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Supplier Evaluation in Supply Chain Environment Based on Radial Basis Function Neural Network

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ABSTRACT

The comprehensive evaluation and selection of suppliers under the environment of supply chain management has become a key factor affecting the success of supply chain. How to select suppliers and the strategic partnership between suppliers under the environment of supply chain management has become an important challenge. To solve this problem, this paper takes the supplier evaluation and selection of Guangzhou Automobile Toyota Company as the research object, constructs the index system of supplier comprehensive evaluation and selection, uses the RBF neural network algorithm to establish the supplier evaluation and selection model, and makes an experimental study. The results show that radial basis function neural network is a local approximation network, which has a unique and definite solution to the problem, and there is no local minimum problem in BP network. It is a method that enables enterprises and suppliers to have a clear understanding and seek further promotion together. The research provides theoretical data support for enterprise managers to make decisions.

KEYWORDS

Analytic Hierarchy Process, Neural Network, Supplier Evaluation, Supply Chain

With the intensification of globalization and market competition, supply chain has become an important research hotspot in the business community (Luo & Ierapetritou, 2023). The comprehensive evaluation and selection of suppliers in the supply chain management environment has become a key factor affecting the success of the supply chain (Roozkhosh et al., 2023). How to select suppliers and establish strategic partnerships between suppliers in the supply chain management environment has become an important challenge. This article takes the supplier evaluation and selection of GAC Toyota as the research object. Based on an actual investigation of GAC Toyota, a comprehensive evaluation and selection index system for suppliers was constructed according to the standards of supplier evaluation and selection. Meanwhile, the authors established a supplier evaluation and selection model using a radial basis function neural network algorithm and conducted experimental research. This article provides theoretical data support for the decision-making of enterprise managers, helping them to

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better evaluate and select suppliers, optimize the supply chain structure, and thereby improve the efficiency and effectiveness of supply chain management.

LITERATURE REVIEW

Supply chain refers to an open system composed of suppliers, manufacturers, sellers, and customers that connects all parties in the supply chain through feed-forward information flow, feedback material flow, and information flow, thus forming a whole supply chain management mode (Zhang et al., 2023). With the economic globalization and the rapid development of modern information technology, customers' expectations of products are too high, and the competitive environment of enterprise market has changed from the traditional seller's market to the buyer's market (Ghalandari et al., 2023). Customers are pursuing high standard requirements such as better quality, more choices, higher value, and lower price. Faced with this situation, in order to maintain the core competitiveness, enterprises constantly improve their competitiveness by shortening product development time, improving product quality, reducing production costs, and shortening the delivery cycle (Konstantakis et al., 2023). As the source of the whole supply chain, the evaluation and selection of suppliers is the foundation of supply chain formation (Zaare Tajabadi & Daneshvar, 2023). The supplier's delivery efficiency, product quality, inventory level, design advantage, and other aspects directly affect the manufacturer's income (Delgoshaei et al., 2023). At the same time, the supplier's product price and quality also determine the final customer satisfaction, product market competitiveness, possession, and viability and also have a certain impact on the core competitiveness of each component of the supply chain (Jo et al., 2023). With the development of economic globalization, enterprises devote themselves to their core business, and a large number of spare parts are purchased externally, which makes them more dependent on suppliers (Q.Wang et al., 2023). It has become the key for manufacturing enterprises to improve their competitive advantage by actively developing supplier partnerships and establishing a win-win situation (Sangwa et al., 2023). Market competition is the competition between supply chain and other supply chains, and a weak link will destroy the competitiveness of the whole chain (Esmaeili et al., 2023). Therefore, it is of great practical significance to study supplier selection and evaluation based on supply chain environment (Mohammadnazari et al., 2023).

The theoretical and practical research on supplier selection in supply chain environment at home and abroad has made rich achievements, mainly studying the index system adopted by purchasing enterprises when selecting suppliers, reasonably processing and quantifying the index values, and establishing supplier evaluation and selection models. Some researchers suggest that manufacturers should consider not only basic factors such as cost, quality, and delivery time but also soft indicators such as management compatibility and target consistency when selecting suppliers (Celent et al., 2023). Some researchers put forward three evaluation criteria: risk factors, enterprise demand factors, and measurable cost factors. Through the investigation of Ford Motor Co., Ltd. and its 20 auto parts suppliers, they put forward that the supplier evaluation should be based on product quality, delivery date, price, trade-off among various factors, etc. and not just on price. Some researchers divide the supplier evaluation index system into quality system, enterprise performance, business structure, production capacity, and enterprise environment, mainly aiming at the supplier evaluation system of different product types with retailers as the core (Singh et al., 2023).

With the rapid development of artificial neural network technology, neural network has been widely used in supplier evaluation system (Yu & Lou, 2023). Some researchers put forward the radial basis function method to solve the multivariate interpolation problem and introduced it into the neural network, forming the radial basis function network, which mainly solves the problem of function approximation and pattern classification (Sihotang et al., 2023). Compared with the BP neural network, the radial basis function network is a local approximation neural network, and its optimization process can be regarded as surface fitting in high-dimensional space and its training process is to constantly find the best surface fitted by training data. Some researchers believe that the

RBF neural network has the characteristics of fast learning speed, good approximation effect, and low calculation cost. Some researchers put forward the particle swarm optimization (PSO) algorithm, which generates multiple test speeds and positions for each particle in each iteration and uses the radial basis function neural network proxy model to select the best test position for particles. Some researchers put forward an evolutionary algorithm based on a hierarchical agent, which is used as a global agent to pre-screen promising individuals in the Gaussian process and then uses the radial basis function neural network as a local agent to accelerate convergence based on gradient search strategy, showing certain advantages (Y. Wang et al., 2023).

RELATED MATERIALS AND METHODS

Supply Chain Management

Supply chain management refers to the process of coordinating, controlling, and optimizing activities throughout the entire supply chain network to achieve efficient logistics operations and meet customer needs (Diaz & Nguyen, 2023). It involves the entire process from raw material procurement to final product delivery to customers. The goal of supply chain management is to achieve higher efficiency, lower costs, and better customer satisfaction by optimizing the coordination and cooperation of various links in the supply chain. The key contents of supply chain management are as follows:

1. Supplier management: including supplier selection and evaluation, contract negotiation, and establishing cooperative relationships with suppliers. Enterprises need to choose suitable suppliers based on their own needs and establish stable cooperative relationships with them.
2. Order management: involves receiving, processing, and tracking orders to ensure timely delivery of products or services required by customers. Order management requires close coordination with suppliers, production departments, and logistics departments.
3. Inventory management: reasonable control of inventory levels to meet customer needs and avoid excessive inventory backlog. Inventory management needs to consider factors such as sales forecasting, supply chain reliability, and costs.
4. Logistics management: including logistics planning, transportation management, warehousing management, etc. The goal of logistics management is to improve logistics efficiency, reduce transportation costs, and ensure that products arrive at their destination on time.
5. Information flow management: Collecting, processing, and transmitting information in the supply chain through information technology systems to support decision-making and coordinate various links. Information flow management can improve the visibility and responsiveness of the supply chain.
6. Risk management: identify and evaluate risks in the supply chain and develop corresponding response measures. Risk management includes supplier risk, demand risk, natural disasters, etc.
7. Sustainable development: consider the sustainability of the environment, society, and economy, and take corresponding measures to reduce resource consumption and carbon emissions.

The implementation of supply chain management requires cross departmental collaboration and information sharing as well as close cooperation with suppliers and customers (Choi et al., 2023). Through effective supply chain management, enterprises can improve operational efficiency, reduce costs, enhance customer satisfaction, and gain competitive advantages. It is very important to select suppliers and establish strategic partnerships between suppliers in the supply chain management environment (Cui et al., 2023). The criteria for supplier selection usually include quality, cost, delivery time, reliability, service level, and other aspects. Enterprises need to develop corresponding standards based on their own needs and characteristics (Aranha & Bolar, 2023). In order to evaluate suppliers more accurately, enterprises can use various evaluation methods to evaluate suppliers, such as subjective evaluation, objective evaluation, comprehensive evaluation, etc.

Supplier evaluation refers to the evaluation of potential or existing suppliers to determine whether they can meet the needs of the enterprise and select the most suitable supplier (Li & Zhu, 2023). The purpose of supplier evaluation is to select the most suitable supplier to ensure that the quality of products or services, delivery time, cost (Babaveisi et al., 2023). At the same time, it can also promote the continuous improvement and development of suppliers and establish long-term stable supply chain relationships. Supplier evaluation mainly includes the following key steps:

1. Develop evaluation standards: develop corresponding evaluation standards based on the needs and characteristics of the enterprise, including quality, delivery time, price, service level, reliability, safety, environmental protection, and other aspects.
2. Collect supplier information: collect basic information, business operations, performance records, certifications, and qualifications of suppliers for evaluation purposes.
3. Conduct subjective evaluation: through communication and exchange with suppliers, understand their business philosophy, management level, technical ability, service attitude, and other aspects and make subjective evaluations.
4. Objective evaluation: conduct objective evaluations through on-site inspections, sample testing, user surveys, and other methods to verify the supplier's capabilities and reliability.
5. Comprehensive evaluation results: conduct a comprehensive analysis of subjective and objective evaluation results and provide a supplier evaluation report and ranking.
6. Continuous monitoring: conduct continuous monitoring and evaluation of selected suppliers to ensure they meet the requirements of the enterprise and promptly identify and resolve issues.

Radial Basis Function Neural Network

Scholars first put forward the path of multivariate interpolation and then applied the radial basis function to neural network design and compared the relationship between the radial basis function and the multilayer neural network. By studying the uniform approximation performance of the radial basis function network to nonlinear continuous function, the radial basis function network is proposed, which brings new vitality to the research of the neural network. The radial neural network determines the topological structure of the network according to the problem, which has a fast training and learning speed and avoids the local minimum problem. Its excellent characteristics have stronger vitality than the BP network, and it is becoming a new type of network instead of the BP network.

Radial Basis Function Neural Network (RBFNN) is an artificial neural network model that uses radial basis functions as activation functions and has certain characteristics and applications (Zhong et al., 2023). The basic structure of RBFNN includes input layer, hidden layer, and output layer (Zheng et al., 2023). The neurons in the hidden layer use radial basis functions as activation functions, and common radial basis functions include Gaussian functions, multi aperture functions, etc. The neurons in the hidden layer calculate the response value based on the distance between the input data and the center it represents, which determines the degree of activation of the neurons. The output layer is usually a linear combination layer, where the output of the hidden layer is weighted and summed to obtain the final output result. The characteristics of RBFNN are as follows:

1. Highly nonlinear: due to the nonlinear nature of radial basis functions, RBFNN can handle complex nonlinear problems and is suitable for tasks such as pattern classification and function approximation.
2. Local approximation ability: each hidden layer neuron has a strong response ability to input data within a certain range, which enables RBFNN to perform local approximation and has a good processing effect on local data.

3. Fast training: the training process of RBFNN is relatively simple and fast compared to other neural network models, usually using a weight adjustment method based on the least squares method.
4. Suitable for small sample data: RBFNN has strong processing ability for small sample data and can effectively avoid overfitting problems.

RBFNN has a wide range of practical applications, such as pattern recognition, time series prediction, data mining, and other applications. It can serve as an auxiliary tool for other algorithms to solve complex nonlinear problems. However, RBFNN also has some limitations, such as the relatively difficult processing of high-dimensional data and the need to pay attention to selecting appropriate parameters such as radial basis functions and the number of hidden layer neurons.

The relationship between input space and hidden layer space of radial basis networks is nonlinear, but the transformation from hidden layer space to output layer space is linear. The function of the hidden unit is to transform the input pattern once, transforming the low-dimensional input data pattern into the high-dimensional space, which is beneficial to classification and recognition. At the same time, the transformation function of the hidden unit can be regarded as the extraction of input data features.

In the radial basis function neural network, when the input dimension is n, the number of hidden layer units is p, and the output dimension is 0, the mapping relation of the radial basis function neural network can be a nonlinear transformation layer from the input space to the hidden layer space, and the ith hidden unit outputs. The main function of the radial neural network is to regard the network as an approximator to the unknown function f(x), and any function can be expressed as a weighted sum of a set of basis functions. The function of each hidden unit is selected to form a set of basis functions for approximating the function f(x).

The nonlinear problem in the low-dimensional space can be mapped into a high-dimensional space, making it linearly separable in the high-dimensional space. In the radial basis function neural network, the mapping from input to hidden layer is nonlinear and the function of the hidden unit is nonlinear, while the mapping from hidden layer to output is linear. The output unit is regarded as a single-layer perceptron. As long as the number of hidden units, dimension of high-dimensional space, and function are reasonably selected, the original problem will be mapped into a linear separable problem and finally a linear unit will be used to solve the problem. In the radial basis function (RBF), the Gaussian function is one of the most commonly used activation functions. The main function of the Gaussian function is to map input data to hidden layer neurons, determining the nonlinear characteristics of the model. The mathematical representation of the Gaussian function is shown in Eq. (1):

$$\varphi\left(x\right) = \mathrm{a}e^{\frac{-\left(x-c\right)^2}{2\sigma^2}} \tag{1}$$

Among them, x is the input vector, and c is the center point of the Gaussian function, σ is the standard deviation of a Gaussian function, and a is a real constant.

Choosing the parameters (center point and standard deviation) of the Gaussian function is crucial for constructing an effective RBF neural network model. Here are some common methods and criteria for selecting parameters of Gaussian functions:

1. Center point selection: the selection of center points can be based on the distribution of data. A common method is to use clustering algorithms (such as K-means) to determine the center point. Divide the data sample into different clusters, and the centroid of each cluster can serve as the center point of the Gaussian function.

2. Standard deviation selection: the standard deviation determines the rate of change of the Gaussian function. A smaller standard deviation can make the Gaussian function steeper, while a larger standard deviation makes it flatter. A common method of selecting standard deviation is to use the average distance between samples in the dataset as a reference. A larger average distance usually corresponds to a larger standard deviation.
3. Parameter optimization: after selecting the initial parameters, optimization algorithms can be used to further adjust the parameters of the Gaussian function to improve the performance of the model. For example, optimization methods such as gradient descent can be used to minimize the loss function and find the optimal parameter settings.

It should be noted that the parameter selection of Gaussian functions is closely related to specific problems and datasets. Different problems may require different parameter settings. Therefore, in practical applications, methods such as empirical adjustment and cross validation can help determine appropriate parameter values. In summary, Gaussian functions play an important role in radial basis functions. By selecting the parameters of Gaussian functions reasonably, the performance and effectiveness of the RBF neural network can be improved, and it can better adapt to different datasets and problems.

RBF neural network (Radial Basis Function Neural Network) is an artificial neural network model designed with inspiration from radial basis functions. RBF neural networks have certain advantages in the conversion from qualitative analysis to quantitative output. The working principle will be explained in more detail below.

1. Basic principle: the RBF neural network maps input data to a high-dimensional feature space and models and represents the input using radial basis functions. It consists of three layers: input layer, hidden layer, and output layer. The neurons in the hidden layer use radial basis functions as activation functions, which are responsible for feature extraction and transformation of input data. The neurons in the output layer are responsible for converting the features of the hidden layer into quantitative output.
2. Feature extraction: the hidden layer of the RBF neural network uses radial basis functions to calculate the similarity between input data and each neuron. The commonly used radial basis functions include Gaussian functions and polynomial functions. These functions calculate a response value based on the distance between the input and the neuron, representing the position and relationship of the input data in the feature space. Through this approach, RBF neural networks can extract different features from input data and perform qualitative analysis.
3. Weight learning: the output layer of the RBF neural network is responsible for converting the features of the hidden layer into quantitative output. This process involves learning and adjusting weights. Usually, least squares or gradient descent algorithms are used to optimize the weights of neural networks to make the output results as close as possible to the target value. By continuously iterating and adjusting weights, RBF neural networks can learn and establish mapping relationships between input data and output.
4. Quantitative output: the RBF neural network converts qualitative analysis of input data into quantitative output through the weight relationship between the hidden layer and the output layer. The radial basis function of the hidden layer effectively extracts and transforms the features of the input data, while the weights in the output layer convert these features into specific numerical values. In this way, the RBF neural network can transform the original qualitative data into quantifiable output results.

In summary, the RBF neural network achieves the transformation from qualitative analysis to quantitative output by mapping input data to a high-dimensional feature space and using radial basis functions to model and represent the input. It can transform the qualitative features of input data into specific numerical outputs through the process of feature extraction and weight learning. This gives RBF neural networks certain advantages in dealing with problems that require converting qualitative analysis to quantitative output.

Selection Strategy of Center Point

The selection of the center point is very important. The methods of selecting the center point mainly include the random selection method, the clustering algorithm, and the neural network construction method. The random selection method is also a direct calculation method. The center point of the network is randomly selected from the input samples of the network. After the center point is fixed, the output of the hidden layer is fixed, and the weight of the neural network is calculated by the equation. This method is more suitable for the problem that the distribution of training data has obvious characteristics. Clustering algorithm belongs to the self-organizing method of selecting the center point. Because the classification of clustering algorithm has not been unified, the definition of classification will be different in different algorithms. A set with similar sample data is called a class. The emphasis of this paper is to select the center point of kernel function, classify the sample points by distance, and calculate the center point of each category. According to this way, the center point position of kernel function in the network can be determined. The neural network construction method is a cascade correlation algorithm, a top-down method, which mainly trains the neural network by increasing the number of neurons in the hidden layer and stops increasing when the training error of the neural network reaches a reasonable requirement. There is a cascade relationship between the newly added neurons and the positions of the original neurons. By adjusting the corresponding weights of newly added neurons, the output of the new network has the greatest correlation with that of the original network, thus ensuring the maximum reduction of the output error of the network.

When the kernel function and center point of the network are determined, it is necessary to train the network, and the training process is also the network learning process. Through training, the weight vector from the hidden layer to the output layer of the radial basis function neural network is obtained. In this paper, the supervised learning method and gradient descent method are used to train the radial basis function neural network. By calculating the error between the output value and the real value of the network, the weight parameters of the neural network are gradually adjusted, and the training is stopped until the error reaches the required minimum error or the maximum number of iterations.

RESULTS AND ANALYSIS

Analysis of Supplier Evaluation Model

After completing the programming of the radial basis function neural network, the network structure is determined by systematic experiments. Besides organizing the input data, the establishment of the neural network mainly considers the determination of network topology and the adjustment of learning parameters. For a specific classification problem, there is no standard pattern to construct the network model structure; only an appropriate network structure can be obtained through experimental methods.

MATLAB is a widely used numerical calculation and data analysis software, which can also be used to train RBF neural networks. When training RBF neural networks using MATLAB, there are some limitations and considerations to consider:

1. Data preprocessing: before training an RBF neural network using MATLAB, it is necessary to perform appropriate preprocessing on the input data, such as normalization. Otherwise, it may lead to slow convergence speed and unstable results of the model.
2. Neural Network Toolbox: MATLAB provides a neural network toolbox that facilitates the construction, training, and testing of RBF neural networks. However, the use of this toolbox requires some MATLAB programming experience and understanding.

3. Parameter settings: when training RBF neural networks using MATLAB, it is necessary to set the model parameters reasonably, such as the number of center points, standard deviation, learning rate, etc. Different parameter settings may produce different results; therefore parameter adjustments and cross validation are needed to optimize model performance.
4. Computing resources: training RBF neural networks requires a significant amount of computing resources, such as memory, processors, and runtimes. Therefore, when training RBF neural networks using MATLAB, it is necessary to consider the limitations and feasibility of computing resources.
5. Underfitting and overfitting: when training RBF neural networks in MATLAB, underfitting and overfitting problems may be encountered. Underfitting refers to the model's inability to capture the complexity of the data, while overfitting refers to the model's good performance on the training set but poor performance on the test set. To avoid these issues, it is necessary to perform model selection and regularization operations.

In summary, training RBF neural networks using MATLAB requires considering many factors. Researchers should set parameters, preprocess data, and use appropriate adjustment methods based on specific problems and the characteristics of the dataset to achieve optimal network performance and effectiveness. The radial basis function neural network is trained by MATLAB, the network structure is determined by actual network training, and the suppliers are evaluated and selected.

During the supplier evaluation experiment, the required data mainly include the supplier's operating data and the expert evaluation data used to determine the index weight. The collection of business data is mainly aimed at the quantitative indicators in the evaluation system, most of which cannot be obtained directly but can be obtained only after some available data are calculated and processed. Qualitative indicators are mainly carried out by means of expert scoring. The data selected in this paper comes from the data of Guangzhou Automobile Toyota Company in 2019.

For suppliers, the order completion rate is an important guarantee for product production. Table 1 and Figure 1 show the order quantity and completion status of Guangzhou Automobile Toyota Company and supplier A in each month in 2019. It can be concluded that the order quantity of Guangzhou Automobile Toyota Company and supplier A can be completed every month in 2019, with a total of 122,464 orders and 122,463 completed orders.

According to the performance appraisal data of supplier A, Table 2 and Figure 2 count the on-time delivery of Guangzhou Automobile Toyota Company and supplier A in each month in 2019. It can be concluded that the on-time delivery order quantity in 2019 was 122,432 pieces.

After counting the order quantity and on-time delivery quantity of Guangzhou Automobile Toyota Company and supplier A in each month in 2019, Table 3 counts the delivery time and average value of each order. It can be seen that the average delivery time is three days and the longest is no more than seven days. Overall, the average delivery flexibility of supplier A in 2019 is 85.71%.

Table 4 shows the average demand, standard deviation, profit margin, and quantity flexibility VF of four major products operated by supplier A in 2019. It can be seen from Table 4 that product 3

Table 1. Order Quantity and Order Completion Quantity of the Company and Supplier A in Each Month in 2019

Month	January	February	March	April	May	June
Order quantity	15,929	11,453	14,218	10,227	8,503	7,825
Completed order quantity	15,929	11,453	14,218	10,227	8,503	7,825
Month	July	August	September	October	November	December
Order quantity	5,729	12,453	9,218	8,227	8,830	9,852
Completed order quantity	5,728	12,453	9,218	8,227	8,830	9,852

Figure 1. Order Quantity and Completion of Each Month Between the Company and Supplier A in 2019

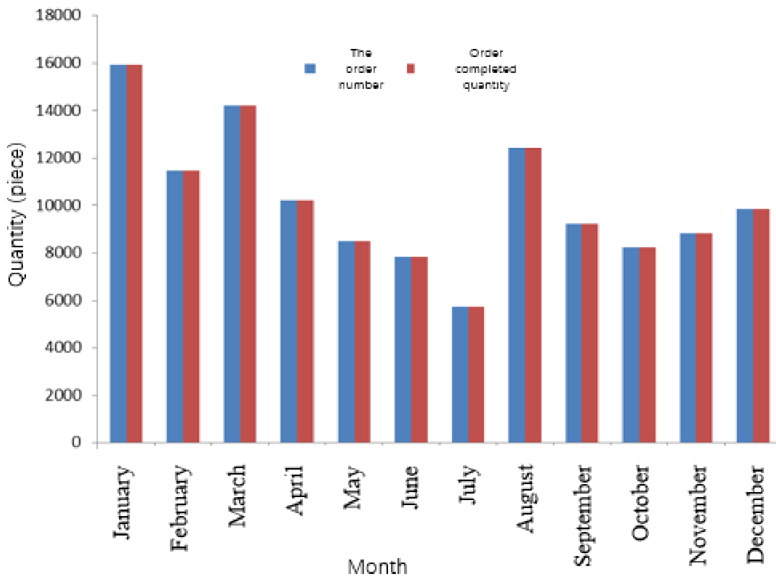


Table 2. 2019 Monthly Order Quantity and On-Time Delivery Quantity of the Company and Supplier A

Month	January	February	March	April	May	June
Order quantity	15,929	11,453	14,218	10,227	8,503	7,825
Quantity delivered on time	15,927	11,450	14,213	10,227	8,501	7,824
Month	July	August	September	October	November	December
Order quantity	5,729	12,453	9,218	8,227	8,830	9,852
Quantity delivered on time	5,724	12,453	9,211	8,227	8,825	9,850

has the largest demand and the highest quantity flexibility among the four major products. Although product 1 has a relatively small demand, the quantity flexibility is not low. The quantity flexibility VF of four major products operated by supplier A is 0.8693. Figure 3 shows the quantity and quantity flexibility of four main products operated by supplier A in 2019.

The choice of network structure is very important. Reasonable choice can reduce the number of network training and improve the accuracy of network learning.

The indicator system is a key framework for evaluating enterprise suppliers, which involves various aspects that affect supplier performance. To determine the 20 main indicators, the authors have gone through the following steps:

1. Goal setting: the authors first clarify the goals and requirements for evaluating enterprise suppliers. For example, the authors pay more attention to suppliers' on-time delivery, product quality, cost-effectiveness, technical capabilities, etc.
2. Literature review: the authors conducted a literature review to understand the indicator systems that have been used in the field of supply chain management as well as research on supplier evaluation in enterprises. This helps the authors identify indicators that may be applicable to their research.

Figure 2. Order Quantity and On-Time Delivery Quantity of the Company and Supplier A in Each Month in 2019

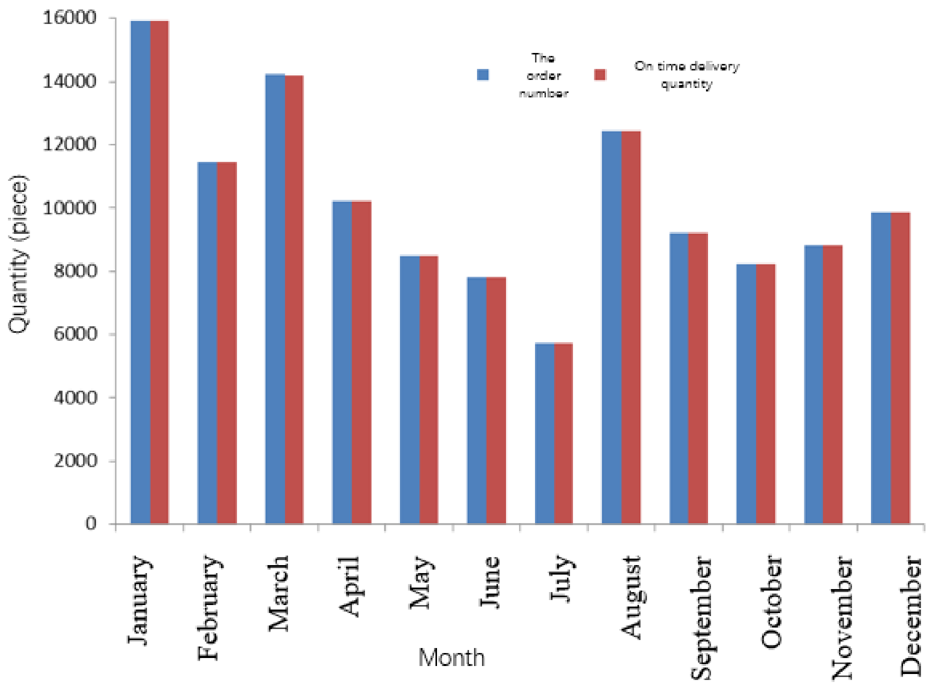


Table 3. Delivery Time of Guangzhou Automobile Toyota Company and Supplier A's Order in 2019

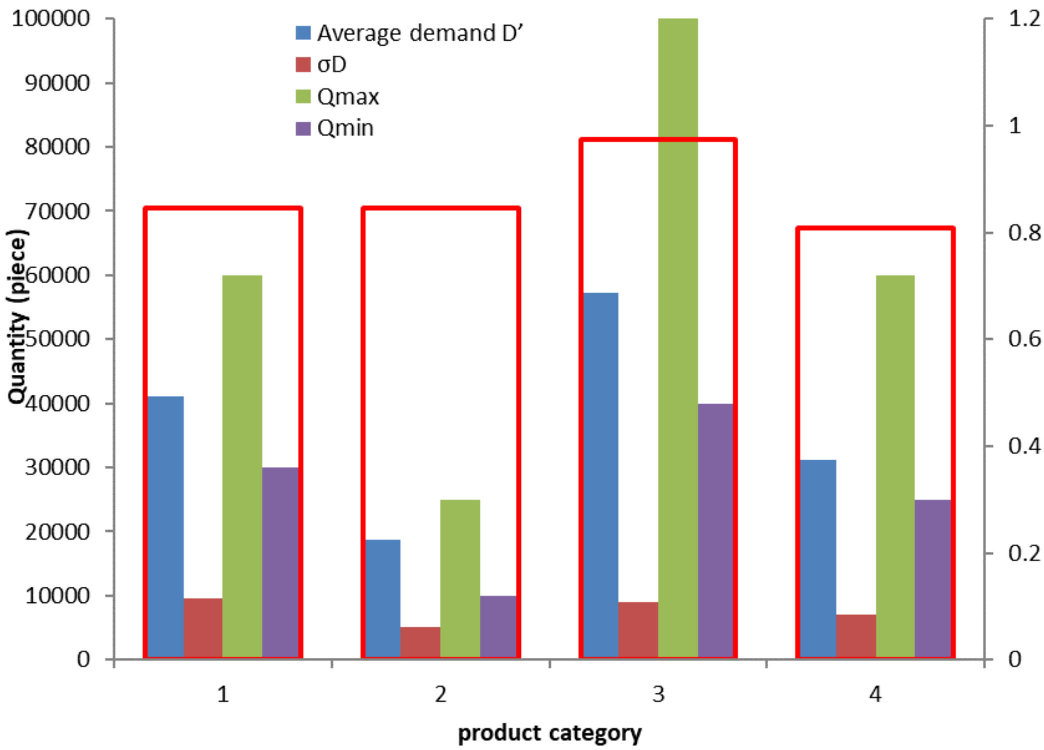
Average delivery time (days)	Maximum delivery time (days)	Minimum delivery time (days)
3	7	1

Table 4. Table of Product Quantity

Product category	Average demand D'	σD	Qmax	Qmin	VF
1	41,134	9,658	60,000	30,000	0.8463
2	18,652	5,112	25,000	10,000	0.8470
3	57,302	8,945	100,000	40,000	0.9732
4	3,1205	7,145	60,000	25,000	0.8078

3. Expert opinion: the authors have discussed with experts in the field of supply chain management and collected their opinions and suggestions. Through the experience and knowledge of experts, the authors can obtain important indicators and understand their role in practical environments.
4. Data collection: the authors collected data related to enterprise suppliers, such as data on on-time delivery and product quality evaluation. These data help the authors analyze the importance and impact of each indicator.
5. Correlation analysis: through statistical analysis and correlation analysis, the authors have identified 20 indicators that are most relevant to the evaluation of enterprise suppliers. These indicators are considered the most important factors affecting supplier performance.

Figure 3. Quantity and Quantity Flexibility of Four Main Products Operated by Supplier A in 2019



The structure of the radial basis function network model in this paper is as follows: according to the index system, 20 items that affect the main indexes of suppliers are selected, and the number of input layers n = 20 is determined. The evaluation of enterprise suppliers is a process from qualitative to quantitative and then to qualitative. Based on the radial basis function neural network model, the qualitative analysis is converted into quantitative output, and then the output results are comprehensively evaluated, so as to qualitatively evaluate enterprise suppliers.

In this paper, the number of neurons in the output layer is set to one, the number of output layers is m=1, and the evaluation value is [0,1]. Limiting the output range between [0, 1] can achieve standardization and normalization effects. By limiting the evaluation values to a fixed range, the dimensional differences between different evaluation indicators can be eliminated, allowing them to be compared and comprehensively considered. This is very useful for the comprehensive evaluation of multiple evaluation indicators. Limiting the range of evaluation values to between [0, 1] can make the results more intuitive and easy to interpret. Zero represents the worst evaluation result, while 1 represents the best evaluation result. This linear relationship makes the interpretation and understanding of evaluation results simpler and clearer. The more hidden layers, the slower the learning speed of the neural network. Increasing the number of hidden layers can enhance the nonlinear expression ability of the network, enabling it to better approximate complex nonlinear function relationships. However, as the number of hidden layers increases, the complexity of the network also increases, which may make network training more difficult and time-consuming. Because during the training process, weight adjustment between hidden layers needs to be achieved through back-propagation algorithms. Therefore, increasing the number of hidden layers may lead to a decrease in learning speed. In this paper, under the condition of reasonable structure and proper weight, the three-layer radial basis function neural network is selected to approximate any continuous function. The number of hidden layer neurons is determined by the convergence performance of the network. On the basis of summarizing a large number of network structures, according to market experience and actual network training, the number of hidden layer neurons is 34. The basic principle of selecting 34 hidden layer neurons can be explained from the following aspects:

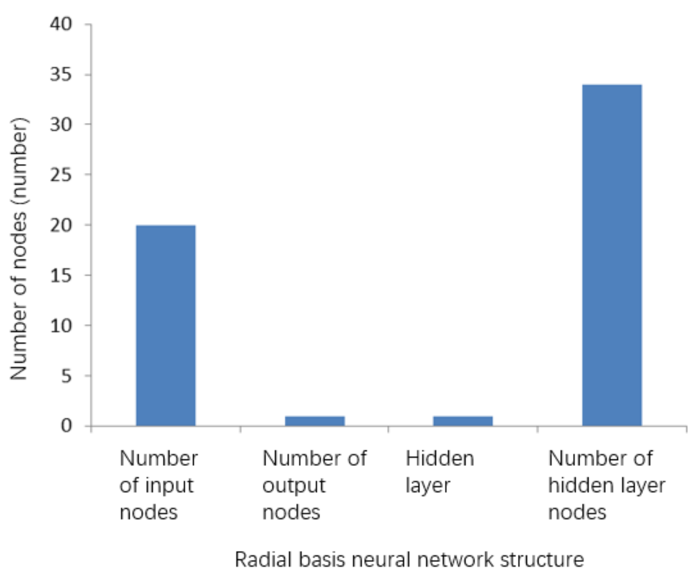
1. Convergence performance: the number of hidden layer neurons has a certain impact on the convergence performance of neural networks. If the number of hidden layer neurons is too small to fully represent the complex patterns and relationships in the input data, it leads to insufficient network learning and the inability to accurately approximate the objective function. On the contrary, if there are too many neurons in the hidden layer, the network's capacity will be too large, leading to overfitting problems, resulting in good performance on the training set but poor generalization ability on unknown data. Therefore, selecting an appropriate number of hidden layer neurons is key to ensuring the convergence performance of the network.
2. Network structure optimization: based on summarizing a large number of network structures, the selection of 34 hidden layer neurons was concluded through experiments and practice. Through practical network training and market experience accumulation, researchers may find that using 34 hidden layer neurons can achieve good performance on specific problems and datasets under conditions of reasonable structure and appropriate weights. This choice may be a combination of experimentation and experience to optimize the network structure.

In this paper, the concrete network model structure based on the RBF network is selected. The input nodes are composed of indicators in the indicator layer, and the output nodes are the results of comprehensive evaluation of suppliers.

Table 5. Structure of the Radial Basis Function Neural Network

Enter the number of nodes	Enter the number of nodes	Implicit layer number	Number of hidden layer nodes
2 0	1	1	3 4

Figure 4. Number of Radial Basis Function Neural Network Structures



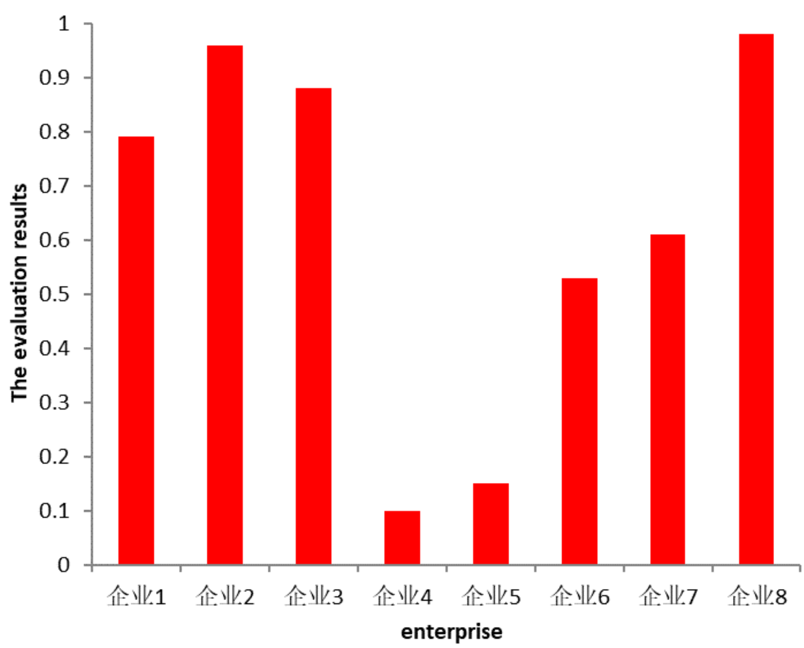
In this paper, according to the input evaluation of eight potential suppliers, through the quantitative values of each evaluation index, the trained radial basis function neural network is used for test calculation. After the test calculation results, as shown in Figure 5, it can be seen from the figure that the evaluation value of Enterprise 8 is 0.98, which is the most suitable supplier, while Enterprise 4 is the least suitable supplier among the eight enterprises.

After the radial basis function neural network was tested and evaluated, GAC Toyota invited experts to score according to the actual situation. According to the evaluation criteria, the evaluation results were basically consistent with those of the radial basis function neural network. Therefore, the supplier evaluation and selection method based on the neural network can effectively deal with complex supplier evaluation and selection problems, and at the same time, quantitative data of different index values and evaluation indexes of different properties can be comprehensively processed, which is a very promising method.

Application Analysis of RBF Neural Network

With the continuous development of artificial intelligence technology, neural networks have become one of the important tools for solving various complex problems. Among numerous neural network models, the Radial Basis Function Neural Network (RBFNN) has attracted much attention in practical applications due to its unique structure and characteristics. RBFNN utilizes radial basis functions as activation functions, and through the nonlinear approximation ability and local response characteristics of the hidden layer, it can handle problems in multiple fields such as pattern recognition, time series prediction, and data mining. However, when applying RBFNN, the authors also need to pay attention to selecting appropriate parameters such as radial basis functions and the number of hidden layer neurons while fully understanding its advantages and limitations in practical applications. Radial basis function neural networks (RBFNN) have various applications and fields in practical applications. Here are some common practical application analyses:

Figure 5. Supplier Evaluation Results



1. Pattern recognition and classification: RBFNN can be used for pattern recognition and classification problems, such as facial recognition, handwritten digit recognition, speech recognition, etc. Its nonlinear approximation ability and local response characteristics make it excellent in handling complex pattern classification tasks.
2. Time series prediction: RBFNN can be used for time series prediction, such as stock prices, traffic flow, weather forecasting, etc. It can capture nonlinear relationships in time series data and make accurate predictions in the future.
3. Function approximation: RBFNN can be used to approximate any complex function. By training the network, RBFNN can be used to fit the mapping relationship between input and output, thereby achieving the goal of function approximation.
4. Data mining: RBFNN can be used for data mining tasks such as clustering, anomaly detection, association rule mining, etc. It can effectively cluster and classify data based on its characteristics and similarity, thereby helping to discover patterns hidden in large amounts of data.
5. Control system: RBFNN is also applied in control systems, such as robot control, adaptive control, etc. It can adjust the output based on input signals and system status, achieving precise control of complex systems.

Although radial basis function neural networks (RBFNN) perform well in many practical applications, there are also some limitations that need to be recognized and considered. Here are some common limitations:

1. Difficulty in processing high-dimensional data: RBFNN faces challenges in processing high-dimensional data. High dimensional data often leads to explosive growth in the number of hidden layer neurons, thereby increasing computational complexity and training difficulty. For high-dimensional data, preprocessing methods such as feature selection and dimensionality reduction may be necessary to improve the performance and efficiency of the model.
2. Imbalanced data samples: when the data samples are imbalanced, the performance of RBFNN may be affected. If the number of samples in a certain category is small, the RBFNN neurons in that category may receive less training, resulting in biased classification results. In this case, it is necessary to adopt appropriate sampling strategies or use other processing methods to solve the problem of imbalanced data samples.
3. The dependency of parameter selection: the performance and effectiveness of RBFNN are influenced by parameter selection. For example, selecting appropriate parameters such as radial basis functions, number of hidden layer neurons, and position of center points is a key issue. Different problems may require different parameter settings, which require empirical adjustments based on specific situations as well as model selection and performance evaluation.
4. Long training time: compared to other neural network models, the training time of RBFNN may be longer. This is because during the training process, it is necessary to determine the position and width of hidden layer neurons and adjust their weights. Especially when dealing with large-scale datasets, training time will further increase. Therefore, in practical applications, time cost and computational resources need to be considered.
5. Sensitivity to initial parameters: RBFNN is more sensitive to the selection of initial parameters, and different initial parameters may lead to different results. This requires multiple trainings and parameter optimizations to find the optimal parameter settings. Meanwhile, in order to avoid getting stuck in local optima, it may be necessary to use some heuristic methods or improved training algorithms.

CONCLUSION

In the context of supply chain management, selecting suitable suppliers and establishing strategic partnerships are important challenges. Using actual survey data from GAC Toyota, the authors constructed an indicator system for comprehensive supplier evaluation and selection and established a supplier evaluation and selection model using the RBF neural network algorithm. Experimental studies have shown that this model can provide theoretical data support for enterprise managers, thereby helping them make more accurate and reliable decisions. Through the study of supplier evaluation and selection, this article constructs a complete indicator system, providing a theoretical framework for enterprises to choose suppliers in supply chain management. Meanwhile, the evaluation and selection model established using the RBF neural network algorithm provides a feasible evaluation method for enterprise managers. The selection of suppliers and the establishment of strategic partnerships are crucial for the operation and development of enterprises. The research findings of this article can provide practical guidance for enterprise managers to evaluate and select suppliers more scientifically, thereby improving the efficiency and quality of the supply chain. This article focuses on GAC Toyota as the research object, but due to data limitations, it cannot cover the situation of other industries and companies. Therefore, the applicability of research conclusions may have certain limitations.

In the future, expanding the scope of research samples to cover different industries and companies, as well as collecting more comprehensive and reliable data, can increase the representativeness and generalization ability of research. In addition, this article constructs an indicator system for comprehensive evaluation and selection of suppliers, but in practical applications, the needs and conditions of different enterprises may vary. Therefore, adjustments and optimizations need to be made according to specific circumstances to meet the actual needs of the enterprise. In the future, it is possible to consider screening, adjusting, and optimizing indicators based on the actual needs and conditions of the enterprise to meet different management needs. Meanwhile, multiple indicator systems can be considered to evaluate the comprehensive quality of suppliers and compare and analyze them. The future development in the field of comprehensive supplier evaluation and selection can be expanded in the following directions, which will help improve the effectiveness and level of supplier management and promote the optimization and collaboration of the supply chain.

1. Multidimensional indicator system: establish a more comprehensive and detailed supplier evaluation indicator system, including quality, on-time delivery, cost-effectiveness, technical ability, innovation ability, sustainable development, and other indicators, to comprehensively measure the comprehensive quality of suppliers.
2. Data driven evaluation model: by utilizing technologies such as big data, artificial intelligence, and machine learning, a data-driven supplier evaluation model is constructed. By analyzing and mining historical and real-time data of suppliers, more accurate and precise evaluation and selection can be achieved.
3. Visual decision support tool: develop a visual decision support tool for comprehensive evaluation and selection of suppliers, enabling decision-makers to intuitively understand the situation and evaluation results of suppliers and make flexible decisions and optimizations.
4. Application of blockchain technology: utilizing blockchain technology to ensure the authenticity and credibility of supplier information, establishing a decentralized supplier evaluation and selection mechanism, and improving information security and data privacy protection.

DATA AVAILABILITY

The figures and tables used to support the findings of this study are included in the article.

COMPETING OF INTEREST

The authors declare that they have no competitive interests.

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REFERENCES

Aranha, M., & Bolar, K. (2023). Efficacies of artificial neural networks ushering improvement in the prediction of extant credit risk models. *Cogent Economics & Finance*, *11*(1), 2210916. doi:10.1080/23322039.2023.2210916

Babaveisi, V., Teimoury, E., Gholamian, M. R., & Rostami-Tabar, B. (2023). Integrated demand forecasting and planning model for repairable spare part: An empirical investigation. *International Journal of Production Research*, *61*(20), 6791–6807. doi:10.1080/00207543.2022.2137596

Celent, L., Bajić, D., Jozić, S., & Mladineo, M. (2023). Hard milling process based on compressed cold air-cooling using vortex tube for sustainable and smart manufacturing. *Machines*, *11*(2), 264. doi:10.3390/machines11020264

Choi, S. W., Seo, B. G., & Lee, E. B. (2023). Machine learning-based tap temperature prediction and control for optimized power consumption in stainless electric arc furnaces (EAF) of steel plants. *Sustainability (Basel)*, *15*(8), 6393. doi:10.3390/su15086393

Cui, F., Zheng, S., Wang, D., Tan, X., Li, Q., Li, J., & Li, T. (2023). Recent advances in shelf life prediction models for monitoring food quality. *Comprehensive Reviews in Food Science and Food Safety*, *22*(2), 1257–1284. doi:10.1111/1541-4337.13110 PMID:36710649

Delgoshaei, A., Beighizadeh, R., Arffin, M. K. A. B. M., Leman, Z. B., & Ali, A. (2023). Forecast innovative development level in green supply chains using a comprehensive fuzzy algorithm. *International Journal of Fuzzy Systems*, *25*(2), 880–895. doi:10.1007/s40815-022-01416-7

Diaz, J. F., & Nguyen, T. T. (2023). Application of grey relational analysis and artificial neural networks on corporate social responsibility (CSR) indices. *Journal of Sustainable Finance & Investment*, *13*(3), 1181–1199. doi:10.1080/20430795.2021.1929805

Esmaeili, F., Mafakheri, F., & Nasiri, F. (2023). Biomass supply chain resilience: Integrating demand and availability predictions into routing decisions using machine learning. *Smart Science*, *11*(2), 293–317. doi:10.1080/23080477.2023.2176749

Ghalandari, M., Amirkhan, M., & Amoozad-Khalili, H. (2023). A hybrid model for robust design of sustainable closed-loop supply chain in lead-acid battery industry. *Environmental Science and Pollution Research International*, *30*(1), 451–476. doi:10.1007/s11356-022-21840-4 PMID:35902520

Jo, J., Kim, U., Lee, E., Lee, J., & Kim, S. (2023). A supply chain-oriented model to predict crude oil import prices in South Korea based on the hybrid approach. *Sustainability (Basel)*, *15*(24), 16725. doi:10.3390/su152416725

Konstantakis, K. N., Cheilas, P. T., Melissaropoulos, I. G., Xidonas, P., & Michaelides, P. G. (2023). Supply chains and fake news: A novel input–output neural network approach for the US food sector. *Annals of Operations Research*, *327*(2), 779–794. doi:10.1007/s10479-022-04817-x

Li, X., & Zhu, G. (2023). Green supply chain coordination considering carbon emissions and product green level dependent demand. *Mathematics*, *11*(10), 2355. doi:10.3390/math11102355

Luo, Y., & Ierapetritou, M. (2023). Multifeedstock and multiproduct process design using neural network surrogate flexibility constraints. *Industrial & Engineering Chemistry Research*, *62*(5), 2067–2079. doi:10.1021/acs.iecr.2c02968

Mohammadnazari, Z., Aghsami, A., & Rabbani, M. (2023). A hybrid novel approach for evaluation of resiliency and sustainability in construction environment using data envelopment analysis, principal component analysis, and mathematical formulation. *Environment, Development and Sustainability*, *25*(5), 4453–4490. doi:10.1007/s10668-022-02210-z

Roozkhosh, P., Pooya, A., & Agarwal, R. (2023). Blockchain acceptance rate prediction in the resilient supply chain with hybrid system dynamics and machine learning approach. *Operations Management Research : Advancing Practice Through Research*, *16*(2), 705–725. doi:10.1007/s12063-022-00336-x

Sangwa, N. R., Sangwan, K. S., Paidipati, K. K., & Shah, B. (2023). Lean performance measurement system for an Indian automotive supply chain. *International Journal of Quality & Reliability Management*, *40*(5), 1292–1315. doi:10.1108/IJQRM-03-2022-0113

Sihotang, H. T., Lavemaau, J., Riandari, F., Panjaitan, F. S., Gorat, S. E., & Batubara, J. (2023). Integrating the neural network into the stochastic DEA model. *Idea: Future Research*, *1*(1), 5–13. doi:10.35335/idea.v1i1.2

Singh, A. K., Kumar, V. P., Irfan, M., Mohandes, S. R., & Awan, U. (2023). Revealing the barriers of blockchain technology for supply chain transparency and sustainability in the construction industry: An application of pythagorean FAHP methods. *Sustainability (Basel)*, *15*(13), 10681. doi:10.3390/su151310681

Wang, Q., Zhao, Z., & Wang, Z. (2023). Data-driven analysis of risk-assessment methods for cold food chains. *Foods*, *12*(8), 1677. doi:10.3390/foods12081677 PMID:37107471

Wang, Y., Sun, R., Ren, L., Geng, X., Wang, X., & Lv, L. (2023). Risk propagation model and simulation of an assembled building supply chain network. *Buildings*, *13*(4), 981. doi:10.3390/buildings13040981

Yu, X., & Lou, W. (2023). An exploration of prediction performance based on projection pursuit regression in conjunction with data envelopment analysis: A comparison with artificial neural networks and support vector regression. *Mathematics*, *11*(23), 4775. doi:10.3390/math11234775

Zaare Tajabadi, F., & Daneshvar, S. (2023). Benchmark approach for efficiency improvement in green supply chain management with DEA models. *Sustainability (Basel)*, *15*(5), 4433. doi:10.3390/su15054433

Zhang, Y., Zheng, K., An, Y., & Bai, L. (2023). Service provider portfolio selection across the project life cycle considering synergy effect. *Buildings*, *13*(10), 2550. doi:10.3390/buildings13102550

Zheng, S., Yahya, Z., Wang, L., Zhang, R., & Hoshyar, A. N. (2023). Multiheaded deep learning chatbot for increasing production and marketing. *Information Processing & Management*, *60*(5), 103446. doi:10.1016/j.ipm.2023.103446

Zhong, J., Sun, L., Zuo, E., Chen, C., Chen, C., Jiang, H., Li, H., & Lv, X. (2023). An ensemble of AHP-EW and AE-RNN for food safety risk early warning. *PLoS One*, *18*(4), e0284144. doi:10.1371/journal.pone.0284144 PMID:37099538

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