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An ANP-Hopfield Neural Network Based Approach for Supply Chain Stress Testing

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Abstract: Supply chain resilience is increasingly critical in today's globalized and volatile business environment. This study proposes a novel approach to supply chain stress testing by combining Analytic Network Process (ANP) with Hopfield Neural Networks. The method constructs a stress testing index system based on product review, elasticity, agility, and cultural motivation. ANP is used to weight each index, while a discrete Hopfield neural network is employed to design equilibrium points corresponding to different stress levels. The model is applied to an automobile manufacturing case study, demonstrating its effectiveness in classifying supply chain stress levels. Results show that the proposed method can effectively identify key factors affecting supply chain stress and provide a comprehensive evaluation of supply chain resilience. This approach offers a new tool for supply chain managers to assess and enhance their networks' ability to withstand external pressures.

Keywords: analytical network process; Hopfield neural network; stress testing; supply chain

1 INTRODUCTION

The impact of global market globalization has resulted in unstable supply and demand, shortened product and technology lifecycles, external turmoil in the corporate environment, complex cooperative networks, and various other factors. These have led to increasing complexity in supply chain relationships and have been manifested in some negative characteristics [1]. In the global environment, gradual developments and frequent changes are unpredictable phenomena. Therefore, research on supply chain is still faced with many threats of interrupting activities and destroying performance, which leads to the risk of unstable supply chain management and resonates throughout the global production process. This process is not only important from the point of view of enterprises directly affected by interruptions, but is also important for decision makers to evaluate the potential imbalance between supply and demand and the resulting supply chain pressures [2-6].

Scholars discuss that during supply chain disruptions, there are disadvantages in terms of flexibility, time, and recovery capabilities [7]. In response to the supply chain stress problem, some scholars have worked on a more complete framework of their network to optimise the multi-objective supply network to cope with the expected existence of supply chain stress problems by optimising the supply chain network. However, it is important to recognise that supply chain networks are often plagued by uncertainty, inaccurate information, and qualitative factors, which will challenge the validity of the traditional supply chain stress testing methodology for real-world applications [8]. Some scholars have also focused on research and practical innovations covering some of the information including flexibility, redundancy, risk pooling, and capacity building. However, in the traditional supply chain stress test structure, test barriers often arise due to decentralised information sharing and time lags, resulting in uncoordinated competency levels between various interrelated components that do not comprehensively answer different stress test results from the same set of supply chain external environments faced. It was then suggested that supply chain organisations may have different levels of capability levels (agility, adaptability, etc.) within them, which ultimately is what leads to different results [9, 10]. Currently, exploring the implementation path of supply chain stability and security actions based on the supply chain organizational structure is a major research focus. Simchi-Levi published a ground-breaking paper titled "We Need a Stress Test for Critical Supply Chains", introducing the term "supply chain stress test". The paper clearly outlines the necessity of supply chain stress testing in the face of geopolitical tensions, product shortages, and technological bottlenecks [11]. However, there is an urgent need for practical solutions on how to carry out supply chain stress tests to effectively test out a stable supply chain network in the face of extreme and unexpected events, so as to enable the supply chain to operate securely and to anticipate possible supply chain risks. ANP is a method to consider the relationship among various factors in the decision-making process. The network in ANP method takes into account the internal dependencies between factors and factors in decision making problems modelled with structures. Because of this characteristic of ANP, it can solve decision-making problems in a more effective and realistic way. Therefore, the ANP method can be used for decision-making and decision-making problems in finance, marketing, health, politics and society. Although it has been used in many fields that need to be estimated, its application field is expanding day by day [12]. The Hopfield neural network system operates in the way of neurodynamic evolution. The working process is the evolution process of the initial state. For the initial operating state of a given system, it evolves in the way of capacity reduction and finally reaches a stable state [13]. Aiming at the supply chain pressure, this paper puts forward a supply chain pressure testing method based on ANP-Hopfield neural network, studies the factors that affect the supply chain pressure index in combination with ANP, uses Hopfield neural network to evolve the system to reach a stable state, and grades the supply chain enterprises according to the supply chain pressure testing index. Through the actual case study of an automobile manufacturing enterprise, the applicability and effectiveness of this testing method are verified, the ability to cope with the pressure of supply chain is improved, and new theoretical support and method direction are provided. This exploration has considerable theoretical and practical value, which has promoted the wider application of the ANP method and Hopfield neural network in the supply chain field.

2 LITERATURE REVIEW

2.1 Research on Supply Chain Stress Testing

Many experts and scholars in various fields study the external factors of the supply chain to enhance its economic benefits in green development [14-16], but due to the expansion of the global market, technological advancements, and shifts in consumer preferences, it is necessary to continuously reevaluate supply chain strategies [17]. In the production process of modern manufacturing enterprises, internal pressures and technological pressures within the supply chain have a positive impact on sustainable development practices. Whether from an industrial or agricultural perspective [18], businesses and governments are increasingly focusing on the internal issues within the supply chain and calling for their review and stress testing [19, 20]. Existing stress tests have become a practical tool for risk managers to assess and control all types of institutions and enterprises, improving the level of risk management and capital planning of the institutions tested [21]. But from a fundamental perspective, stress testing refers to the analysis of unexpected losses in an unknown but significant domain. Therefore, the application of stress testing is not limited to the scope of financial systems, financial institutions, and asset portfolios. In theory, any system facing risk exposure can undergo stress testing for the corresponding scenarios, such as in software engineering, medicine, and other fields. This also provides theoretical basis for the application of stress testing methods in supply chain management. Therefore, this paper introduces the idea of combining stress testing method in the financial field with supply chain risk management, defines the concept of supply chain stress testing, and clarifies its connotation, so that decision makers can evaluate the stability of supply chain more objectively and improve the risk management and planning level of supply chain system.

Stress testing is performed to ascertain the stability of a given system or entity. Assessing the resilience to extreme events, including tests beyond normal operational capacity, typically to a breaking point, to observe the outcomes [22]. When stress testing is used as one of the risk quantification tools in the financial domain, it reflects the potential losses that the financial industry may suffer when extreme adverse low-probability events occur.

The comprehensive analysis above indicates that stress testing is a risk analysis tool. The current supply chain system extends to the whole world and has the characteristics of complexity and fragility, that is, every node is a "fragile point", and the supply collapse of one node may destroy the whole supply system. It is particularly important to analyze the performance of the tested object under the sudden change pressure of key market variables, estimate the possible losses caused by this impact, and analyze the negative impact brought by these losses, so as to evaluate the vulnerability of the object [23]. This concept is introduced into supply chain risk management, where supply chain stress testing is defined as "a risk assessment technique or method used to measure the potential losses or negative impacts that may occur at the supply chain nodes or as a whole in the face of external shocks."

2.2 Research on Relevant Methods

Analytic Hierarchy Process (AHP) is a commonly used method in the comprehensive evaluation model, but it assumes that all elements of the decision-making problem are independent, which may not be true in complex practical problems. In order to overcome this limitation, Thomas L. Saaty put forward the Analytic Network Process (ANP) model, which is an extension of AHP and can deal with the interdependence and feedback between elements. It is considered to be a more general form of ANP. ANP helps to address more complex situations, relationships, and interdependencies, and even provides feedback between elements in a hierarchical structure. The application of ANP can also be found in various fields such as engineering, social sciences, and environmental research, providing a deeper focus on risk and uncertainty [24]. At the core of it, the Analytic Network Process (ANP) thoroughly considers the interdependencies between different levels and the interactions among elements within the same level, to comprehensively evaluate various alternatives and arrive at the optimal decision. As a rapid multi-attribute decision-making tool, ANP is capable of enhancing supply chain performance and integrating different alternative options into the decision model. It takes into account the interrelationships between hierarchical structures, enabling the integration of decision-makers' opinions and assessments to design complex problems into a simple, high-level decision system, which is effective in understanding both qualitative and quantitative factors [25, 26].

Scholars have conducted extensive research on enhancing the security level of the supply chain and have proposed numerous excellent theoretical analyses. However, in the process of supply chain risk assessment, without conducting a thorough risk assessment to prioritize risks, proactive planning and mitigation strategies are built on an unreliable foundation. Despite the clear need to assess supply chain risks, research on specifically developing a widely applicable risk assessment model remains limited [27]. Therefore, this article proposes a comprehensive model to further enhance supply chain resilience and improve supply chain security levels. ANP can help decision-makers to face complex problems. When establishing an ANP network hierarchy with a large number of elements, decision makers should try to arrange them in clusters, so that they will not be extremely different. It allows policymakers to sensitively evaluate the relative weights of multiple standards or multiple options relative to given standard. When quantitative ratings are not available, policy makers or evaluators can recognize whether one standard is more important than another.

The Hopfield neural network is a recurrent associative neural network model that takes input from all neurons and retrieves memories from partial or noisy inputs. After receiving an input, the Hopfield neural network uses iterative updating to update the state of the neuron either synchronously or asynchronously to converge to one of the stored memories and reach a stable state that recalls the information on which it was trained [28]. From the calculation point of view, it has strong calculation ability. Such a system focuses on the stability of the system. Stability is the core of this kind of neural network model with associative memory function, and the process of learning and memory is the process of the system developing to a stable state. Combined with the criteria formulated by ANP, the problem can be explained stably.

This paper combines the Analytic Network Process (ANP) and the discrete Hopfield neural network method to conduct stress testing on the supply chain security. On one hand, it leverages the advantages of ANP in multi-criteria decision analysis, comprehensively considering the interdependency of multiple factors and conducting structured analysis. On the other hand, it harnesses the advantages of Hopfield neural networks in solving combinatorial optimization problems, parallel computation, processing real-time data, and real-time pattern recognition, providing powerful tools for supply chain security. The existence, uniqueness, and global asymptotic stability (GAS) of its equilibrium points provide reliable, stable, and accurate data results for supply chain risk stress testing. Steps of the ANP-Hopfield neural network method: (1) Determine the pressures and construct a hierarchical model of the network for priority ranking; (2) Establish a comparison judgement matrix and calculate the weight vector; (3) Construction and normalisation of the supermatrix; (4) Determine the normalised weights for each pressure category and for a specific pressure; (5) Combine the average value of each evaluation indicator corresponding to the samples of each class with the ANP analysis weight values as the ideal evaluation index for each class, i.e., as the equilibrium point of the Hopfield network; (6) coding the ideal class evaluation indexes and the class evaluation indexes to be classified; and (7) creating the network for simulation training and analysis. The decision maker then makes a comprehensive evaluation and decision on the results.

3 METHODOLOGY DESIGN

3.1 Supply Chain Stress Test Lndicator System Construction

Based on the study by Dubey et al. [24], it is believed that future supply chain management will become more complex. In traditional supply chains, the focus has been on cost, quality, and service. However, in the future, supply chains will also need to focus on three new indicators that can enhance supply chain resilience - elasticity, agility, and cultural intrinsicness. Thus, this paper uses product review (including product quality, cost, and service reviews), elasticity, agility, and cultural intrinsicness as the four criteria for supply chain stress testing, and the supply chain stress testing index system is shown in Tab. 1. The higher the product review score, the greater the supply chain elasticity, the better the agility, and the stronger the cultural intrinsicness, the smaller the potential losses or negative impacts that may occur when the supply chain faces external shocks. In other words, the stronger the supply chain's ability to withstand pressure, the lower its fragility.

Product review includes the examination of product quality, cost, and service, with the selection of product qualification rate as the evaluation criteria for product quality review; product cost advantage as the evaluation criteria for product cost review; and customer complaint rate as the evaluation criteria for service review. That is, based on the quality review, cost review, and service review of the main products in the supply chain as the standard for stress testing, the supply chain pressure is diagnosed.

Table 1 Supply chain stress test indicator system

Test criteria	Specific test indicators
Product review P1	Product pass rate C1
	Product cost advantage C2
	Customer complaint rate C3
Elasticity P2	Resilience of production network C4
	Resilience of logistics network C5
	Resilience of sourcing network C6
Agility P3	Degree of digitization C7
	Degree of intelligence C8
	Operational management efficiency C9
	Risk monitoring capability C10
Cultural motivation P3	Risk management team C11
	Consistency of objectives C12
	Organizational risk awareness C13
	Learning and innovation ability C14

The term "supply chain resilience" refers to the ability of a supply chain to maintain continuous supply and quickly recover to normal supply status in the event of partial failure [25]. Goldspink and Kay [26] applied complex system theory to organizations as network structures in order to explain the dynamic evolution of organizations, especially the dynamic evolution of resilience, by analyzing the coexistence and consistency of connection units. Zamboni [27] suggests that the most effective way to achieve supply chain resilience is to create a supply chain collaboration network that can quickly respond to changes in status. Therefore, this paper characterizes the level of supply chain resilience from the perspective of supply chain network collaboration and resilience, and takes production network resilience, logistics network resilience, and sourcing network resilience as its stress testing indicators.

The agility of the supply chain places special emphasis on unforeseen changes in market and customer demands. A highly agile supply chain allows a company to rapidly respond to unpredictable changes in customer demands, in a way that meets these changes without incurring significant losses or negative impacts on other customers. Therefore, supply chain agility is considered a dynamic capability [27]. From the perspective of dynamic capabilities, supply chain agility stems from four aspects: the flexibility of manufacturing processes, the lean nature of manufacturing, the relationships between entities in the supply chain, and the ability to perceive risks [28, 29]. Therefore, this paper selects digitalization, the level of intelligence, operational efficiency, and risk monitoring capabilities as the testing indicators for supply chain agility.

The intrinsic culture of the supply chain is a characteristic of the continual pursuit of new development capabilities within the supply chain. Enterprises and governments are increasingly emphasizing the creation of better culture and creative environment to drive better economic development benefits [30]. The process of adapting to new development capabilities within the supply chain is often chaotic and unbalanced. Existing internal culture and structures hinders the adaptation process in order to "sustain their own existence" [31]. A strong internal culture requires consistency between the organization's values, beliefs, and norms. Therefore, organizations with high intrinsic supply chain culture will facilitate healthier relationships and more proactive knowledge sharing internally, leading to innovation, responsiveness, better decision-making, increased productivity and competitiveness, as well as collaborative risk management [32, 33]. Hence, this paper selects risk management team, goal consistency, organizational risk awareness, and learning innovation capabilities as test indicators for the intrinsic culture of the supply chain.

3.2 Algorithm for Weighting Stress Test Metrics

In the process of designing a stress test scale for the supply chain, there is a clear hierarchical structure between the same stress dimensions, and a strong interdependence between different stress dimensions. The interrelationship between different levels and indicators within the same level is more significant. Therefore, this article uses the Analytic Network Process (ANP) to accurately characterize the interactions among various elements within the supply chain, as well as the non-independent hierarchical structure.

The basic structure of ANP includes the control layer, the network layer, and the scheme layer, and there are influencing relationships between elements within the same layer. Furthermore, the super matrix algorithm is used to handle the influences and feedback relationships between stress test indicators. This paper designs an ANP hierarchical structure diagram for the supply chain stress test, as shown in Fig. 1.

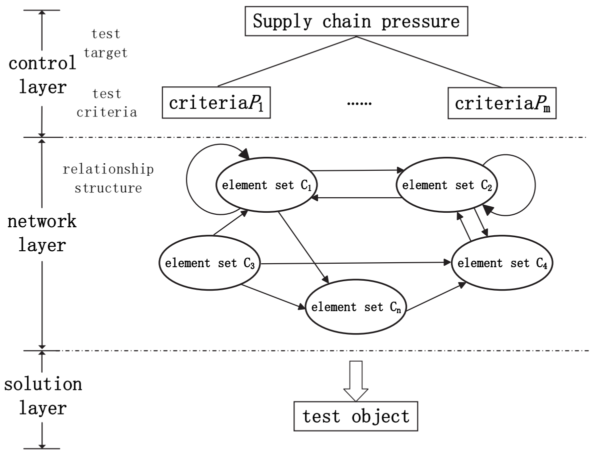

Figure 1 ANP network diagram

3.2.1 The Algorithm for Supermatrix Calculations

In the ANP control layer, the criterion element for P_s $(s = 1, 2, \cdots, m)$ is identified, with the network layer element set as C_N $(N = 1, 2, \cdots, n)$, where C_i contains element $C_N C_{i1}, C_{i2}, \cdots, C_{in}$ $(i = 1, 2, \cdots, N)$. Using P_s as the criterion, and C_j element C_{j1} as the sub-criteria, pairwise comparisons between elements are made using the nine-point scale (as shown in Tab. 2), thereby constructing a judgment matrix $(w_{i1}, w_{i2}, \cdots, w_{in})^T$, obtaining the normalized characteristic vector, and conducting a consistency check. This ultimately yields a supermatrix W_{ij}:

$$W_{ij} = \begin{bmatrix} w_{i1}^{(j1)} & w_{i2}^{(j2)} & \cdots & w_{i1}^{(jn_j)} \\ w_{i2}^{(j1)} & w_{i2}^{(j2)} & \cdots & w_{i2}^{(jn_j)} \\ \vdots & \vdots & \ddots & \vdots \\ w_{in_i}^{(j1)} & w_{in_i}^{(j2)} & \cdots & w_{in_i}^{(jn_j)} \end{bmatrix}$$

where, C_i element $C_{i1}, C_{i2}, \cdots, C_{in}$ is the column vector of W_{ij}. If $C_{i1}, C_{i2}, \cdots, C_{in}$ has no effect on the elements of C_j, then $W_{ij} = 0$. Eventually, under the P_s criterion, the supermatrix W is obtained:

$$W = \begin{bmatrix} w_{11} & w_{12} & \cdots & w_{1N} \\ w_{21} & w_{22} & \cdots & w_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ w_{N1} & w_{N2} & \cdots & w_{NN} \end{bmatrix}$$

Table 2 Nine-point scale of relative importance

Scale	Definition
1	*i* element is equally important as *j* element
3	*i* element is slightly more important than *j* element
5	*i* element is moderately more important than *j* element
7	*i* element is very important compared to *j* element
9	*i* element is absolutely more important than *j* element
2，4，6，8	Intermediate value between adjacent judgments
Reciprocal value	Importance scale of *j* element to *i* element

3.2.2 Weighted Matrix and Weighted Supermatrix Algorithm

Under the P_s criterion, by comparing the relative importance of C_j $(j = 1, 2, \cdots, N)$ elements to the criterion, a normalized ranking column vector $a_{1j}, a_{2j}, \cdots, a_{Nj}$ is obtained, and then a weighted matrix A is constructed:

$$A = \begin{bmatrix} A_{11} & A_{12} & \cdots & A_{1N} \\ A_{21} & A_{22} & \cdots & A_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ A_{N1} & A_{N2} & \cdots & A_{NN} \end{bmatrix}$$

$$\left(a_{ij} \in [0,1]; \sum a_{ij} = 1\right)$$

If there is no interaction between the elements, then $a_{ij} = 0$. Finally, a weighted supermatrix $\bar{W}$ is constructed:

$$\bar{W} = \bar{W}_{ij} = A \cdot W = \left(a_{ij} \cdot W_{ij}\right)$$

$$\left(i = 1, 2, \cdots, N; j = 1, 2, \cdots, N\right)$$

where the local weights of each criterion can be obtained from the result of the supermatrix, and the global weights of each criterion can be obtained from the result of the weighted supermatrix.

3.3 Modelling Supply Chain Stress Testing

Based on the weight algorithm of stress testing indicators, the stress level of the supply chain is designed according to the indicator weight, and the stress level code is used to create a discrete Hopfield neural network (DHNN). Binary neurons are used, and the network evolves in the direction of reducing the initial state energy (Lyapunov function) until the stable state output network is reached, depicting the activation or inhibition results of different stress levels in the supply chain. The stress index data of the supply chain is pre-trained with the Hopfield neural network, using its associative memory ability to gradually approach the balance points of different stress levels, and establish a discrete Hopfield supply chain stress test model.

3.3.1 Network Structure and Algorithm

The DHNN is a single-layer, binary output feedback network, where each neuron's output is connected to the input of other neurons, and there is no self-feedback at each node. The first layer serves as the network input, the second layer consists of neurons that perform the summation of the product of the input information and the weight coefficients, and produce output information after being processed by the non-linear function f. The structure of the discrete Hopfield neural network consisting of three neurons is shown in Fig. 2.

The first layer is the network input layer, and the second layer is the neural unit, which computes the sum of the products of the input information and the weights, and generates the output information after being processed by the non-linear threshold function, f (sigmoid function).

Output rule: If the output information of the neural unit is greater than the threshold θ, the output value is 1; if it is less than the threshold θ, the output value is –1.

The threshold function is represented by: $f\left(t\right)=(1+e^{-t})^{-1}$.

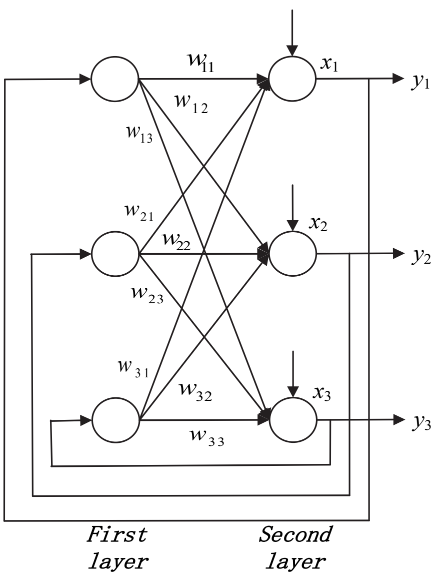

Figure 2 Structure of DHNN

According to the output pattern of the industry chain stress test, binary neurons are used to calculate the output result:

$$\omega_j=\sum_i \sigma_{ij} y_i + x_i$$

where x_i is an external input, and there exists:

$$\begin{cases} y_j=1 & , \ \omega_j \geq \theta_j \\ y_j=-1 & , \ \omega_j < \theta_j \end{cases}$$

Therefore, for the output layer with a network of n neurons, the state of time t is represented by an n-dimensional vector:

$$Y\left(t\right)=[y_1\left(t\right), y_2\left(t\right), \cdots, y_n\left(t\right),]^T$$

Using $y_j\left(t\right)$ to represent the state of the j-th neuron at time t, the algorithm for the state of the node at time $(t + 1)$ is as follows:

$$y_j\left(t+1\right)=f\left[\omega_i\left(t\right)\right]=\begin{cases} 1 & , \ \omega_j\left(t\right)\geq\theta_j \\ -1 & , \ \omega_j\left(t\right)<\theta_j \end{cases},$$

$$\omega_i\left(t\right)=\sum_{i=1}^{n}\omega_{ij} y_i\left(t\right)+x_j-\theta_j .$$

Simulate the supply chain pressure transmission process in a dynamic way, and the neurons evolve from the initial state in the direction of "energy" reduction (Lyapunov function), using asynchronous running mode (i.e., at any time t, only one neuron i changes, while the states of other neurons remain unchanged) until the stable state (when the weight coefficient matrix is a symmetric matrix and the diagonal elements are 0, the network is stable), which is the network output. The evaluation indexes corresponding to several typical classification grades are designed as the equilibrium point of discrete Hopfield neural network, and the learning process of Hopfield neural network is the process in which the evaluation indexes of typical classification grades gradually approach the equilibrium point of Hopfield neural network. After learning, the equilibrium point stored by Hopfield neural network is the evaluation index corresponding to each classification level. When the evaluation index of the problem to be classified is input, Hopfield neural network gradually approaches a stored equilibrium point by using its associative memory ability. When the state does not change, the equilibrium point corresponds to the classification level to be solved. In MATLAB, by creating a weight matrix W with the size of $N \times N$, where n is the number of neurons. The weight matrix satisfies symmetry and all diagonal elements are 0, which ensures the stability of the network.

3.3.2 Model Construction

In order to ensure the symmetry of the network weight and the convergence of the network to the equilibrium point, the Hopfield network for supply chain stress testing is designed by orthogonal method, that is, the weight W and deviation b are generated according to the given target vector design. Make the stable output vector of Hopfield network consistent with the given target vector. Firstly, setting n input modes; $t=\left\{t^2,t^2,\cdots,t^{N-1},t^N\right\}$ and parameters τ and h, where τ is a parameter greater than –1, and its default value is set to 10, which plays a key role in constructing the connection weight matrix of Hopfield network. As a scaling factor (or learning rate), parameter H is used to adjust the range of weight updating.

Calculate and solve singular value decomposition, and calculate the rank of A as:

$$A=\left\{t^2-t^N,t^2-t^N,\cdots,t^{N-1}-t^N\right\};$$
$$A=USV^T K-rank\left(A\right)$$

Then calculate the sum from and respectively;

$$T^P=\sum_{I=1}^{K}u^i(u^i)^T T^m=\sum_{i=K+1}^{N}u^i(u^i)^T$$
$$U^P=\left\{U^1,U^2,\cdots,U^k\right\}U^m=\left\{U^{K+1},U^{K+2},\cdots,U^N\right\}$$

Then solves $W^t=T^P-\tau\times T^m;b^t=t^N-W^t\times t^N$.

where T is a parameter greater than -1, and the default value is 10. Both T^P and T^m satisfy the symmetry condition, so the component in W^t also satisfies the symmetry condition. This ensures that the system can converge when asynchronous and there will be no limit cycle.

Finally, calculate $W=\exp(h\times W^t)$. Among them, h, as a scaling factor, affects the learning rate of the network in the process of learning or training, that is, how the network quickly or slowly adjusts its weight to adapt to the input data or optimization objectives.

$$b=U\times\begin{bmatrix} C_1\times I\left(K\right) & 0\left(K,N-K\right) \\ 0\left(N-K,K\right) & C_2\times I\left(N-K\right)\end{bmatrix}\times U^T\times b^t$$

where $C_1=\exp(h)-1$, $C_2=-\left[\exp(-\tau\times h)-1\right]/\tau$.

4 EXAMPLE ANALYSIS

This paper selects the automobile manufacturing field as a case study, analyzes the indicators in the supply chain stress test scale, and applies the above indicator system and model to empirical research to illustrate the application process and practical value of the ANP-Hopfield neural network method.

4.1 Determination of Indicator Weights and Extraction of Core Indicators

Based on the dimensions and the relationship between the indicators in the supply chain pressure test scale, it can be seen that product review, flexibility, agility, and cultural drive are the internal independent indicator layer (control layer), and their weights are determined to use the Analytic Network Process (ANP); there exist certain influences or dependencies between elements within the element group as shown in Fig. 3, and by constructing the supermatrix to solve the limit supermatrix, the weights of each element are obtained.

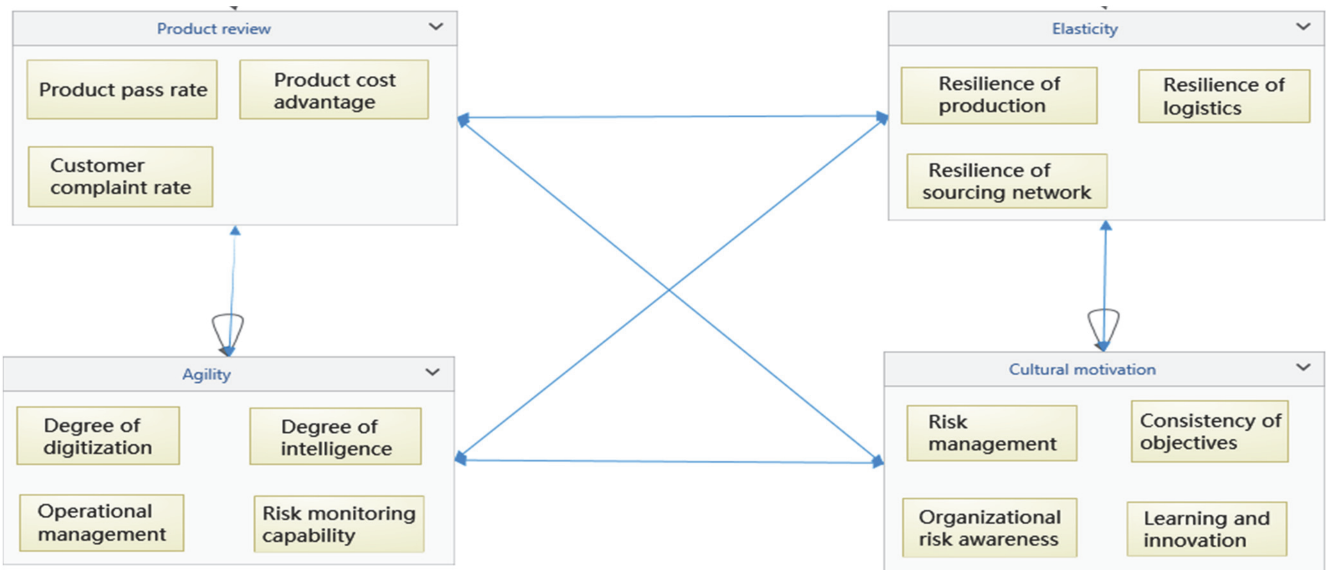

Figure 3 ANP network structure of a certain automobile manufacturing company JH

In this paper, using the software yaanp, after inputting element groups and elements, comparing between element groups and elements in pairs, constructing a judgment matrix, quantifying the relative importance of each element, and calculating the weight vector of the judgment matrix by eigenvalue method. For each judgment matrix, the maximum eigenvalue and its corresponding eigenvector are solved and normalized. A hypermatrix is constructed, and its column vectors are composed of the weight vectors of each element. The weighted hypermatrix (Tab. 3) is obtained, which includes the mutual influence among the elements. Then the weighted hypermatrix is squared until it converges, and finally the limit matrix is obtained. When the result of the limit matrix tends to be stable, the corresponding index weight, that is, the stable state of the hypermatrix, can be obtained. The comprehensive weight of each alternative is calculated by the extreme hypermatrix, and the comprehensive evaluation is carried out. The index system of supply chain stress test (Tab. 4) can be used to determine the ranking of each index pressure level through the global weight.

Table 3 Weighted Supermatrix

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14
C1	0	0.077	0.089	0.252	0.213	0.213	0.056	0.168	0.118	0.171	0.064	0	0.046	0
C2	0.013	0	0.013	0.032	0.071	0.071	0.168	0.056	0.031	0.027	0.021	0	0	0.19
C3	0.089	0.026	0	0	0	0	0	0	0.074	0.026	0.143	0.228	0.182	0.038
C4	0.322	0.106	0	0	0.367	0.229	0.34	0.358	0.191	0.086	0.015	0.026	0.026	0
C5	0.04	0.317	0	0.066	0	0.229	0.09	0.137	0.191	0.072	0.006	0.026	0.026	0
C6	0.108	0.047	0	0.393	0.092	0	0.143	0.078	0.191	0.415	0.056	0.026	0.026	0
C7	0.02	0.198	0	0.052	0.106	0.116	0	0.075	0.021	0.076	0.008	0.009	0.014	0.01
C8	0.087	0.105	0	0.013	0.061	0.045	0.076	0	0.092	0.011	0.005	0.013	0.034	0.039
C9	0.04	0.045	0.053	0.102	0.018	0.021	0.029	0.014	0	0.034	0.018	0.029	0.005	0.005
C10	0.228	0.027	0.32	0.026	0.009	0.011	0.017	0.033	0.01	0	0.027	0.006	0.004	0.003
C11	0.013	0.008	0.028	0.01	0.009	0.014	0.011	0.005	0.02	0.038	0	0.178	0.4	0.1
C12	0	0	0.005	0.047	0.04	0.043	0.021	0.021	0.011	0.009	0.106	0	0.06	0.475
C13	0.04	0	0.016	0.007	0.015	0.008	0.008	0.012	0.005	0.025	0.472	0.046	0	0.063
C14	0	0.046	0.005	0	0	0	0.041	0.044	0.046	0.008	0.06	0.414	0.178	0

Table 4 Supply chain pressure test indicator system

Target level	Primary indicators	Weight	Secondary indicators	Local weight	Global weight	Pressure level ranking
Supply chain pressure test index system	P1	0.225543	C1	0.485084	0.13402	3
			C2	0.163039	0.048552	7
			C3	0.351877	0.042971	10
	P2	0.399854	C4	0.418055	0.166176	1
			C5	0.250859	0.090702	4
			C6	0.331086	0.142976	2
	P3	0.21101	C7	0.288834	0.058047	6
			C8	0.267726	0.043487	9
			C9	0.269805	0.040571	12
			C10	0.173635	0.068905	5
	P4	0.163594	C11	0.279695	0.040753	11
			C12	0.224731	0.047427	8
			C13	0.278283	0.03734	14
			C14	0.217291	0.038074	13

4.2 Supply Chain Stress Testing Hopfield Neural Network Establishment

Based on the construction of the supply chain stress test model, this case study divides the first level (I), second level (II), third level (III), fourth level (IV), and fifth level (V) into five levels of cases (I level has the highest security and the lowest level of stress), and establishes a flow chart, Fig. 4, to show the detailed steps.

Based on the establishment of the discrete neural network model, the stress of the supply chain of 20 automobile manufacturers is taken as sample data, with 14 evaluation indicators, and a 100-point scoring method is used for secondary indicators. After taking the average and multiplying by the corresponding global weight obtained by ANP analysis, the global score of the secondary indicators is obtained. Then, the total evaluation score of each sample is calculated, and the total evaluation score of each evaluation indicator corresponding to the samples of each level is taken as the ideal evaluation indicator of each level, which is the balance point of the Hopfield neural network. After relevant calculations, the ideal evaluation indicators of the 14 ideal evaluation indicators of the 5 levels are obtained as shown in Tab. 5.

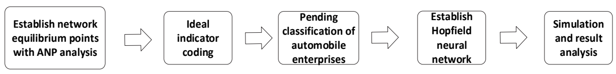

Figure 4 Network establishment process diagram

Table 5 Ideal evaluation indicators for supply chain stress testing levels

Ideal evaluation indicators for levels														
Indicators / Levels	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14
I	12.20	4.47	3.87	15.29	8.07	13.30	5.28	3.91	3.65	6.27	3.75	4.22	3.47	3.46
II	10.05	3.84	3.39	12.63	7.26	11.58	4.47	3.31	3.25	5.37	3.26	3.75	3.06	2.93
III	8.18	3.16	2.66	10.14	5.90	8.86	3.72	2.83	2.68	4.48	2.57	3.18	2.39	2.55
IV	5.76	2.28	2.11	8.81	4.81	6.72	2.55	2.13	2.03	3.93	1.87	2.13	1.83	1.68
V	3.35	1.51	1.29	4.49	2.27	4.43	1.63	1.04	1.18	2.21	1.10	1.33	0.93	1.18

In order to visualize the data, when mapping the evaluation indicators to the neuron state, it needs to be encoded. Here, it is stipulated that when the value is greater than or equal to the ideal evaluation indicator, the state of the neuron is set as 1, and vice versa, the state of the neuron is taken as –1. The coding of the ideal evaluation indicators for the five levels is as follows in sequence, where ● indicates the state of the neuron as 1, i.e., greater than or equal to the corresponding level's ideal evaluation indicator value, and otherwise, ○ is used to represent it. ● and ○ as a representation of the result of the encoding can be replaced by other conformities.

The evaluation indicators for the five classified automotive supply chain pressure levels are listed in Tab. 6, and the corresponding code for Fig. 6 is obtained based on the above coding rules.

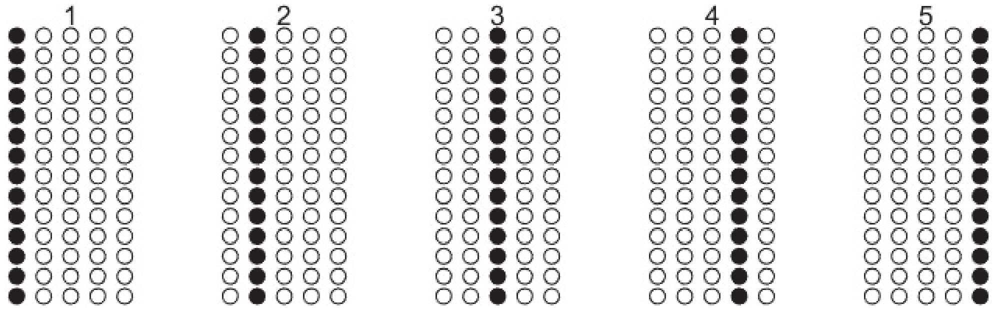

Figure 5 Coding of ideal evaluation indicators for the five levels

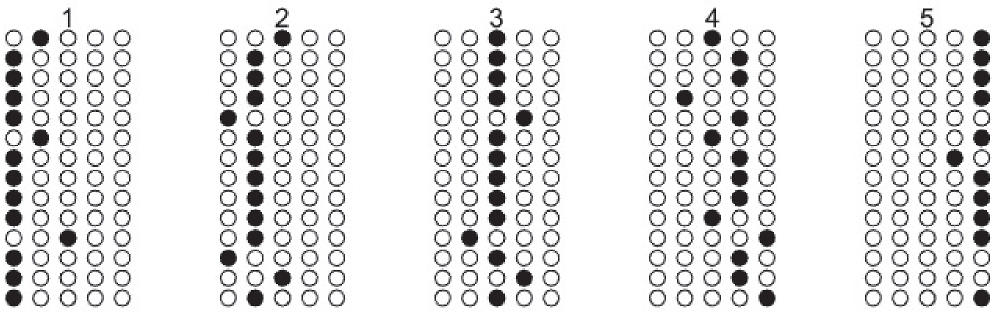

Figure 6 Coding of supply chain stress test grade index of five automobile companies to be classified

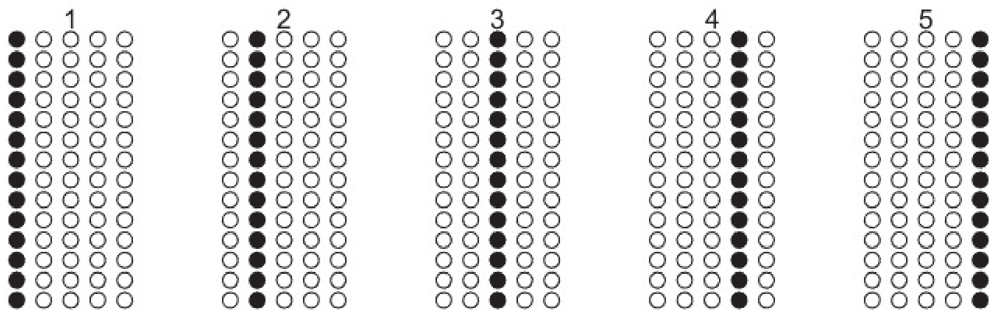

Figure 7 Evaluation results of supply chain stress test index codes of five representative automobile companies to be classified

Table 6 Grade index of supply chain stress test of five automobile companies to be classified

Ideal evaluation indicators for levels														
Indicators / Group	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14
1	11.53	4.56	3.91	15.62	8.62	12.87	5.40	3.96	3.65	6.41	3.10	4.32	3.55	3.54
2	9.52	4.18	3.39	12.63	8.53	11.58	5.05	3.31	3.25	5.72	3.34	4.22	2.84	3.01
3	8.44	3.40	2.88	10.97	5.17	9.58	4.12	3.04	2.88	4.82	3.34	3.27	2.09	2.63
4	8.31	2.86	2.19	14.13	4.99	10.44	3.25	2.22	2.11	5.03	1.83	2.23	1.90	1.45
5	3.75	1.60	1.80	4.82	2.18	4.72	2.84	1.13	1.26	2.34	1.18	1.23	0.78	1.26

After the network is created, the coding of the evaluation indicators for the supply chain pressure testing levels of the five representative automobile companies will be used as the input for the Hopfield neural network. Through programming using MATLAB software to build and train the discrete neural network, simulation results can be obtained, as shown in Fig. 6.

SPSS was used to test the significance of grades, and 70 supply chain pressure grade index data of five automobile manufacturers were selected from the sample data, and 70 supply chain pressure grade evaluation index data of five representative automobile companies were tested for significance between different pressure grade levels. According to the test results, sig value = 0.028 is less than 0.05, so the observed difference is statistically significant, that is, statistically significant.

Table 7 Test statistics[a]

	level
Mann-Whitney U	1762.000
Wilcoxon W	4040.000
Z	–2.196
Asymp.Sig.(2-tailed)	0.028

a. Grouping Variable: group

As a result of the simulation run, the supply chain stress test levels of the five representative automobile companies to be classified are I, II, III, IV and V, respectively. The designed Hopfield network can effectively classify and thus provide an objective and fair evaluation of the automotive supply chain pressure testing levels.

5 CONCLUDING REMARKS

This study demonstrates the effectiveness of combining ANP with Hopfield Neural Networks for supply chain stress testing. The proposed method provides a comprehensive framework for assessing supply chain resilience, considering multiple factors such as product review, elasticity, agility, and cultural motivation. The application to an automobile manufacturing case study validates the model's ability to classify different stress levels and identify key factors affecting supply chain resilience. However, limitations exist, such as the need for extensive data and expert judgment in the ANP process. Future research should focus on expanding the model to different industries, incorporating real-time data, and developing more automated methods for stress level classification. The findings of this study offer valuable insights for supply chain managers seeking to enhance their networks' resilience in the face of increasing global uncertainties.

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