Hindawi
Security and Communication Networks
Volume 2023, Article ID 9798716, 1 page
https://doi.org/10.1155/2023/9798716

Retraction

Retracted: Enterprise Supply Chain Risk Assessment Based on the Support Vector Machine Algorithm and Fuzzy Model

Security and Communication Networks

Received 10 October 2023; Accepted 10 October 2023; Published 11 October 2023

This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope
(2) Discrepancies in the description of the research reported
(3) Discrepancies between the availability of data and the research described
(4) Inappropriate citations
(5) Incoherent, meaningless and/or irrelevant content included in the article
(6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

[1] X. Zhang, "Enterprise Supply Chain Risk Assessment Based on the Support Vector Machine Algorithm and Fuzzy Model," *Security and Communication Networks*, vol. 2022, Article ID 3692628, 7 pages, 2022.

Hindawi
Security and Communication Networks
Volume 2022, Article ID 3692628, 7 pages
https://doi.org/10.1155/2022/3692628

Research Article

Enterprise Supply Chain Risk Assessment Based on the Support Vector Machine Algorithm and Fuzzy Model

Xiaoni Zhang

Xi'an Peihua University, Xi'an, Shaanxi 710125, China

Correspondence should be addressed to Xiaoni Zhang; zhangxiaoni@peihua.edu.cn

Received 5 May 2022; Revised 22 June 2022; Accepted 4 July 2022; Published 21 July 2022

Academic Editor: Mukesh Soni

In systems with uncertain information, ambiguity must be taken into account. In this paper, fuzzy set theory concepts are incorporated into support vector machines (SVM). This ensemble preserves the benefits of SVM regression models and fuzzy regression models, where SVM learning theory describes the properties of learning machines that enable them to generalize well, and fuzzy set theory offers an efficient method for capturing the approximate, imprecise properties of the real world. In accordance with the phase space reconstruction theory of dynamical systems, a fuzzy model for enterprise supply chain risk assessment is proposed using the robust nonlinear mapping capability of support vector machines and the characteristic of fuzzy logic that makes it easy to combine prior system knowledge into fuzzy rules. The results demonstrate that the prediction model can not only automatically acquire knowledge from learning data to generate fuzzy rules but can also extract support vectors that can represent the inherent laws of enterprise supply chain risks, drastically reduce the number of support vectors, and accurately predict. Future risk can be accurately predicted. This conclusion suggests that the support vector machine based on a fuzzy model is an effective method for analyzing enterprise supply chain risk.

1. Introduction

As global production has become more decentralized in recent years, production cooperation between cross-regional and even global enterprises has become closer, which directly promotes the popularization and maturity of the global production chain, as well as the rational allocation of scarce resources. The global production chain allows businesses from all over the world, including many small- and medium-sized enterprises to participate in industrialization and pursue their own objectives. The global supply chain has become the defining characteristic of the world's manufacturing and service sectors.

In the two decades between 1990 and 2010, natural and man-made disasters wreaked havoc on the global supply networks of corporations. Today's supply chain is more vulnerable to external shocks as a result of globalization, and even seemingly isolated external shocks will have an amplified effect in a globally integrated context [1]. This is the fundamental reason [2] for the increase in risk: these supply chains contain more probable sources of disruption than production methods that were previously restricted to a single region or country. In the event of a disruption, global supply chains will be slower to react due to their lengthy lead times and high levels of uncertainty, resulting in slower decision-making and response times. Locally resolved friction in one section of a supply chain will be promptly communicated to the other sections of the supply chain, and vice versa. As a result of today's global value chain production style, many organizations are extending their supply chains to external partners in various countries. This is done to reduce costs and product development cycles and to enter new markets. In order to reduce safety stocks and operating expenses, this lean manufacturing strategy encourages companies to focus on a single link in the production chain. Therefore, when external shocks occur, the friction between upstream and downstream supply and demand will have a substantial impact on the performance of the majority of organizations' shock.

In response to the outbreak of novel coronavirus pneumonia in China in the end of 2019, all provinces adopted a first-level response policy, and all localities joined the fight against the epidemic by delaying the resumption of work and controlling the flow of people in order to effectively control the outbreak. The effects of the pandemic in China, the world's factory, have also affected the global supply chain arrangements for a variety of goods. Due to the widespread production halt, many small and medium-sized businesses in the United States are at risk of going out of business. To survive in this environment, the first and most essential requirement for a business is to rationally design the operation mode of the organization within the context of global supply in order to strike a balance between risks and benefits. Currently, domestic expert research focuses primarily on the macroeconomic environment, whereas research on managing supply chain risk from the firm's perspective is scarce [3–6]. Consequently, research into company supply chain risk management solutions under the influence of the epidemic has substantial practical and academic implications.

When modeling systems for which knowledge is inherently insecure, it is necessary to account for the unclear structure of the system under investigation. As a fuzzy function, the structure is represented by fuzzy sets, which also serve as the parameters of the function [7–9]. It has been proposed [10, 11] to conduct a fuzzy regression analysis using the fuzzy function as the fuzzy structural model of the fuzzy system.

When applied to pattern classification and function estimation problems using clean data, the SVM developed by Vapnik and colleagues [12, 13] at the Labs has proven to be highly effective. It is possible to achieve high generalization performance by keeping this limit as low as possible. Burges [14] has provided a comprehensive explanation of support vector machines (SVMs). In addition, outstanding performance has been achieved in applications such as regression and time series forecasting [15]. Some researchers [16, 17] were the first to propose fuzzy set theory as a solution to the SVM classification problem. In a variety of contexts, other researchers [18] have adapted SVM theory to fuzzy rule-based modeling.

Using fuzzy set theory concepts, we are able to incorporate them into the SVM regression model used in this study. Set the parameters to be identified in the SVM regression model, such as the weight vector and bias term components, as fuzzy numbers to facilitate recognition. In the training samples, the predicted output is also a fuzzy number, further complicating the situation. The integration of fuzzy set theory into SVM regression preserves the benefits of both SVM regression and fuzzy regression, where VC theory characterizes the characteristics of learning machines that enable them to generalize well to new data. Lastly, the fuzzy model of SVM regression is quite advantageous for determining the fuzzy structure in enterprise supply chain risk assessment, which is crucial.

2. Related Work

2.1. Supply Chain Risk Assessment. Risk is characterized differently in the SCRM literature than it is in the general public. The boundary between risk and uncertainty in supply chain activities, in particular, is not clearly delineated. While risk is sometimes viewed as supply chain disruption caused by unreliable and unpredictable resources, uncertainty can be interpreted as the risk of matching supply and demand during the course of a supply chain transaction. When it comes to risk, we feel that two aspects are vital to consider. They are the outcome of risk impact and the anticipation of risk source, which are related to each other. We also agree that the issue of risk is related to the negative effects of impacts, which is supported by the majority of the literature [19–21]. The second component of risk expectations is the most difficult to categorize and quantify. Should risk events [22] or unexpected events [23] be expected in a business environment? In addition, expectations can be expressed in terms of probability distributions. And how do you do it? These problems have been argued for centuries, which is why the term risk is so broad and ambiguous today.

Managing risk in a modern context is becoming increasingly difficult [19], mostly as a result of supply and demand instability, global outsourcing, and short product life cycles, among other factors. When applied to an event or action, risk can be defined as the possibility of undesirable effects as a result of the event or activity. A variety of issues, including financial instability, immediate outsourcing, corporate mergers and acquisitions, new technology, electronic commerce, and shorter time-to-market, among others, have an impact on the current global business environment. As a result, firms are being forced to adapt a new method of doing business [24]. However, because of operational and external interruptions in today's leaner, more timely worldwide supply chains are more prone than ever before to failure. When it comes to supply chain vulnerability, it is described as exposure to significant disruptions induced by risks occurring within the supply chain and risks occurring outside the supply chain [19].

SC risk is the exposure to events that disrupt the operation of supply chain networks, which can have a negative impact on the efficiency of supply chain network management. Risk management is gaining significance in the overall design of SCM systems. There are numerous classifications of supply chain risk that can be discovered in the literature. Risk can be described as disruptive, vulnerable, uncertain, catastrophic, dangerous, and perilous, among other terms. As a result, the risk may range from being completely unknown to being a well-known imminent and dangerous threat.

Some scholars define a condition in a supply chain in which decision makers lack sufficient information about the network and environment of the supply chain and, as a result, are unable to predict the impact of an event on supply chain behavior [25]. Despite the fact that risk and uncertainty are frequently used interchangeably in SC literature [26], uncertainty is not measured since it lacks total assurance and has more than one possible outcome. Risk, on the other hand, is quantifiable because it is the result of uncertainty, some of which may result in financial losses or other unfavorable results [27]. Supply chain security, according to the reference [28], is a subcomponent of the overall risk management strategy inside a business.

Many organizations have an excellent understanding of the downstream path to the market, but a deficient comprehension of the upstream supply chain. Only with a comprehensive understanding of the upstream and downstream firms in the supply chain can we detect changes in the supply chain in real time and take effective steps to mitigate and eliminate supply chain risks. Streamlining the supply chain, increasing the process's reliability on a consistent basis, and reducing unpredictability and complexity are all ways to enhance supply chain performance. In numerous ways, the unpredictability and complexity of markets and environments increase the risk associated with the supply chain. Variability results in a fluctuating process that cannot be predicted. Numerous factors impact the complexity of a supply chain, including the number of variations and products produced, the number of components, the number of suppliers and consumers, and the method of distribution. Supply chain risk management must be properly implemented in order to determine what is essential. If not, the supply chain will suffer a substantial setback.

All businesses are required to identify essential pathways that must be maintained and monitored to ensure supply chain continuity. Step one in a methodology for identifying crucial elements of supply chain risk management is to examine each node and each connection and then to ask three questions about them. What possibly could go wrong? What will occur if you make an error? What, in your opinion, are the most significant causes of failure? In the second stage, each potential failure consequence is evaluated based on the following criteria.

In addition, the analytic hierarchy approach can be utilized to compute and define the risk type and risk weight, as well as to determine the critical path of risk management. In order to manage the critical path, it is essential to have contingency plans to deal with unforeseen circumstances, and in extreme cases, the supply chain can be rebuilt. Take a causal analysis approach to eliminating or avoiding the cause, seek to differentiate the symptoms from the underlying cause, and eliminate the risk of developing the condition. Increasing the flexibility and agility of the supply chain, promoting the commonality of components, and standardizing production platforms in the manufacturing process may all contribute to the reduction of complexity, the continuation of downstream node logistics activities, and the avoidance of risks. Essential to the supply chain are cohesive teams upstream and downstream with the ability to complete comprehensive environmental analyses, successfully execute the supply chain's risk management process, and prepare risk memorandums highlighting weak points. Even though many supply chains are opaque, effective integration, strong cooperation, and increased visibility are necessary both within and outside the organization. Boost the speed and acceleration of the supply chain by streamlining operations, reducing delivery lead times, and eliminating extra time that is not productive. There are documented instances of successful collaboration with suppliers and customers to reduce supply chain risk in a number of specific industries. Through collaborative work with suppliers and consumers, it can not only ensure that upstream and downstream products meet high quality requirements but it can also enable suppliers to monitor their supply chain risks at any time and reduce supply chain risks. It is possible to create a snowball effect and achieve the risk management objective in this way.

2.2. Overview of Model Algorithms. Developed by Tipping in 2001 [29], the relevance vector machine (RVM) is a supervised machine learning method based on Bayesian statistical learning theory that may be used to handle classification and prediction issues. Following the introduction of the correlation vector machine theory, it immediately became a research hotspot of the new statistical learning theory, achieving rapid progress and widespread application, and eventually becoming a separate study direction in machine learning algorithms. The RVM technique, when compared to the SVM [13], can produce probabilistic results and has superior generalization ability, higher sparsity, more flexibility in kernel function selection, and simpler parameter tuning, among other advantages. With automatic correlation, the correlation vector machine is based on the sparse Bayesian framework, employing the conditional distribution in mathematical statistics as well as the estimation concept of maximum likelihood. The SVM is used to limit the model, but decision theory (automatic relevance determination, ARD) is utilized to generate a more sparse model than the SVM. Correlation vector machines, in contrast to the SVM, do not require that the kernel function be positive semidefinite in order to produce a probabilistic output. Instead, they can produce a probabilistic output if the kernel function is not a positive semidefinite. In 2003, researchers in the literature [30] developed a fast sequential sparse Bayesian learning algorithm, which considerably increased the training pace of the model during training. Using a combination of two-class classifiers, Thayananthan achieves the creation of multiclass classifiers, which are then utilized to solve the training problems of multivariate output regression and multiclass classification, as well as to generalize the model [31]. The fuzzy support vector machine (FSVM) algorithm reflects the relevance of distinct samples by assigning appropriate fuzzy membership values to different samples in a given set of conditions. The methodology, on the other hand, does not explicitly specify the mechanism by which the fuzzy membership value is calculated, and the factors that influence the results of the FSVM algorithm are not optimally optimized. Some researchers have investigated a method that could increase the accuracy of SVM predictions. The fuzzy c-means clustering (FCM) approach is used to optimize the model by employing the newly discovered cluster centers as additional support vectors, which is implemented in the set. However, the FCM method itself has flaws, and the number of clusters chosen will have a significant impact on the overall effect of clustering to a significant degree.

Modern science and technology is advancing at a breakneck pace, and the problems that people face are becoming more complex and changeable. This is primarily reflected in the scarcity of accurate mathematical models of the system, a high-dimensional decision space, distributed sensors and driving devices, and high noise levels, among other things. These sophisticated systems frequently outstrip the capabilities of standard control technology and information processing technology. Nonetheless, competent operators and experts are capable of handling and controlling these complicated objects adequately.

On the basis of traditional information processing and control theory, algorithms served as the basis for the development of a new processing technology that combines heuristic acquisition processing and utilization with intelligent information processing technology and intelligent control. Intelligent information processing is defined as information processing that integrates higher-level knowledge with lower-level processing to produce a more precise result than conventional information processing. He anticipates that it will be able to address ill-conditioned problems with insufficient information, issues with high computing complexity and real-time requirements, and nonlinear problems that are difficult to model with conventional mathematics. The digitization of expertise and knowledge is an example of an employed method. Rule reasoning is transformed into neural network mapping processing and fuzzy neural network technology, which directly and efficiently extract empirical rules from data samples. Only fuzzy system theory and the problem of fuzzy identification will be covered in depth in this section. Since its inception by Yager and Zadeh in the late 1960s, fuzzy theory has been utilized in a variety of fields for over four decades. It has also created new opportunities in the field of control. The expansion of fuzzy mathematics and artificial intelligence technology has resulted in a constant improvement of this fuzzy control theory, but the acquisition of fuzzy rules is one of the most difficult problems to solve. In a sense, the development of fuzzy control theory is centered on the acquisition of fuzzy control rules, which serve as its fundamental building blocks. Four methods of acquiring rules have been described in Ref. [32]. Through the process of fuzzy identification, it is possible to determine the structure and parameters of the fuzzy model by inputting and outputting measurement data. In addition to nonlinear dynamical system modeling, rule-based learning control, and pattern recognition, fuzzy models have been shown to play a significant role.

3. Research Design

3.1. Kernel Fuzzy C-Means Clustering Algorithm (KFCM). Using the KFCM algorithm, each data point is classified according to the degree to which it belongs to a specific class through membership, effectively separating the data point category. Assume that the input samples in the feature space have the following definition:

$$
\begin{aligned}
X = \{x_1, \ldots, x_i, \ldots x_l\}, x_i \in R^u, \\
x_i \in R^u.
\end{aligned} \tag{1}
$$

For the purpose of enlarging the clustering area, the Gaussian kernel function is utilized to map X to the feature space. The Gaussian kernel function is represented by the symbol

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

where σ is the bandwidth of the core.

When using the KFCM algorithm, the objective function expression is as follows:

$$J_m(X, U, V) = \sum_{j=1}^{n}\sum_{i=1}^{c}\mu_{ji}^{m} d^2\left(x_i, v_j\right). \tag{3}$$

The distance between x_i and v_j is represented by the letter $d^2(x_i, v_j) = k(x_i, x_i) - 2k(x_i, v_j) + k(v_j, v_j)$. v_j is the cluster center for the j-th time. The fuzzy index is represented by the number m $(0 \leq m \leq 1)$. The membership degree of the i-th sample belonging to the j-th class is represented by the symbol μ_{ji}.

In accordance with the following constraints

$$
\begin{aligned}
\mu_{ji} \in (0,1) i = 1, 2, \ldots n, j = 1, 2, \ldots k \\
\sum_{j=1}^{k}\mu_{ji} = 1, j = 1, 2, \ldots k.
\end{aligned} \tag{4}
$$

To solve the J_m problem, with formula (4) as the constraint condition, the Lagrange technique is employed to solve it, and the membership degree μ_{ji} and the expression of the cluster center v are computed.

$$\mu_{ji} = \frac{\sqrt[m-1]{1/d^2\left(x_i, v_j\right)}}{\sqrt[m-1]{\sum_{j=1}^{k} 1/d^2\left(x_i, v_j\right)}}, 1 \leq i \leq n, 1 \leq j \leq k, \tag{5}$$

$$v_i = \frac{\sum_{j=1}^{n}\mu_{ji}\left(1 - d^2\left(x_i, v_j\right)x_j\right)}{\sum_{j=1}^{n}\mu_{ji}\left(1 - d^2\left(x_i, v_j\right)\right)}, 1 \leq i \leq c. \tag{6}$$

The following is a full description of the KFCM computation procedure.

Step 1: initialize the number of clusters c, where c equals the optimal number of clusters k calculated by the interval statistics algorithm, the range of the fuzzy parameter m is 0 m1, and the termination parameter ξ is determined.

Step 2: initialize the number of clusters c, where c equals the optimal number of clusters k calculated by the interval statistics algorithm, and the range of the fuzzy parameter m is $0 \leq m \leq 1$. The fuzzy membership degree μ_{ji} is calculated in step 2 according to formula (5).

Step 3: make necessary updates to the cluster center matrix V in accordance with formula (6).

Step 4: to get the desired result, repeat the optimization process of steps 2 and 3 until the specified termination condition $\max\left\{x_{j,i}|\mu_{ji} - \mu^{\text{new}}{}_{ji}|\right\} < \xi$ has been met. Following the conclusion, the number of cluster centers c and the fuzzy membership degree μ_{ji} are obtained.

3.2. Fuzzy Support Vector Machine Prediction Model (FSVM). In the complex nonlinear sample prediction process, the FSVM algorithm is capable of effectively overcoming the overfitting problem of the SVM algorithm. The fuzzy membership function is used by the FSVM method to fuzzify the input samples, and different membership values are assigned to samples with varying degrees of relevance by the algorithm. Assuming that the membership value of each sample is μ_i, the fuzzy input sample is denoted by the letter $S = \{(x_1, y_1, \mu_1), (x_2, y_2, \mu_2), \ldots, (x_i, y_i, \mu_i)\}$, where $x_i \in R^n$, $y_i \in R, \varepsilon \leq \mu_i \leq 1$ and $(i = 1, 2, \ldots, n)$. ε is a tiny enough positive number to be meaningful. The importance of x_i is represented by the user interface μ_i in the sample. The following programming challenge is derived from the FSVM optimal hyperplane issue.

$$J_{\min} = \frac{1}{2}\|\omega\|^2 + C\sum_{i=1}^{l}\mu_i\left(\xi_i + \xi_i^*\right). \tag{7}$$

This programming problem has a constraint function that is as follows:

$$\begin{aligned} &(\omega \cdot x_i + b) - y_i \leq \varepsilon + \xi_i \\ &y_i - (\omega \cdot x_i + b) \leq \varepsilon + \xi_i^* \\ &\xi_i^* \geq 0, i = 1, 2, \ldots, l, \end{aligned} \tag{8}$$

where ω is the vector dividing the hyperplane, C denotes the empirical risk coefficient, ξ_i and ξ_i^* denote slack variables, and b denotes a fixed value. With a smaller membership value μ_i and matching sample point x_i, the effect of the sample point x_i's location on the objective function of the preceding planning issue becomes reduced. Construct the Lagrangian function in order to resolve this planning challenge.

$$\begin{aligned} L = J_{\min} &- \sum_{i=1}^{l}\alpha_i\left(y_i - (\omega \cdot x_i + b) + \varepsilon + \xi_i\right) \\ &- \sum_{i=1}^{l}\alpha_i\left(\omega \cdot x_i + b\right)) - \sum_{i=1}^{l}\left(\eta_i\xi_i + \eta_i^*\xi_i^*\right), \end{aligned} \tag{9}$$

where $\alpha_i, \alpha_i^*, \eta_i, \eta_i^*$ denote the Lagrange coefficient.

The difference between the above planning problem and the SVM planning problem is that the restrictions have been changed, and the membership degree μ_i has been included as a weight in the equation, as opposed to the SVM planning problem. Assume that the partial derivative of L to the variable $\omega, b, \xi_i, \xi_i^*$ is equal to zero, and the FSVM model expression is derived as

$$f(x) = \sum_{i=1}^{l}\left(\alpha_i^* - \alpha_i\right)k\left(x_i, x\right) + b, \tag{10}$$

where $k(x_i, x)$ is the kernel function in this case. In this study, the radial basis function (RBF) kernel function is chosen, and its expression is given by

$$k\left(x_i, x\right) = \exp\left(\frac{-\|x_i - x\|^2}{2\sigma^2}\right). \tag{11}$$

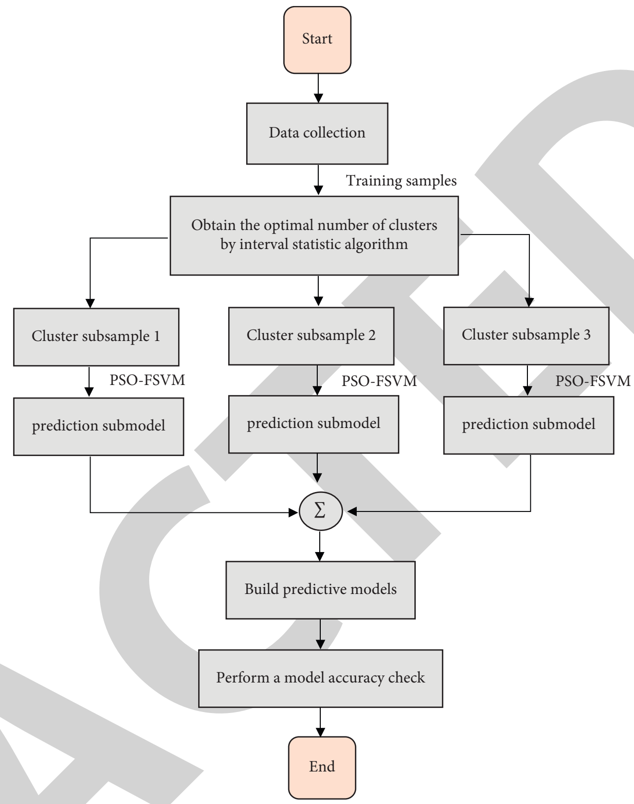

Figure 1: Algorithm flowchart.

3.3. Building a Predictive Model. The information is derived from the enterprise supply chain risk assessment data of a Shanghai-based investment corporation. 70 percent of the data should be used as the training set, and 30 percent of the data should be used as the test set.

Using FSVM based on kernel fuzzy c-means and particle swarm optimization parameters, Figure 1 depicts the exact procedures required for the prediction of enterprise supply chain risk assessment data by FSVM.

(1) The clustering parameter c should be initialized so that the optimal number of clusters obtained by the interval statistics algorithm is used as the value.

(2) Use the KFCM algorithm to cluster the samples. Then, update the fuzzy membership and cluster centers in accordance with formulas (5) and (6), continue until the conditions are met, and construct the fuzzy clustering subsamples (see Figure 1).

(3) After clustering, for each subsample of heat consumption rate, an FSVM prediction model with relevant parameters optimized by PSO is constructed and used to predict the rate of heat consumption.

(4) To create the final prediction model, superimpose each submodel on top of the others.

To determine the accuracy of the prediction model, input the test samples into the model and run it.

FIGURE 2: Change curve of the gap value with cluster number.

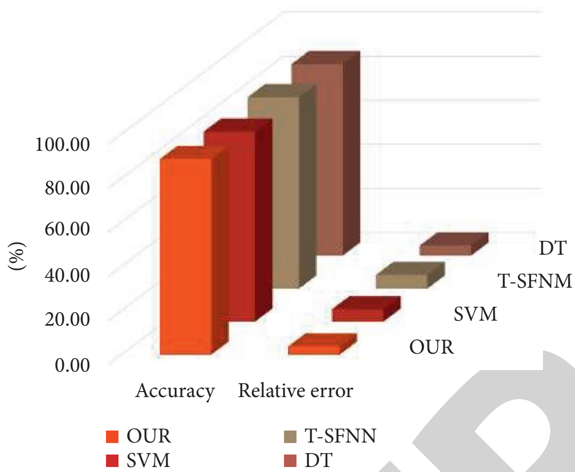

FIGURE 3: Testing set result.

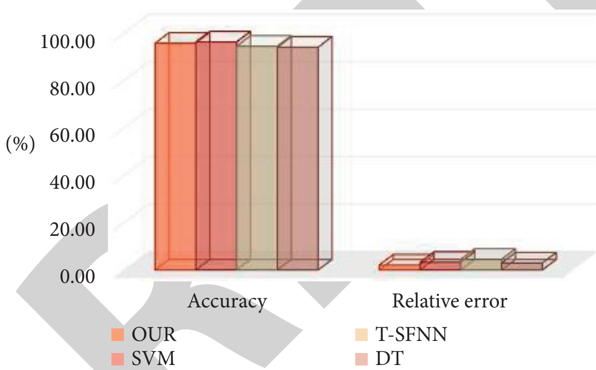

FIGURE 4: Training set result.

4. Results

Figure 2 shows that the ideal number of clusters is six, which is consistent with previous research studies. As a result, we will increase the number of clusters in future models to 6.

Figure 3 depicts the accuracy of our model technique on the test set, where it has the highest accuracy and the lowest error value. In this study, the accuracy of the decision tree (DT) is ranked as the second-best, followed by the accuracy of the T-S fuzzy neural network (T-SFNN) and the accuracy of the support vector machine (SVM). Consequently, the enterprise supply chain risk assessment based on our proposed model is more accurate.

As illustrated in Figure 4, the accuracy rate of OUR model on the training set is not optimal, but the relative error is optimal. Alternately, it is probable that the SVM algorithm overfits the training set.

In summary, the accuracy of the method in this paper is higher than the traditional model SVM and DT and is higher than the neural network model T-SFNN in both the training set and the test set. Moreover, the relative error of the method in this paper is also much lower than that of the comparison method, which fully demonstrates the effectiveness of the method in this paper.

5. Conclusion

As a continuation of the SVM algorithm from the previous paper, this paper proposes an enhanced SVM algorithm that uses kernel fuzzing to predict enterprise supply chain risk. The algorithm's prediction model is then used to assess the risk of the enterprise's supply chain. In this algorithm, it is used to determine the fuzzy membership value of FSVM training samples. The prediction model is FSVM, and its kernel function selects the RBF kernel function. KFCM is employed to compute the fuzzy membership value of FSVM training data. Utilizing interval statistics, the optimal number of clusters in the KFCM model is determined. The PSO method is utilized to optimize the two primary parameters C and CC of the FSVM, namely, C and CC. The enterprise supply chain risk assessment information of a Shanghai-based investment firm is utilized in order to make predictions and run simulations. Based on the findings, the algorithm proposed in this study is more accurate in predicting the complex enterprise supply chain risk assessment, with a greater impact on prediction and a greater capacity for generalization. It contributes to the development of a novel approach to research on corporate supply chain risk assessment and prediction.

Data Availability

The data used to support the findings of this study are included in the article.

Conflicts of Interest

The author states that the publishing of this paper does not include any conflicts of interest.

References

[1] M. M. S. Sodhi and C. S. Tang, *Managing Supply Chain risk [M]*, Springer Science & Business Media, Heidelberg, Germany, 2012.

[2] C. W. Craighead, J. Blackhurst, M. J. Rungtusanatham, and R. B. Handfield, "The severity of supply chain disruptions: design characteristics and mitigation capabilities," *Decision Sciences*, vol. 38, no. 1, pp. 131–156, 2007.

[3] C. S. Tang, "Perspectives in supply chain risk management," *International Journal of Production Economics*, vol. 103, no. 2, pp. 451–488, 2006.
[4] W. Ho, T. Zheng, H. Yildiz, and S. Talluri, "Supply chain risk management: a literature review," *International Journal of Production Research*, vol. 53, no. 16, pp. 5031–5069, 2015.
[5] P. Finch, *Supply chain risk management[J]. Supply Chain Management: International Journal*, 2004.
[6] I. Manuj and J. T. Mentzer, "Global supply chain risk management," *Journal of Business Logistics*, vol. 29, no. 1, pp. 133–155, 2008.
[7] D. Dubois and H. Prade, "Operations on fuzzy numbers," *International Journal of Systems Science*, vol. 9, no. 6, pp. 613–626, 1978.
[8] R. R. Yager, "On solving fuzzy mathematical relationships," *Information and Control*, vol. 41, no. 1, pp. 29–55, 1979.
[9] L. A. Zadeh, "The concept of a linguistic variable and its application to approximate reasoning-I," *Information Sciences*, vol. 8, no. 3, pp. 199–249, 1975.
[10] H. Asai, S. Tanaka, and K. Uegima, "Linear regression analysis with fuzzy model[J]," *IEEE Trans. Systems Man Cybern*, vol. 12, pp. 903–907, 1982.
[11] H. Tanaka and H. Lee, "Interval regression analysis by quadratic programming approach," *IEEE Transactions on Fuzzy Systems*, vol. 6, no. 4, pp. 473–481, 1998.
[12] C. Cortes and V. Vapnik, "Support-vector networks," *Machine Learning*, vol. 20, no. 3, pp. 273–297, 1995.
[13] V. Vapnik, *The Nature of Statistical Learning theory[M]*, Springer science & business media, Berlin/Heidelberg, Germany, 1999.
[14] C. J. C. Burges, "A tutorial on support vector machines for pattern recognition[J]," *Data Mining and Knowledge Discovery*, vol. 2, no. 2, pp. 121–167, 1998.
[15] H. Drucker, C. J. Burges, L. Kaufman, A. Smola, and V. Vapnik, "Support vector regression machines[J]," *Advances in Neural Information Processing Systems*, vol. 9, 1996.
[16] C. F. Chun-Fu Lin and S. D. Sheng-De Wang, "Fuzzy support vector machines," *IEEE Transactions on Neural Networks*, vol. 13, no. 2, pp. 464–471, 2002.
[17] Y. Liu and H. Huang, "Fuzzy support vector machines for pattern recognition and data mining[J]," *International Journal of Fuzzy Systems*, vol. 4, no. 3, pp. 826–835, 2002.
[18] J. H. Chiang and P. Y. Hao, "Support vector learning mechanism for fuzzy rule-based modeling: a new approach," *IEEE Transactions on Fuzzy Systems*, vol. 12, no. 1, pp. 1–12, 2004.
[19] M. Christopher and H. Lee, *Mitigating Supply Chain Risk through Improved confidence[J]*, International journal of physical distribution & logistics management, United Kingdom, 2004.
[20] U. Paulsson, *Developing a Supply Chain Flow Risk model*, in *Proceedings of the Final paper to the NOFOMA 2005-conference*, pp. 9-10, Copenhagen, June 2005.
[21] R. E. Spekman and E. W. Davis, "Risky Business: Expanding the Discussion on Risk and the Extended enterprise[J]," *International Journal of Physical Distribution & Logistics Management*, vol. 34, no. 5, 2004.
[22] S. M. Wagner and C. Bode, "An empirical investigation into supply chain vulnerability," *Journal of Purchasing and Supply Management*, vol. 12, no. 6, pp. 301–312, 2006.
[23] P. R. Kleindorfer and G. H. Saad, "Managing disruption risks in supply chains," *Production and Operations Management*, vol. 14, no. 1, pp. 53–68, 2009.
[24] D. Stefanovic, N. Stefanovic, and B. Radenkovic, "Supply network modelling and simulation methodology," *Simulation Modelling Practice and Theory*, vol. 17, no. 4, pp. 743–766, 2009.
[25] J. G. A. J. Van Der Vorst and A. J. M. Beulens, "Identifying Sources of Uncertainty to Generate Supply Chain Redesign strategies[J]," *International Journal of Physical Distribution & Logistics Management*, vol. 32, no. 6, 2002.
[26] H. Knight Frank, "Risk, Uncertainty and Profit," книГа, vol. 2, 1921.
[27] H. Douglas, *The failure of risk management: why it's broken and how to fix it[J]*, J. Wiley& Sons, vol. 46, p. 271, NY, 2009.
[28] Z. Williams, J. E. Lueg, and S. A. LeMay, "Supply Chain Security: An Overview and Research agenda[J]," *The International Journal of Logistics Management*, vol. 19, no. 2, 2008.
[29] M. E. Tipping, "Sparse Bayesian learning and the relevance vector machine[J]," *Journal of Machine Learning Research*, vol. 1, no. Jun, pp. 211–244, 2001.
[30] M. E. Tipping and A. C. Faul, "Fast marginal likelihood maximisation for sparse Bayesian models[C]//International workshop on artificial intelligence and statistics," *PMLR*, pp. 276–283, 2003.
[31] A. Thayananthan, *Template-based Pose Estimation and Tracking of 3D Hand motion[D]*, University of Cambridge, Cambridge, 2006.
[32] R. R. Yager and L. A. Zadeh, *An Introduction to Fuzzy Logic Applications in Intelligent systems[M]*, Springer Science & Business Media, Heidelberg, Germany, 2012.