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A Safety Stock Forecasting Model of the Third-Party Logistics Based on Least Squares Support Vector Machine

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Abstract: The third-party logistics company that uses a centralized supply model to supply parts to automakers in a timely manner is an important part of the automotive supply chain. In order to improve customer service and control cost, the accurate forecasting of the third-party company safety stock becomes the core concern of enterprises. For the limited data samples, low linear correlation and high latitude in the third-party logistics inventory forecast, a safety stock forecasting model based on LS-SVM was proposed. An example analysis was performed on the historical data of a third-party automobile logistics center to verify the accuracy and sensitivity of the model.

1. Introduction

The automotive supply chain places high demands on related companies with its multiple participants, wide cross regions and multiple intermediate links. The third-party logistics integrates upstream suppliers and downstream manufacturers in the supply chain, making it easier to leverage the overall advantages[1][2][3][4]. When meeting the requirements for the centralized supply of parts and components it has gradually become an important part of the automotive supply chain and has effectively reduced the number of participants and optimized the intermediate links. As an important factor that affects the input cost of the third-party logistics and enterprise benefit, safety stock guarantees the supply and demand relationship timely between the manufacturers and the suppliers[5][6]. Therefore, it is of great importance to accurately forecast safety stock of the third-party logistics.

Safety stock refers to the amount of inventory that a third-party logistics stocks to ensure its operation, taking into account the lead time and production time of its parts suppliers, and various uncertain factors in the supply chain[7][8]. If the safety stock is too large, it will greatly increase the cost and the risk of the third-party logistics as well as the capital occupancy rate of the automotive supply chain. If the safety stock is too small, it will not only lower the third-party logistics service layer and the customer experience of the logistics services, but also ruin the continuity and reliability of the automotive supply chain. At present, there are mainly two ways to forecast safety stock. The first type adopts statistical methods. The safety stock is forecasted with the help of data analysis and the practitioners' experience. Many forecast errors may occur during the forecasting process and human interference may be unavoidable in some cases which hindered its popularization and application[9]. The second method uses a model to forecast the safety stock, which is more scientific and greatly increases the accuracy of the forecast. Neural network algorithms are often used in present safety stock forecasting models.

In order to solve the problems such as the limited number of samples, difficulties in obtaining high-dimensional data, low linear correlation of the data and difficulties in controlling the forecast accuracy during the actual forecast of the third party logistics inventory, this paper proposes a forecasting model based on the Least Squares Support Vector Machine (LS-SVM)[10]. As a typical kernel-based learning algorithm, support vector machine (SVM) has gained a wide range of applications since it was proposed[11][12][13]。 Its advantages are as follows: first, compared with the intelligent algorithms, such as neural networks, the LS-SVM method is more suitable for practices with small samples and low linear correlation. It solves the overfitting problem and local minimums problem in neural network algorithms and processes high-latitude data more quickly, which greatly reduces the number of samples required. Secondly, based on the optimization and selection of the original related parameters, it takes the manufacturer attributes and warehouse attributes as the objective parameters and improves the forecast accuracy while improving the comprehensiveness of the data type. Finally, in terms of the model functions, the present forecasting models can only forecast the safety stock data with no quantitative research function on the objective parameters of the safety stock. Therefore, the calculation of the parameter weights should be included in the model to guide the third-party logistics to optimize its safety stock and promote the healthy development of the automotive supply chain.

2. Literature review

Since safety stock formulation goes nonlinear in nature, the efforts to forecast safety stock in supply chain network have been made either in empirical or in rigorous way. Typical empirical method is to formulate safety stock level by a function of shipment volume. Empirical studies by Ballou [14] showed that average inventory level including safety stock can typically be expressed by a power function of throughput. Following this result, Shapiro [15]provided supply chain network optimization model with power function base safety stock model and converted it into MIP model with piecewise linear functions. Kenichi Funaki[16] present a strategic safety stock placement model in supply chain design for assembly-type product with due-date based demand, where demand data are based on dates when company has to ship to customers rather than order receiving dates. As a half-empirical and half-theoretical approach, Miranda and Garrido [17] incorporated safety stock model with constant replenishment time together with cycle stock model by EOQ modeling into network optimization problem.

Advanced machine learning algorithms bring new opportunities for safety stock forecasting in empirical. The prediction accuracy of safety stock increases based on the machine learning model. The existing safety stock prediction models often use neural network algorithm in the present literature. Neural network algorithms which include BP neural network algorithm, improved BP algorithm, GRNN neural network algorithm, chaotic neural network algorithm, etc. [18][19][20][21][22]. However, fewer Support Vector Machine algorithms are used in the forecast models. Although the neural network algorithm has strong self-adaptability and learning function, it is easily affected by the network structure and sample complexity. Through structural risk optimization, the SVM algorithm solves the problem of the local minimum point solution and the number of the hidden layers of the traditional neural networks. The principle of the LS-SVM is to determine the location of the straight line through "the minimum residual sum of square". In addition to its convenience in calculation, the estimator drawn by using such method also had excellent feature[10].

As known that most forecasting models need large amount of input parameters. However, the parameter descriptions of manufacturers and warehouse attributes are missing in the predicated data types[23][24]. Only the parameters of the supplier attributes and material attributes are selected. Manufacturer, as one of the main bodies of the automotive supply chain, has a great influence on the safety stock. At the same time, warehouse attributes whose various attributes directly affect the forecasting and setting of the safety stock are factors that cannot be ignored in the actual forecast of the safety stock. Therefore, based on the optimization and selection of the original related parameters, the manufacturer attributes and the warehouse attributes are also selected as input data to improve the comprehensiveness of the data type. In terms of the scope of application, the present neural network model is more suitable for those large third-party logistics centers with large historical data. For that third-party logistics in the establishment or development period, it has more restrictions. However, the forecasting model based on the LS-SVM has the small samples learning ability, strong robustness and generalization therefore making it suitable for the safety stock forecast of the third-party logistics in the establishment or development period. At the same time, applying SVM to the forecast of safety stock has stronger feasibility[25].

3. The establishment of a safety stock forecasting model of third-party logistics in manufacturing industry

The specific steps for establishing the safety stock forecasting model of third-party logistics are shown in Fig. 1.

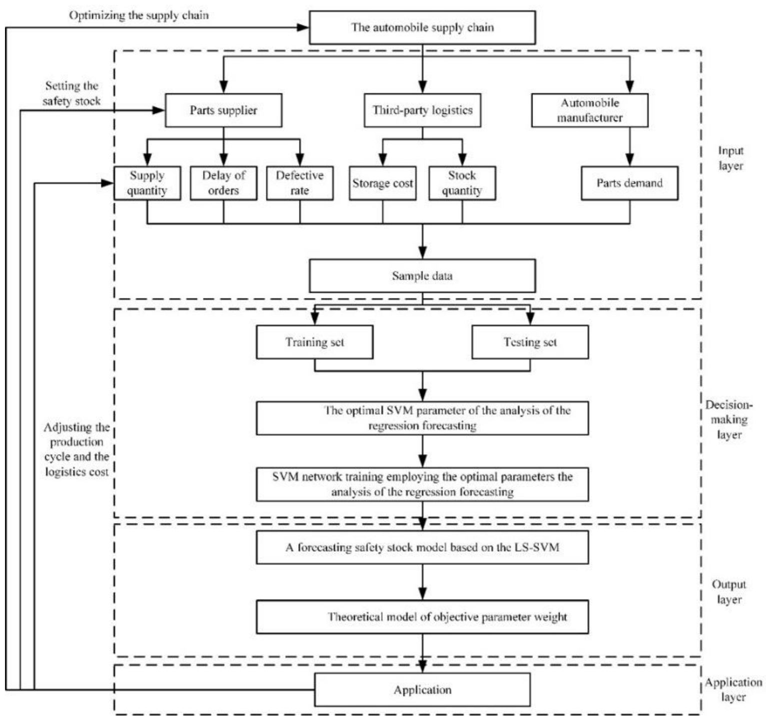

Figure 1: Safety stock forecasting model

Firstly, six factors which affect the safety stock are selected as objective input parameters as has been described by the previous literature on the automobile supply chain. Then the safety stock forecasting model is obtained by using the LS-SVM regression forecasting model for training and forecast. At the same time, based on the safety stock forecasting model, the six objective parameters selected are studied, and an objective theoretical parameter weight analysis model is established. The model has a closed-loop structure which is composed of the input layer, decision-making layer, output layer and application layer, providing theoretical rationale for the optimization of the supply chain, the setting of the safety stock, the adjusting of the production cycle and the logistics cost. This model overcomes the shortcomings of the slow convergence problem, the local minimum problem and the random network structure selection of the neural network stock forecast algorithm. Compared with other SVM-based forecasting models, the forecast accuracy is higher as the parameters of the input layer are more comprehensive because the third-party logistics' attributes are incorporated. Meanwhile, the weight of input parameters of the safety stock gained from the forecasting model has practical significance to the reduction of the actual production efficiency and logistics cost.

N samples of the given training data can be presented as $\{x_k, y_k\}_{k=1}^{N}$, where the input data $x_k \in R^m$, the output data $y_k \in R$. And the optimization of SVM can be presented as

$$s.t. y_k = w^T\varphi(x_k) + b + e_k \qquad k = 1,2,3\ldots\ldots n \tag{1}$$

As to the cases of non-linearity, the SVM can be processed by a kernel function whose fitting model is

$$f(x) = \sum_{k=1}^{N} \alpha k\, K(xk, x) + b \tag{2}$$

Where αk stands for the support vector, and $K(x_i, x_j)$ a kernel function, which are generally in the form of Gaussian kernel

$$\min_{w,s} J(w,s) = \frac{1}{2}w^T w + \frac{1}{2}y\sum_{k=1}^{N} e_k^2 \tag{3}$$

$$K(x_i, x_j) = exp(-\frac{\|x_j - x_i\|^2}{2\sigma^2}) \tag{4}$$

(1) The setting of input/output layer

The safety stock forecasting model established in this paper predicts the safety stock and calculates the weight of each objective parameter through influencing the objective parameters of the safety stock. Therefore, it is determined that each objective parameter belongs to the input layer, and the weight of the safety stock and the objective parameter belong to the output layer.

(2) The selection of objective parameters

For the insufficient and limited input parameters in the present safety stock forecasting model, this model considers the selection of objective parameters from the perspective of the supply chain, which improves the accuracy of the model and reduces the accidental error. The automobile supply chain mainly consists of parts suppliers, third-party logistics and automobile manufacturers. The input parameters of the current model lack the description of the parameters of the third-party logistics, and there is large error between the forecasted safety stock data and the actual storage of the third-party logistics. Thus, with the perspective of the automobile supply chain the characteristic parameters of the third-party logistics is added into the input layer, which optimizes the main parameters, and 6 dimensions (i.e. the stock quantity, supply quantity, order delay, defective rate, storage cost and stock demand, which have the greatest effect on the safety stock) are selected as the input layer parameters. This will not only minimize the number of the parameters, but also make the data more comprehensive. Accordingly, the weight of each parameter can be calculated quantitatively using the theoretical parameter weight analysis model.

(3) Selection of kernel function

Selecting the kernel function is a key step in establishing a model, and the properties of the kernel function are directly related to the performance of the model. Commonly used kernel functions include linear kernel function, polynomial kernel function and radial basis function, etc. [40] In our model, the Gaussian radial basis function which has relatively small average relative error is selected as the kernel function of the LS-SVM forecasting model, namely

$$K(x,x) = \exp\left(-\frac{\|x-x\|^2}{2\sigma^2}\right) \tag{5}$$

(4) Optimization of forecasting model parameters

By analyzing the principle of SVM nonlinear regression forecasting, it can be seen that the penalty factor C and the kernel function parameter σ have greater impact on the accuracy of the model. Therefore, Grid-Search_PSO is used to optimize the SVM parameters with two steps. First, the Grid-Search method is used to search roughly to determine the optimal parameter range. Then, the PSO is applied to search precisely for secondary optimization. The Grid-Search method is used to divide the space of the parameters to be searched into a grid and then each point in the grid is traversed to find the optimal parameters. When searching for the optimal parameters, the current optimal position of each point is compared with the group optimal position, and is changed dynamically. In this way, the parameter is optimized iteratively with a faster convergence speed and the global optimal solution is found.

Only the support vector can be used by the decision function in the fitting model. The sensitivity of the output of the SVM to the mth feature input can be obtained by calculating the approximation of partial derivatives

$$\frac{\partial f(x_i)}{\partial x_{im}} = \frac{\partial(\sum_{i=1}^{N}[(a_i-a_i*)K(x_i,x_i)+b])}{\partial x_{im}} = \sum_{i=1}^{N}(a_i - a_i*)\frac{\partial K(x_i,x_j)}{\partial x_{im}} \tag{6}$$

Where M is the dimension of the input vector and N is the number of support vectors obtained from training. The eigenvector weight calculation formula is

$$C(m) = \frac{\sum_{i=1}^{T}\left|-2g\sum_{i=1}^{N}(\alpha_i-\alpha_i*)(x_{im}-x_{jm})\exp[-g\sum_{i=1}^{M}(x_{il}-x_{il})^2]\right|}{\sum_{m=1}^{M}\sum_{i=1}^{T}\left|-2g\sum_{i=1}^{N}(\alpha_i-\alpha_i*)(x_{im}-x_{jm})\exp[-g\sum_{i=1}^{M}(x_{il}-x_{il})^2]\right|} \tag{7}$$

Where T is the number of training samples.

The parameter selection is mainly used to find the optimal parameter c and g of the regression, which is implemented by SVMcgForRegress.m. Its function interface is:

[mse,bestc,bestg]=SVMcgForRegress(train_label,train,cmin,cmax,gmin,gmax,v,cstep,gstep,msestep) (8)

(5) Model testing, training and forecasting

In order to improve the forecasting accuracy, the sample data is divided into a training set and a test set after being filtered and normalized. The training set is larger and is used to build a specific model. The testing set is smaller and is used to trim to check whether the model meets the requirements. When the model meets the requirements, it will be output.

(6) Weights analysis of the objective evaluation parameters

The relationship between the objective evaluation parameters and the forecasted safety stock data is complicated and has greater uncertainty and high nonlinearity, which can't be described with accurate mathematical models. The influence weights of the input variables on output variables is studied and a theoretical parameter weight analysis model is established based on the the LS-SVM safety stock forecasting model.

4. Example verification

In order to verify the performance of LS-SVM safety stock forecasting model we established, some historical data of logistics company A is selected as samples to forecast the safety stock.

(1) Collection of forecasting parameters

50-week historical data of the related parameters of a part of the logistics company A was selected as the forecast sample, as is shown in Table 1.

Table 1: Raw data of the safety stock forecasting of logistics enterprise A

Time (Week)	Supply volume (Torr)	Order delay (Day)	Defective rate (%)	Storage cost (Torr/Yuan)	Inventory demand (Torr)	Inventory of last week (Torr)
1	630	0	4	65	520	730
2	520	1	3	70	470	640
3	500	3	5	88	460	580
4	640	0	2	90	580	820
5	620	2	3	97	570	880
6	580	1	4	89	530	730
……						
45	510	2	5	78	450	690
46	490	3	3	74	440	660
47	620	1	4	83	580	770
48	530	0	5	95	490	710
49	550	0	2	90	500	700
50	600	1	4	92	560	820

(2) Selecting independent and dependent variables based on the model

The inventory, supply, order delay, defective rate, storage cost, and inventory demand of the last week were taken as the independent variables of this week's safety stock and this week's safety stock was taken as the dependent variable.

(3) Input data preprocessing

The independent variable and the dependent variable sets were normalized. The normalized original data are within the range of [1,2], that is $\in[1,2]$, i=1,2,3…n.

The result of the normalized weekly inventory of the original warehouse is shown in Fig. 2.

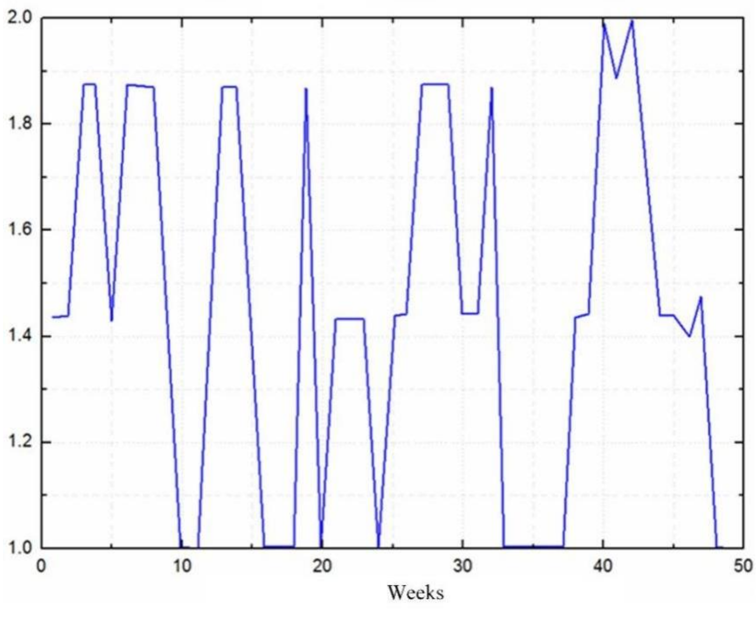

Figure 2: Image of the normalized raw data

(4) Model parameter optimization

After the parameter optimization with the Grid-Search method and the particle swarm optimization algorithm, the optimal SVM is eventually calculated, where the parameter penalty factor C = 8, kernel function parameter g = 2.8284, (g = -1 / 2σ2). Therefore, the kernel function K (xgxi) = exp (-2.8284 | x-xi | 2).

(5) Training regression forecasting

SVM is trained using the optimal parameters c and g obtained in step (4). During the modeling, the 50 sets of data that have undergone regression processing are used as input, and the safety stock is used as the output. The first 45 sets of data are taken as the training sample set, and the 46-50 sets of data are used as forecasting samples.

The 50 sets of sample data were mapped according to the obtained kernel function and linearly fitted in the high-dimensional feature space. Fig. 3 shows the comparison between the raw data and the regression forecasting data. It can be seen from the figure that there is a high degree of agreement between the regression forecasting value and the measured value. By calculation, the average absolute relative error is 0.96%, the mean square error (MSE) 0.00045342 and the correlation coefficient (R) is 99.6734%, which indicate that the learning and training is effective.

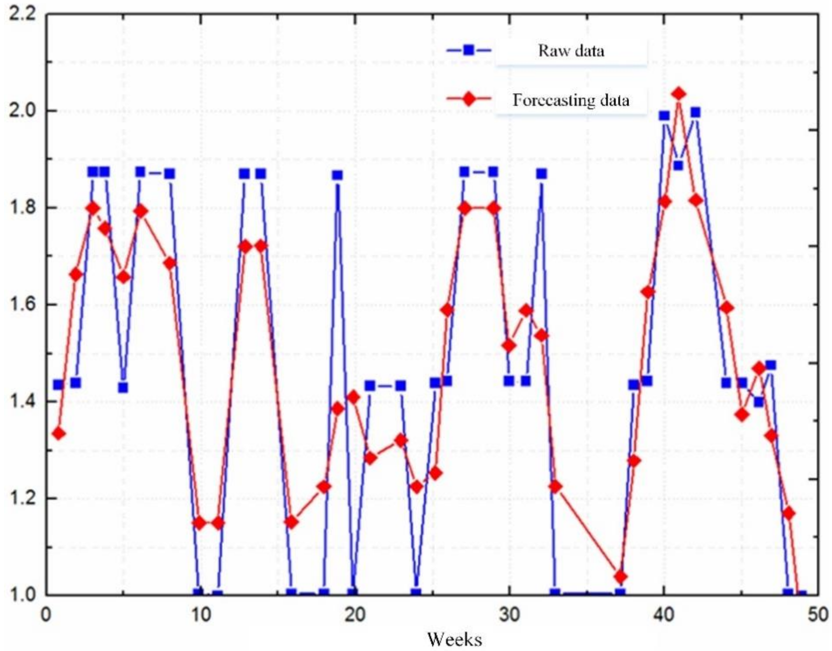

Figure 3: Comparison of the raw data and the regression forecasting data

(6) Output forecasting model

The variables obtained from the model show that the formula of the safety stock forecasting model is

$$y = \sum_{i=1}^{48} w_i \, exp(-2.8284||x_i - x||^2) - 1.4921 \quad (9)$$

Where, w_i is the coefficient of the support vector in the decision function. x_i is the support vector. And x is the sample vector with forecasting.

(7) Parameter weight analysis of the input layer

The input layer parameter weights of the safety stock forecasting model are

$$C(m) = \frac{\sum_{t=1}^{50}\left|-5.6568\sum_{i=1}^{48}(ai-ai*)(xim-xjm)\,exp[-2.8284\sum_{l=1}^{6}(xil-xjl)^2]\right|}{\sum_{m=1}^{6}\sum_{t=1}^{50}\left|-5.6568\sum_{i=1}^{48}(ai-ai*)(xim-xjm)\,exp[-2.8284\sum_{l=1}^{6}(xil-xjl)^2]\right|} \quad (10)$$

According to the input layer parameter weight calculation formula of the safety stock forcating model, Matlab software is used to calculate the relative contribution of each parameter to the safety stock forecasting result, as is shown in Table 2. It can be seen from Table 2 that the parameter that has the greatest impact on the safety forecasting of the third-party logistics is the demand for parts.

Table 2: Influence weight of the safety stock forecasting model input parameter

Input parameters	Supply quantity	Order delay	Defective rate	Storage cost	Inventory quantity	Parts demand
Weighting factor	0.1872	0.1323	0.1232	0.1148	0.2084	0.2341

5. Comparative analysis

The forecasted safety stock of the 15 weeks data of a certain part in logistics company A using the LS-SVM forecasting model and the actual safety stock data are compared, and the results are shown in Fig. 4. The forecasted result of the model is in good agreement with the actual value, which indicates that the forecasting model has higher accuracy and applicable ability. Furthermore, it proves that the SVM model has good learning ability and generalization ability for small samples.

The LS-SVM safety stock forecasting model not only solves the problem of the limited third-party logistics historical data samples, but also the supplier attributes, material attributes, manufacturer attributes, and warehouse attributes are selected as the objective parameters of the input layer based on the consideration of the integrity and continuity of the supply chain. All this improves the forecasting accuracy and efficiency. On the basis of the LS-SVM safety stock forecasting model, an objective theoretical evaluation parameter weight analysis stock safety model is further established based on the SVM, and the process of solving the safety stock objective evaluation parameter weight factor is completed. The weight analysis model can accurately calculate the weight of every parameter, which provides a theoretical basis for the accurate setting and the improvement of the safety stock.

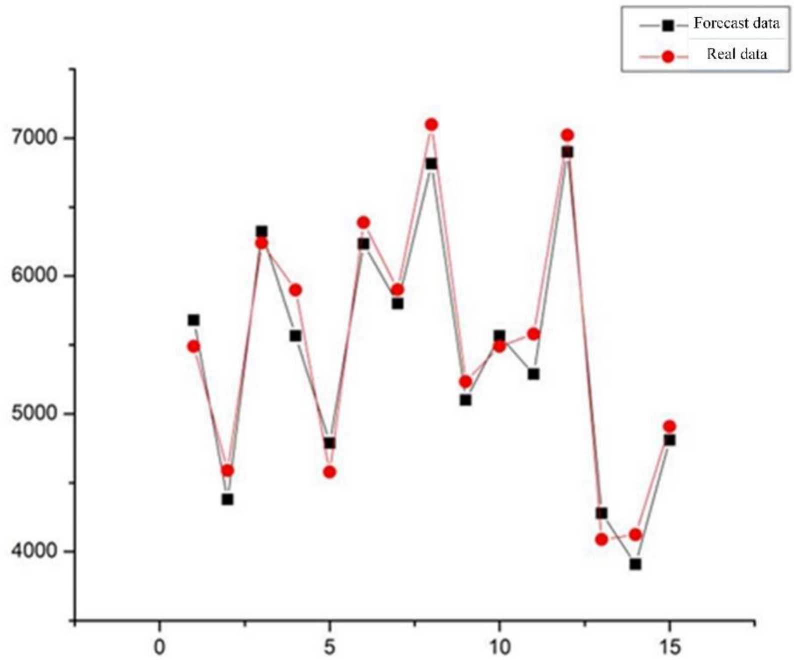

Figure 4: Safety stock forecast results comparison

6. Conclusions and Perspectives

6.1. Conclusions

This paper presents a novel model based on the LS-SVM as means of forecasting of safety stock in the supply chain. The method constructs a completed process from the index selected to the structured method. This paper first selects six factors that affect the safety stock from the perspective of the automotive supply chain, and then combines these six factors to obtain new input parameters. The LS-SVM regression forecasting model is used for training and forecasting. This algorithm overcomes the shortcomings of the slow convergence rate of the safety stock forecast algorithm that is based on neural network, the local minimum problem, and the randomness of network structure selection. Compared with other forecasting models based on SVM, the forecasting accuracy is higher because the input layer parameters are more comprehensive with the third-party logistics' own description attributes.

In conclusion, this paper has made contribution to forecast of the third-party logistics safety stock of the supply chain including the large automobile manufacturer. It has significant meaning for inventory planning and control. The accurate safety stock forecasting with our method can aid manufacturer to produce smoothly.

6.2. Limitations and future studies

There are some limitations in this study, which provide directions for future study.

One of the limitations is that the safety stock forecasting model in this study is small forecasting data and the high correlation, the forecasting of non-linear data still needs to be improved.

Furthermore, the model of this study is based on the data collected from manufacturing firm. As cultures and business processes may be different from firm to firm, the model of this study may be limited to the selected firm. Findings of this study may need to be confirmed and reinforced by longitudinal studies during longer term periods.

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Declare 1

The authors declare that there is no conflict of interest regarding the publication of this paper.

Declare 2

The data used to support the findings of this study have not been made available because that the firm`s whole raw data are only used to solve problem and publish paper, not used to share with other Peer Enterprises

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