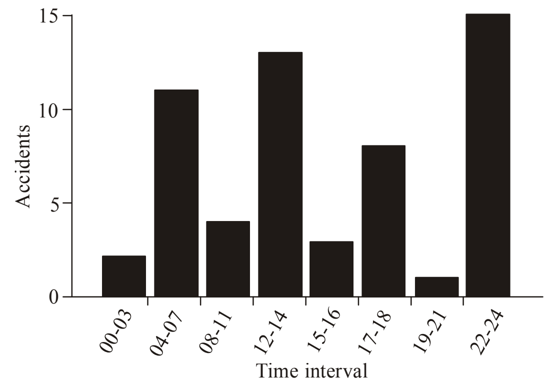

Fig. 4: The relationship of the shipping time and the crash accidents

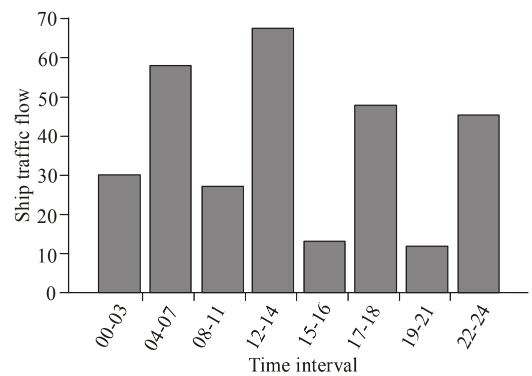

Fig. 5: The relationship of the shipping time and the traffic flow

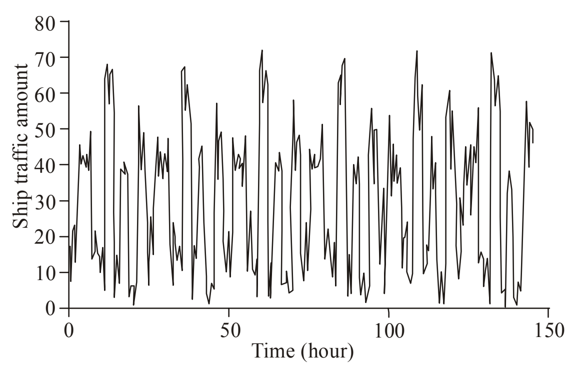

Fig. 6: The ship traffic flow curve for the first 6 days

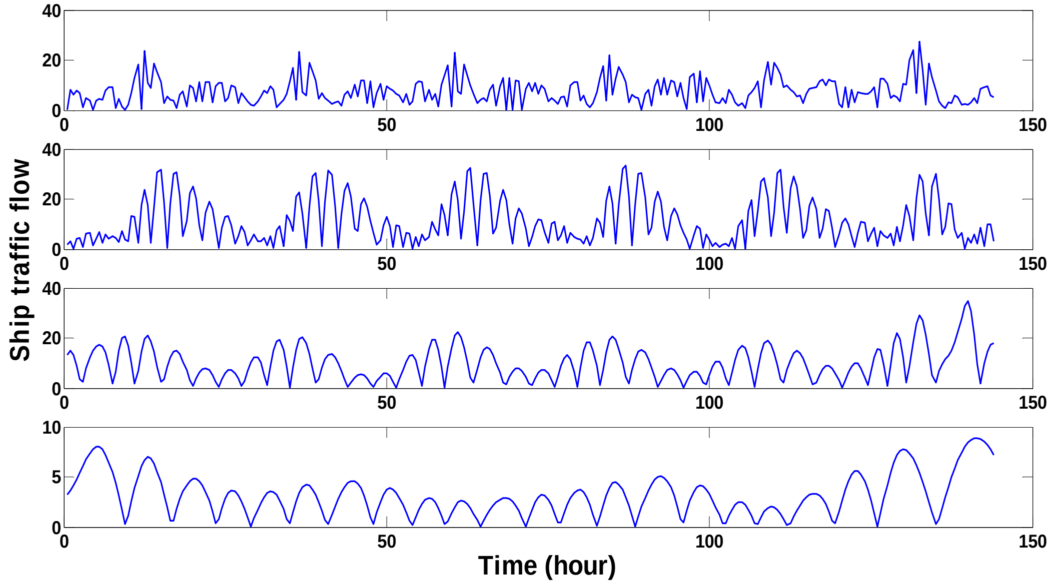

Fig. 7: The time spectra of the four IMFs

However, the nonlinearity of the traffic flow data may reduce the ANN based traffic flow prediction rate. To investigate the influence of the nonlinear components, the EMD has been employed to enhance the prediction performance in this study.

The original ship traffic flow data is firstly decomposed into 4 IMFs using the EMD technique. Figure 7 shows the 4 IMFs. It can be seen from Fig. 7 that the first and second IMFs have the main characteristics of the original signal. They have presented the overall flow trend. Compared with the first and second IMFs, the third and forth IMFs can be regarded as the randomness terms. The randomness terms are very sensitive for the accurate traffic flow prediction. If they can be processed well, high prediction performance could be obtained. Hence, we have established four Chaos-PSO-FNN prediction models to deal with the four IMFs, respectively. By doing so, high prediction performance may be gotten due to the consideration of the randomness terms.

The parameters of the Chaos-PSO-SVM model are as follows: $\omega_i = 0.5$, $c_1 = c_2 = 1.75$, $\eta = 5$, $a_i = 1.1$ and $b_i = 0.2$. The particle swarm size is 20.

The traditional way is to train the FNN by BP learning. To improve the training procedure, the global searching ability of the Chaos-PSO has been employed to train the FNN. The neuron number of the hidden layer and the coefficients of the Gaussian function are the optimization objectives of the Chaos-PSO. The

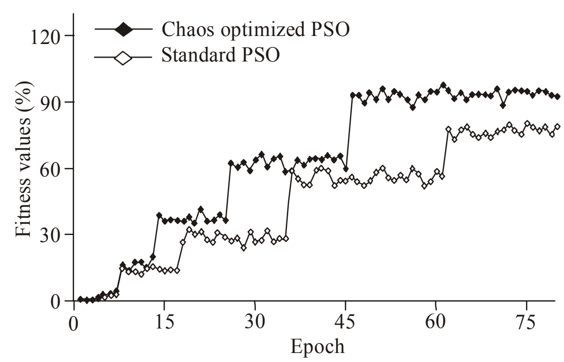

Fig. 8: The performance of PSO optimization

fitness function selects the pattern identification precision of the FNN, e.g:

$$\text{Fitness}=\frac{\text{correct recognition patterns}}{\text{total patterns}}\times 100\% \quad (10)$$

The optimization of the FNN is shown in Fig. 8. The Chaos-PSO approach has been compared with standard PSO algorithm. The optimization performance of the Chaos-PSO is superior to the standard PSO with respect to the fitness value. From the result one can note that the PSO employing the Chaos algorithm can overcome the premature problem and hence the global optimization can be achieved.

Then, the Chaos-PSO optimized FNN models have been established for the prediction of the four IMFs.

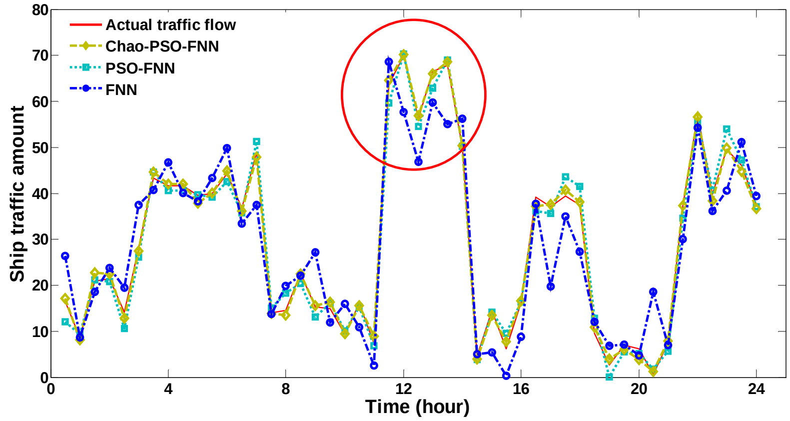

Fig. 9: The ship traffic flow forecasting results

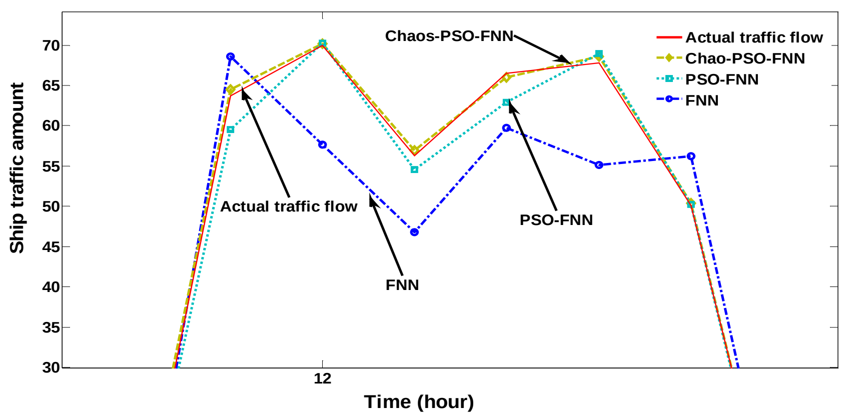

Fig. 10: Zoomed picture of Fig. 9

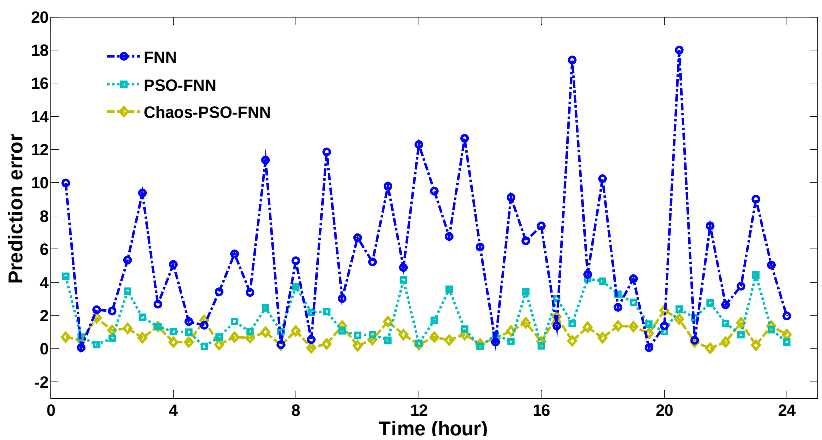

Fig. 11: The prediction error of the three methods

The trained FNNs are used to get the prediction components of all the IMFs and the ultimate prediction flow is the sum of the outputs of the four FNN models. In the experiments, the proposed prediction method has been used to forecast the ship traffic flow of the last day.

Figure 9 shows the prediction performance of FNN, PSO based FNN and the proposed method.

Table 1: The comparative results of the different models

Prediction model	Prediction performance MAPE (%)	MSE (%)	MSPE (%)
FNN	2.53	2.41	1.96
EMD-FNN	2.04	2.12	1.57
PSO-FNN	2.21	2.17	1.45
EMD- PSO-FNN	1.57	1.46	1.28
Chaos-PSO-FNN	1.81	1.67	1.32
EMD-Chaos-PSO-FNN	1.23	1.31	1.01

Compared with the FNN and PSO-FNN approaches, the proposed Chaos optimized PSO-FNN gives the best prediction rate. The prediction results can be seen clearer in the zoomed picture in Fig. 10. One can also find in Fig. 11 that the prediction error of the proposed method is smaller than the other two approaches. Hence, the future ship traffic flow can be predicted accurately by the proposed Chaos-PSO-FNN model and the prediction performance is better than the traditional methods.

To further evaluate the ship traffic flow prediction performance, the following indexes have been chosen, where f denotes the actual value and f' denotes the predicted value:

- The Mean Absolute Percent Error (MAPE):

$$MAPE = \frac{1}{N}\sum_{t=1}^{N}\left|\frac{f - f'}{f}\right| \tag{11}$$

- The Mean Square Error (MSE):

$$MSE = \frac{1}{N}\sqrt{\sum_{t=1}^{N}\left|f - f'\right|^{2}} \tag{12}$$

- The Mean Square Percent Error (MSPE):

$$MSPE = \frac{1}{N}\sqrt{\sum_{t=1}^{N}\left|\frac{f - f'}{f}\right|^{2}} \tag{13}$$

The analysis results are shown in Table 1. The performance of the proposed maritime traffic forecasting method has been compared with other approaches. The results suggest that the best prediction performance is produced by the proposed Chaos-PSO-FNN model.

DISCUSSION

It can be seen from Table 1 that by the EMD processing, the general trend and the nonlinear components can be extracted separately in the form of IMFs. Thus, the FNN can prediction each of the IMFs to enhance the forecasting rate. From the analysis results in Table 1 the prediction error is decreased by 0.29% or better by the EMD preprocessing.

On the other hand, the PSO can make the FNN parameter proper and then the FNN can provide better performance. Table 1 shows that the PSO optimized FNN model can reduce the prediction error by 0.24% or better. In addition, the prediction error can be further decreased by the Chaos searching. One can note that the Chaos-PSO-FNN gives the best prediction error by 1.01% in the maritime traffic flow prediction.

Based on the precise prediction of the maritime traffic flow, the fishing boat managers can arrange the shipping scheme reasonably to average the traffic flow along the time interval. By doing so, the ship can avoid the rush hours and hence reduce the accident significantly. by the use of the proposed intelligent maritime traffic flow prediction model, the fishing boats may operate more safely and effectively than before.

CONCLUSION

The fishing boats always operate in severe marine environment and are readily to damages. Through the history data analysis it found a strong link between the marine accident and traffic flow. That means to a certain extent the intelligent fishing boat forecasting control and management relies on accurate and reliable maritime traffic flow prediction. Therefore, it is critical to carry on effective prediction model for the ship traffic flow. This paper presents a novel intelligent prediction model for the maritime traffic flow forecasting. The newly proposed approach takes the advantages of the Empirical Mode Decomposition (EMD) and intelligent Fuzzy Neural Network (FNN) to discover potential and useful information of the real ship traffic flow data. In addition, the Chaos-Particle Swarm Optimization (PSO) optimization has been employed to update the FNN structure. The experiment analysis using the real ship flow data has been implemented. The testing results show that the newly proposed prediction model is precise and powerful for the ship traffic flow prediction. Based on the precise prediction of the maritime traffic flow, the fishing boats can operate in the reasonable shipping scheme and thus their security may be ensured.

ACKNOWLEDGMENT

This research is supported by the National Transportation Scientific Project in Western Regions (No. 200932881106), The Fundamental Research Funds for Ministry of Education (No. 2010-II-010), The research was supported by the Hubei Province Key Laboratory of Intelligent Robot (HBRI 200907), The youths science foundation of Wuhan institute of technology and the president fund of Wuhan institute of technology.

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