Intelligent Shipyard Inventory Non-Surplus Inventory Control Algorithm and Empirical Research

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Abstract. There is still a big gap between China and other advanced shipbuilding countries, such as digital fields, networking and intellectualization. The inventory management leads to more inventories, growing cost, slower construction progress, and so on. Therefore, the idea of "no surplus" inventory management was put forward, which was established on scientific and effective prediction of the stock allowance of shipbuilding materials. Then, the appropriate algorithms were studied to serve the idea above. This study considered two-stage predictor construction. First stage 3 single predictors were constructed, including ARIMA model, improved PSO (particle swarm optimization) -SVR (support vector machine) and Wavelet Neural Network. Then the second stage constructed a strong predictor formed by the integrated algorithm. The effectiveness of the algorithm is verified by the contrast test. Then an empirical case was used to show how a non-surplus inventory scheme came to be. At last, the relevant countermeasures for the above scheme were proposed.

1. Introduction

After the rapid development in the early 21st century, China's shipbuilding industry is in the stage of development and upgrading to the shipbuilding power. Under the guidance of the 10-year Action Plan of "Made in China 2025", in order to meet the needs of the "Marine power" strategy, China's shipbuilding industry has opened up a "new era" for building smart shipyards.

Intelligent shipyard is a system engineering that relies on information depth self-awareness, intelligent optimization self-decision and precise control self-execution. It can effectively improve production efficiency, improve product quality, and reduce resource consumption [1]. The intelligent realization of system engineering relies on the coordination between various subsystems, and inventory is one of the most important subsystems of this system engineering. Inventory management, as the basis of production, planning and control, provides an important basis for production management and cost control [2].

At present, the inventory concept tends to zero inventory management. However, absolute zero inventory is still an ideal state, so blind pursuit of zero inventories is impossible and unnecessary. Inspired by the matching problem of components in industrial processing [3] [4] [5], this paper puts forward the idea of “no margin” inventory management and constructs an algorithm combining this management idea.
2. Literature Review and Theoretical Basis

2.1. Zero Inventory Management and Inventory-free Management

The “zero inventory” means that materials (including raw materials, semi-finished products and finished products, etc.) are in a state of turnover in one or several links of procurement, production, sales, distribution, etc., rather than the state of warehouse storage. Zero inventories are based on “zero distance” supply, which not only requires high reliability from suppliers, but also requires the shipyard to fully trust suppliers [6]. Therefore, Toyota Motor has set up its supporting factories of hundreds of spare parts suppliers around its factory to ensure timely and accurate delivery [7]. However, the conditions of achieving zero inventories are severe and full of risks, such as out-of-stock risk, single source supply risk, supply chain breakage risk, chain-amplified effect risk, distribution cost increase risk, and risk of long lead times. It also includes the risk of cooperation between upstream and downstream companies in the supply chain, the risk of requiring suppliers to deliver materials directly to the site of use, etc [8]. China's ships are international special products produced in small batches. The materials used in the construction process are large and complex, so that the suppliers are numerous, the geographical distribution is wide, and some key components still rely on imports. Therefore, there are natural disadvantages in both "zero distance" and "trust".

On the basis of the zero inventory concept, this paper regards the material in the turnover as the residual material, regards the storage location of the residual material as the residual material warehouse, and sets the residual material turnover cycle according to the actual situation. “Inventory No Margin Management” provides “no margin control” for materials to ensure orderly turnover of materials and reduce distance risk and supplier trust risk. It also ensures efficient and orderly operation of shipbuilding companies. The basic idea of margin-free control is to determine the required materials according to the procurement cycle, and to determine the materials used when there are enough materials in the workshop, so as to achieve the minimum inventory. The method of providing the material is determined according to “Supplier Supply” and “Inventory Minimum Margin”, and the remaining material is changed with the supplier's supply update to avoid inventory risk. In essence, the "no margin" control is Nash equilibrium of inventory strategy on the premise of ensuring sufficient raw materials and minimum inventory.

Such as steel, the main raw material of the shipping company. Suppose the shipyard has n steel pretreatment production lines. Each line has different machine status and different number of workers every day, so the processing volume of each production line is different; Based on the analysis of the steel market, the procurement department determines that the best emergency procurement cycle $T^*$, and this cycle will also change as market changes. As steel is affected by many factors such as fluctuations in the international market, domestic market demand, and steel mill production and processing, Suppliers are at risk of shortage Therefore, it is necessary to set up a residual material warehouse to avoid the risk of material loss. It is assumed that the steel has a storage risk such as moisture, rust, etc., and the remaining stock has storage costs. Therefore, the goal of inventory-free management is how to achieve uninterrupted production and minimum inventory management costs within the time specified in the order.
Figure 1. Model of No-surplus Inventory Management.

Figure 1 is an inventory-free management model designed in this paper. During the process of no-waste management, in order to ensure the normal and orderly production of workshop, it is necessary to consider the margin of surplus material warehouse and supplier. The predictive model can predict the amount of excess material needed in the production plant and then replenish the residual warehouse. The purchasing department can determine the risk of material shortages, so the procurement time of the supply chain is also a key step in the control of no margin. Under normal circumstances, the 28-day material turnover period can meet the situation that the procurement department can purchase raw materials at a relatively low price in time when the supplier is out of stock[9][10].

2.2. Non-surplus Inventory Control Algorithm
In order to achieve control of no surplus inventory, the key is to predict the materials needed for the remaining warehouses and workshops in the next cycle. The key to control is accurate prediction, so the prediction algorithm is the core algorithm. Since the smart shipyard has the function of automatic data collection, it is easy to obtain the required data.

At present, there are many methods for improving prediction accuracy by using the method of stack integration. Zhibin Xiong analyzed the prediction characteristics and advantages and disadvantages of the single autoregressive moving average model (ARIMA) and the neural network model (NN), and based on this, realized the GDP time series prediction model and algorithm integrated with ARIMA model and NN model [10]. Sheng Liu used differential autoregressive moving average (ARIMA), support vector machine (single-factor SVM and multi-factor SVM) and combined model to predict and compare the number of domestic tourists. The results show that the combined model prediction is more accurate and more generalized[11]. Shuquan Li and Shijie Liu used the improved particle swarm optimization (PSO) algorithm to optimize the parameters of support vector machine (SVM), constructed the project safety prediction model, and carried out simulation and verification analysis. The results show that the model has higher prediction accuracy and better performance. Practicality and effectiveness [12]. Wenjuan Liang and Xueyan Li applied the combined model of differential autoregressive moving average model (ARIMA), least squares support vector machine model and BP neural network model (BPNN) to predict and analyse the monthly flight accident rate of an airline. The accuracy is also ideal [13].

The offline data of the shipyard production workshop is the input data at the time of prediction, and most of the data is nonlinear, so the accuracy of the nonlinear function approximation directly affects the accuracy of the prediction result. Therefore, in view of the accuracy requirements, this paper uses multi-classifier integration decision as a predictive model.
3. No-remaining Inventory Management Algorithm Construction

3.1. Algorithm Construction
Considering the possible limitations of a single prediction algorithm and the actual situation of shipyard data, the algorithm can give full play to the different advantages of different types of models. The design idea of the algorithm is to train several weak classifiers first, and then optimize the weights of each weak classifier through continuous iterative optimization, and train them into strong classifiers to improve the classification accuracy. Combined with the characteristics of off-line data in the shipyard's production workshop, this paper considers the ARIMA model, the improved PSO-SVR model, and the wavelet neural network as weak predictors, and then integrates these three models to form a strong predictor (Figure 2). In the next cycle of the shipyard, it can accurately predict the amount of material to be stocked in the surplus stock and the demand of the workshop to achieve control of inventory without margin.

![Figure 2. Construction Procedure of Strong Prediction Container.](image)

3.2. Selection and Construction of Weak Predictors

3.2.1. ARIMA algorithm. The ARIMA model is derived from the ARMA model by difference. ARIMA has three parameters p, d and q. In the application process, the model usually needs to smooth the non-stationary sequence. Let d be the number of differences when the time series becomes stationary, and y denote the difference equation of Y at time t. That is, when d=0, \( y_t = Y_t \), when d=1, \( y_t = Y_t - Y_{t-1} \), when d =2, \( y_t = (Y_t - Y_{t-1}) - (Y_{t-1} - Y_{t-2}) \); Let p denote the autoregressive term. The principle of the autoregressive model (AR) is to use the same variable in the early and late characteristics of the change, namely predicting itself. When determining the parameter p of the AR model, \( Y_t \) is only related to \( Y_{t-1}, Y_{t-2}, \ldots, Y_{t-p} \). That is \( Y_t = \theta_0 + \theta_1 Y_{t-1} + \theta_2 Y_{t-2} + \ldots + \theta_p Y_{t-p} + \epsilon_t \), Where \( \theta \) represents the autoregressive parameter and \( \epsilon \) is the residual or white noise sequence. q is the moving average number, and the moving average method (MA) predicts the future period or periods by a series of recent actual data values. The data method, when determining the MA model parameter is q, \( Y_t \) only with \( Y_{t-1}, Y_{t-2}, \ldots, Y_{t-q} \) is related, the expression of the model is \( Y_t = u + \beta_1 \epsilon_{t-1} + \beta_2 \epsilon_{t-2} + \ldots + \beta_q \epsilon_{t-q} \). The formula \( \beta \) represents the moving average parameter and \( \epsilon \) represents the residual in the sequence. The ARMA model can be represented as the superposition of the AR and MA processes, and the ARIMA is the post-model of the ARMA. The final model \( Y_t \) represents a time series, which is a linear combination of interference values \( \epsilon_t \) and \( \epsilon_{t-i} \), and sequence \( Y_{t-i} \) values.

Model selection basis: AIC, Akaike Information Criterion: AIC=2k-L*ln(n), where k is the number of model parameters and L is a likelihood function. BIC, Bayesian information criterion:
BIC = k*ln(n) - 2ln(L), where k is the number of model parameters, n is the number of samples, and L is a likelihood function. For general model parameter selection, choose parameters that can make AIC and BIC smaller. In addition, white noise test is carried out to test the residual white noise of the model, to determine whether the model has information that can be extracted, and to analyse and predict with the original data. Finally, the final ARIMA model is determined based on the determined p, d, q parameters.

The input of the model is a set of \([Y_1, Y_2, Y_3, ..., Y_t]\) time series data, and finally the p, d, q parameters are determined to obtain the final model. For example, if p, d, and q are finally confirmed as (2, 1, 2), the final model is 

\[
\hat{y}_t = u + \theta_1 (y_{t-1} - y_{t-2}) + \theta_2 (y_{t-2} - y_{t-3}) - \beta_1 (y_{t-1} - \hat{y}_{t-1}) - \beta_2 (y_{t-2} - \hat{y}_{t-2})
\]

3.2.2. Improved PSO-SVR model. The input to train the SVR model is \(\{x_i, y\}\), where i represent the number of features, which is usually extracted by feature engineering, y represents the actual label. There is a Sklearn library in Python. After the package is adjusted, cross-validation is performed by GridSearchCV, and the parameters are adjusted to obtain the model. For example, \(\{x_1, x_2, x_3, y\}\) represents a sample of data, and the set of data is input into the model. The model considers the entire other sample and finally discriminates.

The support vector regression algorithm SVR realizes linear regression by constructing a linear decision function in high-dimensional space after up-dimensionality. When using insensitive functions, the basis is mainly insensitive function and kernel function algorithm. Its core formula is as follows:

\[
\min \frac{1}{2} \|\omega\|^2 + C \sum_{i=1}^{l} (\xi_i + \xi_i^*)
\]

s.t. \(y_i - (\omega^T x_i + b) < \epsilon + \xi_i\)

\(\xi_i^* - y_i < \epsilon + \xi_i\)

\(\xi_i, \xi_i^* \geq 0\) \hspace{1cm} (1)

It can be known from equations (1) and (2) that the SVR model penalty factor C is an artificially given empirical parameter. In the determined data space, the penalty factor C is used to adjust the learning machine's confidence range and empirical risk, so that the learning machine has the highest generalization ability. Different data subspaces have different optimal penalty factors C. In the determined data subspace, the smaller the C value, the smaller the penalty for the sample data beyond the pipeline, and the greater the training error. The larger the C, the higher the learning accuracy, but the poor generalization ability of the model. Improper selection of C may lead to "over-learning" and "less-learning" phenomena.

\[
K(x, x) = \exp\left(-\frac{\|x - y\|^2}{2\sigma^2}\right)
\]

As in equation (3), the kernel parameter \(\sigma\) affects the complexity of the distribution of sample data in the high-dimensional feature space, reflecting the degree of correlation between the support vectors. If \(\sigma\) is small, it indicates the looseness of the connection between the support vectors. The model is relatively complex and the generalization ability is weak. If \(\sigma\) is large, it indicates that the connection between the support vectors is too strong, which affects the accuracy of the model. And the kernel function parameter \(\sigma\) (the span of the radial basis kernel function) is too large and easily leads to over-fitting.

There is no uniform standard for SVR \(\sigma\) and C parameter determination, and it has great influence on the accuracy of the model. Therefore, in order to improve \(\sigma\) and C the disadvantages, which is caused by manual selection of parameters and parameters, this paper uses particle swarm optimization to optimize it.
The traditional particle swarm algorithm iterative weight $W_k$ is linearly decreasing. We know that the adaptation and adjustment ability of $W$ is limited, which leads to the decline of particle swarm optimization ability and premature convergence, so the global optimal solution is not obtained. Therefore, this paper introduces adaptive adjustment of inertia weights. The optimal individual position of the traditional PSO particle swarm is directly used as the term in the displacement update formula, which reduces the diversity of the population and the ability to use the effective information of the optimal position of the individual. Therefore, the average position of an individual in all particles is replaced by a Gauss perturbation factor. It can effectively reflect the diversity of population and further improve the utilization rate of effective information of individual optimal location.

First, define the concept of Normalized Fitness Value (NFV) [13] to guide the particles to converge to the global optimal particle position more quickly.

$$NFV = \frac{f_{gbest} - f_{min}}{f_{max} - f_{min}}$$  \hspace{1cm} (4)

In formula (4), $f_{gbest}$ is the global optimal fitness of the population; $f_{max}$ is the historical maximum fitness of the individual particles; $f_{min}$ is the historical. $K_{max}$ minimum fitness of the individual particles. The maximum number $K$ of iterations, $K$ representing the first iteration.

Second, redefine the variables according to NFV.

$$W_k = W_{max} - \left( \frac{W_{max} - \frac{NFV + W_{k-1}}{2}}{K_{max}} \right) \times K$$  \hspace{1cm} (5)

The value of the $W_k$ is $K$ iteration in equation (5) $W_{k-1}$ is the value of the $k$-th iteration, which is the maximum value before the second iteration. It can be seen from equation (5) that the main control $W_k$ is the size of the fitness. If the value of $NFV$ in the $K$-th iteration is higher than the value in the $K-1$-th iteration, it indicates that the region where the particle is located has a higher probability than the global optimal value. At this time, $W_k$ should be reduced to improve the local optimization ability of the algorithm. On the contrary, increase $W_k$, so that the particles can jump out of the current area faster and improve the global search ability. This method of inertia weight is continuously adjusted according to the value of the fitness value, and the situation that the particles fall into the local optimum is avoided. It increases the speed of convergence and makes particle swarms easier to find global optimal values.

Third, enhance the escape ability of the particles. The traditional particle swarm particle velocity and particle position are set as shown in equation (6) and (7):

$$v_id(t + 1) = wv_id(t) + c_1r_1(p_id(t) - x_id(t)) + c_2r_2(p_gd(t) - x_id(t))$$  \hspace{1cm} (6)

$$x_id(t + 1) = x_id(t) + v_id(t + 1)$$  \hspace{1cm} (7)

This method makes single particles independent of each other and there is no information sharing between groups. However, particle swarms tend to fall into local optimum and cannot find global optimal solutions. Taking this as a consideration, the optimal position of all individual particles is summed and then the Gaussian perturbation term is added, and the mean is taken as the optimal position of the individual, as in equation (8).

$$v_id(t + 1) = wv_id(t) + Gauss_id(t) + c_2r_2(p_gd(t) - x_id(t))$$  \hspace{1cm} (8)

$$Gauss_id(t) = c_1r_1(\sum_{i=1}^{N} p_id(t) + r_1 \times Gaussian(\mu \ , \sigma^2))/N - x_id(t)$$  \hspace{1cm} (9)
In equation (9), $Gauss_{id}(t)$ is the Gaussian perturbation term in the $t$th iteration. This method can effectively enhance the escape ability of particles and facilitate the sharing of optimal information between particles [14].

The improved PSO-VSR algorithm flow is shown in Figure 3.

The radial basis kernel function is a universal kernel function. In the process of nonlinear function approximation, the sample distribution has good robustness [15]. Therefore, the radial basis kernel function (RBF) is chosen in this paper.

In Table 1, under the same conditions, when the single SVR model is selected as the optimal parameters and other conditions are the same, the improved PSO-SVR model prediction accuracy is still significantly higher than the single SVR model.

3.2.3. Wavelet Neural Network (WNN). Wavelet neural networks have the advantages of global optimal approximation and fast operation speed. And it avoids the shortage of traditional neural network types such as BP network in these aspects [16]. The wavelet neural network input is $\{x_i, y\}$, where $i$ represents the number of features, $x_i$ is the eigenvalue of the $i$th feature, and $y$ is the label. The model is trained with training data, and the parameters of the hidden layer are updated according to the mechanism of backpropagation. The model in which the loss function eventually converges is used as an alternative model. The model is then further evaluated by the data set to obtain the optimal model.

The compact wavelet neural network uses the wavelet basis function as the activation function of the hidden layer nodes of the neural network. It not only inherits the advantages of wavelet analysis, but also solves the problem of difficult parameter selection with appropriate learning rate. At the same time, it can freely choose the appropriate wavelet function according to needs. Therefore, this paper chooses a compact wavelet neural network.

The output of the hidden layer of the wavelet neural network is $h_j = h\left(\sum_{i=1}^{m} w_{ij} x_i - b_j \right) / a_j$, where $j = 1, 2, \ldots, m, b_j$ is the wavelet basis function translation factor, $a_j$ is the wavelet basis function expansion factor, and $h$ is the wavelet basis function. The network output is $y_i = \sum_{j=1}^{m} w_j h_j$, where $k = 1, 2, \ldots, n$, the error value $e_i = y_i' - y_i$, and the error performance indicator function is $E = \frac{1}{2} e_i^2$. The error signal is propagated backwards, and the parameters are adjusted according to the
gradient descent algorithm.

In order to solve the shortcomings of slow convergence of wavelet neural networks, the momentum term method is used to improve the gradient descent algorithm as shown in (10). Among them, $\alpha$ is the momentum factor, $\alpha \in [0, 1]$.

$$
\begin{align*}
w^{(d+1)}_y &= w^{(d)}_y + \Delta w^{(d+1)}_y + \alpha(w^{(d)}_y - w^{(d-1)}_y) \\
w^{(d+1)}_j &= w^{(d)}_j + \Delta w^{(d+1)}_j + \alpha(w^{(d)}_j - w^{(d-1)}_j) \\
a^{(d+1)}_j &= a^{(d)}_j + \Delta a^{(d+1)}_j + \alpha(a^{(d)}_j - a^{(d-1)}_j) \\
b^{(d+1)}_j &= b^{(d)}_j + \Delta b^{(d+1)}_j + \alpha(b^{(d)}_j - b^{(d-1)}_j)
\end{align*}
$$

(10)

The Morlet wavelet exhibits strong anti-interference characteristics and stable characteristics in the nonlinear function approximation. Therefore, Morlet wavelet is selected as the wavelet neural network basis function, Morlet wavelet: $y = \cos(1.75x)e^{-\frac{x^2}{2}}$.

### 3.3. Integrated model

In this paper, the optimal weighting method is used to determine the weight of each submodel of the integrated model [17]. Let $X_t$, ($t = 3, 2, 1$) be the original time series, $n$ be the data sample size and $m$ be the weak prediction models. There are $m$ weak prediction models on prediction, and they constitute a strong prediction model, as shown in equation (11).

$$
\hat{y}_t = \sum_{i=1}^{m} W_i y_i
$$

(11)

In equation (11), $\hat{y}_t$ represents the predicted value of the strong prediction model at time $t$, $W_i$ represents the weight of the $i$-th weak prediction model, and $y_i$ represents the predicted value of the $i$-th single model at time $t$. $W_i$ is non-negative, and the sum of $W_i$ is 1. That is $\sum_{i=1}^{m} W_i = 1$, $W_i \geq 0, i = 1, 2, 3, \ldots, m$. The essence of the optimal weighting method is similar to OLS, which is to determine the weighting coefficient of each single prediction model based on the principle that the squared sum of the prediction errors of the strong prediction model is the smallest. Let the $i$-th weak prediction model have a prediction error of $e_i = y_i - y_{i\hat{}}$ at time $t$ and $y_i$ denote the actual value at time $t$. The planning model at this time is equation (12).

$$
\begin{align*}
\min M = \sum_{i=1}^{n} e_i^2 \\
\text{s.t.} \sum_{i=1}^{m} W_i = 1, W_i \geq 0, i = 1, 2, 3, \ldots, m
\end{align*}
$$

(12)

$W = [w_1, w_2, \ldots, w_m]^T$, error information matrix is $E = \begin{bmatrix} e_1(1) & \cdots & e_1(m) \\ \vdots & \ddots & \vdots \\ \vdots & \ddots & \vdots \\ e_n(1) & \cdots & e_n(m) \end{bmatrix}$.

Let $R = [1,1,1,\ldots,1]$ be a one-dimensional vector with all elements of 1, then the sum of squared $Q$ of the combined prediction model is:
The optimization problem is converted to equation (14):

\[
\begin{align*}
\min Q &= W^T EW \\
\text{s.t.} \quad R^TW &= 1 \\
W &\geq 0
\end{align*}
\]  

(14)

When the Lagrangian multiplier factor \( \lambda \) is introduced, the partial derivative is obtained for \( Q = W^T EW + \lambda (R^TW - 1) \), and \( W = \frac{E^{-1}R}{R^TE^{-1}R} \), \( \min Q = \frac{1}{R^TER} \) is obtained.

4. Empirical Analysis

4.1. Empirical Object Description

The 300,000-ton VICC tanker order signed by a smart shipyard uses the robotized digital steel pretreatment production line to cut, weld and split the steel plate. There are three production lines in the smart shipyard. After the daily production line is shut down, the production control platform based on intelligent control will record the offline data onto the processing volume of the day. The time series data from August 2013 to October 2017 has been obtained. Based on the analysis of the steel market, the procurement department determines the best emergency procurement cycle as \( T_i \), which changes with time. Now we use the idea of no surplus stock management to generate a no surplus stock management program.

4.2. Empirical Data as Input of the Model

This paper selects the number of steel used in the three production lines of the robotic processing of the intelligent shipyard as the input characteristics \( (x_1, x_2, x_3) \). The quantity of steel is in days. The intelligent shipyard steel entering the factory should prepare the residual material data as the label \( y \) of the input data. The main function of the model is to process the data of three production lines by robots, and predict the data of the remaining materials. It can prepare the production task amount in the environment with strong market competition and high uncertainty, and then improve the processing speed of the robot.

The overall shipyard data sample size is 4170 offline data. Each model adopts 75% of the data sample as training data, a total of 3,000, and 25% is the test data, a total of 1200. There are 30 intersection data. Because these data dimension is not high, and each attribute is necessary, the feature extraction is not considered. Data with missing and outliers is replaced by the mean of the data samples.

According to the quartile chart of the box line, after the data is cleaned, there is no dirty read in the shipyard 1, 2, and 3 workshops and the residual material warehouse.
4.3. ARIMA Model Calculation Results

The key to the realization of the ARIMA model is the need to determine the values of p, d, q. This article uses Eviews8.0 to make predictions. It can be seen intuitively that the margin data of the shipyard inventory is not stable, as shown in Figure 5.

![Figure 5. Data trend.](image)

As shown in Figure 6, after the first-order difference, the data tends to be stable. After the ADF test on the data, it can be seen that the result rejects the null hypothesis, further confirming that the data is a stationary sequence. Therefore, the ARIMA model parameter d=1 is determined.

![Figure 6. Unit root test.](image)

According to the sequence correlation difference diagram of Figure 7, it can be preliminarily determined that the possible parameters of the ARIMA model are (2, 1, 2), (1, 1, 1), (2, 1, 1). The parameters are input into the model for processing. The results are shown in Table 1.

![Figure 7. First-order difference sequence autocorrelation, partial correlation.](image)

| parameter | (2,1,2) | (1,1,1) | (2,1,1) |
|-----------|---------|---------|---------|
| SC        | 2.929911| 2.997659| 2.997379|
| AIC       | 2.922310| 2.994659| 2.993338|

The model is selected with AIC and the SC value which is the lowest, so the ARIMA parameter is selected as the prediction result of (2, 1, 2).
Figure 8. Model parameter.

The MAPE value of the model is 1.85, which further confirms the scientific and accurate prediction results from the prediction curve. The last two data are subtracted to obtain the error information matrix as an input to the integrated model.

Figure 9. ARIMA forecast result graph.

4.4. Improved PSO-SVR Model Calculation Results

This article uses python3.6, MATLAB software for empirical analysis. In the process, root mean square error (RMSE) is used as a measure of model accuracy. In order to improve the prediction accuracy, the number of cross-validation of the model is 5 times and the particle swarm size is 50. The following results were obtained. During the continuous updating of the particles and the iterative update of the population, 50 sets of two-dimensional particles \((C, \sigma)\) are continuously transmitted to the SVR model for training. The process of obtaining the value of RMSE by iteratively updating, as shown in Fig. 5, shows that the generalization ability of SVR model training is the strongest when \(C\) is 33.24 and \(\sigma\) is 6.902. Figure 6 is a diagram showing the learning process when the SVR model parameter \(C\) is 33.24, \(\sigma\) is 6.902, \(cv\) is 5, and the number of training times is 3000 times.

Figure 10. RMSE value of SVR model under optimization particle swarm optimization.
The hyperparameter is set to get a better model effect. It optimizes the metric standard by reducing the target loss function. The figure shows that the setting of the penalty factor C will affect the accuracy of the final model, and the metrics standards obtained by different hyperparameters will have a large difference. It further embodies the necessity of using particle swarm optimization to optimize SVR hyperparameters.

As shown in the Figure13, the $\sigma$ parameter is similar to the $C$ parameter. Different $\sigma$ parameter values have greater impact on the metric.

When the single SVR model selects parameters, in the set $\{0.01, 0.1, 1, 3, 5, 7, 10, 20, 30, 40, 50, 60, 70, 80, 90, 100, 150, 200\}$, the $C$ parameter selects the value which could optimize the model. Considering that the parameter selection of the comparison model should be fully given in the comparative analysis, the values of the $C$ parameter and the $\sigma$ parameter under different magnitudes are selected for model selection. When the cross-validation reached 5, we got the highest accuracy for single SVR model.

The information error matrix $e_2$ is obtained by using the detected data as a difference. Through the comparison of single SVR and PSO-SVR’s model results, combined with the graph and figure, after the final convergence of the model, the SVR model with PSO tuning is better than the single SVR model. The experimental results are shown in Table 2. After the experiment, the $e_2$ obtained by
the difference between the predicted value and the detected data is used as the input of the integrated model.

Table 2. Comparison table of results between SVR model and improved PSO-SVR model.

|                  | Use standardized data | SVR model | Improved PSO-SVR model |
|------------------|-----------------------|-----------|------------------------|
| RMSE             | 0.023                 | 0.0053366327446 |
| CV               | 5                     | 5         |
| C                | Select the optimal parameter from the list 1,2,3,4,5,6,...200 | Improved pso make sure model optimal parameters |
| gamma            | 1,12,3...20 (ibid.)   | (ibid.)   |
| Kernel function  | Radial basis function | Radial basis function |

4.5. Wavelet Neural Network Model Calculation Results

By normalizing the input data, this paper eliminates the influence of the data due to the dimension, so that the gradient descent algorithm could work faster and better. The weight, the wavelet basis function translation factor, and the wavelet basis function scaling factor of the model are randomly assigned according to the normal distribution. Weight learns increment and nodes initialized as 0. The model performs forward propagation, and after the end of the forward propagation, the error signal is propagated back. Update the weight parameter and the implicit layer input weight $W_{ij}$, the output weight $W_{jk}$, the wavelet basis function translation factor, the wavelet basis function scaling factor. The weight learning increment is initialized and reset to zero, and the whole process is continuously updated cyclically.

Initial parameter setting: As the number of hidden layers increases, the prediction effect becomes more accurate, but the parameters to be updated will be much higher. Studies have shown that the 3-layer neural network has been able to approach most systems. At the same time, due to the consideration of the materials used in the smart shipyard, this paper chooses a 3-layer neural network structure and 6 layers of hidden layers. Studies have shown that the hidden layer is the best for 5, 6 nonlinear function approximation. When the hidden layer inputs the weight $W_{ij}$ and the output weight $W_{jk}$, the learning rate is 0.1; The learning rate of the wavelet basis function translation factor and the wavelet basis function expansion factor is 0.01; There are 3000 training samples and 1200 test samples. The momentum factor is 0.3; Hyperparameter setting: initial weight, translation factor, and scaling factor are randomly assigned according to normal distribution.

With the premise of non-normalization, the model RMSE value is 0.0163. It’s obvious that the model error is small, and the wavelet neural network prediction result is shown in Fig. 15. After the end of the experiment, the $e_j$ obtained by making the difference between the predicted value and the detected data is used as the input of the integrated model.

![Figure 15. Wavelet neural network model prediction results](image)
4.6. Integrated Model Application

From the three models above, the information error moment \( E = [e_1, e_2, e_3] \) of the shipyard workshop prediction data is obtained, wherein the specifications of \( e_1, e_2, e_3 \) are all 117\times 1. According to the theoretical application and algorithm construction above, the data is processed by MATLAB software, and the \( W \) in the simultaneous equation is \([0.011, 0.5821, 0.4069]\). Get the final strong predictor. The final strong predictor is the residual material reserve = ARIMA model prediction result value \times 0.0110 + improved PSO-SVR model prediction value \times 0.5821 + wavelet neural network prediction value \times 0.4069. The resulting errors obtained using different models are shown in Table 3.

Table 3. Error results of ARIMA model improved PSO-SVR model, wavelet neural network and integrated model.

| Unstandardized raw data | ARIMA | Wavelet neural network | Improved PSO-SVR model | Integrated model |
|-------------------------|-------|------------------------|-------------------------|------------------|
| RMSE                    | 0.763 | 0.52                   | 0.4075                  | 0.368            |
| MAE                     | 0.796 | 0.687                  | 0.537                   | 0.501            |
| MSE                     | 0.582169 | 0.2704               | 0.166056               | 0.135            |

It obvious that the integrated model is superior to the ARIMA model, the wavelet neural network model and the improved PSO-SVR model in terms of model prediction accuracy.

At present, in order to meet the needs of production, all shipbuilding enterprises are supposed to set up a steel plate yard of a certain scale as a site for feeding, sorting, stacking, storage and supply of steel raw materials. This forms a traditional steel management method of “first storage and later assembly [18]”. Sufficient storage capacity provides a storage basis for shipyard inventory.

Shipyard materials need to consider both internal and external factors. Internal changes include changes or frequent revisions in design quotas, derailment of schedules and actual construction plans, and insufficient procurement planning. The external change factors are mainly reflected on the insufficient performance of the supplier's contract performance. For example, the supply period of the urgently updated steel is too long; the materials of different order batches are not delivered in the order of batches. Considering this, the shipyard's demand is irregular and the steel stacking site is sufficient, according to the no-storage management mode and the integrated forecasting algorithm, this paper establishes a strategy model of inventory-free control:

Assume that the shipyard's procurement cycle is \( T \), based on the 28-day optimal emergency procurement cycle of the smart shipyard production and operation. Apply a trained multi-classifier integrated decision model. By designing the quota, the planned production number \((a_1, a_2, a_3)\) of the three production lines is used as an input to the integrated model. The integrated model predicts the steel demand \( C_2 \) for the next procurement cycle \( T_2 \) and the predicted feed \( Y_2 \) for 28 days after \( T_2 \). At this time, the raw material entering the production line is \( Y_1 + C_2 - Y_1 \), and the remaining material storage is \( Y_2 \), and the total purchase amount is \( C_2 + Y_2 - Y_1 \).

The no-margin control strategy has the following safeguards and implementation conditions:

- To make sure the intelligent shipyard works, it’s necessary to ensure the complete smooth of data flow. Forecasts in the production, manufacturing, processing, etc. of smart shipyards rely on data. In the intelligent shipyard, there are three major systems, including based on an effective data flow, with ERP for production planning, PDM for product lifecycle management, and MES for inter-plant production management and scheduling execution. Only when they achieve a high degree of information sharing can the feed time, the amount of feed, and the accurate distribution of feeds be achieved.
- A series of decisions for smart shipyard decision maker are the premise of Non-surplus inventory control, such as market situation, planning strategy deployment, and shipowner order demand. After the decision makers revise the overall production target and production
schedule, the target system is decomposed, and the robot processes the steel materials of the three production lines. The robot has a high degree of automatic execution when handling 3 production lines. The robot can automatically read the production plan data in the ERP, call the design data of the corresponding product in the PDM system, and generate the machining process instructions. Therefore, misjudgment of production decision makers can cause irreversible problems throughout the operating system.

- The intelligent shipyard supply chain management department controls the procurement cycle and price of raw materials required by the enterprise, which is an important part of the inventory. According to procurement department's procurement risk expectations, non-surplus inventory control adjusts the stocking of the remaining stock. When the procurement department's deviation from the procurement risk expectation is too large, it will lead to loss of meaning or even failure of the non-surplus inventory control.

In summary, the inventory-free control requires coordination of all aspects of the entire smart shipyard, including efficient information circulation, reasonable decision-making by decision makers, accurate forecasting of the supply chain, and multiple dimensions of horizontal and vertical multi-agents.

5. Conclusion and Outlook

Based on the scientific and effective prediction of the balance of shipbuilding raw materials and the demand for workshop materials, this paper puts forward the idea of “no surplus” inventory management. The two-stage predictor construction idea is adopted and the integration of strong predictors is carried out. Then the shipyard industrial big data was collected for empirical research, and based on the data analysis, a strategy model with no surplus in inventory was established. The conclusions obtained are as follows:

- This paper introduces the adaptive adjustment of inertia weight and the Gaussian perturbation method to optimize the particle swarm optimization algorithm. They can enhance the approximation ability of nonlinear functions and effectively improve the global optimization ability of particle swarm optimization.
- The optimized particle swarm optimization algorithm can be used to optimize the parameters of support vector machine (SVR). This reduces the influence of the parameters set by the artificial experience on the accuracy of the model and improves the accuracy of the prediction model. Under the classical statistical metrics, the improved PSO-SVR has higher prediction accuracy than wavelet neural network and ARIMA.
- Adding the momentum factor to the weight update, the wavelet neural network can significantly improve the convergence speed.
- Using the integrated algorithm stacking idea, PSO-SVR, ARIMA, and wavelet neural network are integrated into the strong predictor to further improve the prediction accuracy. The integration model has greatly improved the learning speed, generalization ability and prediction effect. It has high prediction accuracy and strong adaptability in the shipyard non-surplus inventory control, and has a good application value for inventory management.
- Controlling costs and reducing risks are the cornerstones and guarantees for the long-term development of enterprises. The non-surplus inventory control can effectively reduce the risk of raw material shortage in the production workshop and the cost of enterprise inventory management and material storage. It has theoretical reference and practical application significance in the shipbuilding industry.

In the future work, the prediction accuracy will be further improved, and the coordination and convergence of the supply chain will be required to strengthen the non-surplus inventory control, and the effect of the non-surplus inventory control will be further optimized.

6. References

[1] MengYu Li, Research on the Construction of Panoramic Management Logistics Decision Mechanism in China's Intelligent Shipyard [D], Harbin Engineering University, 2017.
[2] Ping Cheng, YunYun Xu Research on Enterprise Inventory Management Based on Cloud Accounting in Big Data Era[J],Friends of Accounting,2015 (06):134-136.

[3] Xin Wang, Yi Zhang,RuiXia Zhao Application of non-remaining assembly technology on composite fuselage structure section[J]. Aviation manufacturing technology2017 (04):106-109.

[4] XiLu Liu Practice of hull section without margin construction and segmentation in segmentation [J]. China Water Transport (Academic Edition), 2007(11):53-55.

[5] XinZhu Ma Practice of Sectional and Non-remaining Construction Technology for Small and Medium-sized Ships [J].CHINA SCIENCE AND TECHNOLOGY INFORMATION, 2013(10):137.

[6] Dong Peng, Guoqiang Qu, Shanwei Xu, etc.effection on zero inventory of China's manufacturing industry from the perspective of supply chain [J]. China Electromechanical Industry, 2015(04): 84-89.

[7] Hua Xin, Lu Junping. The Enlightenment of Toyota Zero Inventory Management to the Optimization of China's Enterprise Inventory Management [J].Study Theory, 2010(35):103-105.

[8] Wu Danjie, Su Junhua, Zheng Jianyang. Analysis of the Application and Risk of Zero Inventories in Enterprises [J]. Reform and Strategy, 2015, 31(05): 83-91.

[9] Xiong Zhibin. Research on GDP Time Series Prediction Based on ARIMA and Neural Network Integration [J]. Mathematical Statistics and Management, 2011, 30(02): 306-314.

[10] Sheng Liu. Research on domestic tourism market forecast based on ARIMA and SVM combination model [D]. Donghua University of Technology, 2017.

[11] Shuquan Li, Shijie Liu. Simulation and Verification of Safety Prediction Model Based on Improved PSO-SVM Project[J].Statistics & Decision Making, 2018,34(02):182-185.

[12] Wenjuan Liang, Xueyan Li. Prediction of Air Traffic Flight Accidents Based on ARIMA, LS-SVM and BP Neural Network Combined Model [J]. Safety and Environmental Engineering, 2018, 25 (01): 130-136.

[13] Bing Ai, Minggang Dong. Improved particle swarm optimization algorithm based on Gaussian perturbation and natural selection [J]. Journal of Computer Applications, 2016, 36(03): 687-691.

[14] Xiaoping Luo, Xuhui Shen, Du Pengying. Weighted KPCA Analysis Based on Distance and Radial Basis Kernel Function [J].Control Engineering, 2012, 19(02):214-217.

[15] Wenjun Zhang. Wavelet neural network algorithm and its application to ship motion control [D]. Dalian Maritime University, 2014.

[16] Ling Zhao, Hongke Xu, Cheng Hongliang. Road Traffic Accident Prediction Based on Optimal Weighted Combination Model [J]. Computer Engineering and Applications, 2013, 49(24): 11-15.

[17] Qiuping He.Discussion on the management method of steel inventory in shipbuilding enterprises [J]. Guangchuan Technology, 2013, 33(03):50-53.