Study of economic order lot based on improved ABC

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Abstract. When making product orders, it is necessary to calculate the required order quantity accurately on the basis of ensuring the minimum cost. However, the existing economic order lot model is relatively inaccurate in order quantity prediction. Accordingly, the study optimizes the existing support vector machine order prediction model by the improved artificial bee colony algorithm. Results showed that the MSE values of the improved bee colony algorithm in the training and test sets were 0.0164 and 0.004, significantly lower than those of the improved artificial bee colony algorithm. This indicates that the improved artificial bee colony algorithm has better data seeking capability and can predict the required order quantity better in the economic order lot model.

Keywords: Improved artificial bee colony algorithm; Economic ordering; Support vector machine; Order prediction

1 Introduction

Economic lot size is the order quantity that minimizes the cost of inventory by calculating the cost of each product. Inventory is managed in such a way as to minimize the cost of inventory and maximize the inventory turnover rate while maintaining the normal production of goods.[1] . The basic economic ordering model requires three basic conditions to be met: a balanced relationship between the annual demand for inventory and daily consumption, a fixed time interval between the arrival of inventory and goods, a one-time arrival of the same batch of goods, and no shortage of goods without taking into account discounts. The economic ordering model is often constrained by too many factors in its practical application, so its scope of application is easily limited[2-3] . Therefore, an accurate forecast of the required orders is required before the order lot can be placed. Support Vector Machine (SVM) is widely used for calculating the number of previous orders and the number of subsequent orders in product lot ordering. The Artificial Bee Colony Algorithm (ABC) is a colony intelligence optimization algorithm that simulates honey harvesting and has the advantages of fewer control parameters, easy implementation, and high robustness.[4-5] . However, the method is prone to problems such as premature

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convergence and local optima when solving relatively complex problems, and at the same time, the intelligent algorithm has a strong exploration capability but relatively insufficient development capability. Therefore, in order to better calculate the product order lot, ABC is studied to improve it to solve the problems of convergence, local optimality and weak exploitation ability. The improved artificial swarm algorithm is applied to the order prediction problem in the optimized economic order lot model, and it is expected that the method will optimize the economic order lot model to achieve more accurate order quantity prediction.

2 Economic order lot Construction BY improved ABC

2.1 Economic order lot construction by improved ABC

ABC accomplishes the search for optimal solutions by simulating the honey-harvesting behavior of colony bees. The whole model contains food sources and three kinds of bees that accomplish different tasks, i.e., hiring bees, following bees and detecting bees[6] . During the ABC initialization, each detecting bee initiates a randomized search for food sources in the surrounding space, which generates a viable solution to the optimization problem. Subsequently, the hired bees perform an initial search within their food source's proximity. If the new food source $Fit_i^{'}$ yields a better fitness value than the existing food source Fit_i , then the hired bees are moved from the original location to the new location, and vice versa kept unchanged[7]. When they complete the search, the following bees make a roulette selection based on the information obtained about the quality of the nectar source. Once the follower bee selects the honey source, it explores the vicinity around the chosen source and reports the results of the search to the following hiring bee, which also retains the better solution according to the greedy algorithm. The hired bee updates the solution as shown in Equation (1).

$$x_{ij}^{'} = x_{ij} + r_{ij} * (x_{ij} - x_{kj}) \tag{1}$$

In Equation (1), k, j denotes the location of the nectar source where different bees are located, x_{kj} denotes the first j dimension of the location of the nectar source, r_{ij} denotes a uniformly distributed random number, and $r_{ij} \in [-1,1]$. The probability that a follower bee selects a hired bee is shown in Equation (2), determined by the quality of the food source delivered by the hired bee as assessed by the fitness value.

$$p_i = \frac{Fit_i}{\sum_{i=1}^{NP} Fit_i} \tag{2}$$

In equation (2), NP denotes a problem that has not been solved. Upon searching for a new nectar source in the global range, the scout bee will shift back to the role of employed bee. The basic ABC flow is shown in Figure 1.

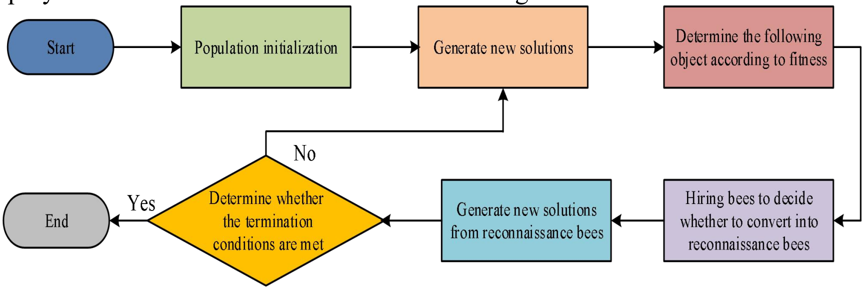

Fig. 1. ABC process

However, ABC searches for the optimal solution by replacing the original solution with another solution selected randomly, resulting in two solutions of different quality being selected with equal probability, and therefore, the method is deficient in selecting the optimal solution. Meanwhile, the artificial bee colony algorithm itself has a strong exploration capability, but its development capability is insufficient. Commonly used bee colony optimization algorithms are Bare-bones based ABC algorithm (BB-ABC) and Hybrid Bee Colony based ABC algorithm (HBC-ABC). BB-ABC method uses Gaussian algorithm to search for the optimal parameters. Parameter adaption enhances the development performance of this algorithm by dynamically adjusting the optimal parameters according to different fitness values.[8-9] . HBC-ABC is improved by Metropolis feature of the simulated annealing algorithm. This method improves the ABC algorithm by introducing a parameter to simulate the annealing temperature. When the parameter value is high, the quality of the searched solution is poor, and as the annealing temperature decreases, the global search capability is enhanced and the quality of the desired solution is better[10-11] . However, none of the above optimization algorithms can better adapt to the prediction of economic ordering lot data. BB-ABC is optimized in convergence speed and development performance, but it easily falls into local optimal solutions and has weaker robustness. HBC-ABC method introduces more parameters in the optimization process, which leads to more complex parameter selection and increases the computational effort. To address the shortcomings of the above algorithms, the study combines the advantages of BB-ABC and HBC-ABC in optimizing artificial bee colony algorithms and proposes a new ABC algorithm (HBABC), which slows down the formation and growth of bee colonies by increasing the diversity of bee colonies[12-13] . In the improved method, the nectar source of the employed bees is exploited in the way shown in Equation (3).

$$v_{ij} = x_{ij} + r_{ij}(x_{ij} - x_{kj}) + r'(T'_{X_g^j} - x_{ij}) \tag{3}$$

In Equation (3), $r' \in [0,1.5]$, $T'_{X_g^i}$ denote alternative values that move the algorithm away from the direction of that solution during the iterative process, increasing the diversity and the search ability. The following bee is calculated by introducing a simulated annealing 3D time factor in the selection of the hiring bee, as shown in Equation (4).

$$p_i = \left[\frac{fit_i}{\sum_{i=1}^{NP} fit_i} + (re^{\frac{fit_i - fit_{best}}{t}}) \right] / 2 \tag{4}$$

In Equation (4), fit_{best} represents the best fitness value, the time factor t shrinks with time to increase the difference of fitness values between different solutions, and r is the random number between $[0,1]$. In the initial stage, the relatively poor hired bee individuals in the algorithm can get more selection and update probability through Equation (4), and when the algorithm runs to the middle and later stages, the probability of better quality hired bees being selected gradually increases for better development ability. Specifically, if the obtained fitness value is better than the original fitness value, the new solution is accepted. Vice versa, a random number between 0 and 1 is generated for comparison. Taking any iteration as an example, the fuzzy maximum completion time for two production processes is calculated. If the obtained time is better than the initial time, the new solution is accepted, that is, a higher quality hired bee is chose. Then, this solution is used to replace the initial solution, thereby obtaining more potential optimal solutions to avoid local optima and improve development capabilities.

2.2 Construction of SVM economic order lot model by improved ABC

The improved ABC balances the tasks of both data exploitation and merit search. SVM constructs the sample set so that each subset has the minimum empirical risk[14] . In economic order lot studies, economic order models are constructed by support vector institutions, which are able to calculate past order amounts and predict subsequent order amounts, and thus find the value of the economic order lot. Compared with neural networks, SVM has unique advantages in small samples, nonlinear pattern recognition, etc. Therefore, SVM can better solve the problems of local extremes and over-learning that tend to occur in neural networks[15-16] . If the set of training samples is $D = \{(x_1, y_1), (x_2, y_2), ..., (x_n, y_n), x_i, y_i \in R\}$, the linear equation to obtain the optimal hyperplane in this sample space is shown in Equation (5).

$$f(x) = \omega^T x + b \tag{5}$$

In Equation (5), $\omega = (\omega_1, \omega_2, ..., \omega_d)$ denotes the normal vector, b is the displacement term, and the distance between any point in the sample space x and the hyperplane (ω, b) is shown in Equation (6) when predicting the order quantity, the training sample is . $(x_i, y_i) \in D$

$$d = \frac{\left|\omega^T x + b\right|}{\|\omega\|} \tag{6}$$

The point that makes this formula hold is SVM, and the sum of the distances between two different support vector machines to the hyperplane is the interval, as shown in Equation (7).

$$\gamma = \frac{2}{\|\omega\|} \tag{7}$$

The final computational purpose is that the solved sample needs to make the maximum value of γ , i.e., the optimal solution for the maximum interval, and the basic model of support vector machines, etc., is shown in Figure 2.

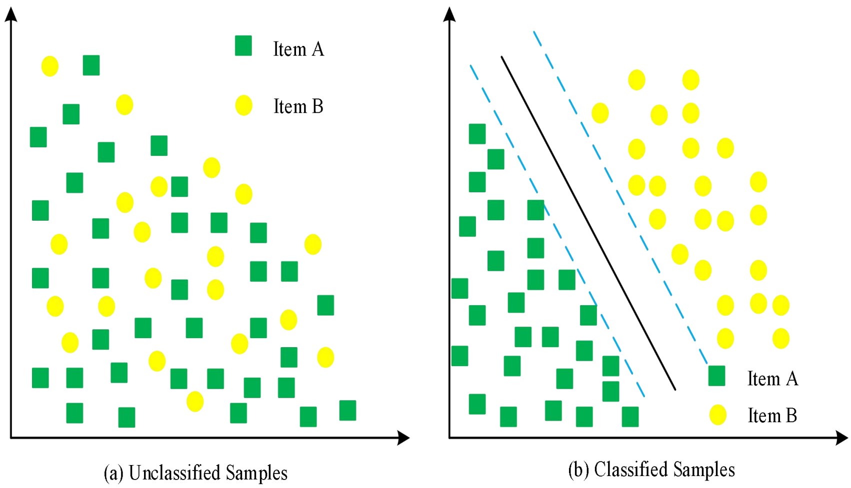

Fig. 2. SVM schematic diagram

When classifying the order data of goods, if $f(a) > 0$, it will be classified as 1, and if $f(a) < 0$, it will be classified as -1. From this, it can be obtained that the optimal hyperplane in SVM classification should have the feature of maximum interval with two straight lines, and the maximum classification interval is shown in Equation (8).

$$y \times (\beta a + b) = y \times f(a) \tag{8}$$

In Equation (8), $|f(a)|$ is the classification interval, and the model performance is improved by optimizing its loss function when using this model for order quantity analysis. That is, the loss function optimization is achieved by optimizing ω and b in

Equation (6). The loss function optimization of this model can be translated into solving the optimization problem of Eq. (9).

$$\begin{cases} \min J(w,\varsigma) = \frac{1}{2} w^T w + \frac{C}{2} \sum_{i=1}^{n} \varsigma_i^2 \\ s.t. \begin{cases} y_i - w\varphi(x_i) - b \le \theta + \varsigma_i \\ -y_i + w\varphi(x_i) + b \le \theta + \varsigma_i^* \\ \varsigma_i \ge 0, \varsigma_i^* \ge 0 (i = 1, 2, ..., n) \end{cases} \end{cases} \tag{9}$$

In Equation (9), C is a penalty factor for the complexity reduction. If the value of C is smaller, the error fluctuation is smaller. $\varsigma_i, \varsigma_i^*$ is the relaxation factor to establish the model constraints. Equation (10) is obtained by solving it with Lagrange multiplier method.

$$L(w,b,e,a) = J(w,e) - \sum_{i=1}^{n} a_i \left[w^T \varphi(x_i) + b + e - y_i \right] \tag{10}$$

In Equation (10), a_i is the multiplier of the Lagrangian function. w, b, e_i, a_i is the variable. The matrix equation can be obtained by differential solution as shown in Equation (11).

$$\begin{bmatrix} 0 & 1^T \\ 1 & \alpha + \frac{1}{\gamma} \end{bmatrix} \begin{bmatrix} a \\ b \end{bmatrix} = \begin{bmatrix} o \\ y \end{bmatrix} \tag{11}$$

In Equation (11), a, b is the calculation parameter. The above process is used to analyze the number of commodity merchandise orders and historical inventory quantities that have been generated, where the penalty factor C in the SVM model can be used to adjust the confidence range and empirical risk degree of the SVM to ensure analysis accuracy. Based on the above process, an SVM economic order lot analysis model by the improved ABC is constructed.

3 Performance analysis of economic order lot BY improved ABC

3.1 Performance analysis based on improved ABC

To verify its effectiveness, the IRIS dataset was used to validate the performance of the improved ABC algorithm. The performance of the method was tested using MATLAB2015 to compare the performance of ABC, BB-ABC, HBC-ABC, and HBABC proposed in the study. The problem size used in the algorithm is 100, and the parameters during the ABC operation are as follows: the number of bees is 50, the number of employed bees and following bees is half of the population size, the maximum number of iterations is 2500, and each function is performed for 40 trials. The convergence effect of the algorithm was first tested by using four Benchmark test functions, Sphere function, Sumsquare function, Elliptic function and Quartic function, and the test results are shown in Figure 3. ABC convergence accuracy is lower than the rest of the improved methods in all four different test functions. However, both BB-ABC and HBC-ABC have unavoidable defects. After combining the two approaches, the HB-ABC method combines the advantages of the BB-ABC and HBC-ABC algorithms to achieve more desirable convergence accuracy. HB-ABC convergence accuracy is better than that of ABC in both cases. In the Elliptic function, HB-ABC convergence accuracy is slightly lower than that of HBC-ABC when the number of iterations reaches 1000. In the Sphere function, the HB-ABC algorithm has the worst convergence in the initial stage, but the advantage of the method gradually increases as the number of iterations increases. After the final function converges, the average optimal convergence values of the HB-ABC algorithm on the four tested functions are 1.604e-13, 1.197e-14, 6.245e-7, and 0.946. The above results indicate that HB-ABC has stronger advantages in convergence speed, solution accuracy, robustness, and stability.

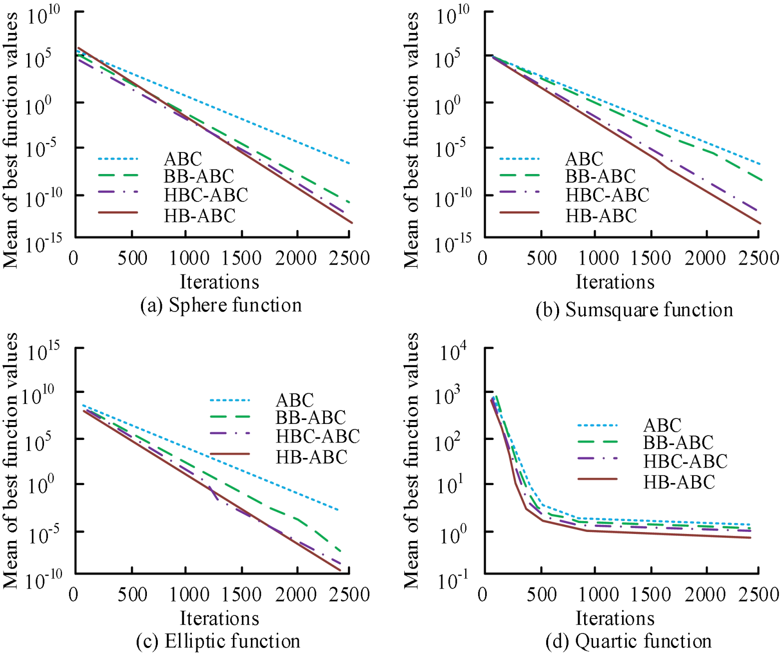

Fig. 3. Convergence Analysis of Improved ABC Algorithm

To validate the data prediction effectiveness by the improved ABC, models were constructed based on ABC-SVM, BB-ABC-SVM, HBC-ABC-SVM, and HB-ABC-SVM, respectively. The detection accuracies of the three models are shown in Figure 4. The HB-ABC accuracy is significantly higher than remaining three ABCs accuracy. Among them, the accuracy of the HB-ABC model reached 98.52%, the accuracy of the BB-ABC model was 96.93%, which was 1.59% lower than that of HB-ABC; the accuracy of HBC-ABC was 96.62%, which was 1.9% lower than that of HB-ABC. The accuracy of the unoptimized basic ABC model was 96.21%, which was 2.31% lower than that of the optimized HB-ABC model. In the above description, it can be concluded that the HB-ABC model constructed by studying the respective advantages of the pooled HBC-ABC and BB-ABC models is significantly better than its comparison method.

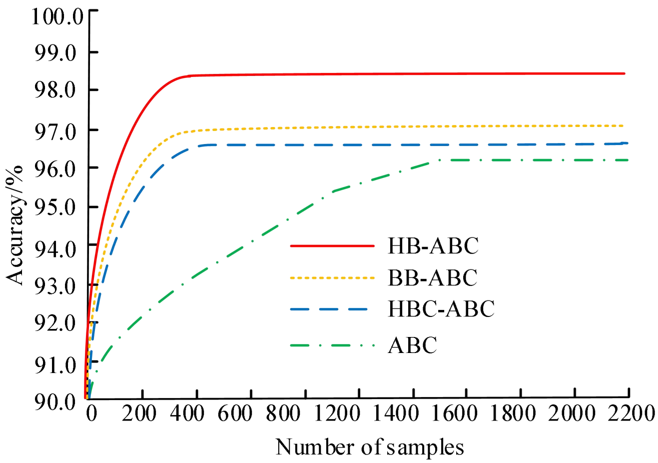

Fig. 4. Detection accuracy of three models

3.2 Economic order lot data analysis by improved ABC

To verify the effectiveness of the improved ABC in the economic order lot data analysis model, the method was applied to the actual order data analysis of a company. Therefore, the research obtained the existing order and sales data of the relevant goods from the company to analyze the demand of the goods, analyze the demand of the goods in the future period based on the analysis results, and adjust the ordering strategy of the goods in time. The proposed HBABC is compared with the existing ABC, BBABC and HBC-ABC to optimize the SVM, and the Mean Standard Error (MSE) is used as the evaluation index. The study constructs three data sets by collecting commodity data in different time ranges. The specific data transactions are shown below.

Table 1. Statistics of Commodity Trading Data

Dataset number	Start time	End time	Transaction days
D1	2013.05.01	2015.11.30	943
D2	2015.08.01	2016.11.29	482
D3	2013.05.01	2015.02.04	643

The method proposed in the study was used to fit the number of orders required for this item and the results of the order amount fitting were obtained as shown in Table 2. MSE values of the ABC method are larger for all three different datasets. In the first data set, MSE values of the HB-ABC method in the training set test set are 0.0073 and 0.0046, respectively. In the second data set, MSE values of BB-ABC are significantly higher than the other three methods; MSE values of the HB-ABC method in the training set test set are 0.0068 and 0.0522, respectively, which have poor performance. In the third data set, ABC and BB-ABC had larger error values and lower accuracy in the test set. The MSE values of the HB-ABC method in the training set test set were 0.0164 and 0.0043, respectively.

Table 2. Error in Fitting Results of Order Quantity

Database	algorithm	Experimental dataset	MSE
D1	ABC	Train	0.0061
		Test	0.1259
	BB-ABC	Train	0.0061
		Test	0.0042
	HBC-ABC	Train	0.0037
		Test	0.0055
	HB-ABC	Train	0.0073
		Test	0.0046
D2	ABC	Train	0.1289
		Test	0.0517
	BB-ABC	Train	0.2436
		Test	0.2278
	HBC-ABC	Train	0.1253
		Test	0.1804
	HB-ABC	Train	0.0068
		Test	0.0522
D3	ABC	Train	0.0387
		Test	0.1651
	BB-ABC	Train	0.0097
		Test	0.5643
	HBC-ABC	Train	0.0338
		Test	1.0057
	HB-ABC	Train	0.0164
		Test	0.0043

Taking the data of D1 dataset as an example, the relative errors of the prediction results obtained after optimizing SVM's by ABC, BBABC, and HBABC algorithms are shown in Figure 5. A negative error rate indicates that the predicted number of item orders is lower than the required number of items. In Figure 5(a), the maximum error rate of ABC method reaches -24, and the error variation is the largest. In Figure 5(b), the BB-ABC maximum error is -22, in Figure 5(c), the HBC-ABC maximum error rate is -18, and in Figure 5(d), the maximum error of the HB-ABC algorithm is -10. The fluctuation of the error curve of this algorithm is significantly reduced. Overall, the study proposes that the HB-ABC algorithm predicts the number of orders significantly better than the remaining three approaches.

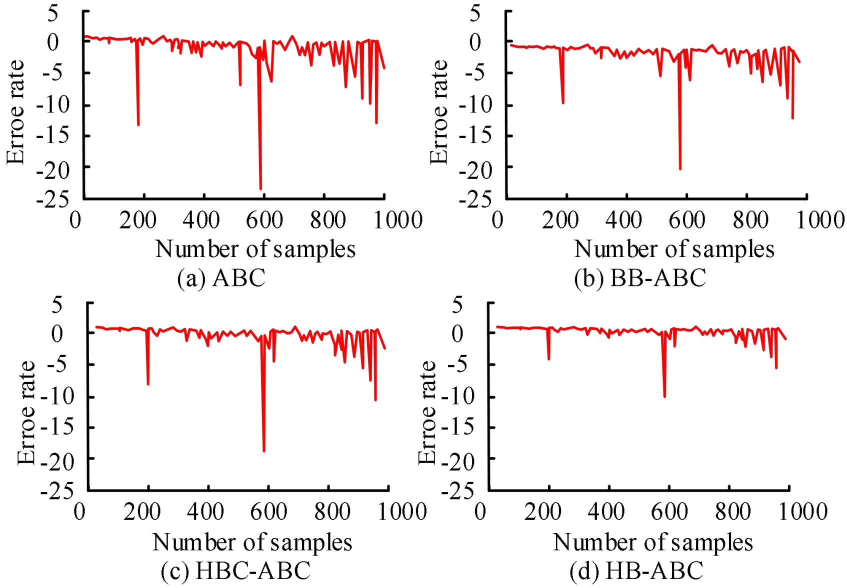

Fig. 5. Comparison of Improved Algorithm Prediction Results

4 Conclusion

The quantity of goods demanded is a dynamically changing value that is influenced by many factors, and an effective economic ordering model can provide a relatively accurate forecast of the quantity of goods needed. In order to better analyze the quantity of goods needed in economic activities, the study proposes an improved ABC algorithm to optimize its SVM economic ordering model based on the SVM goods quantity forecasting model. Rresults show that the average optimal HB-ABC convergence values on the four test functions after the final functions converge are 1.604e-13, 1.197e-14, 6.245e-7, and 0.946, respectively. The training and testing MSE values of HB-ABC are 0.0073 and 0.0046, respectively, on the first data set. The training and testing MSE values of HB-ABC on the training and testing MSE values for the second dataset are 0.0068 and 0.0522, respectively, and those for the third dataset are 0.0164 and 0.0043, respectively, and the MSE values of this method are significantly better than those of the algorithm before improvement. In summary, the economic ordering prediction model based on HB-ABC-SVM proposed in the study has higher accuracy in predicting the quantity of required goods, and the method has better stability, which makes it more practical for practical use. However, there are still shortcomings in the study. ABC involves a large number of parameters, and the values of each parameter will have a direct impact on the performance of the algorithm. Therefore, a more in-depth study is needed in the determination of the optimal parameters in the subsequent research to ensure that ABC's performance is better.

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