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Integrating the Fuzzy Cloud Model with Back Propagation Neural Network in Supply Chain Management under FinTech Innovation*

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This paper aims to analyze the influencing factors of supply chain risk management under FinTech innovation. It takes Enterprise A as the research object. To begin with, the basic knowledge of supply chain risk management is introduced, and its five influencing factors are discussed. Furthermore, the relevant theories of the cloud model are analyzed and three kinds of cloud generators are compared. Combined with Back Propagation Fuzzy Neural Network (BPFNN), a supply chain management model is constructed based on the fuzzy cloud model – BPFNN. Eventually, the middle-level and above managers at Enterprise A and experts are provided with questionnaires to assess the various factors impacting supply chain risk. The model's effectiveness is verified through error convergence in training samples and the fitting of test samples. The results show that the test set sample's mean square error is stable at 0.0137, indicating the model's strong generalization ability. The cloud fuzzy neural network model for financial supply chain collaborative innovation's risk assessment is successfully established. According to the weight analysis, the highest risk factors in the financial industry's supply chain collaborative innovation management are trust risk, capability risk, loss of key customers, and changes in customer demand. This research on the influencing factors of supply chain risk management under collaborative innovation has certain practical significance for the risk management of collaborative innovation.

Keywords: supply chain risk management, cloud model, back propagation fuzzy neural network, collaborative innovation, cloud fuzzy neural network

1. INTRODUCTION

Supply chain management (SCM) is to integrally manage the flow of products, information, and capital from suppliers to customers to maximize the value of the supply chain. In addition to procurement and logistics, SCM in enterprises extends forward to the stage of new product design and development, and backward to product lifecycle management, involving in capital flow and profit management. It contributes value-added services to the company's profit margin and has become an indispensable department. However, traditional SCM methods still face issues such as delayed data collection and incomplete product flow information. Therefore, it is crucial to establish models and adopt technological

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means to further ensure the efficiency and security of the supply chain. In recent years, internet technology has developed rapidly and penetrated various industries, generating massive data in various fields. These data are unstable, fuzzy, random, and complex, and contain many outliers. However, these data can extract values and knowledge related to daily life and industry [1]. Thereby, analyzing, extracting, and applying these big data is essential. The cloud model has great advantages in dealing with uncertainty. It can realize the unified processing of data randomness and fuzziness and ensure the transmission of uncertainty through digital characteristics, uncertainty, and uncertainty cloud generator. It is more suitable for the expression of uncertain concepts. However, it is prone to "rule disaster" when processing large datasets [2].

Many business models have been disrupted in the modern, fast-paced global economy, coupled with the availability of mobile internet and social networks. This disruption has brought opportunities and challenges to the organization and SCM field. Many large-scale supply chain networks include thousands, even hundreds of thousands of raw materials, intermediate products, and final products. These networks face quite complex production and inventory management issues. With the advanced Artificial Intelligence technology, neural network technology is gradually closely related to daily life. The neural network has the characteristics of universality and strong learning and fault-tolerance ability, and it has quickly become a research hotspot. It has been applied to multiple fields, such as life, industry, and medical treatment [3]. The fuzzy neural network is the product of the intelligent combination of fuzzy theory and neural network technology. It considers the fuzziness of data to a certain extent by dividing fuzzy intervals, determining membership functions, and other methods. It improves the defects of traditional neural network technology "hard classification". However, problems still easily fall into local optimal solutions, human factors have a significant impact, and initial values are determined randomly [4, 5]. Therefore, the combination of a cloud model and fuzzy neural network can be considered to deal with uncertainty problems. The data characteristics and the learning efficiency of the algorithm can be considered to ensure the efficiency and accuracy of the algorithm. The supply chain simulation and optimization algorithm using neural network architecture can greatly improve the simulation and optimization speed and effectively solve large-scale supply chain networks' inventory management optimization problem.

This paper takes FinTech innovation as the background, analyzes the influencing factors of supply chain risk management under collaborative innovation, and introduces the relevant theories of cloud models. It considers the basic knowledge of supply chain risk management in terms of research content, and also delves into five factors that affect supply chain risk management, providing useful reference for research in related fields. In terms of research methods, this paper innovatively combines cloud models with the Back Propagation Fuzzy Neural Network (BPFNN) to construct a supply chain management model based on the fuzzy cloud model – BPFNN. The innovation of this method can more accurately predict supply chain risks and provide better solutions for practical applications. Besides, the questionnaire survey is adopted. The questionnaire is distributed to middle-level and above management personnel and experts of Enterprise A. The factors influencing the supply chain risk of the enterprise are rated and evaluated. Finally, the degree of impact of risk impact indicators is obtained through weight analysis. The use of internet technology has led to new research directions in SCM. This paper is significant for further improving the enterprise's SCM system and enhancing its risk prevention capabilities.

This paper includes five parts. Section 1 is the introduction, which introduces the research background and significance. Section 2 is the literature review, which reviews the current status and SCM problems. Section 3 establishes a Back Propagation Neural Network (BPNN) based on cloud models for optimizing SCM. Section 4 is the experiment and results. Through the model validation and the questionnaire survey of the enterprise in Section 1, the data results are presented in graphical and textual form and discussed. Section 5 is the conclusion, summarizing the research results and contributions of the entire paper.

2. LITERATURE REVIEW

In modern globalized and highly industrialized economies, sustainability issues that negatively impact the population and external environment are increasing. Hence, a more reliable and efficient SCM approach is needed to ensure the safe operation of the company. Lim *et al.* [6] investigated the synergistic combination of SCM and quality management practices to enhance the sustainable development performance of Malaysian manufacturing companies. Artificial neural network (ANN) was applied to measure the relationship between each predictive factor (supply chain integration, quality leadership, supplier focus, customer centeredness, and information sharing) and the dependent variable (sustained performance). The relative significance of each predictive variable was sorted based on the normalized importance value through sensitivity analysis [6]. Aamer *et al.* [7] emphasized the application of machine learning in demand forecasting and elucidated its potential role in improving supply chain efficiency. The results indicate that neural networks, ANN, support vector regression, and support vector machines are the most widely adopted algorithms in demand forecasting [7]. Data analysis transforms data into meaningful information, which plays a vital role in SCM. Fanoodi *et al.* [8] predicted platelet supply chain demand based on some factors, and the application of ANN and autoregressive integral moving average models was explored to reduce uncertainty in the supply chain [8].

There are many types of research on cloud models and neural networks. Gu *et al.* proposed a short-term wind power prediction method based on improved Long Short-Term Memory (LSTM), which the cloud model qualitatively describes. The results show that the proposed method can accurately predict the uncertainty of wind power prediction at different confidence levels [9]. Bhardwaj *et al.* adopted the well-placed stacked sparse autoencoder for feature learning in a deep neural network to classify network traffic as benign and distributed denial of service attacks. They compared the proposed method with the ten most advanced methods using performance metrics and appropriately designed technical tuning parameters to optimize distributed denial of service attack detection. Scholars have found that the proposed method is superior to existing methods [10]. Sheik and Muniyandi investigated cloud security issues, existing authentication schemes, and data storage technologies in view of the security threats of cloud computing. They introduced the ANN applied to cloud security [11]. Ismayilov and Topcuoglu modeled the dynamic workflow scheduling problem in cloud computing as a dynamic multi-objective optimization problem. A dynamic multi-objective evolutionary algorithm based on prediction was proposed combining ANN and a non-dominated ranking genetic algorithm. Empirical studies suggested that this algorithm was significantly better than other alternatives in terms of being used for indicators with Pareto optimal frontiers [12]. Wu *et al.* evaluated the operational safety of urban rail transit based on the cloud model and the improved inter-criteria correlation method. They built a two-level indicator system to evaluate the operational safety of urban rail transit and obtained the cloud evaluation set and determination through the indicator system [13]. Qin *et al.* established a regional energy internet evaluation standard system from the four dimensions of technology, economy, society, and engineering. The cloud model described the fuzziness and randomness that are indispensable in uncertainty. The evaluation results of the actual case were completely consistent with the actual situation, indicating the strong practical value of the evaluation method [14].

The above studies either use the combination of the cloud model and neural network or use the cloud model alone to analyze various problems. Still, few studies combine the cloud model's uncertainty with the fuzzy neural network's fuzziness to study the problems in SCM. Therefore, this paper starts from the cloud model and combines BPNN to analyze the influencing factors of supply chain risk management.

2.1 Analysis of Factors Influencing Supply Chain Risk Management under Collaborative Innovation

The supply chain is controlled and added value through decentralized channels, including upstream suppliers and downstream users. The source is supplied, and the endpoint is consumption. It integrates internal and external enterprises [15]. Supply chain risk management uses scientific and reasonable methods to identify the risk factors in the supply chain. It evaluates risks through qualitative and quantitative methods, adopts measures to promptly avoid, share, accept and respond to supply chain risks, effectively manages risks, and enhances the supply chain's robustness and competitive advantages [16]. Fig. 1 presents the steps.

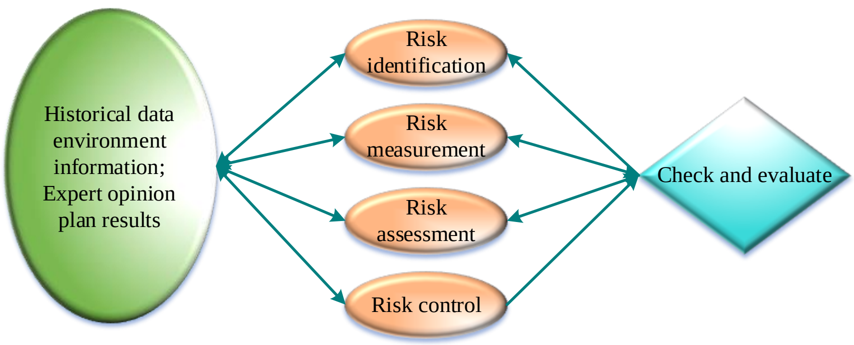

Fig. 1. Steps of supply chain risk management.

In Fig. 1, supply chain risk management is to apply the idea of risk management to the field of SCM, analyze historical data environment information, consult and communicate with experts, and use expert opinions to plan the results. Furthermore, management steps such as risk identification, measurement, evaluation, and control are applied. Finally, the supply chain risk is checked and evaluated. The supply chain collaborative innovation process can be divided into four links: partner selection, cooperative research and development, market operation, and benefit distribution. Each link has risks, and the external environment risk will run through the whole process [17, 18]. The risks in supply chain collaborative innovation should also be analyzed from these five parts. Fig. 2 displays specific factors.

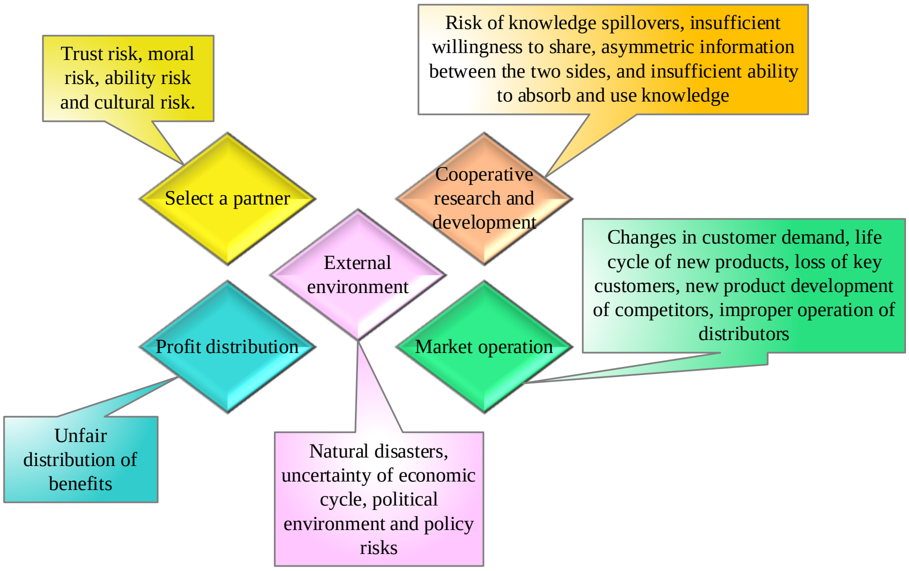

Fig. 2. Analysis of risk factors in supply chain collaborative innovation.

Fig. 2 illustrates the risks in supply chain collaborative innovation analyzed from five aspects: partner selection, cooperative research and development, market operation, benefit distribution, and external environment [19, 20]. The first part is the partner selection. The risks of selecting partners include trust, morale, ability, and cultural risk.

The second part is cooperative research and development. It is mainly conducted from four aspects when considering the risk of cooperative research and development between supply chain enterprises. They are knowledge spillover risk, insufficient willingness to share, information asymmetry between both sides, and insufficient knowledge absorption and utilization capacity. The third part is market operation. Nowadays, the market competition is increasingly fierce, and the primary market operation risks include the change in customer demand, the life cycle of new products, the loss of key customers, the development of new products by competitors, and the improper operation of distributors. The fourth part is benefit distribution. If the interests are distributed unfairly, some enterprises' interests will increase, reducing the interests of other partners and damaging the overall interests of cooperation. The fifth part is the external environment. The economic society is in a dynamic environment, and the external environment changes are uncontrollable. It mainly includes natural disasters, the uncertainty of the economic cycle, the political environment, and policy risks, which impact the process of collaborative innovation.

2.2 Theoretical Analysis of the Cloud Model

In human cognition and decision-making, the language, concept, and way of human thinking cannot be defined by rules or represented by a number or a symbol. In order to better align with human thinking, some scholars have proposed the cloud model. In this way, accurate symbols and languages humans use can be converted through a certain medium and the correlation between various data features can be maintained. The cloud model mainly reflects the uncertainty, fuzziness, and randomness of things in the objective world or concepts in human knowledge. This model integrates them to form the mapping between qualitative and quantitative [21].

Generally, the data in the dataset or the samples used in the research are incomplete. The data may be missing, or the dataset in some fields is small. The cloud model can expand the incomplete data or small sets, determine the sample expectation through the existing data, and generate cloud droplets based on the positive cloud algorithm. The number of cloud droplets can be determined by itself, so that the expanded data conform to the dataset's characteristics. It has a certain theoretical basis. The data characteristics of the cloud model are expectation, entropy, and hyper-entropy [22, 23]. The expectation is to represent a typical sample of the whole. Entropy represents the width of the cloud model. The larger the width is, the more macroscopic the concept it represents. Hypertrophy represents the thickness of the cloud model. The thicker the cloud layer is, the more dispersed the cloud droplets are, and the higher the degree of dispersion of the data is.

Specific algorithms establish the relationship between directional concepts and quantitative data. Cloud generators can be divided into three types: forward, reverse, and conditional cloud generators. Table 1 shows the comparison of the three cloud generators [24].

Table 1. Types of cloud generators.

Cloud Generator	Technological Process	Advantage	Defect
Forward	Convert the input data into cloud droplets through a forward cloud algorithm	The fuzziness and randomness of data are considered in the overall calculation process.	For the same data, the results of multiple uncertainty calculations are not necessarily the same and have uncertainty.
Reverse	The process of computing digital cloud features through data uncertainty	It is more accurate than the traditional mean solution.	It needs to be performed when the curve expression of the cloud model is known
Condition	When the input data is determined, one data may correspond to multiple uncertainties within a certain range. When the input conditions are determined, the data corresponding to a certain degree of certainty is symmetric about the expectation, representing different data can also belong to the same concept	It greatly improves reasoning accuracy.	The difficulty of calculation increases exponentially with the increase of conditions and rules.

2.3 Research Summary

The above research reveals that previous studies have generally focused on the impact of SCM and quality management practices on the sustainable development performance of enterprises, and the application of machine learning and ANN in SCM and other fields. Many scholars have applied various algorithms to SCM, cloud models, and ANN in different fields. However, there are still shortcomings in current research. For example, there is a lack of research on how to balance conflicts between different stakeholders in the supply chain and how to prevent algorithm bias and data privacy breaches. Based on these trends, this paper further delves into how to combine cloud models and ANNs to improve SCM efficiency and sustainable development performance of enterprises. According to the research theme, it explores the combination of fuzzy cloud models and BPNN to improve SCM efficiency and sustainability performance under financial technology innovation, and solve related problems. These problems include enhancing SCM efficiency, optimizing enterprise sustainable development performance, and responding to financial technology innovation.

3. RESEARCH METHODOLOGY

3.1 BPFNN Algorithm Based on Cloud Model

BPNN is a data processing model based on a biological neural network connected by many neurons for operation. It can change its structure according to various input information, model the input data by continuously adjusting the weights between neurons, and solve practical problems [25]. The uncertainty reasoning of the cloud model is a soft computing operation that conforms to the thinking mode of the human brain. According to the different reasoning rules, it mainly depends on the "soft AND" and "soft OR" algorithms. When the inference result requires all conditional attributes to meet the requirements, a logical "AND" operation is performed, and the "soft AND" algorithm is adopted at this time. When the inference result satisfies one or more conditions, a logical "OR" operation is performed and the "soft OR" algorithm is used. The "soft AND" algorithm is mostly used for logical soft computing in the practical application process. Fuzzy theory is based on the actual data situation. It artificially divides the data into several sets, then determines the membership function's expression equation based on research experience. Finally, it calculates the membership degree of each data through the membership function to determine which set the data belongs to. The BPFNN fuzzies the data, uses the BPNN algorithm in the network model for training and learning, and outputs and expresses the results through ambiguity resolution [26, 27]. The cloud model is applied to the BPFNN. The membership function is replaced by the degree of certainty. The fuzzy neural network is initialized with digital features. The SCM model based on the fuzzy cloud model - BPFNN is constructed. Fig. 3 displays its structure.

In Fig. 3, the structure of the BPFNN algorithm based on the cloud model includes input, clouding boundary, rule, hidden, inverse clouding, and output layers [28, 29]. The input layer is the entrance of the cloud fuzzy neural network, which transmits data to the cloud layer. The cloud boundary layer processes the uncertainty of data and reduces the conceptual cloud model. The regular layer operates based on the "soft AND" algorithm to conceptually elevate the degree of certainty of multiple sub-cloud models, generate a comprehensive degree of certainty, and output the results to the hidden layer. The hidden layer learns and trains the "soft AND" results to ensure the learning efficiency of the network model. The inverse cloud layer quantitatively transforms the qualitative concepts, and outputs the reasoning results and their corresponding degree of certainty. It is realized through the conditional cloud generator. The output layer averages and outputs the calculation results of the inverse cloud layer.

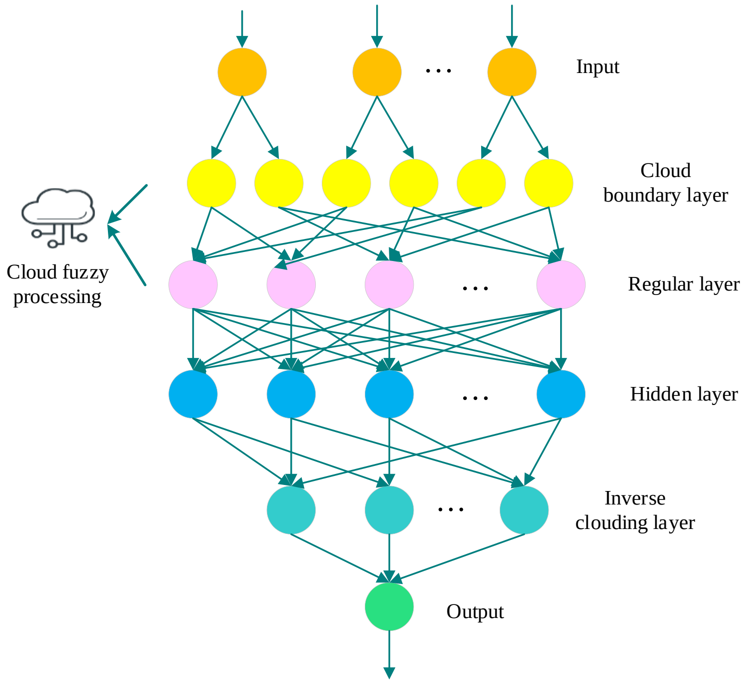

Fig. 3. Structure of BPFNN algorithm based on the cloud model.

3.2 The Algorithm Flow of Cloud Fuzzy Neural Network

Fig. 4 displays the algorithm flow of the cloud fuzzy neural network.

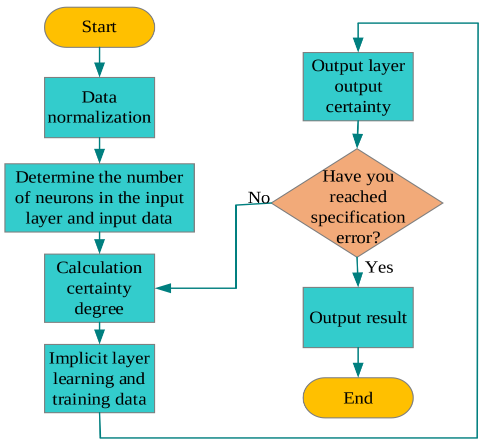

Fig. 4. Algorithm flow of cloud fuzzy neural network.

In Fig. 4, the algorithm process is classified into 7 steps. The first step is data normalization, which involves using certain methods to standardize the input data. The second step is to determine the number of neurons in the input layer and input data of the network model. The third step is to calculate the uncertainty of the network. The fourth step is to train the data and learn the hidden layer. The fifth step is to determine the certainty of the output layer. The sixth step is to determine whether the target error range has been achieved. If not, it is essential to return to continue training. If it is reached, it is essential to proceed to the final step to output the result.

Unlike the traditional BPNN algorithm, cloud fuzzy neural network initialization no longer uses random values but uses the expectation and entropy of the cloud model. Therefore, the dataset should be pre-processed and normalized before calculating the cloud model digital feature. During error adjustment, the adjustment of weight value is converted into the adjustment of cloud model expectation and entropy. It reduces error iterations to a certain extent, improving the operation efficiency of the algorithm [30]. It is assumed that the number of learning samples is N, the network output of the nth learning sample is h_n, and the expected output is r_n. The definition of the target learning function of the network reads:

$$K = \frac{1}{2}\sum_{n=1}^{N}(h_n - r_n)^2. \tag{1}$$

The initialization of weight and threshold of the BPNN algorithm generally adopts normal distribution with a mean value of 0 and a variance of 1. The normal cloud model can initialize the BPNN algorithm. The expectation Ex is taken as the initial weight, and the entropy En is taken as the initial threshold. The adjustment of the weight value differs from the traditional BPNN algorithm, as shown in Eqs. (2) and (3) [31].

$$Ex_{uv}(t+1) = Ex_{uv}(t) - \delta\frac{\partial K}{\partial Ex_{uv}}(u = 1, 2, ..., n; v = 1, 2, ..., m) \tag{2}$$

$$En_{uv}(t+1) = En_{uv}(t) - \delta\frac{\partial K}{\partial En_{uv}}(u = 1, 2, ..., n; v = 1, 2, ..., m) \tag{3}$$

In Eqs. (2) and (3), δ is the learning rate.

3.3 Construction of SCM Model based on Fuzzy Cloud Model – BPFNN

This method is applied to risk management and prediction in the supply chain, which can effectively evaluate the financial risk of enterprises and has certain reference significance for their future development and policy formulation. In the supply chain information sharing evaluation model, the model has strong learning and generalization abilities. Parameters and network structure directly influence the performance of network models. Therefore, the determination of the final model is quite a complex process. In order to obtain a scientific and reasonable evaluation model for supply chain information sharing, it is essential to combine rich experience, continuously adjust parameters, and compare results. This paper sets the BPNN model, a cloud model for evaluating supply chain information sharing, as the input layer, fuzzy cloud computing layer, hidden layer, and output layer. The information-sharing indicators are set as the input layer of the BPNN model, and the quality of supply chain information-sharing is set as the output layer. The dimensions of information-sharing quality measurement are shared information's timeliness, accuracy, completeness, and reliability. In this model, the fuzzy theory is adopted to process uncertain data to more accurately evaluate the quality of supply chain information sharing. Meanwhile, using cloud environments also helps improve the robustness and flexibility of network models, thereby better addressing the challenges of uncertainty and complexity. Specifically, fuzzy sets are used to represent various indicators of supply chain information sharing, such as timeliness, accuracy, integrity and reliability. Moreover, cloud environments are applied to manage and process massive supply chain information sharing data, and provide efficient information exchange and transmission services. These functions help to improve the reliability and performance of network models, and provide strong support for quality evaluation of supply chain information sharing. Fig. 5 displays the specific evaluation model for supply chain information sharing based on the cloud model-BPNN.

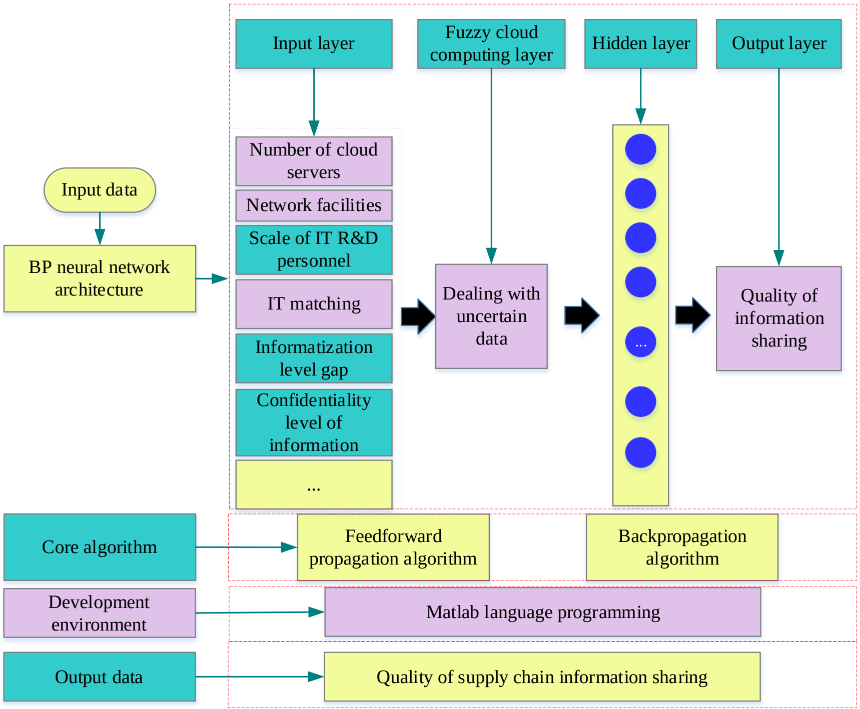

Fig. 5. Supply chain information sharing evaluation model based on cloud model-BPNN.

4. EXPERIMENTAL DESIGN AND PERFORMANCE EVALUATION

4.1 Datasets Collection

A financial company A is selected as the research object. Currently, there are 249 suppliers and more than 560 dealers in Enterprise A, which aligns with the research on collaborative innovation risk of the financial supply chain. Questionnaires are randomly distributed to the company's middle and above managers and experts. The risks in supply chain collaborative innovation analyzed above include trust risk, moral risk, ability risk and cultural risk; knowledge spillover risk, insufficient willingness to share, information asymmetry between both parties, and insufficient ability to absorb and apply knowledge; changes in customer needs, the life cycle of new products, loss of key customers, competitors' new product development, and improper operation of distributors; unfair distribution of benefits; natural disasters, uncertainty of economic cycle, policy risk in the political environment and financial technology innovation. Overall, 18 indicators (recorded as X1-X18) are scored. The specific meanings of each factor are as follows,

X1 (Trust): In SCM, the level of trust between parties can affect decision-making, information sharing, and risk sharing.
X2 (Morality): Companies should uphold ethical principles such as honesty and responsibility in the supply chain to avoid improper behavior.
X3 (Ability): SCM requires all parties to have the corresponding abilities and technical support, including logistics, production, and supplier management.
X4 (Culture): Cultural differences in different countries and regions can also impact SCM, such as communication methods, and values.
X5 (Knowledge spillover): Knowledge exchange and sharing between parties in the supply chain can promote innovation and improve efficiency.
X6 (Insufficient willingness to share): Due to competition and other reasons, some supply chain members may not be willing to share information or technology with others.
X7 (Asymmetric information): Asymmetric information in the supply chain may lead to the breakdown of cooperative relationships or decision-making errors.
X8 (Insufficient ability to absorb and apply knowledge): Some companies may be unable to effectively absorb and apply advanced technology and experience from other companies due to their own limitations.
X9 (Changes in customer demand): Changes in customer demand can impact various aspects of the supply chain and require timely adjustments to strategy.
X10 (The life cycle of new products): Companies need to develop corresponding supply chain strategies based on the lifecycle of new products.
X11 (Loss of key customers): Losing key customers can have a huge impact on a company's supply chain and must be resolved promptly.
X12 (Competitors' new product development): Competitors' new products may threaten a company's existing market share and require corresponding response strategies.
X13 (Improper operation of distributors): Improper distributor operations can lead to problems such as inventory backlog.
X14 (Unfair distribution of benefits): How benefits are allocated among parties in the supply chain is an important issue, and unfair distribution methods may lead to conflicts in cooperative relationships.
X15 (Natural disasters): Natural disasters may affect logistics, inventory, and other aspects of the supply chain.
X16 (Uncertainty of economic cycle): The uncertainty of the economic cycle can pose challenges for SCM and require timely adjustments to strategy.
X17 (Policy risk in the political environment): The political environment and policy changes can also impact SCM.

X18 (Financial technology innovation): The development of financial technology has brought new SCM methods and tools and new management challenges.

In each risk indicator, the interviewee should give a comprehensive score based on the possibility of each risk indicator and the impact of the risk on the supply chain. At the end of the questionnaire, experts must give their overall supply chain risk value. Overall, 40 questionnaires are distributed. According to whether the basic information of the questionnaire is complete, whether the scoring value is valid and whether it is complete, the unqualified questionnaire is rejected. Finally, thirty-eight valid questionnaires are obtained. Subsequently, these data are normalized, and data attributes are reduced.

4.2 Experimental Environment and Parameters Setting

MATLAB is a technology application software with interactive systems launched by Mathworks in the United States. It is widely applied in the fields of engineering calculation and numerical analysis and has become internationally recognized as the best engineering application development environment. The neural network model is developed in the MATLAB 2018a environment, and the software includes the MATLAB neural network toolbox. The toolbox automatically calls the functions it needs to complete neural network learning, training, and simulation operations. The number of layers of the BPFNN is set to 3, with 19 neurons in the input layer and 1 neuron in the output layer. The learning rate is 0.03, the prediction error is 10–3, and the maximum number of iterations is 500. Table 2 presents the specific experimental environment and parameter settings.

Table 2. Experimental environment and parameter setting.

Development environment	PyCharm
operating system	Windows10 system
Central Processing Unit	Intel Core i5 3.20GHz
Memory	4GB
Number of layers of neural network	Three layers
Neural network input layer neuron	19
Output layer neuron	1
Learning rate	0.03
Expected error	10-3
Maximum Iterations	500 times

Among the 38 groups of samples, 29 groups are randomly selected as training set samples. The remaining 9 groups are selected as test set samples.

4.3 Performance Evaluation

This paper uses accuracy, recall, F1 values and precision to evaluate the algorithm's ability to evaluate the proposed algorithm and traditional BPNN's ability to assess credit risk in supply chain finance. Their calculation expressions read:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{3}$$

$$Recall = \frac{TP}{TP + FN} \tag{4}$$

$$F1 = 2 \times \frac{Precision \times Recall}{Precision \times Recall} \tag{5}$$

$$Recall = \frac{TP}{TP + FN} \tag{6}$$

$$Precision = \frac{TP}{TP + FN} \tag{7}$$

TP (True Positive) represents the number of true-positive samples, which is the number of samples that are actually positive and predicted by the classifier to be positive. TN (True Negative) represents the number of true-negative examples, that is, the number of samples that are actually negative examples and predicted by the classifier as negative examples. FP (False Positive) represents the number of false-positive examples, that is, the number of samples that are actually negative examples but predicted by the classifier as positive examples. FN (False Negative) represents the number of false-negative examples, which is the number of samples that are actually positive but predicted by the classifier to be negative.

The training set samples are trained to achieve the expected error. Fig. 6 displays the training results.

In Fig. 6, the mean square error (MSE) decreases gradually with the increase in training times. When the number of training reaches 138, the MSE is 0.000994, reaching the expected level of 10-3, and the training process is over. The error of training set samples is small in the training process, and the MSE is mostly 0.2%-0.3%. The maximum MSE is 0.55%, less than 1%, proving the training process is reasonable. Subsequently, the test set samples are put into the trained cloud fuzzy neural network model. Fig. 7 presents the fitting results.

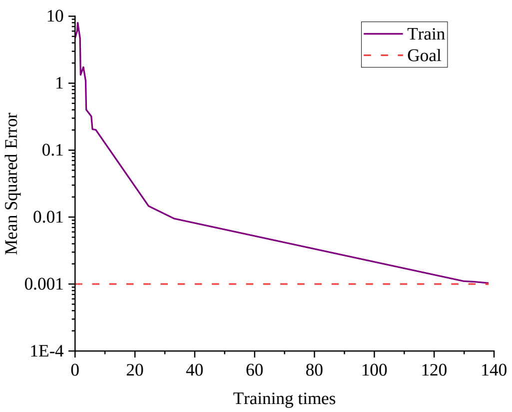

Fig. 6. Error convergence results of cloud fuzzy neural network.

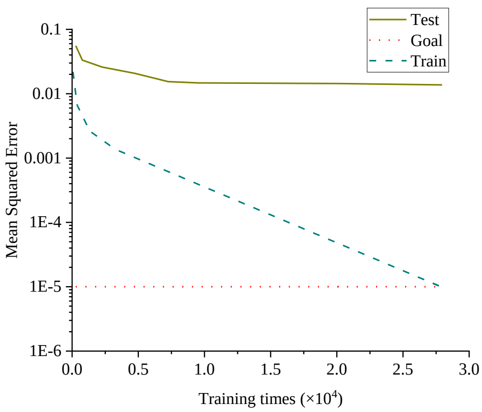

Fig. 7. Test sample fitting of cloud fuzzy neural network.

In Fig. 7, the MSE of test set samples gradually decreases with increasing training times. When training 27754 times, the MSE is 9.98 × 10 – 6, reaching the expected error of 10 – 5. Currently, the test MSE of the test set sample is stable at 0.0137, indicating the model's strong generalization ability. Therefore, the cloud fuzzy neural network model for risk assessment of collaborative innovation in the financial supply chain has been successfully established. According to the connection weight of each neuron in the neural network model obtained by the BPNN algorithm, several paths exist between each neuron in the input layer and each neuron in the output layer. The weights on these paths are multiplied and normalized to obtain the impact of each index on the overall risk of financial supply chain collaborative innovation, as shown in Fig. 8.

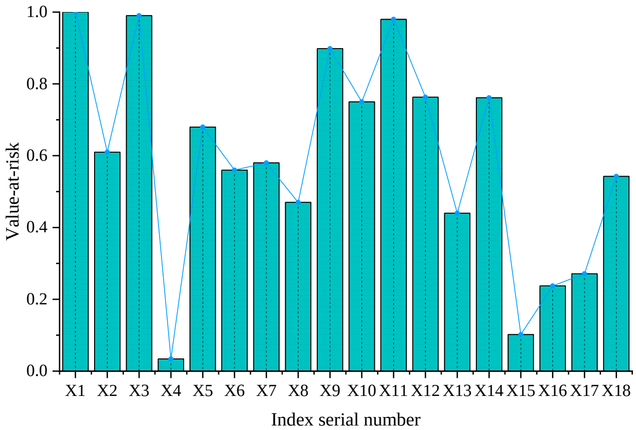

Fig. 8. Impact degree of each risk indicator.

In Fig. 8, the highest risk value is trust risk, up to 1.00. The lowest is a cultural risk, with a risk value of 0.034. The value of the risk index coefficient includes five parts. High-risk factors (risk value > 0.8) include trust, ability, loss of key customers, and changes in customer needs. Medium and high-risk factors (0.6 > risk value > 0.8) include new product development of competitors, unfair distribution of benefits, the life cycle of new products, knowledge spillover risk, and moral risk. Medium risk factors (0.4 > risk value > 0.6) include asymmetric information, insufficient willingness to share, policy risk, insufficient ability to absorb and apply knowledge, and improper operation of distributors. Medium and low-risk factors (0.2 > risk value > 0.4) are political risks and uncertainty of the economic cycle. The low-risk factors (risk value < 0.2) are natural disasters and cultural risks.

The supply chain finance industry will generate capital and commodity flows when providing financing services for small and medium-sized enterprises. At this point, banks will face multiple risks, such as policy, operational, market, and credit. It is essential to conduct supply chain finance investigations under information sharing from the perspective of credit risk assessment. To further demonstrate the advantages of the proposed method in the optimization process of SCM processes, the algorithm proposed is compared with traditional BPNN and similar algorithms mentioned in similar studies [32, 33]. Supply chain finance's credit risk evaluation capability is compared, with the accuracy, precision, and F1 value of enterprise risk evaluation results as indicators. Fig. 9 displays the results.

Fig. 9 presents that compared with traditional BPNN and current research results in advanced references, the proposed BPNN optimized by cloud models shows advantages in supply chain financial management and risk assessment processes. The accuracy, precision, and F1 value of the risk evaluation results for the sample enterprises reach 94.8%, 86.9%, and 85.3%, respectively. The indicator value is higher than that of traditional BPNN. The accuracy, precision, and F1 value of traditional BPNN reach 87.5%, 79.8%, and 77.3%, respectively. It means that BPNN optimized by fuzzy cloud model has advantages in the process of supply chain risk management.

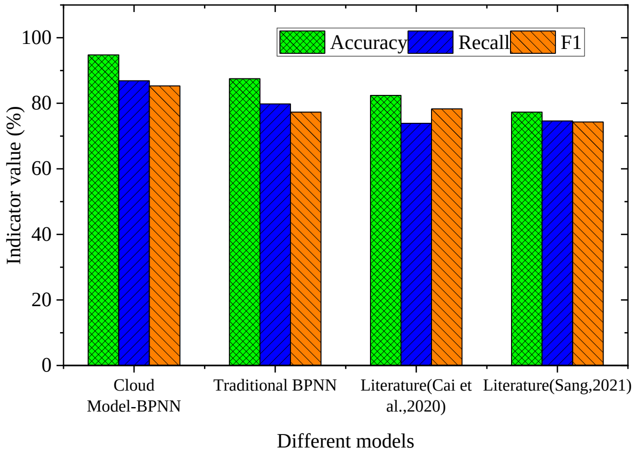

Fig. 9. Performance comparison of different models in the SCM process.

4.4 Discussion

The highest risk factors in supply chain collaborative innovation management are trust, capability, loss of key customers, and changes in customer demand. The results are compared with other similar studies. Das *et al.* [34] used the Analytic Hierarchy Process combined with the multi-standard decision-making method of the decision-making test and evaluation laboratory to analyze the factors affecting the supply chain network during the Corona Virus Disease 2019 (COVID-19) epidemic broke out [34]. Their research results believe that cost optimization is the most crucial factor in reducing the vulnerability of the supply chain network, and human resource management is the most critical factor. Government support is a significant causal factor that can effectively eliminate the problems that plagued the supply chain during the pandemic. Their research mainly focuses on the analysis of influencing factors of the supply chain network without the analysis of risk management. Munir *et al.* [35] discussed the relationship between supply chain integration and risk management based on risk management's information processing perspective to improve operational performance. The results show that the integration of internal, supplier, and customer positively impacts supply chain risk management. The supplier and customer integration partially mediates the impact of internal integration [35]. Their research explores the influencing factors of supply chain risk management from the perspective of supply chain integration. Unlike the research perspective, this research focuses on the whole supply chain process. El Baz and Ruel [36] investigated the role of supply chain risk management in mitigating the impact of disruptions on supply chain resilience and robustness in the context of COVID-19. The results reveal the intermediary role of practices of supply chain risk management and their prominent role in promoting supply chain resilience and robustness [36]. Unlike the research direction, their research analyzes the role of supply chain risk management. This paper studies the influencing factors of risk management in the supply chain.

5. CONCLUSIONS

In order to explore the risk factors in the financial industry's supply chain collaborative innovation management, this paper analyzes the influencing factors of supply chain risk management under collaborative innovation based on FinTech innovation. It introduces the relevant theories of the cloud model. This paper also innovatively combines BPFNN to establish a cloud fuzzy neural network model and algorithms based on cloud models. The method of questionnaire survey is adopted. With Enterprise A as the object, survey questionnaires are distributed to middle-level and above management personnel and experts of the company to score and evaluate the factors affecting the supply chain risk of the enterprise. Finally, the degree of impact of risk impact indicators is obtained through weight analysis. The results indicate that: (1) when the number of training reaches 138, the MSE reaches the expected level, and the maximum MSE in the training process is 0.55%, less than 1%, which proves that the training process is reasonable. (2) The test MSE of the test set sample finally stabilizes at 0.0137. It indicates that the model has strong generalization ability and the cloud fuzzy neural network model for the risk assessment of financial supply chain collaborative innovation is successfully established. (3) Based on weight analysis, the highest risk factors in the financial industry's supply chain collaborative innovation management are trust risk, capability risk, loss of key customers, and changes in customer demand. However, some deficiencies still exist. When selecting the evaluation indicators, the financial supply chain is a huge system with many influencing factors. The indicators selected here are not comprehensive. Hence, the follow-up research can consider the influencing factors of supply chain risk management from more aspects.

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