Online Order Priority Evaluation Based on Hybrid Harmony Search Algorithm of Optimized Support Vector Machines

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***Abstract*—To make production plan, online order priority evaluation is the current priority weakness of online order evaluation model. This thesis proposes an online order priority evaluation model based on hybrid harmony search algorithm of optimized support vector machine (HHS-SVM). Firstly, an online order priority evaluation index system is build, and then support vector machine is adopted to build an online order priority evaluation model; secondly, harmony search algorithm is used to optimize the parameters of support vector machine; what's more, in the parameter optimization process the foraging behavior of AFSA is introduced to improve the ability and convergence speed of algorithm escaping from the local optimal solution; finally, simulation test is used to test the performance of the model. The simulation results show that HHS-SVM improves the accuracy of the online order priority evaluation relative to the comparison model. What's more, the online order priority evaluation model is feasible and effective.**

***Index Terms*—Online Order Priority; Supply Chain; Support Vector Machine; Harmony Search Algorithm**

I. INTRODUCTION

Currently, global resources and the environment have become increasingly prominent, the world increasing emphasis on sustainable development and recycling economy, have introduced legislation to improve and extend the consciousness and responsibility of enterprises to reuse waste materials [1]. The closed-loop supply chain mode which is traditional supply chain plus reverse supply chain has become a enterprise and academic research focus [2]. In the production enterprises, often appear simultaneously into multiple online orders to deal with, or online order processing is not completed, add to the mix of new online orders, while the production capacity is limited, in a moment of online orders production tasks exceeds production ability, you can only make a choice in a number of lesser, which needs to know the online order priority. Some companies will process the online order according to the FIFO principle, from the surface, it is fair to all customers, but it will bring a range of troubles to companies and customers. Treat all customers equally will extend the average online order processing time, not even in time to meet some of the customer service requirements, and thus lose an important long-term customer online orders. When online order backlog, you should take the appropriate method to sort online order processing, rules may involve delivery, amount, cost, profit, quality, etc., derived by some algorithm integrated priority online orders, resulting in ranking between online orders or online order, to help executives make the right decisions. In production capacity and material inventory capabilities limited circumstances, help companies try to arrange the relative importance of production online orders priority to optimize resource utilization, improve production efficiency. Sort, also known as classification, is a set of data or things in certain online order or online order rules. Sorting method based on a quantitative linear weighting method, ABC cost method, fuzzy comprehensive evaluation, neural network algorithm and AHP, etc.

In the current fiercely market competitive circumstances, quick release and implementation of the task online orders, provide customers with accurate, real-time online order information, and enable enterprises quickly respond to customer delivery requirements is more important. Online order processing capabilities are an important part of customer service, and determine of online order production priority is the most important aspect, so how to evaluate single production priority scientifically and rationally, and improve service efficiency become an important topic in the study [3]. Supply chain disruption management was firstly proposed by Clausen, aimed at resolving the airlines to respond to emergencies areas and get a good application [4]. Currently the supply chain for emergency research focuses on positive aspects : the literature [5-10] investigate the demand caused by unexpected events, promotional investment or cost sensitivity coefficient and market size changes were studied by adjusting the original contract to coordinate the supply chain; literature [7] based on literature [8] extended the study object to one supplier and a leading position in the composition of multiple retailer supply chain coordination problems,

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propose use amended quantity discount contract to coordinate disruption event; literature [9-11] introduces the time factor, demand and prices will be set to a function of time, revenue sharing contract research coordinated response to emergencies; literature [12] investigated the event when the interference caused by production costs, market size and price-sensitive coefficient simultaneously disturbance, build two supply chain game model, the results show that the period of stability of the contract on production plan has some robustness, but when the disturbance exceeds a certain limit, you need to adjust the production plan and design a new contract to coordinate the supply chain; literature [13-16] study the market demand when unexpected events lead to changes in the distribution, the original revenue sharing contract is no longer coordinate the supply chain, but through the amendment of the contract to coordinate the interests among the members.

For production online orders priority evaluation issues, many scholars have done a lot of research, proposed online orders priority evaluation model [17-19] based on the theory of constraints, linear programming theory, strategic theory, AHP and entropy weight method and so on. These models are considered from different perspectives priority online orders, their advantages and disadvantages are present, such as the analytic hierarchy process is simple, easy to implement, but the results of the evaluation is subjective; relationship between linear programming assuming online order priority and influencing factors is a linear relationship, but in fact corporate online orders priority evaluation issues affected by many factors, is a nonlinear problem, so the scope of application of these models is limited. In recent years, Tang Lichun [20] and other people put forward an online order production priority evaluation nonlinear model based on the RBF neural network, neural network has a strong self-organizing and nonlinear approximation capability, increased online order evaluation accuracy of production priority evaluation and make the results more scientific [21]. However, neural network is based on empirical risk minimization principle and the "large sample" the theory of machine learning algorithms, however, online order history data is a small sample size problem, when you can not meet the "large sample" requirement, so neural networks prone to "over-fitting" phenomenon, while there is difficult to overcome their own shortcomings, such as the complexity of network structure [22], etc. Support vector machine (SVM) better overcome the defects of the neural network over-fitting, generalization ability is superior, and provides a new research idea for solving problem of online order production priority. SVM in practical applications, its performance is closely related to parameter selection, the current major genetic algorithm, particle swarm algorithm to optimize the SVM parameters, these algorithms have advantages and disadvantages, such as genetic algorithms for parameter optimization, demand is set different genetic operators, complex operation; particle swarm algorithm, while having a faster convergence speed, but also easy to fall into local minima [23]. Harmony Search (HS) algorithm is developed in recent years as a heuristic global search algorithm, which has better optimization precision and the ability to escape from local optima, has been used in engineering practice [24].

To solve the problem like the company's own production capacity, profitability and customer relations and other issues, faced with numerous demands orders enterprises should identify critical sequence of completing the orders, and meet each customer’s need within their abilities. Overall, the previous studies on this issue are focused on decision analysis methods and analytic hierarchy process method. These methods require policy makers having in-depth understanding of index system of preferred order, the general terms of business operations, market conditions and customers. For the various indicators in order selection system, policy makers need to be given different weights to obtain a decision matrix, and then the final calculation is processed to get the order of priorities; after that, program development and scheduling are performed. But such a decision-making process requires not only tedious calculations, but need a lot of subjective factors. Not using the existing success stories tends to make biased results of the decisions.

The innovation of this paper is as follows:

(a) In online order to improve the accuracy of the online order priority evaluation, present a hybrid harmony search (HHS) algorithm optimizing SVM parameters of online order priority evaluation model (HHS-SVM), while online order backlog, need to do sort processing for online orders, this paper adopt online order evaluation model to scheduling online order processing sequence, the other nodes companies in the supply chain sharing information are used to construct the index system process.

(b) In the supply chain environment, supply chain node enterprises to establish coordination mechanisms between upstream and downstream, and thus the implementation of information sharing. In this environment, the processing of customer online orders sequentially arranged, not only consider their own master data, the choice of delivery, profit limits, the importance of the customer, the amount of online orders, production costs, quality requirements, online order material satisfaction factors such as the agile enterprise production management system evaluation online order priority targets, but also from other nodes to extract business information provided valuable part, take advantage of the value of information sharing, and using genetic algorithms to solve programming by analyzing the generated image and calculation results to determine the solution obtained by this method converges, and through simulation testing to test the effectiveness and superiority of HHS-SVM.

II. Online order Priority Evaluation Model Frame for IHS-SVM

A. Online order Priority Evaluation Model Frame

Online orders priority evaluation is a dynamic, non-linear decision-making process, many factors affect

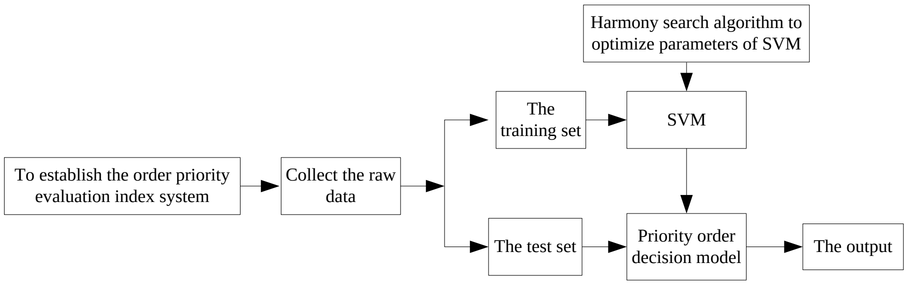

Figure 1. Online order priority model framework of IHS-SVM

the online order priority evaluation, each factor affect the results of the online order priority evaluation with varying degrees, the online order priority evaluation between input and output is a kind of complex nonlinear relationship, and it is difficult to establish a reasonable and precise mathematical expression. Set online orders priority evaluation indicators as{x1,x2,…,xm}, then the mathematical model of online order priority evaluation is

$$y = f\left(x_1, x_2, \cdots, x_m\right) \tag{1}$$

In formula, f() represents an evaluation function.

Establish online order priority evaluation model, in essence, is to find a best adapted f (), you can accurately portray online order priority evaluation system whose relationship between input and output is complex nonlinear relationship. Online order priority evaluation model based on HHS-SVM framework is shown in Figure 1. First, establish the correct online order priority index system, and then use HHS algorithm to optimize SVM parameters, get the optimal SVM parameters, and finally create an online order priority evaluation model, and evaluate the performance of the model.

B. The Centralized Decision-making Model under Disruption Event

In the manufacturer leading of centralized decision situations, in online order to facilitate the discussion, consider the closed-loop supply chain manufacturers optimal countermeasures. The goal centralization decision at this time is to maximize the benefit of closed-loop supply chain. Therefore, interference with the incident, the closed-loop supply chain profit function is:

$$\begin{aligned}\pi_{scd}(Q) = {} & ((D + \Delta D - Q)/k_1 - c_0 + (\eta + \Delta\eta) \\ & (\Delta_0 - \Delta c_m - c_r))Q - C(\eta + \Delta\eta)^2 \\ & - \lambda_1 (Q - \bar{Q})^+ - \lambda_2 (\bar{Q} - Q)^+\end{aligned} \tag{2}$$

Here $(x)^+ = \max\{x, 0\}$. Similar to the proof of literature [16], lemma 1 can be obtained.

Lemma 1 Suppose under condition of centralized decision-making, the optimal solution of formula(2) is Q^*, when market scale D, remanufacturing cost c_m, and recovery rate η are changed and fulfill $\Delta D > k_1\eta\Delta c_m - k_1\Delta\eta(\Delta_0 - \Delta c_m - c_r)$, there is $Q^* \ge \bar{Q}$; when $\Delta D < k_1\eta\Delta c_m - k_1\Delta\eta(\Delta_0 - \Delta c_m - c_r)$, there is $Q^* \le \bar{Q}$.

From Lemma 1, when the market demand size increases which caused by the interference event, and the remanufacturing cost and recoveries rate and the amount of change to meet the above conditions, the manufacturer want to maximize profits of the closed-loop supply chain, should increase production to meet market demand, and vice versa, its regularity realistic scenarios.

Learn from lemma 1, the following situations can be considered.

(1) When $\Delta D < k_1(\eta\Delta c_m - \Delta\eta(\Delta_0 - \Delta c_m - c_r))$, get $Q^* \le \bar{Q}$ from lemma 1, so $\pi_{scd}(Q)$ can get the best explain in region $[0, \bar{Q}]$. Now there is:

$$\begin{aligned}\pi_{scd}(Q) = {} & ((D + \Delta D - Q)/k_1 - c_0 + (\eta + \Delta\eta) \\ & (\Delta_0 - \Delta c_m - c_r))Q - C(\eta + \Delta\eta)^2 - \lambda_2(\bar{Q} - Q)\end{aligned} \tag{3}$$

According to the first class optimality condition $\partial\pi_{scd}(Q)/\partial Q = 0$, can know that the optimal value of Q is:

$$Q^{**} = (D - c_0 k_1 + k_1(\eta + \Delta\eta)(\Delta_0 - \Delta c_m - c_r) + k_1\lambda_2 + \Delta D)/2 \tag{4}$$

1) When $\Delta D < k_1\eta\Delta c_m - k_1\Delta\eta(\Delta_0 - \Delta c_m - c_r) - k_1\lambda_2$, from $k_1, \lambda_2 > 0$, ΔD obviously fulfill $\Delta D < k_1\eta\Delta c_m - k_1\Delta\eta(\Delta_0 - \Delta c_m - c_r)$, now $Q^{**} \le \bar{Q}$, as $\pi_{scd}(Q)$ is strict concave function, get the only best explain during region $[0, \bar{Q}]$ for $\pi_{scd}(Q)$ is Q^*, which means:

$$\begin{aligned}Q^* = Q^{**} = \bar{Q} + {} & (k_1\eta\Delta c_m + k_1\Delta\eta(\Delta_0 - \Delta c_m - c_r) \\ & + k_1\lambda_2 + \Delta D)/2\end{aligned}$$

Opposite optimal retail price is:

$$p^* = \bar{p} + (\Delta D + k_1\eta\Delta c_m - k_1\Delta\eta(\Delta_0 - \Delta c_m - c_r) - k_1\lambda_2)/2k_1.$$

2) When $\Delta D \ge k_1\eta\Delta c_m - k_1\Delta\eta(\Delta_0 - \Delta c_m - c_r) - k_1\lambda_2$, get $Q^{**} \ge \bar{Q}$. Besides, $\pi_{scd}(Q)$ in region $[0, \bar{Q}]$ is strict concave function about Q, so $\pi_{scd}(Q)$ get the maximum value at the end point, compare with $\pi_{scd}(0) < \pi_{scd}(\bar{Q})$, so the optimal result is $Q^* = \bar{Q}$, At this time, the best price for closed-loop supply chain is:

$$p^* = \bar{p} + (\Delta D - k_1\eta c_r)/k_1.$$

(2) When $\Delta D > k_1\eta\Delta c_m - k_1\Delta\eta(\Delta_0 - \Delta c_m - c_r)$, get $Q^* \ge \bar{Q}$ from lemma 1, so $\pi_{scd}(Q)$ get the maximum value in $[\bar{Q}, +\infty)$, the current optimal benefit is:

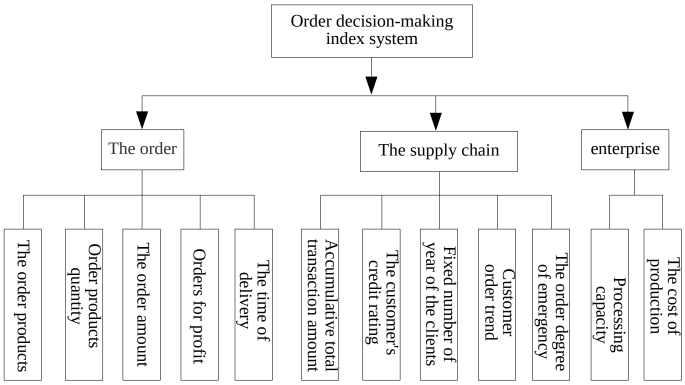

Figure 2. Online orders priority evaluation index system

$$\pi_{scd}(Q) = ((D + (\Delta D - Q)/k_1 - c_0 + (\eta + \Delta\eta)$$
$$(\Delta_0 - \Delta c_m - c_r))Q - C(\eta + \Delta\eta)^2 - \lambda_1(Q - \bar{Q}).$$

Similar to the discussion on (1), get the following conclusions:

1) When $k_1\eta\Delta c_m - k_1\Delta\eta(\Delta_0 - \Delta c_m - c_r) < \Delta D < k_1\eta\Delta c_m - k_1\Delta\eta(\Delta_0 - \Delta c_m - c_r) + k_1\lambda_1$, the optimal output for closed-loop supply chain is $Q^* = \bar{Q}$, optimal retail price is:

$$p^* = \bar{p} + (\Delta D - k_1\eta c_r)/k_1.$$

2) When $\Delta D \geq k_1\eta\Delta c_m - k_1\Delta\eta(\Delta_0 - \Delta c_m - c_r) + k_1\lambda_1$, optimal output and optimal retail price of supply chain is:

$$Q^* = \bar{Q} + (k_1\eta\Delta c_m + k_1\Delta\eta(\Delta_0 - \Delta c_m - c_r) - k_1\lambda_1 + \Delta D)/2,$$
$$p^* = \bar{p} + (\Delta D + k_1\eta\Delta c_m - k_1\Delta\eta(\Delta_0 - \Delta c_m - c_r) + k_1\lambda_1)/2k_1.$$

In summary, we can get the following Theorem 1.

C. Online orders Priority Evaluation Index System

The first step to establish online orders priority evaluation model is to build a whole set of index system, and index system is scientific and reasonable or not is directly related to the scientific and practical of evaluation model, but the online order priority is affected by many factors, such as production capacity, online order profits, customer online order trends. This paper establishes the online order priority index system which shown in Figure 2 through system analysis and expert commentary, and with reference to relevant literature and research.

III. HHS OPTIMIZE SVM ONLINE ORDER PRIORITY EVALUATION MODEL

HS algorithm simulates that musicians do musical creation with their own memories, by repeatedly adjust the pitch of each instrument in the orchestra, and ultimately achieve a wonderful harmonies state process [12]. In HS, the harmony memory storage feasible solution vector, harmony memory size determines the number of feasible solutions, harmony memory retention rate is selected from the newly generated solution probability, and tone adjustment probabilities are generated new solutions for the probability of disturbance. In online order to find better SVM parameters, in the HS algorithm, combines AFSA foraging behavior, and enhance the ability to escape from local optima and convergence speed, resulting in a hybrid harmony search algorithm (HHS). Steps for online orders priority evaluation of HHS-SVM are:

Step 1: according to expert systems and related research and production enterprise real-world conditions, establish online order priority evaluation index system.

Step 2: According to the corresponding data which index system collected, according to experts on the online order priority evaluation index system for comprehensive analysis of the expected output, and gives the corresponding quantized value, larger value indicates a higher priority for the online order, y∈(0,l), thereby construct an online order priority evaluation sample of HS-SVM modeling.

Step3: divide the sample into designated set and training set, the training set for the HS-SVM learning, the establishment of online order priority evaluation model, the test set is used to verify the priority online order established evaluation model performance.

Step 4: normalize index, dimensionless index difference eliminate the adverse effects on the online order priority evaluation samples normalization:

$$x_i^{'} = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}} \tag{5}$$

In this formula, $x_i^{'}$ means the data after normalization, and $x_{\max}$, $x_{\min}$ separately means maximum value and minimum value.

Step 5: Set parameter range of SVM. According to the related literature, the range of the parameter C determined as [1, 1000], the parameter σ range is set to [0.1, 100], and set the related parameters for HS algorithm: harmony memory size (HMS), harmony memory considering rate (HMCR), pitch adjustment probability (PAR), maximum number of iterations NI.

Step 6: Harmony memory initialization. A number of HMS initial solutions randomly generated and stored in the harmony memory (HM). HM is treated as a matrix:

$$HM = \begin{bmatrix} X^1 \\ X^2 \\ \vdots \\ X^{HMS} \end{bmatrix} = \begin{bmatrix} x_1^1 & x_2^1 & \cdots & x_n^1 & f(X^1) \\ x_1^2 & x_2^2 & \cdots & x_n^2 & f(X^2) \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ x_1^{HMS} & x_2^{HMS} & \cdots & x_n^{HMS} & f(X^{HMS}) \end{bmatrix} \tag{6}$$

In this formula, x_j^i means $i(i=1,2,\cdots,HMS)$ of component No $j(j=1,2,\cdots,N)$ for harmony vector, $x_{jL} \le x_j^i \le x_{jU}$, in this formula x_{jL} and x_{jU} separately stands for the under and up boundary of j, $f(X^m)$ is target function value.

This paper takes the RMSE between output value y_i of HS-SVM and expect output y_i as target function value, and there is:

$$f(X^m) = RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - y_i)^2} \tag{7}$$

In this formula, n represents the number of samples in the training set.

Step7: Based on HMCR, PAR, take extemporaneous creation on vector $x' = [x_1', x_2', \cdots, x_N']$, generate a new harmony vector. If harmony memory consideration rate HMCR is fulfilled, and primary adjusting rate PAR can not be fulfilled, then execute harmony memory consideration. Refer to harmony memory consideration, it means select one x_j' from harmony memory bank $\{x_j^1, x_j^2, \cdots, x_j^{HMS}\}$, $j=1,2,\cdots,N$,constitute vector x'; If harmony memory consideration rate HMCR is fulfilled, and primary adjusting rate PAR is also fulfilled, then adjust the primary.

HHS algorithm and basic harmony algorithm are different in the following two aspects:

(1) In harmony memory base, in the current optimal solution implemented on the basis of pitch adjustment operation, so you can give full play harmonies memory guiding role in the optimal solution, and improve the convergence speed.

(2) In the pitch adjustment operation, introduce AFSA foraging thought. Treat the optimal harmony vector x^{best} in the harmony memory base as the current state of artificial fish, and calculate the objective function; when optimization, random remove x^{best} a candidate solution which has been selected, and randomly select a solution has been selected as substitute candidate solutions, obtain harmony vector x^j. If the objective function value of harmony vector x^j is bigger than the objective function value of harmony vector x^{best}, then let the resulting new harmony vector $x' = x^j$; contrary, again randomly select a solution has been selected as a substitute candidate solutions, build status x^j, to determine whether meet the requirements, repeated a few times, if you still can not meet the requirements, then let the last harmony vector x^j which based on foraging behavior to be the newly generate harmony vector x', the introduction of fish feeding ideas is good to do fine search in optimum harmony vector field.

Step 8: According to equation (11) which generate a new individual X', and calculating a new individual objective function value, if the individual memory than the worst harmony vector x^{worst}, then replace x^{worst} with the replacement X'.

Step 9: iteration k = k +1, if k is bigger than the maximum number of iterations, then select the harmony vector of optimal objective function value in harmony memory bank, it means to find the optimal SVM parameters (C, σ), otherwise go to step (7) to continue optimization.

Step 10: training set input SVM, according to the most optimal parameters (C, σ), to establish the optimal online order priority evaluation model.

Step 11: Enter the test set priority online order to establish the optimal evaluation model, get the online order priority value.

IV. Experimental Results

A. Data Sources

To test the performance of online order priority evaluation model of HHS-SVM. Set a Shanghai company whose main business is apparel products as an example, online order priority evaluation indicators include online order quantity (x1), online order amount (x2), online order profit (x3), online order delivery time (x4), online order accumulated transaction amount (x5), customer credit rating (x6), customer online order trend (x7), customer cooperation time (x8), online order urgency degree(x9), and production cost(x10), total 10 indicators (x10), collected the company's 100 online orders, of which the first 70 online orders data as the training set, after 30 as the test set. Specific data is shown in Table 1. In the environment of PIV 3.0GHZ CPU, 2G RAM, and Windows XP, do simulation through MATLAB 2009a toolbox.

TABLE I. Normalized Online Order History Data

Number	x_1	x_2	x_3	x_4	…	x_{10}	y
1	0.202	0.202	0.027	0.491		0.058	0.354
2	0.405	0.405	0.003	0.895		0.033	0.191
3	0.180	0.180	0.117	0.216		0.184	0.404
4	0.311	0.311	0.009	0.906		0.058	0.574
5	0.259	0.259	0.042	0.513		0.052	0.037
6	0.476	0.476	0.008	0.478		0.011	0.393
7	0.134	0.134	0.014	0.592		0.004	0.976
8	0.129	0.129	0.008	0.888		0.018	0.043
9	0.028	0.028	0.285	0.471		0.049	0.071
…	…	…	…	…	…	…	…
100	0.886	0.886	0.653	0.337	0.234	0.453	0.359

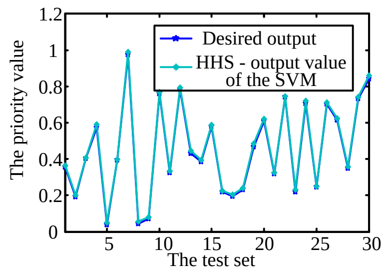

Figure 3. HHS-SVM online order priority evaluation results

B. Model Implementation

Put training set into SVM for learning, and use HHS algorithm to optimize SVM parameters, get the optimal parameters C = 175.15, σ = 19.228, finally use C = 175.15, σ = 19.228 to establish the optimal online order priority evaluation model , and test testing set, the results shown in Figure 3. From Figure 3 shows, HHS-SVM actual output is very close to the model output, precision of evaluation result is very high, it shows that, HHS-SVM is an evaluation of high precision, reliable results online orders priority evaluation model.

C. Compare with Other Algorithms Optimized SVM Model Performance

To allow HHS-SVM results become more convincing, select genetic algorithm optimization SVM (GA-SVM), particle swarm optimization SVM (PSO-SVM) and basic harmony search algorithm (HS-SVM) to do comparing experiments, using both rams error (RMSE) and the mean relative error (MAPE) as a measure of performance of the model, and their values are shown in Table 2. The correlation curve of actual output and the model output for GA-SVM, PSO-SVM and HS-SVM are shown in Figure 4-6.

TABLE II. COMPARISON OF EVALUATION ERRORS BETWEEN VARIOUS MODELS

Evaluation Model	*RMSE*	*MAPE (%)*
GA-SVM	0.064	10.41
PSO-SVM	0.057	9.75
HS-SVM	0.023	3.41
HHS-SVM	0.019	3.08

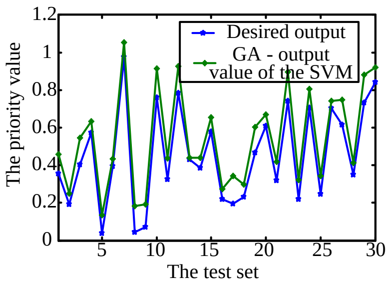

Figure 4. Online order priority evaluation results for GA-SVM

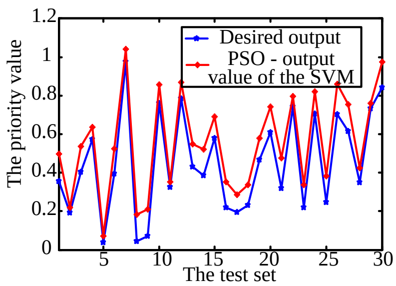

Figure 5. Order priority evaluation results for PSO-SVM

After comparing and analyzing the simulation results on table 2 and Figure 4-6, overall performance of HHS-SVM is better than comparison model, and can get the following conclusions:

(1) Evaluation accuracy of HS-SVM is slightly better than GA-SVM, PSO, which indicates HS algorithm has better global search ability than GA, PSO, get better SVM parameters C, σ, can reduce the error rate of online order optimization evaluation, effectively improve the evaluation accuracy of online order priority evaluation.

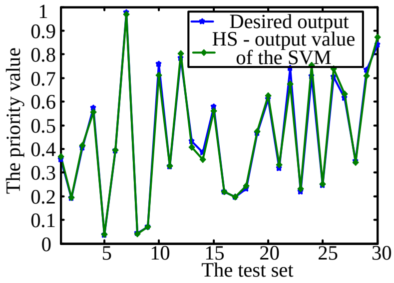

Figure 6. Order priority evaluation results for HS-SVM

(3) The evaluation accuracy of HHS-SVM is the highest, evaluation error is much smaller than the comparison model HS-SVM, which indicates HHS algorithm introduces the foraging behavior of artificial fish swarm algorithm based on HS algorithm, it can further improve the capacity that algorithm jumps out of local optima, thus improving the quality of the optimization algorithm. Apply it to SVM parameter optimization, you can get a better SVM parameters, and work with small samples, nonlinear approximation ability of SVM, and the obtained result of the online order priority evaluation is completely the same as the evaluation result from expert. The comparative result shows that HHS-SVM model can more accurately describe the complex non-linear relationship between online order priority value and its affect factors, so the evaluation result for online order priority value is more accurate.

V. CONCLUSIONS

To the problem of online order priority evaluation in Supply Chain, propose a nonlinear online order priority evaluation model based on HHS-SVM. The model introduces the foraging behavior of artificial fish swarm algorithm based on HS algorithm to improve the algorithm optimization ability, and combined with the results of SVM applying to online orders priority evaluation problem to get the answer. The result shows that, the evaluation accuracy of HHS-SVM is obviously better than other online order priority evaluation method, well ensured the objectivity of online order priority evaluation results, and the evaluation results will help enterprises to enhance their competitiveness.

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REFERENCES

[1] Wu Chong, David Barnes, Duska Rosenberg, et al. An analytic network process-mixed integer multi-objective programming model for partner selection in agile supply chains. *Production Planning &Control*, 2009, 20 (3) pp. 254-275.

[2] Ren J, Yusuf Y Y, Burns N D. A decision-support framework for agile enterprise partnering. *International Journal of Advanced Manufacturing Technology*, 2009, 41 (1-2) pp. 180-192.
[3] Mahdav IM. Global-best harmony search. Applied Mathematics and Computation, 2008, 198(2) pp. 643-656.
[4] Bojarski, A. et al. Life cycle assessment coupled with process simulation under uncertainty for reduced environmental impact: application to phosphoric acid production. *Industrial & Engineering Chemistry Research*, 05 November 2008, vol. 47
[5] Cholette S., K. Venkat. The Energy and Carbon Intensity of Wine Distribution: A Study of Logistical Options for Delivering Wine to Consumers. *Journal of Cleaner Production*, (2009)17(16), 1401-1413.
[6] B. Sundarakani, R. Souza, M. ZGoh etc. Modeling carbon footprints across the supply chain. Int. *Production Economics,* 2010(128) pp. 43-50.
[7] Nhan N, Insoo K. An enhanced cooperative spectrum sensing scheme based on evidence theory and reliability source evaluation in cognitive radio context. *IEEE Communications Letters*, 2009, 13(7) pp. 492-494, 760.
[8] YANG S, NAGAMACH M, LEE S. Rule-based inference model for the Kansei engineer systems. *International Journal of Industrial Ergonomics*, 1999, 24(5) pp. 459-471.
[9] XU R, WUNSCH DC. Clustering. New York: Wiley-IEEE Press, 2008.
[10] KYUNGMEE C, CHANGRIM J. A systematic approach to the Kansei factors of tactile sense regarding the surface roughness. *Applied Ergonomics,* 2007, 38(1) pp. 53-63.
[11] GUHA S, MUNAGALA K. Exceeding expectations and clustering uncertain data: Proceedings of the twenty-eighth ACM SIGMOD-SIGACT-SIGART symposium on Principles of database systems, *Rhode Island, 2009. USA: ACM, 2009*, pp. 269-278.
[12] GRIMSAETH K. Kansei Engineering: Linking Emotions and Product Features. Norwegian: *Norwegian University of Science and Technology,* 2005.
[13] Yuexiang HUANG, Chun-Hsien CHEN, Li Pheng Khoo. Kansei clustering for emotional design using a combined design structure matrix. *International Journal of Industrial Ergonomics,* 2012, 42(5) pp. 416-427.
[14] STEWARD D V. Systems Analysis and Management: Structure, Strategy and Design. *New York: Petrocelli*, 1981.
[15] EPPINGER S D. Mode-l based Approaches to Man-aging Concurrent Engineering. *Journal of Engineering Design,* 1991, 2(4) pp. 283-290.
[16] SMITH R P, EPPINGER S D. A Predictive Model of Sequential Iteration in Engineering Design. *Management Science*, 1997, 43(8) pp. 1104-1120.