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Parameter Prediction of Marine Seawater Cooling System Based on Chaos-Elman Combined Model

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ABSTRACT To improve the accuracy of short-term prediction of marine seawater cooling system parameters and reduce the accuracy loss caused by chaotic data, a combined prediction model combining chaos theory and Elman feedback neural network was proposed in this paper. Firstly, the C-C algorithm and G-P algorithm were used to calculate the two reconstruction parameters respectively, and according to the properties of the maximum Lyapunov exponent, it could be determined that the original one-dimensional time series had chaotic characteristics. Secondly, phase space reconstruction technique was used to map the one-dimensional seawater outlet temperature time series of intercooler to the high-dimensional space to find its chaotic phase trajectory, and the number of adjacent points was determined by HQ (Hannan Quinn) information criterion. Finally, the Chaos-Elman combined prediction model was used to train and test 300 sets of seawater outlet temperature data of intercooler, and the accuracy of prediction was compared with that of single structure model. The experimental results were as follows: the average prediction accuracy based on chaos theory was 95.5%, the prediction accuracy of Elman neural network was 95.1%, and the prediction accuracy of Chaos-Elman combined model could reach 98.7%. In this study, the Chaos-Elman combined model has better prediction accuracy than the single model. It can be concluded that the Chaos-Elman combined model can be used for the short-term prediction of seawater cooling system parameters, and the prediction accuracy and reliability are high.

INDEX TERMS Marine seawater cooling system, parameter prediction, chaotic time series, phase space reconstruction, Elman feedback neural network.

I. INTRODUCTION

At present, under the background of ''Industry 4.0'', the world shipping industry is in a golden stage of development. Intelligent ships and intelligent shipping emerge at the historic moment and have gradually become the focus of research in this era. The prerequisite for realizing full intelligence of ship is to be able to predict the parameters of ship sailing in a period of time accurately, identify all kinds of faults that may occur in engine room accurately, and make processing decisions. The cooling water system plays a crucial role in the normal navigation of a ship, and the seawater cooling system undertakes the heat exchange between the whole ship system and the seawater. Consequently, it is very important to predict the state parameters of the marine seawater cooling system in the short term for the normal navigation of ships.

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Meanwhile, a large number of experts and scholars have done extensive research on parameter prediction. In the early stage, stationary time series were mostly predicted, and typical models mainly included Autoregressive Moving Average Model (ARMA) [1], Autoregressive Integrated Moving Average Model (ARIMA) [2] and Generalized Autoregressive Conditional Heteroscedasticity Model (GARCH) [3]. The traditional classical sequence does not follow the homoscedasticity and linearity, so it is impossible to describe the complete dynamics and make relevant predictions only by the traditional prediction model [4], [5]. Therefore, many scholars proposed to use Bayesian Network (BN) [6], Gauss Process (GP) [7], Support Vector Machine (SVM) [8]–[11] and other ML algorithms to predict nonlinear time series, and achieved good results. In addition, Cujia *et al.* [12] used intervention analysis to estimate shortages through outliers and obtained the best estimate with the Seasonal Autoregressive Integrated Moving Average Model (SARIMA); ZANG *et al.* [13] proposed a

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new Double-Encoder model composed of two Encoder modules, ST-Encoder and FR-Encoder, which could construct a model of space-time and daily flow to predict crowd flow; Uĝur *et al.* [14] modified the Sequential Monte Carlo method to produce an adaptive probabilistic model; Bisoyi [15] used Back Propagation Neural Network (BPNN) training algorithm to predict the daily sediment transport of Narmada River; Herbert *et al.* [16] proposed a combination of SARNA algorithm and thermodynamic model to predict the molecular structure of RNA; Marple [17] proposed to extend the matrix structure of linear parameter estimation to two dimensions to improve the application of spectral analysis; Ramoni *et al.* [18] proposed a bidirectional parameterized model in wireless communication system, which can forecast the M-to-M channel effectively; JIANG *et al.* [19] found that DNN and Random Forest show good performance to predict the abundance of *Vibrio* spp.; Ana *et al.* [20] through three different methods to predict the time series generated by chaotic oscillator, found that the error of artificial neural network is the least, and introduced a multi-layer perceptron in this way to predict chaotic time series; LU *et al.* [21] designed a multistep statistical workflow and integrated the support vector machine, neural networks and random forest to calculate non-linear prediction of spatial abundance; Alfonso *et al.* [22] used machine-learning and deep-learning to predict traffic flow at an intersection, and all algorithms scored good performance metrics.

The above methods have common defects, that is, large errors in dealing with nonlinear problems and are susceptible to the influence of external environment. To solve these problems, five models are established in this paper: maximum Lyapunov exponential prediction model, third-order Volterra adaptive prediction model, weighted first-order local prediction model, Elman feedback neural network prediction model and the combination of Chaos theory and Elman feedback neural network prediction model. The purpose of this paper is to apply the combined prediction model of Chaos theory and Elman feedback neural network to modern control theory of intelligent ship, so as to make the prediction of engine room parameters more accurate and intelligent. The experimental method is to collect the operation data of the seawater cooling system of the real ship "YU KUN" and compare the accuracy of the model in the seawater outlet temperature prediction task. Experimental results show:

(1) The proposed Chaos - Elman combined model can be gained through online data for training, and model training efficiency is higher;
(2) The combined model proposed in this paper effectively makes up for the defects of nonlinear trend fitting in subsequent prediction of chaos theory, thus greatly improving the accuracy and efficiency, finally get some objective conclusions and the idea of parameter prediction for the future;
(3) This research not only contributes to the prediction of seawater cooling system status parameters, but also has important significance for monitoring the operating status of the entire engine room equipment or system, so as to achieve the level of complete engine room automation.

The rest of this paper is organized as follows: Section II describes the reconstruction methods and steps of chaotic phase space and the method of selecting adjacent points. In section III, the method of distinguishing chaotic characteristics and four indexes for evaluating model performance are introduced. Section IV introduces the prediction theory of the combined model proposed in this paper. Section V describes the application results of the combined model on a real ship. Section VI describes the conclusions and future work.

II. RECONSTRUCTION OF CHAOTIC PHASE SPACE AND SELECTION OF ADJACENT POINTS

Chaos is a natural phenomenon discovered by Poincare when he studied the orbit of celestial bodies. He believed that the solution of three-body problem is random in a certain range, and the essence of this nonlinear random phenomenon is chaos. For chaotic sequence, there are two characteristics. One is that it is difficult to find its evolution law intuitively. Even though the change seems simple, it is also very difficult to predict its subsequent situation or state. The other is seemingly random, but exist a regular trend weakly in a certain range. The state parameters of seawater cooling system are in line with the characteristics of the above two points, and their changes are subject to the influence of external factors and internal mechanism. However, there is a standard state interval to monitor the operation and health of the system, which is in line with the characteristics of chaotic sequence.

A. PHASE SPACE RECONSTRUCTION

For a chaotic system, the variation law of its state parameters is jointly determined by the changes of all subsystems in the system, which indicates that the information corresponding to the system state is mutually influenced and interacts with each other, and also indicates that the hidden information contained in the multi-subsystem exists in the one-dimensional sequence displayed. In one-dimensional space, the evolution law seems random and has no rules to follow, but when mapped to higher-dimensional space, it will show a traceable trajectory. Therefore, if we want to dig out the hidden evolution law of data, we need to use phase space reconstruction technology to map one-dimensional time series to high dimensional space to recover its chaotic attractor, so as to find out its hidden law. Considering noise sensitivity and calculation error, this paper decides to adopt the delay coordinate method for phase space reconstruction.

Assume that the one-dimensional original chaotic time series is $x = \{x_i \mid i = 1, 2, \cdots, N\}$, N is the length of time series, and the delay time t and embedded dimension m will be combined with original time series. According to a certain rule, the phase space will be reconstructed into $m \times M$ order high dimension matrix which collects all phase points for finding its chaotic attractor, so as to find hidden evolution rule.

$$X = \begin{bmatrix} x_1 & x_2 & \cdots & x_{N-(m-1)t} \\ x_{1+t} & x_{2+t} & \cdots & x_{N-(m-2)t} \\ \vdots & \vdots & \vdots & \vdots \\ x_{1+(m-1)t} & x_{2+(m-1)t} & \cdots & x_N \end{bmatrix} \tag{1}$$

where $X_i = \left[x_i, x_{i+t}, \cdots, x_{i+(m-1)t},\right]^{\mathrm{T}}$, $i = 1, 2, \cdots, M$ is any phase point in the phase space, and the number of phase points is $M = N$-$(m-1)t$. If this theory is applied to the sea water cooling system, the one-dimensional time series here represents the data set collected according to the time variation of a certain state parameter of the sea water cooling system. The reconstruction process is to divide the data set according to this rule, and then the regular set of multiple data points is obtained as the column matrix of phase points, and in this process, the key point is to calculate the reconstruct parameters exactly [23].

B. C-C ALGORITHM TO CALCULATE THE DELAY TIME

This paper adopts C-C algorithm [24] to calculate the optimal delay time. The theoretical model of the algorithm is as follows: The correlation integral is defined based on the phase point X_i obtained above.

$$C(m, N, r, t) = \frac{2}{M(M-1)} \sum_{1 \le i < j \le M} \theta\left(r - \|X_i - X_j\|_{(\infty)}\right) \tag{2}$$

where r is the neighborhood radius, an integer greater than 0, $\theta(x)$ is the Heaviside function, and the value condition is

$$\theta(x) = \begin{cases} 0 & x < 0 \\ 1 & x \ge 0 \end{cases} \tag{3}$$

Define validation statistics

$$S_1(m, N, r, t) = C(m, N, r, t) - \mathrm{C}^m(1, N, r, t) \tag{4}$$

To reduce the complexity of the computation, the original sequence is decomposed into t mutually non-interactive sub-sequences, as follows

$$\begin{cases} x^1 = \{x_i \mid i = 1, t+1, 2t+1, \ldots\} \\ x^2 = \{x_i \mid i = 2, t+2, 2t+2, \ldots\} \\ \quad \cdots\cdots \\ x^t = \{x_i \mid i = t, 2t, 3t, \ldots\} \end{cases} \tag{5}$$

The block average strategy is adopted to calculate the statistics, and that will obtain formula (6)

$$S_2(m, N, r, t) = \frac{1}{t} \sum_{s=1}^{t} \left[C_s(m, N/t, r, t) - C_s^m(1, N/t, r, t)\right] \tag{6}$$

If N goes to infinity, get formula (7)

$$S_2(m, r, t) = \frac{1}{t} \sum_{s=1}^{t} \left[C_s(m, r, t) - C_s^m(1, r, t)\right] \tag{7}$$

Choose two extreme values of neighborhood radius r and define the difference as formula (8)

$$\Delta S_2(m, t) = \max\left\{S_2\left(m, r_j, t\right)\right\} - \min\left\{S_2\left(m, r_j, t\right)\right\} \tag{8}$$

In combination with the BDS statistical conclusion, the value of parameters can be reasonably estimated, and take $i = 1, 2, 3, 4$, $m = 2, 3, 4$, $r_i = i \times \sigma/2$, where σ is the standard deviation of the sequence, and obtain formula group (9)

$$\begin{aligned} \bar{S}_2(t) &= \frac{1}{16} \sum_{m=2}^{5} \sum_{i=1}^{4} S_2(m, r_i, t) \\ \Delta \bar{S}_2(t) &= \frac{1}{4} \sum_{m=2}^{5} \Delta S_2(m, t) \end{aligned} \tag{9}$$

The original C-C algorithm considers that the first zero of $\bar{S}_2(t)$ or the first local minimum of $\Delta\bar{S}_2(t)$ is the optimal choice of delay time in the theoretical sense. However, Lu [25] proposed an improved C-C algorithm for the original algorithm shortcomings. According to the wave rule of $S_2(m, N, r, t) \sim t$ image and the process of obtaining $\bar{S}_2(t)$ and $\Delta\bar{S}_2(t)$ by referring to $S_2(m, N, r, t)$, it is proposed to use $S_1(m, N, r, t)$ to calculate $\Delta\bar{S}_1(t)$, and take the first local minimum of $\Delta\bar{S}_1(t) \sim t$ as the optimal delay time t.

C. G-P ALGORITHM TO CALCULATE THE EMBEDDING DIMENSION

At present, saturation correlation dimension method (G-P algorithm) is the most frequently used method to calculate the embedding dimension of chaotic time series. It is expressed in the form of correlation integral, which represents the probability that the distance between any two points in the phase space is less than r [26]. After repeated calculation verification, when m value is fixed and r value tends to 0, there is an exponential relationship between $C(m, N, r, t)$ and neighborhood radius r, which is the relationship between m, r and attractor dimension d, i.e.

$$\lim_{r \to 0} C(m, r) \propto r^d \tag{10}$$

The formula can be obtained by further transformation

$$D(m) = \lim_{r \to 0} \frac{\ln C(m, r)}{\ln r} \tag{11}$$

$D(m)$ is the correlation dimension of chaotic time series. According to the formula (11), if the relationship between $C(m, r)$ and r is used to obtain the value of $D(m)$, the range of change of r needs to be determined. GAO [27] proposed to select the maximum and minimum distance between each phase point in the phase space as the upper and lower limits of neighborhood radius, i.e.

$$\begin{cases} r_{\max} = \max\left(\|X_i - X_j\|_\infty\right) \\ r_{\min} = \min\left(\|X_i - X_j\|_\infty\right) \end{cases} \tag{12}$$

Meanwhile, according to the conclusion of BDS statistical limited range, the final choice of scale-free interval is

$[\ln(\sigma/2), \ln(2\sigma)]$, which can effectively improve the determination accuracy of correlation dimensions.

Since $D(m)$ and m are positively correlated, as m increases, so does $D(m)$. However, in chaotic time series, $D(m)$ will first increase with the increase of m, then the change trend will greatly decrease, and finally converge to a stable value. At this moment, the corresponding m is the optimal embedding dimension. In order to more intuitively calculate embedding dimension, first make the embedded dimension m to take multiple values in a relative interval, and take the corresponding $\ln C(m, r) \sim \ln r$ relation curve in a two-dimensional coordinate system. Then use the least squares to fit out the slope of approximate linear part of the curve, the value of slope is $D(m)$, finally take the relation curve $D(m) \sim$m, when $D(m)$ converges to the maximum value of the associated dimension, the corresponding minimum value of m is the optimal embedded dimension.

D. SELECTION OF THE NUMBER OF ADJACENT POINTS

Based on chaotic time series prediction problem, its main prediction idea is to find the adjacent sequence which has the same evolutionary trend with the sequence to be predicted. The idea needs to determine the number of adjacent points of the original sequence center. If too many adjacent points are selected, there will be a pseudo adjacent points and "fitting" phenomenon, cause large error; If too few adjacent points are selected, the evolutionary trend cannot be accurately found. This paper chose HQ information criterion to determine the number of adjacent points.

The minimum information criterion [28], abbreviated as AIC criterion, was first formally proposed by the Japanese mathematician H. Akaike to determine the complexity of the autoregressive moving average model, namely ARMA (p, q)

$$AIC(p, q) = \ln \sigma^2 + 2(p + q + 1)/N \tag{13}$$

where σ^2 is the fitting variance, N is the length of the fitting sequence, p is the order of autoregression, and q is the order of sliding average process. When the AIC value reaches the minimum, the corresponding p and q are the optimal order. On the basis of AIC criterion, Hannan and Quinn improved it and proposed HQ grading criterion [29]:

$$\Phi(p, q) = \ln \sigma^2 + (p + q + 1)\frac{C \cdot \ln(\ln N)}{N} \tag{14}$$

where C is the weight of the latter term, which is usually a constant greater than 2. When the $\Phi(p, q)$ is minimum, the complexity and precision of the model reach the best ratio.

In this paper, HQ criterion is used to confirm the number of adjacent points of the prediction center, and the general process is as follows:

Firstly, set a wide value range $K \in [K_{\min}, K_{\max}]$ for the number of adjacent points K, and then substitute K values in the range according to formula (15) in turn to calculate the corresponding HQ criterion value.

$$\Phi(K) = \ln \sigma^2(K) + K\frac{C \cdot \ln(\ln N)}{N} \tag{15}$$

$$\sigma^2 = \frac{\frac{1}{l}\sum_{i=1}^{l}\left(x_i - x_i'\right)^2}{(1/N)\sum_{i=1}^{N}(x_i - \bar{x})^2} \tag{16}$$

where, x_i is the data sample point, x_i' is the prediction result corresponding to the sample, $\bar{x}$ is the mean value of the sample point, and l is the number of predicted steps.

After obtaining the criterion value corresponding to each K within the range, the K value corresponding to the minimum value of formula (15) is the number of optimal adjacent points of the sequence.

III. CHAOTIC TIME SERIES PREDICTION THEORY

After reconstructing the phase space of state parameters of seawater cooling system, the one-dimensional series is mapped to the higher-dimensional space, and the higher-dimensional chaotic attractor represents the evolution law of the original series. In essence, the prediction research based on chaos theory is to use nonlinear method to fit in the reconstructed phase space so as to find the change trend closest to the original sequence. At present, the prediction methods using chaos theory alone can be roughly divided into three categories: global prediction method, local prediction method and maximum Lyapunov index prediction method. In this paper, the state parameters of seawater cooling system are predicted and analyzed by these three methods.

A. DISCRIMINATION OF CHAOS CHARACTERISTICS

Before the prediction based on chaos theory, it is indispensable to ensure whether the original time series is chaotic. If the series without chaotic characteristics is reconstructed, not only the evolution law of the system cannot be obtained, but also the original characteristics of the system will be damaged. In this paper, quantitative method is used to judge the chaos of the original system. In 1983, Griboki proposed that as long as the maximum Lyapunov exponent is greater than 0, the adjacent orbits of the system will be separated exponentially with time, so the system must be chaotic. The key point is the calculation and determination of the maximum Lyapunov exponent.

There are many methods to calculate the maximum Lyapunov exponent, including Wolf method, P norm method, small amount of data method, etc. In view of its computational complexity and the size of original data, this paper decides to use the small data sets arithmetic for calculation, and the specific steps are as follows:

Step 1: Perform the Fast Fourier Transform on the original time series to obtain its average period P;

Step 2: According to the delay time t and embedding dimension m calculated above, the phase space is reconstructed to obtain M phase points;

Step 3: Find the nearest phase point $X_{\hat{i}}$ of each phase point X_i and calculate the initial distance:

$$d_i(0) = \min_{\hat{i}} \left\| X_i - X_{\hat{i}} \right\|, |i - \hat{i}| > P \tag{17}$$

Step 4: Calculate the distance of each pair of adjacent phase points obtained in step 3 after h discrete time steps:

$$d_i(h) = \left\| X_{i+h} - X_{\hat{i}+h} \right\|, h = 1, 2, \ldots, \min(M - i, M - \hat{i}) \tag{18}$$

Step 5: According to the definition of Lyapunov index, there is an exponential relationship between $d_i(h)$ and $d_i(0)$, and Lyapunov exponent is represented by the approximate linear relationship of the logarithmic transformation of this relationship formula. Therefore, a fixed h value is used to calculate the average $y(h)$ of all non-zero $d_i(h)$.

$$y(h) = \frac{1}{q\Delta t} \sum_{i=1}^{q} \ln d_i(h) \tag{19}$$

where, q is the number of non-zero $d_i(h)$, and Δt is the sample period.

Step 6: Gradually increase the value of h, calculate the corresponding $y(h)$, and draw $y(h) \sim h$ relation curve. The slope of the curve fitted by the least square method is the maximum Lyapunov exponent λ.

B. MAXIMUM PREDICTABLE TIME OF CHAOTIC SEQUENCES

Chaotic time series is a seemingly random chaotic sequence of single or multiple dependent variables with time as independent variable. According to the definition of chaotic time series, chaotic systems have two obvious characteristics: inherent randomness and initial value sensitivity. Because chaotic system is extremely sensitive to the initial state, it will cause the divergence of neighboring orbits and lose the initial information, so chaotic system can only be predicted in the short term. The maximum Lyapunov index can be used to measure the divergence degree of phase trajectory, so as to determine the maximum predictable scale.

According to experience summary, the reciprocal of the maximum Lyapunov exponent λ is usually used as the longest prediction time, i.e.

$$T_{\max} = \frac{1}{\lambda} \tag{20}$$

Within T_{max}, the prediction accuracy is relatively high. If T_{max} is exceeded, the prediction error will be infinitely amplified and the prediction significance will be lost.

C. BASIS FOR ACCURACY JUDGMENT

In order to quantitatively compare the accuracy of prediction in different models, this paper adopts RMSE, MAPE, R^2 and EV to evaluate the accuracy of each prediction model.

(1) Root Mean Square Error (RMSE)

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} \left[t_i - t_i' \right]^2} \tag{21}$$

where: t_i' is the predicted value, t_i is the true value, and n is the number of sample points.

(2) Mean Absolute Percentage Error (MAPE)

$$MAPE = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{t_i' - t_i}{t_i} \right| \cdot 100\% \tag{22}$$

(3) Determination Coefficient (R^2)

$$R^2 = \frac{\left(n \sum_{i=1}^{n} t_i' \cdot t_i - \sum_{i=1}^{n} t_i' \cdot \sum_{i=1}^{n} t_i \right)^2}{\left[n \sum_{i=1}^{n} t_i'^2 - \left(\sum_{i=1}^{n} t_i' \right)^2 \right] \cdot \left[n \sum_{i=1}^{n} t_i^2 - \left(\sum_{i=1}^{n} t_i \right)^2 \right]} \tag{23}$$

(4) Explained Variance (EV)

$$EV = 1 - \frac{Var(t - t')}{Var(t)} \tag{24}$$

The smaller the values of RMSE and MAPE are, the better the prediction accuracy is. The values of R^2 and EV range from zero to one, and the closer the value is to one, the better the regression model fitting is.

IV. CHAOS-ELMAN COMBINED MODEL PREDICTION THEORY

In this section, the Elman feedback neural network with strong nonlinear mapping ability is combined with the phase space reconstruction technology of chaotic time series to predict the state parameters of one-dimensional seawater cooling system, so as to improve the accuracy of prediction.

A. PREDICTION PRINCIPLE OF CHAOS-ELMAN COMBINED MODEL

One-dimensional time series of seawater cooling system state parameters $\{x_1, x_2, \ldots, x_N\}$ is reconstructed to obtain the high-dimensional matrix $[X_1, X_2, \ldots, X_M]$, where the phase point $X_M = \{x_M, x_{M+t}, \ldots, x_{M+(m-1)t}\}$, and the phase point of further evolution is

$$X_{M+1} = \left\{ x_{M+1}, x_{M+1+t}, \ldots, x_{M+1+(m-1)t} \right\} \tag{25}$$

It can be seen that the last one-dimensional component of X_M is the last point x_N of the original time series, and the last one-dimensional component of X_{M+1} is the next point x_{N+1} of the original time series to be predicted.

According to the above properties, it can be considered that X_M and x_{N+1} have some kind of nonlinear function mapping relationship, which can be expressed as $x_{N+1} = F(X_M)$. According to chaotic evolution, it can be considered that the next point to be predicted of K adjacent phase points of X_M has a nearly consistent mapping relationship with x_{N+1}, thus the specific mapping function $F(\cdot)$ can be found, and the next predicted value of the original sequence can be obtained.

Elman feedback neural network is a typical hierarchical network with input layer, hidden layer, continuity layer and output layer. According to its specific structure, K neighboring points of X_M can be taken as the input of the neural network, and K neighboring points of x_{N+1} can be taken as the output of the neural network. After repeated training, the mapping function can be fitted in the black-box system of the neural network, and then X_M can be taken as the input layer, and the predicted value x_{N+1} can be obtained. Taking the predicted x_{N+1} as the known condition of the new sequence, the multi-step recursive prediction of the time series of seawater cooling system state parameters can be realized by repeated single-step prediction.

B. DETERMINE THE TOPOLOGICAL RELATIONSHIP OF CHAOS-ELMAN COMBINED MODEL

ENN is a dynamic neural network with local feedback and overall feedforward. Therefore, the specific topological structure of Elman feedback neural network needs to be determined before the actual prediction simulation of the combined model. According to the basic theory of ENN, the number of neurons in the input layer and the output layer are confirmed by the actual situation. However, there is no accurate basis condition for the number of hidden layer neurons, and it will directly affect the prediction accuracy. Therefore, empirical formula (26) is used in this paper to determine the number of hidden layer neurons.

$$L_h = \sqrt{L_i + L_o} + a \tag{26}$$

where, L_h, L_i, L_o is the number of neurons in the hidden layer, input layer and output layer respectively, and a is an additional constant, generally valued as [1,8]. According to formula (26), the value range of the number of neurons in the hidden layer can be calculated. Within this range, values are traversed for Elman neural network training, and the value with the minimum mean square error of training is taken as the final number of neurons in the hidden layer.

Based on the above content, the general process of the Chaos-Elman combined prediction model establishment, training and simulation prediction in this paper is shown in Fig. 1.

V. METHODOLOGY APPLICATION

The main research object of this paper is the state parameters of the seawater cooling system, but an important index to measure the operation quality of the seawater cooling system is the seawater outlet temperature of the central cooler, so this paper selected the seawater outlet temperature of the inter-cooler as an example for experiment and analysis. The data used in this paper were collected in real time during the circular voyage of "YU KUN", the school ship of Dalian Maritime University, from Dalian to Qingdao and back to Dalian, and then in the sea area around Dalian. Each data sampling interval was 30min. A total of 300 sets of data were taken, which took 150h to complete in total. Therefore, the one-dimensional time series of 300 groups of seawater outlet temperature of intercooler can be obtained, which is {36.9, 37.1, 37.5, 38.3, 38.1, 37.6, 36.5, 37.8, 37.8, 37.9, ..., 41.8, 40.6, 39.8, 39.2, 38.6, 40.2, 40.3, 41.6, 40.8, 39.2}, the normal value range of intercooler sea water outlet temperature on the ship is [36,42]. It is normal for data to have slight fluctuations outside the normal range. Fig. 2 shows the variation trend of the intercooler sea water outlet temperature of the specific 300 groups.

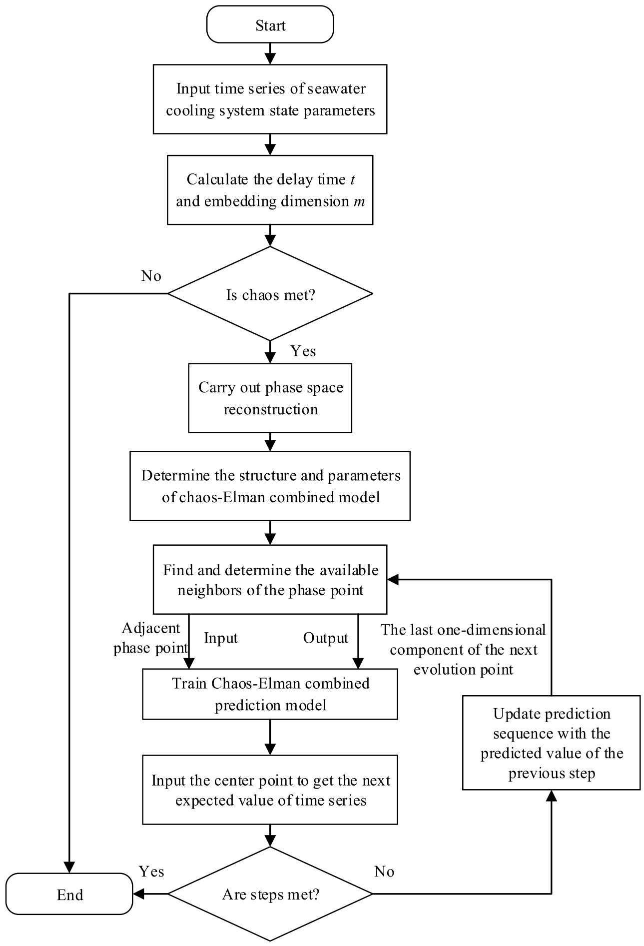


FIGURE 1. Prediction process of Chaos-Elman combined model.

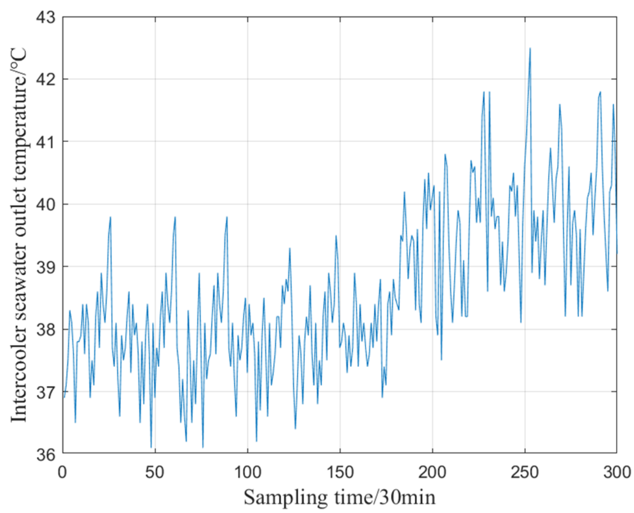


FIGURE 2. Variation trend of intercooler seawater outlet temperature.

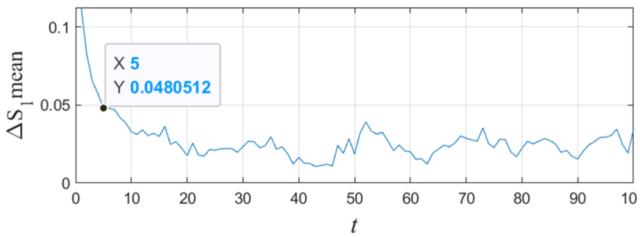


FIGURE 3. Optimization of delay time by improved C-C algorithm.

As shown in Fig. 2, the fluctuation of seawater outlet temperature of intercooler shows the following characteristics:

(1) Nonlinear, there is no linear rule on the curve as a whole, and the general trend is temperature increase;
(2) Seemingly irregular changes, randomness exists to some extent;
(3) The trend of change is stable in a certain range, and the range of change is not large, probably within the range of [36,42].

A. PHASE SPACE RECONSTRUCTION OF INTERCOOLER SEAWATER OUTLET TEMPERATURE TIME SERIES

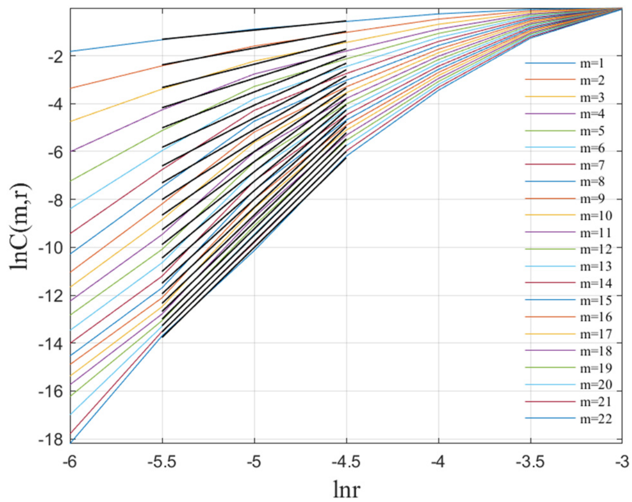
Before the phase space reconstruction of the intercooler seawater outlet temperature time series, its reconstruction parameters, including delay time and embedded dimension, need to be calculated and solved according to the method proposed above sections. The calculation results are shown in Fig. 3 and Fig. 4.

As shown in Fig. 3, the first local minimum point of $\Delta\bar{S}_1(t) \sim t$ is $t = 5$, so the optimal delay time of the sequence is $t = 5$.

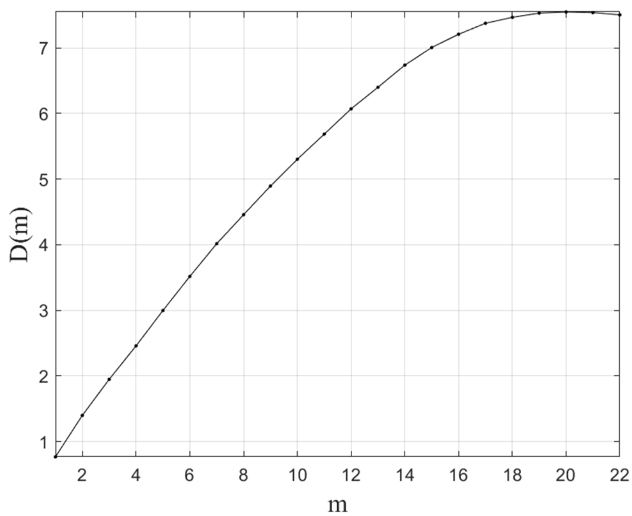
When the G-P algorithm is adopted in this paper, the change of the selected embedding dimension gradually increases from 1 to 22. The specific calculation results are shown in Fig. 4(a). The black linear part in Fig. 4(a) is the selected scale-free interval, which serves as the judgment basis of the embedding dimension. As shown in Fig. 4(b), when $m = 19$, the correlation dimension is saturated, so $m = 19$ is selected as the optimal embedding dimension.

B. SELECTION OF THE NUMBER OF ADJACENT POINTS OF THE SEAWATER OUTLET TEMPERATURE SERIES OF INTERCOOLER

According to HQ criteria and calculation formula, combined with the actual situation in this paper, the value range of K is determined to be $4 \sim 30$, and the weight constant C=8. The single-step prediction was carried out by the local average prediction method of chaotic sequence. The prediction errors corresponding to different K values were calculated, and then the corresponding criterion values were calculated. The corresponding situation of the number of adjacent phase points and their criterion values was obtained as shown in Fig. 5.



(a) Plot double logarithmic curve



(b) The relation between correlation dimension and embedding dimension

FIGURE 4. Embedding dimension obtained by G-P algorithm.

As can be seen from Fig. 5, when $K = 24$, the HQ criterion value reaches the minimum and satisfies the empirical formula $K \geq m + 1 = 20$. Therefore, the optimal number of adjacent points in this paper can be selected as 24.

C. IDENTIFICATION OF CHAOTIC CHARACTERISTICS OF INTERCOOLER SEAWATER OUTLET TEMPERATURE SERIES

According to the calculation steps of the maximum Lyapunov index, the time series of seawater outlet temperature of intercooler in this paper is calculated, and the calculation results of the maximum Lyapunov index are shown in Fig. 6.

The slope of curve fitting in Fig. 6 is $\lambda = 0.0173 > 0$, which indicates that the time series of intercooler seawater outlet temperature in this paper has chaotic characteristics, and the prediction method of chaos theory can be used to predict the subsequent trend of the series.

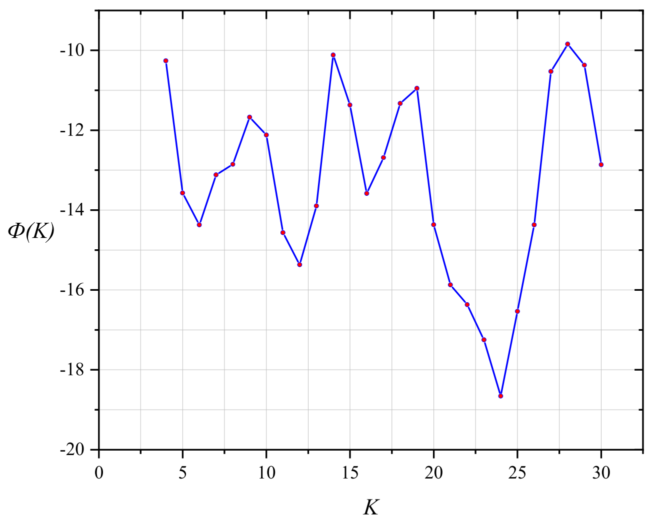


FIGURE 5. **Number of adjacent phase points based on HQ criterion.**

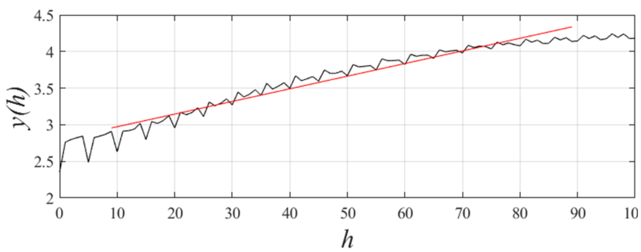
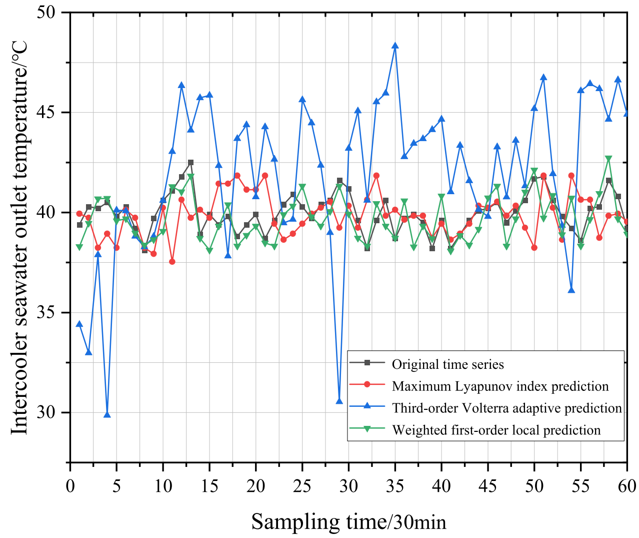


FIGURE 6. **Maximum Lyapunov index of time series of intercooler seawater outlet temperature.**

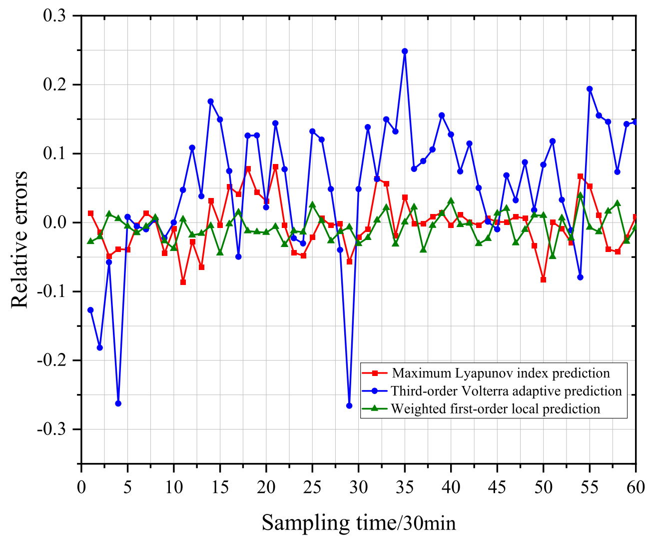
D. PREDICTION ANALYSIS BASED ON THE CHAOS THEORY

In this paper, the maximum Lyapunov index λ of time series of the sea water outlet temperature of the cooler is 0.0173, so the longest prediction time of short-term prediction is $T_{max} = 1/0.0173 \approx 58$, that is, under the condition of not losing the prediction significance, 58 groups of sampling time can be predicted at most. For the convenience of calculation and statistics, T_{max} is 60. Therefore, the time series with the original length of 300 groups can be divided that the first 240 groups are used as training sets for simulation training, and the last 60 groups are used as test sets to verify the accuracy and reliability of the model. The reconstruction parameters are $t = 5$ and $m = 19$ calculated above, and the recursive single-step prediction method is used for repeated prediction to achieve the multi-step prediction result.

In this section, Maximum Lyapunov index prediction method, Third-order Volterra adaptive prediction method and weighted first-order local prediction method [30] in chaos theory are used to predict and analyze the time series of intercooler seawater outlet temperature. Function files and script files were compiled in the environment of MATLAB R2020b to complete 60 groups of prediction. The average time of 60 groups of prediction was 5.2s for different models. The specific prediction results and relative errors are shown in Fig. 7.



(a) Comparison of prediction results of intercooler seawater outlet temperature based on chaos theory



(b) Comparison of relative errors in prediction of intercooler seawater outlet temperature based on chaos theory

FIGURE 7. **Comparison of short-term prediction results and relative errors of intercooler seawater outlet temperature based on chaos theory.**

According to the data shown in Fig. 7, it can be obviously seen the prediction accuracy of the three methods, among which the weighted first-order local prediction method has the highest accuracy, and the third-order Volterra adaptive prediction method has the largest deviation from the actual value. However, in general, the MAPE and RMSE of the three methods are somewhat high, for the following reasons: 1) The maximum Lyapunov exponential prediction method relies too much on the accuracy of λ for prediction, but due to its characteristics, the calculation of accuracy is limited; 2) The third-order Volterra adaptive prediction method corrects the weights through the prediction errors of each order. The closer to the infinite order, the higher the accuracy, but

TABLE 1. Number of different ENN hidden layers nodes and corresponding training errors.

Number of the hidden layer nodes	MSE
6	0.35885
7	0.17121
8	0.15292
9	0.36961
10	0.36436
11	0.22914
12	0.39271
13	0.14203

the infinite order is unrealistic, and the operation complexity of too high order increases exponentially, so the large error is inevitable; 3) The weighted first-order local prediction method uses a linear model to approximate the nonlinear evolutionary trend, which is bound to produce certain errors. Therefore, if only chaos theory is used for prediction, the accuracy is obviously insufficient, and there is still a lot of room for improvement.

E. PREDICTION ANALYSIS BASED ON CHAOS-ELMAN COMBINED MODEL

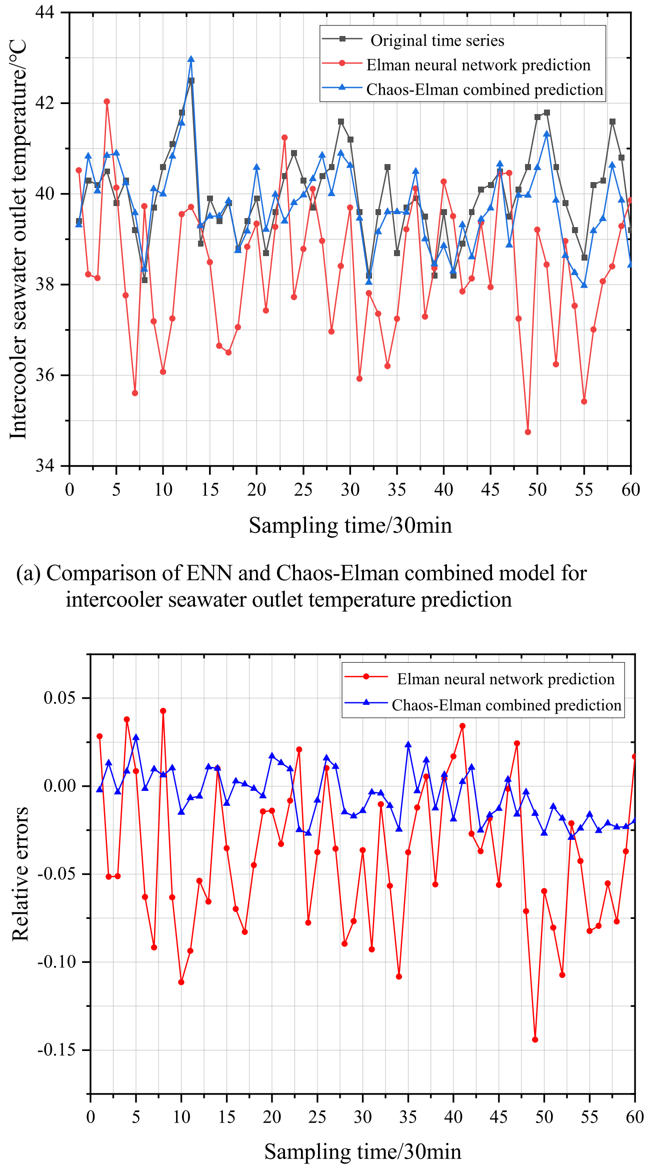
In view of the obvious shortcomings of the prediction method using chaos theory alone, and the calculation accuracy of λ and high order are difficult to realize, so the Chaos-Elman combined model is proposed to predict the time series of intercooled seawater outlet temperature, in order to solve the problem that the weighted first-order local prediction method cannot achieve nonlinear approximation.

Phase space reconstruction technology extends the model theory proposed above. This section only needs to fuse ENN into phase space, so its topological structure and parameters should be determined first. According to the method proposed above, the optimal embedding dimension $m = 19$ is taken as the number of neurons in the input layer, and since it is a single-step prediction, the number of neurons in the output layer is set as 1. According to formula (26), the value range of the number of neurons in the hidden layer can be calculated as [6, 13], and the number of nodes and the corresponding training mean square error are shown in Table 1.

As shown in Table 1, when the number of hidden layer neurons is 13, the trained MSE is the smallest, thus it can be determined that the topological structure of ENN in the Chaos-Elman combination model is 19-13-1.

The prediction simulation experiment was carried out according to the process described in above section. The results and relative errors of 60 sets of data of the intercooler seawater outlet temperature were predicted by ENN alone and Chaos-Elman combined model are shown in Fig. 8.

It can be seen from Fig. 8 that the prediction effect of Chaos-Elman combined prediction model is much better than that of the single Elman feedback neural network model. This is because the time series in this paper has the characteristics of chaos, so it is necessary to reconstruct its phase space first to explore the hidden evolution law to the maximum extent. Better prediction performance can be obtained by combining chaos theory with ENN.



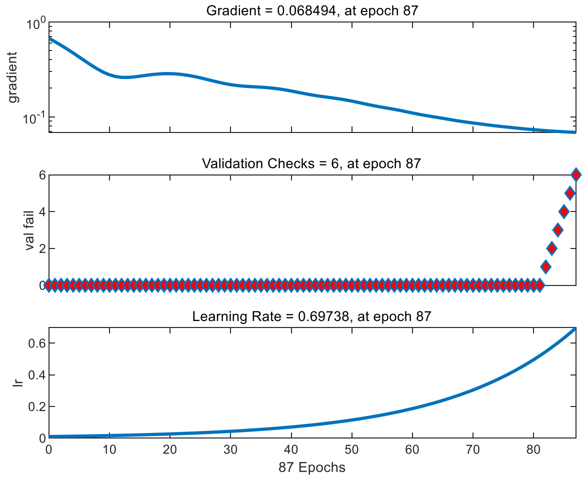
(a) Comparison of ENN and Chaos-Elman combined model for intercooler seawater outlet temperature prediction

(b) Comparison of relative error of ENN and Chaos-Elman combined model for intercooler seawater outlet temperature prediction

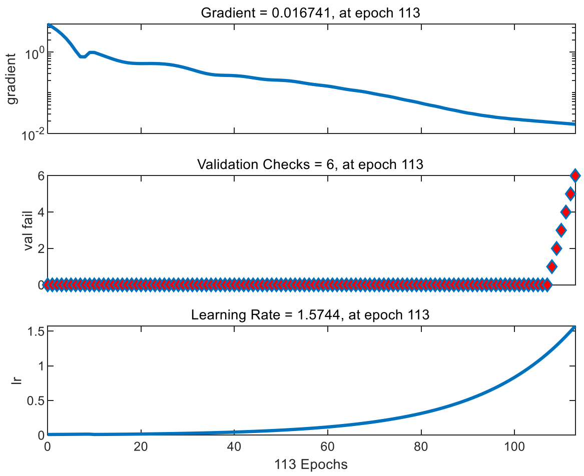
FIGURE 8. Comparison of short-term prediction results and relative errors of ENN and Chaos-Elman combined model for intercooler seawater outlet temperature.

F. RESULTS

In order to evaluate the computational complexity, the variation of parameters during training and the performance of training network of Elman neural network and Chaos-Elman combined model, this paper uses the training tool window of neural network for comparative analysis. In the network, the transfer function of the input layer is tan- sigmoid, and

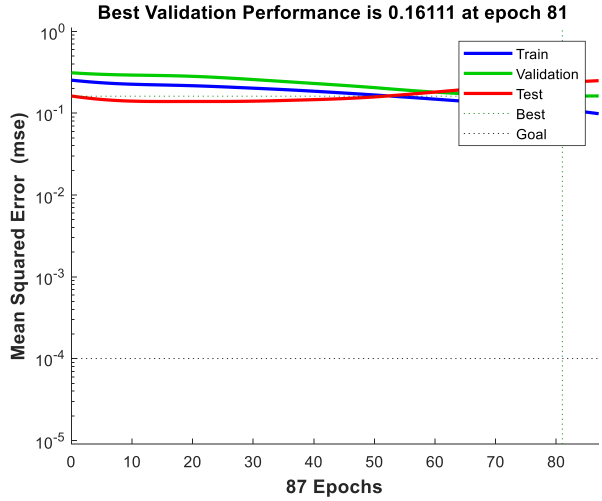


(a) Elman neural network training process

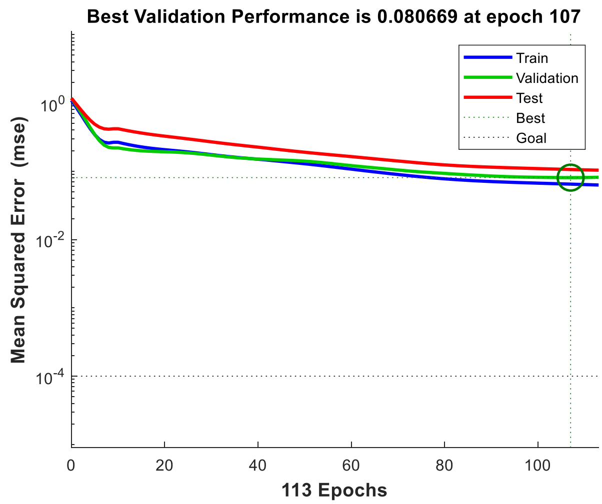


(b) Chaos-Elman combined model training process

FIGURE 9. Comparison of parameters variation during training.



(a) Performance of Elman neural network



(b) Performance of Chaos-Elman combined model

FIGURE 10. Comparison of network performance.

that of the output layer is linear, the training algorithm uses gradient descent with momentum and adaptive LR, the loss function is represented by the mean square error (MSE), the calculation uses MEX function, the maximum training algebra is set as 1000, the limit performance function value is set as 10^{-6}, the limit gradient operator is set as 10^{-5}, and the maximum continuous overfitting times is set as 6. If any of the above conditions reach the termination conditions, the network training will be stopped. The variation process of training parameters and network performance during training are shown in Fig. 9 and Fig. 10.

It can be seen from Fig. 9 and Fig. 10 that both Elman and Chaos-Elman terminate training after 6 times of fitting. Elman has been trained for 87 generations and its learning rate is about 0.6974; Chaos-Elman combined model has been trained for 113 generations and its learning rate is about 1.5744. The training parameters of the combined model are obviously better than that of the single Elman neural network. The minimum MSE of Elman network is 0.1611 at the 81st generation of training, and the minimum MSE of the combined model is about 0.0807 at the 107th generation of training. The network performance of combined model is also significantly higher than that of single Elman neural network.

Table 2 lists the performance indicators of each machine learning method mentioned in this paper. Third-order Volterra adaptive prediction and Elman neural network prediction had RMSE higher than 2.3, R2 lower than 0.89, and EV lower than 0.92. The RMSE of the maximum Lyapunov index prediction and weighted first-order local prediction was lower than 1.5, MAPE was lower than 0.028, R2 was higher than 0.89 and EV was higher than 0.93. The RMSE of Chaos-Elman combination prediction was lower than 0.62, MAPE was lower than 0.014, R2 was higher than 0.95 and EV was higher than 0.971. Therefore, compared with other methods, the Chaos-Elman combination prediction model had the best performance and the highest prediction accuracy.

According to the above analysis, compared with chaotic time series prediction and single Elman neural network

TABLE 2. Comparison of performance metrics of methods.

Prediction method	Performance metrics			
	RMSE	MAPE	R^2	EV
Maximum Lyapunov index prediction method	1.4634	0.0272	0.8971	0.9317
Third-order Volterra adaptive prediction method	4.4665	0.0909	0.7583	0.8836
Weighted first-order local prediction method	0.8433	0.0173	0.9152	0.9408
Elman neural network prediction method	2.3581	0.0489	0.8214	0.9134
Chaos-Elman combined prediction method	0.6179	0.0132	0.9504	0.9713

prediction, the Chaos-Elman combined prediction model can effectively improve the efficiency of model training, obtain the optimal training parameters more quickly, and obtain better prediction accuracy in the testing process of the model.

VI. CONCLUSION

In this paper, one-dimensional time series of seawater outlet temperature of intercooler is taken as an example. Firstly, the maximum Lyapunov index is obtained by calculating its reconstruction parameters t and m, and the sequence is judged to have chaotic characteristics. Then, phase space reconstruction technology is used to excavate the hidden evolution law. Then, the chaos theory and ENN were organically combined to build the chaos-Elman combined prediction model, which made full use of the characteristics and advantages of the two, improved the training efficiency of the model, maximized the evolution trend of phase points, and better used nonlinear approximation to predict chaotic time series. Its prediction effect is much higher than that of the maximum Lyapunov index prediction, third-order Volterra adaptive prediction, weighted first-order local prediction and Elman neural network prediction, and MAPE decreases to 0.0132, R^2 increases to 0.9504, EV reaches 0.9713, indicating that the prediction accuracy is greatly improved. Because this method can make full use of the training data set to obtain the important parameters of the combined model, and avoid the possibility of falling into the local optimal solution, it can perform some parameter prediction of the non-human operating system in the cabin, and obtain good performance. This method still has some room for improvement: for some complex systems or large combined ship systems, if there are strong correlations among multiple systems, and the amount of real-time data collected exceeds the storage capacity of the model, the data dimension can be effectively reduced in the data preprocessing stage, and the threshold of the neural network weight can be further optimized. In addition, this method can introduce an effective state recognition model to achieve the performance of state prediction. With the upgrade of engine room automation, this method can be combined with multiple ship engine room systems to predict the system state in many aspects, and even form a unified function unit, which provides a reference direction for the intelligent development of shipping industry in the future.

REFERENCES

[1] T. C. Mills, *Applied Time Series Analysis: A Practical Guide to Modeling and Forecasting*, vol. 1. New York, NY, USA: Academic, Dec. 2019, pp. 119–122.
[2] M. H. Amini, A. Kargarian, and O. Karabasoglu, "ARIMA-based decoupled time series forecasting of electric vehicle charging demand for stochastic power system operation," *Electr. Power Syst. Res.*, vol. 140, pp. 378–390, Nov. 2016.
[3] P. Sharma and Vipul, "Forecasting stock market volatility using realized GARCH model: International evidence," *Quart. Rev. Econ. Finance*, vol. 59, pp. 222–230, Feb. 2016.
[4] M. P. Clements, P. H. Franses, and N. R. Swanson, "Forecasting economic and financial time-series with non-linear models," *Int. J. Forecasting*, vol. 20, no. 2, pp. 169–183, Apr. 2004.
[5] C. W. J. Granger and T. Terasvirta, "Modelling non-linear economic relationships," OUP Catalogue, Tech. Rep., 1993.
[6] M. S. Geraldi and E. Ghisi, "Short-term instead of long-term rainfall time series in rainwater harvesting simulation in houses: An assessment using Bayesian network," *Resour., Conservation Recycling*, vol. 144, pp. 1–12, May 2019.
[7] L. D. Avendaño-Valencia and E. N. Chatzi, "Modelling long-term vibration monitoring data with Gaussian process time-series models," *IFAC-PapersOnLine*, vol. 52, no. 28, pp. 26–31, 2019.
[8] C. Cortes and V. Vapnik, "Support-vector networks," *Mach. Learn.*, vol. 20, no. 3, pp. 273–297, 1995.
[9] D. Kumar, S. S. Meghwani, and M. Thakur, "Proximal support vector machine based hybrid prediction models for trend forecasting in financial markets," *J. Comput. Sci.*, vol. 17, pp. 1–13, Nov. 2016.
[10] F. Baser and H. Demirhan, "A fuzzy regression with support vector machine approach to the estimation of horizontal global solar radiation," *Energy*, vol. 123, pp. 229–240, Mar. 2017.
[11] C. Ordóñez, F. S. Lasheras, J. Roca-Pardiñas, and F. J. D. C. Juez, "A hybrid ARIMA–SVM model for the study of the remaining useful life of aircraft engines," *J. Comput. Appl. Math.*, vol. 346, pp. 184–191, Jan. 2019.
[12] A. Cujia, D. Agudelo-Castañeda, C. Pacheco-Bustos, and E. C. Teixeira, "Forecast of PM10 time-series data: A study case in Caribbean cities," *Atmos. Pollut. Res.*, vol. 10, no. 6, pp. 2053–2062, Nov. 2019.
[13] T. Zang, Y. Zhu, Y. Xu, and J. Yu, "Jointly modeling spatio–temporal dependencies and daily flow correlations for crowd flow prediction," *ACM Trans. Knowl. Discovery Data*, vol. 15, no. 4, pp. 1–20, Aug. 2021.
[14] U. M. Erdem and S. Sclaroff, "Event prediction in a hybrid camera network," *ACM Trans. Sensor Netw.*, vol. 8, no. 2, pp. 1–27, Mar. 2012.
[15] N. Bisoyi, H. Gupta, N. P. Padhy, and G. J. Chakrapani, "Prediction of daily sediment discharge using a back propagation neural network training algorithm: A case study of the Narmada River, India," *Int. J. Sediment Res.*, vol. 34, no. 2, pp. 125–135, Apr. 2019.
[16] H. H. Tsang and K. C. Wiese, "SARNA-predict: Accuracy improvement of RNA secondary structure prediction using permutation-based simulated annealing," *IEEE/ACM Trans. Comput. Biol. Bioinformatics*, vol. 7, no. 4, pp. 727–740, Oct. 2010.
[17] S. L. Marple, "Two-dimensional lattice linear prediction parameter estimation method and fast algorithm," *IEEE Signal Process. Lett.*, vol. 7, no. 6, pp. 164–168, Jun. 2000.
[18] R. O. Adeogun, P. D. Teal, and P. A. Dmochowski, "Extrapolation of MIMO mobile-to-mobile wireless channels using parametric-model-based prediction," *IEEE Trans. Veh. Technol.*, vol. 64, no. 10, pp. 4487–4498, Oct. 2015.
[19] J. Jiang, H. Zhou, T. Zhang, C. Yao, D. Du, L. Zhao, W. Cai, L. Che, Z. Cao, and X. E. Wu, "Machine learning to predict dynamic changes of pathogenic vibrio spp. Abundance on microplastics in marine environment," *Environ. Pollut.*, vol. 305, Jul. 2022, Art. no. 119257.
[20] A. Pano-Azucena, E. Tlelo-Cuautle, S. Tan, B. Ovilla-Martinez, and L. de la Fraga, "FPGA-based implementation of a multilayer perceptron suitable for chaotic time series prediction," *Technologies*, vol. 6, no. 4, p. 90, Oct. 2018.
[21] X. Lu, S. Saul, and C. Jenkins, "Statistical methods for predicting the spatial abundance of reef fish species," *Ecol. Informat.*, vol. 69, Jul. 2022, Art. no. 101624.
[22] A. Navarro-Espinoza, O. R. López-Bonilla, E. E. García-Guerrero, E. Tlelo-Cuautle, D. López-Mancilla, C. Hernández-Mejía, and E. Inzunza-González, "Traffic flow prediction for smart traffic lights using machine learning algorithms," *Technologies*, vol. 10, no. 1, p. 5, Jan. 2022.

[23] F. Takens, "Detecting strange attractors in turbulence," *Lect. Notes Math.*, vol. 898, pp. 361–381, 1981.
[24] L. Fang, Q. Zeng, Y. Faraj, N. Zhao, Z. Wei, and X. Li, "Analysis of chaos characteristics of gas-liquid two-phase flow noise," *Flow Meas. Instrum.*, vol. 65, pp. 98–109, Mar. 2019.
[25] Z. B. Lu, Z. M. Cai, and K. Y. Jiang, "Parameter selection of phase space reconstruction based on improved C-C method," *J. Syst. Simul.*, vol. 11, pp. 2527–2529, Oct. 2007.
[26] J. Lu, H. J. Chai, and R. C. Jia, "A general framework for flight maneuvers automatic recognition," *Mathematics*, vol. 10, pp. 1–15, Apr. 2022.
[27] J. J. Gao and H. Wang, "Phase space embedding dimension selection based on improved G-P algorithm," *Comput. Eng. Appl.*, vol. 50, pp. 107–110, 2014.
[28] H. Akaike, "A new look at statistical model identification," *IEEE Trans. Autom. Control*, vol. AC-19, no. 6, pp. 7–16, Dec. 1974.
[29] E. J. Hannan and B. G. Quinn, "The determination of the order of an autoregression," *J. Roy. Stat. Soc., B, Methodol.*, vol. 41, no. 2, pp. 190–195, Jan. 1979.
[30] L. Ye, X. Xia, and Z. Chang, "Evaluation of dynamic uncertainty of rolling bearing vibration performance," *Math. Problems Eng.*, vol. 2019, pp. 1–17, Aug. 2019.

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