J. COMBIN. MATH. COMBIN. COMPUT. 127b (2025) 3867--3886

Journal of Combinatorial Mathematics and Combinatorial Computing
www.combinatorialpress.com/jcmcc

Research on Modeling and Efficiency Enhancement of Complex Corporate Financial Networks Based on Topological Computing Optimization

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ABSTRACT

With economic globalization and the increasing complexity of inter-enterprise business linkages, corporate financial systems have gradually taken on the characteristics of complex networks. This paper firstly gives an overview of the complex network and introduces its basic topological properties, such as clustering coefficient and path length. After that, through the principal component analysis method, the enterprise financial risk early warning indicators are identified, and the key indicators are screened to improve the early warning accuracy. Based on these properties, the financial risk conduction network model of complex enterprises is constructed, the characteristics of the network are analyzed, including network density, centrality distribution, etc., and the effect of financial efficiency enhancement of complex enterprises under the optimization of topology computation is verified in real cases. The results show that most of the financial risk indicators of enterprises have strong correlation, and the degree of centrality of 9 indicators such as "gearing ratio and quick ratio" is more than 50%. In addition, the indicators of "current asset turnover ratio, interest coverage multiple, net profit growth rate" can play the role of intermediary and bridge, and the risk transmission effect among the indicators is high. The threshold value of 0.65 is the watershed of the changes in the financial structure of enterprises, and most of the financial risks in the network have a high degree of similarity in the financial structure when the degree value is 70, and it is negatively correlated with the coefficient of agglomeration, and the coefficient of agglomeration decreases with the increase in the intensity of the points.

Keywords: Topological computation optimization, Complex financial network, Risk transmission, Principal component analysis

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Received 15 April 2024; Revised 05 July 2024; Accepted 25 November 2024; Published Online 16 April 2025.
DOI: 10.61091/jcmcc127b-215

1. Introduction

Enterprise financial network at the beginning of the establishment of the company does not have a unified plan, but according to the enterprise's own needs to establish, whether it is financial network planning or financial management software are not in the company group intranet system [1-2]. Relatively speaking, enterprises focus on production and light management, financial network is usually in line with the immediate needs without long-term planning, corporate financial constraints, hardware equipment update speed can not keep up with the speed of software updates, but also can not keep up with the requirements of the modern financial intensive management, at the same time, enterprise personnel update and follow-up training is slow [3-5].

Enterprise financial network construction refers to the deep integration of digital technology and artificial intelligence technology to realize the intelligent collection, processing, analysis and application of data [6-8]. In the field of finance, enterprise financial network construction mainly includes the use of emerging technologies such as big data, cloud computing, artificial intelligence, blockchain, etc., to collect, save and analyze a large amount of financial information, so as to provide a more in-depth and accurate data basis for financial analysis [9]. Utilizing cloud computing technology, financial data can be stored and shared remotely, thus enhancing the security and usefulness of the data [10]. Using various algorithms such as machine learning and deep learning, financial data are analyzed and predicted in an automated manner, thus enhancing the efficiency and accuracy of financial analysis [11-12]. Utilizing blockchain technology, the authenticity and non-tampering of financial information can be ensured, thus enhancing the reliability of financial data [13]. The emergence of enterprise financial network construction has brought new opportunities and challenges for enterprise financial management. Enterprises need to actively embrace the construction of enterprise financial network, and constantly explore and innovate the financial management mode to adapt to the needs of market competition [14-15].

Enterprise financial network construction is mainly manifested in the following aspects, the first is financial process automation. Utilizing Robotic Process Automation (RPA) technology, financial processes can be automated, such as generating financial reports, reviewing invoices, and reimbursing expenses. Automated financial processes help to improve the efficiency and accuracy of financial operations, as well as reduce errors and repetitive labor caused by human factors. The second is data analysis intelligence [16-18]. Using big data, artificial intelligence and other technologies, financial data can be analyzed intelligently, such as financial risk assessment, business performance analysis, budget execution analysis and so on. Intelligent data analysis can help enterprises find problems and make decisions in a timely manner, and improve the management level and competitiveness of enterprises [19-20]. Furthermore, it is real-time financial decision support. Through real-time data collection, analysis and processing, it helps enterprises make more timely and accurate financial decisions, such as providing real-time financial data, analysis results and decision-making recommendations [21]. Real-time financial decision support can help companies respond quickly to market changes and improve the timeliness and accuracy of decision-making. There is also the financial sharing center as an emerging financial management model, through the centralization of financial affairs, standardization of financial processes, and the use of information technology to achieve the optimization of financial functions and improve the quality of financial services [22-24]. Finally, the digitalization of financial management, through the establishment of a digital financial management platform, the digital transformation of financial management can be achieved, such as financial budget management, capital management, cost management and so on. The digitalization of financial management can improve the efficiency and transparency of financial management and reduce management costs and risks [25-26].

In this paper, from the perspective of complex networks, the basic topological properties of complex networks are introduced in detail, including node connectivity and small-world networks. By means of principal component analysis, key indicators are extracted from a large number of financial indicators to establish an early warning analysis method for corporate financial risk. On this basis, the enterprise financial risk conduction model is established, and its network characteristics are analyzed in depth to reveal the characteristics of risk conduction within and between enterprises. Finally, the topological nature of the network of this paper's model under different thresholds and the evolution characteristics of the network under specific thresholds are analyzed through actual cases.

2. Basic characteristics of complex networks

Complex networks [27] are networks consisting of a large number of interconnected nodes, whose connections and structures usually exhibit a certain degree of complexity and non-uniformity. The relationship between the four types of graphs is shown in Figure 1.

A network containing N vertex and M edges can be abstracted as a graph $G=(V,E)$ with the number of vertices $N=|V|$ and the number of edges denoted as $M=|E|$, where $V=\{v_1,v_2,v_3,\ldots,v_N\}$, the set of edges $E\subseteq\{(v_i,v_j);v_i,v_j\in V,i\neq j\}$, is weighted according to whether the edges in the graph are directed or not and whether they are weighted or not.

For an undirected graph, the elements at (i,j) and (j,i) in the adjacency matrix have the value l when there is an edge between node i and node j, and for a directed graph, the element at (i,j) in the adjacency matrix has the value 1 when there is a directed edge between node i and node j.

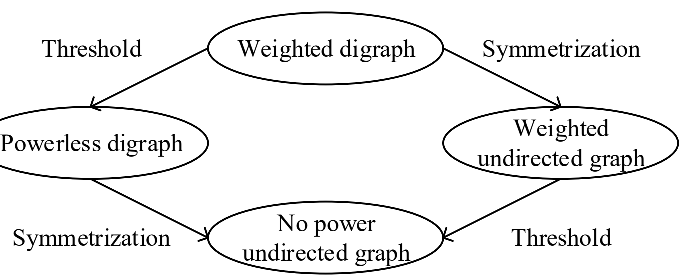

Fig. 1. Relationship between the four types of graphs

The adjacency matrix $A=(a_{ij})$ of Fig. $G=(V,E)$ is a matrix of $N\times N$. The elements on row i and column j are defined as follows:

Weighted directed graph:

$$a_{ij}=\begin{cases} w_{ij}, & \text{If you have edges with weights } w_{ij} \text{ that point from vertex } i \text{ to vertex } j \\ 0, & \text{If there is no edge from vertex } i \text{ to vertex } j \end{cases} \tag{1}$$

Weighted undirected graphs:

$$a_{ij}=\begin{cases} w_{ij}, & \text{If the edge between vertex } i \text{ and vertex } j \text{ has a value of } w_{ij} \\ 0, & \text{If there is no edge between vertex } i \text{ and vertex } j \end{cases} \tag{2}$$

Unprivileged directed graphs:

$$a_{ij}=\begin{cases} 1, & \text{If there are edges from vertex } i \text{ to vertex } j \\ 0, & \text{If there is no edge from vertex } i \text{ to vertex } j \end{cases} \tag{3}$$

Unprivileged undirected graphs:

$$a_{ij}=\begin{cases} 1, & \text{If there is an edge between vertex } i \text{ and vertex } j \\ 0, & \text{If there is no edge between vertex } i \text{ and vertex } j \end{cases} \tag{4}$$

2.1. Basic Network Topology Properties

1) Degree. Degree of a node [28] is an important concept that can be used to measure the importance and degree of connectivity of a node in a network. Generally, k_i is used to denote the degree value of node i, and k_i^{in} and k_i^{out} denote the out-degree and person-degree of node i, respectively. The average of the degree values of all nodes in the network is called the average degree of the network and is denoted as $\langle k \rangle$.

For an undirected network consisting of N nodes, the degree of node i is given by:

$$k_i = \sum_{j=1}^{N} a_{ij} \tag{5}$$

For a directed network consisting of N node, the degree of node i is given by:

$$k_i = k_i^{in} + k_i^{out} \tag{6}$$

Among them:

$$k_i^{in} = \sum_{j=1}^{N} a_{ji} \tag{7}$$

$$k_i^{out} = \sum_{j=1}^{N} a_{ij} \tag{8}$$

The higher the degree of a node, the more influential it is likely to be in the community.

The average degree is the average of the degrees of all the nodes in the graph and is used to measure the average degree of connectivity of the entire network. For a network consisting of N node:

$$\langle k \rangle = \frac{1}{N} \sum_{i=1}^{N} k_i \tag{9}$$

2) Average path length. In an undirected weighted graph, the average path length is the average of the shortest path lengths between all pairs of nodes in the graph. Generally denoted by L, the average path length is:

$$L = \frac{1}{\frac{1}{2} N(N-1)} \sum_{i>j} d_{ij} \tag{10}$$

where N denotes the number of nodes in the network and d_{ij} denotes the length of the shortest path between node i and node j. In addition, the longest of the shortest paths between any two nodes in the network is denoted as D and is called the diameter of the network, i.e:

$$D = \max_{i,j} d_{ij} \tag{11}$$

The smaller the average path length, the more globally connected the network is.

3) Clustering coefficient. The clustering coefficient is an index used to measure the degree of aggregation of nodes in the network. For an unweighted undirected network with N node, the clustering coefficient C_i of node i is calculated as:

$$C_i = \frac{E_i}{(k_i(k_i-1))/2} = \frac{2E_i}{k_i(k_i-1)} \tag{12}$$

where E_i represents the number of edges that actually exist between the k_i neighboring nodes of node i.

The global clustering coefficient is used to measure the degree of clustering of the entire network and is defined as the average of the local clustering coefficients of all nodes:

$$C = \frac{1}{N}\sum_{i=1}^{N} C_i \tag{13}$$

The value of C is in the range of [0, 1], when C is 0, the clustering coefficient of all the nodes in the network is 0, that is, there is no closed triangle formed between the neighbors; when C is 1, the clustering coefficient of all the nodes in the network is 1, that is, the network is a fully connected network.

4) Degree distribution. Degree distribution describes the frequency distribution of the degrees of the nodes in the network. For an undirected network consisting of N nodes, $P(k)$ is:

$$P(k) = \frac{n_k}{N} \tag{14}$$

where n_k is the number of nodes with degree value k.

5) Degree Correlation. Degree correlation is a concept that describes the correlation between the degrees of nodes in a network. The most common degree correlation coefficients are Pearson correlation coefficient and Spearman correlation coefficient, which take values in the range of [-1,1], with positive values indicating positive correlation, negative values indicating negative correlation, and 0 indicating no correlation.

6) Node importance. The importance of a node refers to the degree of influence of a node in a network on the structure and function of the network. For a network with N nodes, the normalized degree center value of a node with degree value k_i is:

$$DC_i = \frac{k_i}{N-1} \tag{15}$$

Proximity centrality is the reciprocal of the average shortest path from a node to other nodes. The proximity centrality of node i is generally denoted by CC_i, i.e.:

$$CC_i = \frac{1}{d_i} = \frac{N}{\sum_{j=1}^{N} d_{ij}} \tag{16}$$

where d_{ij} denotes the distance from node i to node j.

The median centrality is the frequency with which a node acts as a bridge in the shortest path in the network. For a network with number of nodes N, the meso-centrality of node i is:

$$BC_i = \frac{2}{N^2 - 3N + 2}\sum_{s \neq i \neq t} \frac{n_{st}^i}{g_{st}} \tag{17}$$

where g_{st} is the number of shortest paths from node s to node t, and n_{st}^i is the number of shortest paths passing through node i out of the g_{st} shortest paths from s to node t.

2.2. Complex network modeling

Network modeling is an important tool for describing and understanding complex network structures in the real world.

1) Regular Networks. A regular network is a special type of complex network in which the connection patterns between nodes are highly ordered and regular. In regular networks, nodes are usually connected by some fixed rules.

2) Random Network. The counterpart of regular networks is random networks. The former introduced a random graph model called ER random graph model. In this model, each pair of nodes in the network is connected with a certain probability and the connections are independently and identically distributed.

3) Small-world network. Small-world network is a kind of network model between regular network and random network, and its topology has high local connectivity and short average path length. The main construction algorithms for small-world networks are WS model and NW model.

4) Scale-free networks. Scale-free network (BA) is a commonly used scale-free network model. The node degree distribution of a scale-free network has a power law distribution, i.e., there are a small number of highly counted nodes in the network while most of the nodes are less connected, with a high degree of clustering, the nodes in the network tend to form dense subgroups or communities, and the average shortest path between any two nodes in the network is shorter.

The probability of connecting to a node i is:

$$\Pi(i) = \frac{k_i}{\sum_j k_j} \tag{18}$$

where k_i is the degree of node i and $\sum_j k_j$ is the sum of degrees of all existing nodes.

2.3. Construction of enterprise financial index system based on principal component analysis

2.3.1. Enterprise financial indicators:

1) The level of indebtedness is the total amount of debt taken on by a firm and is also referred to as a firm's level of financial leverage. The level of debt is directly linked to the financial risk of the company and is a key financial health assessment indicator.

A higher gearing indicator implies higher financial risk. The formula for calculating it is:

$$\text{Asset-liability ratio} = \text{total liabilities} / \text{total assets} \times 100\% \tag{19}$$

The higher the shareholders' equity ratio, the greater the proportion of shareholders' equity in the total assets of the enterprise, indicating that the enterprise is less dependent on external funds and has a lower financial risk. The formula is:

$$\text{Shareholder equity ratio} = \text{shareholder equity} / \text{total assets} \times 100\% \tag{20}$$

The higher the long-term debt ratio, the greater the proportion of a company's long-term liabilities to its total assets, indicating a higher degree of dependence on long-term debt. The calculation formula is:

$$\text{Long-term debt ratio} = \text{long-term liabilities} / \text{total assets} \times 100\% \tag{21}$$

The higher the interest coverage multiple, the more adequate the operating profit of the enterprise for interest payment, and the stronger its ability to repay interest. The formula is:

$$\text{Interest cover times} = \text{EBIT} / \text{Interest expense} \times 100\% \tag{22}$$

2) Liquidity index refers to the ability of the enterprise to meet the debt and operational needs in the short term, which can not only reflect the short-term solvency of the enterprise, but also an important basis for judging the short-term financial position of the enterprise.

The higher the liquidity index, the more current assets the company has to cover its short-term debt, thus showing the stronger liquidity and short-term solvency. The formula is:

$$\text{Current ratio} = \text{Current assets} / \text{current liabilities} \times 100\% \tag{23}$$

A higher quick ratio indicates that a company is able to respond quickly to financial emergencies and ensure short-term financial stability. The formula is:

$$\text{Quick ratio} = (\text{Current assets - inventory}) / \text{current liabilities} \times 100\% \tag{24}$$

The higher the cash ratio indicator, the stronger the company's ability to rely on cash and near-cash assets to pay off known-period debts, and the more robust its financial position. The formula is:

$$\text{Cash ratio} = \text{Cash and cash equivalents} / \text{current liabilities} \times 100\% \tag{25}$$

The cash flow ratio is used to reflect the short-term solvency of an enterprise and the efficiency of its liquidity management. The higher the ratio, the stronger the enterprise's ability to cover its current liabilities with cash flow generated from operating activities in the short term, and the better its liquidity. The formula is:

$$\text{Cash flow ratio} = \frac{\text{Net cash flow from operations}}{\text{Total current liabilities}} \times 100\% \tag{26}$$

3) Profitability usually indicates an enterprise's ability to generate profits through its operating activities, and it is an important indicator of an enterprise's overall economic performance, reflecting its market competitiveness and cost-control ability.

The level of net operating margin directly reflects the efficiency of an enterprise in market competition and operational management, as well as its ability to generate revenue and withstand market fluctuations. Calculation formula:

$$\text{Net operating margin} = \text{net operating profit} / \text{revenue} \times 100\% \tag{27}$$

The level of operating profit margin is directly related to the operational efficiency, cost control ability and market competitiveness of the enterprise. The calculation formula is:

$$\text{Operating margin} = \text{operating profit} / \text{operating revenue} \times 100\% \tag{28}$$

Gross operating margin expresses the percentage of profit a business makes after deducting the direct costs of operating income. The formula is:

$$\begin{aligned}&\text{Gross operating margin}\\&=[(\text{operating profit - operating cost}) / \text{operating revenue}] \times 100\%\end{aligned} \tag{29}$$

The level of net profit margin on total assets is directly related to the effective utilization and profitability of the total assets of the enterprise. The calculation formula is:

$$\text{Net profit margin on total assets} = \text{net profit} / \text{total assets} \times 100\% \tag{30}$$

Return on assets directly reflects the extent to which the average assets of a business are being utilized and the overall profitability of the business. It is calculated by the formula:

$$\text{Return on assets} = \text{Net profit} / \text{average assets} \times 100\% \tag{31}$$

The level of return on owners' equity is directly related to the return on investors' investment and the efficiency of capital allocation of the enterprise. The higher the indicator, the more efficiently the enterprise can utilize shareholders' equity to generate net profit. Calculation formula:

$$\text{Return on owner's equity} = \frac{\text{Net profit}}{\text{Average owner's equity}} \times 100\% \tag{32}$$

4) Operational efficiency generally indicates an enterprise's ability to utilize resources efficiently and create value through its operations, reflecting its performance in managing and optimizing its operations.

A higher total asset turnover ratio means that an enterprise is able to generate more revenue from each unit of assets. Its calculation formula can be expressed as follows:

$$\text{Turnover of total assets} = \frac{\text{Operating income}}{\text{Average total assets}} \times 100\% \tag{33}$$

Inventory turnover ratio can understand the performance of the enterprise in inventory control and cost management, and help the enterprise to optimize the inventory level and improve the efficiency of capital utilization. The calculation formula is:

$$\text{Inventory turnover} = \text{cost of goods sold} / \text{average inventory} \times 100\% \tag{34}$$

A higher accounts receivable turnover ratio means that a company is more efficient in recovering sales revenue. The formula for calculating this is:

$$\text{Accounts receivable turnover rate} = \frac{\text{Operating income}}{\text{Average accounts receivable}} \times 100\% \tag{35}$$

Fixed asset turnover reflects the utilization and profitability of the fixed assets of an enterprise. It is calculated by the formula:

$$\text{Fixed assets turnover} = \text{operating income} / \text{average fixed assets} \times 100\% \tag{36}$$

5) Innovativeness generally indicates a firm's ability to efficiently utilize resources and drive technological progress through its R&D and marketing activities.

R&D intensity is usually closely related to a firm's long-term competitiveness and growth potential. The calculation formula is:

$$\text{R\&d density} = \text{R\&D investment} / \text{revenue} \times 100\% \tag{37}$$

The percentage of R&D personnel is usually closely related to a company's innovation capability and long-term growth potential. The calculation formula is:

$$\begin{aligned} &\text{Ratio of R\&D personnel} \\ &= \text{Number of R\&D personnel} / \text{total number of employees} \times 100\% \end{aligned} \tag{38}$$

2.3.2. Principal component analysis:

1) Principal component analysis. In the study of financial risk early warning, principal component analysis [29-30] can reduce the dimensionality to get the representative principal components that have a significant impact on the financial risk, which can comprehensively reveal the characteristics of the enterprise's financial risk, and the transformation of the many financial risk indicators into a representative small number of principal components, due to the lack of strong correlation between

the principal components, to avoid the problem of imprecision in the early warning of the financial risk due to the overabundance of the original indicators. The problem.

Assuming that there are n variables among our raw multivariate data, each of which X_i represents a dimension, we would like to find principal components Y_j that best represent the variability of these raw data. a_{ij} represents the elements of the transformation matrix, i.e., the linear relationship between X_i and Y_j, while Y_j consists of a weighted combination of the original variables X_i with the formula:

$$Y_j = a_{j1}X_1 + a_{j2}X_2 + \ldots a_{jn}X_n \tag{39}$$

2) Standardized treatment of indicators. In this paper, all the financial indicators are divided into three categories: forward indicators, reverse indicators, and moderate indicators, and are subject to different standardization treatments.

The formula for calculating positive indicators is as follows:

$$x^{'} \frac{x - mean(x)}{std(x)} \tag{40}$$

where, $x^{'}$ is the standardized value, x is the original data value, $mean(x)$ is the mean of the data set x and $std(x)$ is the standard deviation of the data set.

The formula for calculating the reverse indicator is as follows:

$$x^{'} = \frac{mean(x) - x}{std(x)} \tag{41}$$

where, $x^{'}$ is the standardized value, x is the original data value, $mean(x)$ is the mean of the data set x and $std(x)$ is the standard deviation of the data set.

3) Selection of the number of principal components. One of the purposes of principal component analysis is to reduce the number of variables, so assuming the existence of x variables weighted combination of x principal components, generally do not directly take x principal components, but take $y(y < x)$ principal components, according to the variance to select the y most appropriate value. The formula is:

$$\frac{\sum_{j=1}^{y} CR_j}{\sum_{j=1}^{x} CR_j} \geq 80\% \tag{42}$$

where CR_j is the percentage of variance of the j nd principal component. When the cumulative variance contribution reaches 80%, the number of principal components is the value of y we take.

4) Comprehensive evaluation of principal components. Arrange the initial eigenvalues from the largest to the smallest and filter out all the eigenvalues when the sum of the variance percentages is greater than 80%, which is the principal component we have selected.

Calculate the factor score of each selected principal component and the principal component score with the following formula:

$$PCS_j = \sqrt{\rho_j} \times PCFS_j \tag{43}$$

where PCS_j is the score of the j nd principal component, ρ_j is the eigenvalue of the j th principal component, and $PCFS_j$ is the j th principal component factor score.

3. Characterization of risk correlation network modeling based on financial indicators

3.1. Data sources

The data in this paper comes from the financial statements of new retail companies and the official database of Radish Investment Research, and the financial indicator data of 160 companies in the A-share new retail concept sector are selected as the initial sample data. In this paper, the data time period of 2019-2023 is selected, and 50 eligible companies are selected, with 15 financial indicators and a total of 225 observations for each indicator.

3.2. Indicator correlation networks based on correlation coefficients

Based on complex network theory, this paper transforms the complex financial risk conduction process in the operation and management process of new retail enterprises into a concise and clear network presentation, takes the financial risk indicators of new retail enterprises as the network nodes, constructs the association network of financial risk indicators of new retail enterprises, analyzes the financial risk conduction dynamics of new retail enterprises, and finds out the key risk indicators characterized by the nodes of the network, with the following specific steps:

1) Select new retail enterprise financial risk indicators. This paper designs the financial risk indicator system of new retail enterprises from five aspects: financing risk, operation risk, investment risk, development risk, and cash flow risk.

2) Construct neighbor matrix based on indicator correlation. Firstly, calculate the Spearman correlation coefficient ρ_{ij} between the financial risk indicators to get the symmetric matrix $P=(\rho_{ij})_{n\times n}$ of correlation coefficients with diagonal 1. The formula for correlation coefficients is as follows:

$$\rho_{ij}=1-\frac{6\sum d_i^2}{n(n^2-1)} \tag{44}$$

where d_i is the difference between the rank values of the i nd data pair and n is the total number of observed samples.

Based on the matrix of correlation coefficients the adjacency matrix between indicators can be obtained $A=(a_{ij})_{n\times n}$.

3) Constructing the correlation network of financial risk indicators of new retail enterprises. Complex networks are divided into nodes and the links between nodes as the research object, through the measurement of network characteristic indicators, to explore the interrelationships between nodes in the network structure, in order to analyze the overall and local characteristics of the network. In this paper, we take the financial risk indicators of new retail enterprises as nodes, use the adjacency matrix to determine whether there is a connecting edge between the risk indicators, and use the software UCINET to construct the association network of financial risk indicators of new retail enterprises and analyze the network structure. The association network of financial risk indicators of new retail enterprises is shown in Figure 2. There is no isolated point among the financial risk indicators of new retail enterprises, showing a typical network structure. At the same time, the financial risk indicator network of new retail enterprises presents "scale-free characteristics", most risk indicators are

connected to a few nodes, and a few risk indicators have more connections, so there is obvious heterogeneity in the financial risk transmission network.

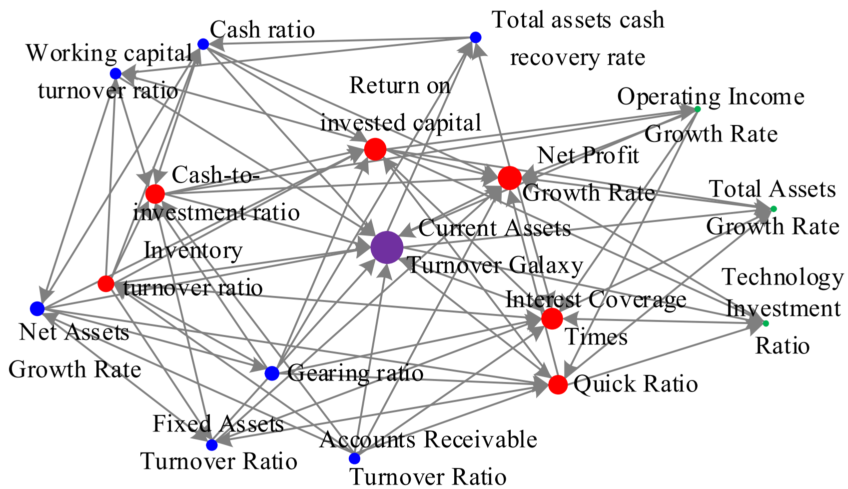

Fig. 2. The network of financial risk indicators for new retail enterprises

3.3. Network characterization

3.3.1. Characterization of the network as a whole. The overall evolution trend of the financial risk indicator correlation network of new retail enterprises from 2019-2023 can be seen by calculating the overall characteristic index of the network, so as to reflect the transmission characteristics of financial risk during these five years. In this paper, we use UCINET software to calculate the overall network characteristic indexes, and select six indexes, namely, network average degree, network density, network diameter, network relevance, network reciprocity, and network average path length, for analysis. The financial risk indicator system of new retail enterprises is shown in Table 1.

Table 1. New retail enterprise financial risk index system

Primary indicator	Secondary indicator	Index representation
Financing risk	Asset ratio	R1
	Speed ratio	R2
	Interest rate	R3
Operating risk	Inventory turnover	R4
	Receivable turnover	R5
	Turnover of current assets	R6
	Fixed asset turnover	R7
	Operating capital turnover	R8
Investment risk	Return on capital	R9
	Technical ratio	R10
Development risk	Revenue growth	R11
	Net profit growth rate	R12
	Net equity growth rate	R13
	Total asset growth rate	R14
Cash flow risk	Cash ratio	R15
	Total asset cash recovery	R16
	Cash to meet the investment ratio	R17

The overall characteristics of the network associated with the financial risk indicators of new retail enterprises are shown in Table 2. It can be seen that the values of six network parameters such as "network average degree and network density" of the financial risk of new retail enterprises in 2019-2023 are 7.1933, 0.4506, 2.9859, 1, 0.6874, and 1.6172, respectively, which indicates that the network can directly transfer the financial risk information to another 7.1933 financial risk indicators, and the maximum number of indicators required to establish a link between any two indicators is three. 7.1933 financial risk indicators and that the maximum number of indicators that need to pass through to establish a link between any two indicators is 3. In addition, the interconnectedness in the network is significant at the same time that on average only two other indicators need to pass through to establish a link between any two risk indicators.

Table 2. The overall characteristics of the network of financial risk indicators

Network parameter	Parameter value
Network average	7.1933
Network density	0.4506
Network diameter	2.9859
Network correlation	1.0000
reciprocity	0.6874
Network average path length	1.6172

3.3.2. Node Centrality Analysis. The centrality of the nodes of the association network of financial risk indicators of new retail enterprises is shown in Table 3. The results of degree centrality show that the mean value of degree centrality of 17 financial risk indicators of new retail enterprises is 44.85726, and the parameter values of 9 indicators are higher than the mean value, which indicates that these financial risk indicators have more direct associations with other indicators in the network. Among them, the degree centrality of R1, R2, R3, R4, R6, R9, R12, R13 and R17 is greater than or equal to 50%, which indicates that more than half of the financial risk indicators have direct correlation, and the risk correlation is strong. Nine of the point-in degrees exceed the mean value, and the point-in degrees of indicators R2, R3, R4, R6, R9, R12 and R17 are higher than their own point-out degrees, which indicates that these indicators are more dependent on other indicators and vulnerable to the output of other risks.

The result of proximity centrality indicates that the mean value of proximity centrality of 17 financial risk indicators of new retail enterprises is 127.88795, of which 9 indicators, such as "R1, R2, R3, R4, R6, R9, R12, R13, and R17" are higher than the centrality, which indicates that the centrality is able to establish connections with other indicators more autonomously. The results show that centrality can be more autonomously linked to other indicators, and that these indicators are not only more risk-transmissive on their own, but also more convenient for transmitting financial risk information to the whole network.

The result of intermediary centrality shows that the average value of intermediary centrality of 17 financial risk indicators is 9.52972, among which, R1, R2, R9, R6, R3, R12, R13 and R17 are the eight indicators with higher degree of centrality, intermediary centrality and proximity to centrality at the same time, which indicates that these indicators are not only at the center of the network, but also play the role of intermediary and bridge.

Table 3. New retail enterprise financial risk index correlation network node center

Risk indicator	Degree of emergence	Degree of entry	Degree	Sort	Proximity center	Sort	Intermediate center	Sort
R1	7.9733	7.9653	50.9986	7	133.3283	8	11.4182	8
R2	8.0135	8.9991	53.1355	6	136.2267	6	21.3298	2
R3	10.0072	11.011	65.6337	2	142.8569	3	22.2113	1
R4	6.9886	9.0224	50.0977	8	133.5459	7	5.6365	9
R5	6.9942	5.0074	37.4852	10	123.2419	10	3.4707	10
R6	8.0054	14.9882	71.8776	1	160.7825	1	18.2601	4
R7	6.9956	4.9775	37.5068	11	123.2436	11	3.4649	11
R8	5.9795	2.9802	28.119	13	107.1517	16	1.3622	13
R9	7.9917	10.9857	59.4	4	142.8583	4	13.8268	7
R10	5.0058	4.0135	28.153	14	112.3273	14	1.1323	16
R11	5.0088	1.9881	21.8795	17	107.7296	15	0.9799	17
R12	7.9982	12.0148	62.4963	3	144.0108	2	14.9203	6
R13	7.9844	7.9906	51.9914	9	133.3309	9	17.2659	5
R14	5.0291	4.9884	31.2559	12	114.4506	12	1.2572	15
R15	6.0008	3.0046	28.138	15	107.1189	17	1.3795	14
R16	6.9864	2.0046	28.1327	16	112.4953	13	2.8768	12
R17	9.0171	10.0066	59.3932	5	139.3959	5	21.2128	3
Mean value	7.17525	7.17341	44.85726	9	127.88795	9	9.52972	9

3.3.3. Block Model Analysis. In this paper, the maximum depth of cut is set to 2, the concentration criterion is set to 0.2, and it is divided into four modules of "net spillover, net spillover, brokerage, and two-way spillover" for analysis. The results of the model analysis of financial risk indicators of new retail enterprises are shown in Table 4. The first block includes seven indicators, R1, R6, R7, R8, R5, R15 and R9, of which the indicators from the operational risk level account for 57%. The second panel includes four indicators, R11, R14, R16 and R10, half of which come from the development risk dimension. The third and fourth panels include three indicators, mainly focusing on the development risk dimension.

There are 128 relationship numbers in the association network of financial risk indicators of new retail enterprises, and the proportion of relationship numbers between boards is 61.96%, indicating that there are obvious association and spillover effects between boards in the network. Among them, the number of relationships sent out by board 1 is 48, and the number of relationships within the board is relatively high, which belongs to the two-way spillover board; the number of relationships sent out by board 2 is 24, and the number of relationships received from outside the board is smaller than the number of relationships sent to outside the board, which belongs to the net spillover board; and board 3 and board 4 are both characterized as broker boards, which receive the association effects of other boards and also have spillover effects on other boards.

Table 4. Analysis of the network block model of enterprise financial risk index

Financial risk index plate	Acceptance relation				Number of plate members	The number of overspilt plates	Plate characteristic
	Plate 1	Plate 2	Plate 3	Plate 4			
Plate 1	17	13	5	13	6	35	Two-way overflow plate
Plate 2	8	1	13	2	2	21	Net overflow plate
Plate 3	13	6	4	5	2	19	Broker plate
Plate 4	14	0	6	8	3	17	Broker plate

4. Analysis of the effect of improving the financial efficiency of complex enterprises under topological computing optimization

4.1. Topological properties of the network at different thresholds

The topological characteristics of financial risk correlation networks in different threshold scenarios are analyzed for 2019-2023. The change in the size of the network is observed in terms of the number of nodes and edges and the average weighting, and the similarity tightness of the nodes in the network is analyzed in terms of the average path length and the network diameter. The overall structural changes of the network are explored in terms of the above two aspects in order to gain a deeper understanding of the characteristics of the current development of the energy financial risk market.

4.1.1. Trends in the size of financial risk affiliate networks. The number of financial risk nodes at different thresholds for 2019-2023 is shown in Figure 3; the number of financial risk connecting edges at different thresholds for 2019-2023 is shown in Figure 4. The results show show that the number of nodes and edges decreases as the threshold increases. For $r \geqslant 0.65$, the number of both decreases dramatically and the size of the whole network decreases rapidly. However, the number of nodes and edges occupies more than 80% at $r = 0.65$. This suggests that there is financial structure similarity between the vast majority of financial risks in the entire energy financial risk network. The maximum percentage of nodes decreasing is 6.66% and the maximum percentage of edges decreasing is 24.65% when the threshold is greater than 0.65. Although the number of disappearing nodes is around 5.4, there are heavy number of connected edges between disappearing nodes, up to 447.11. It indicates that when the degree of similarity is higher, the number of financial risk nodes that have structural similarity with a particular financial risk decreases, and a large number of consecutive edges disappear.

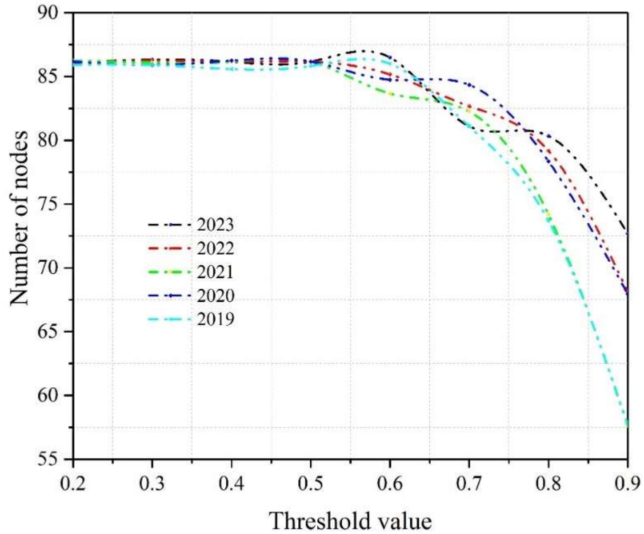

Fig. 3. The number of stock nodes under different threshings in 2019-2023

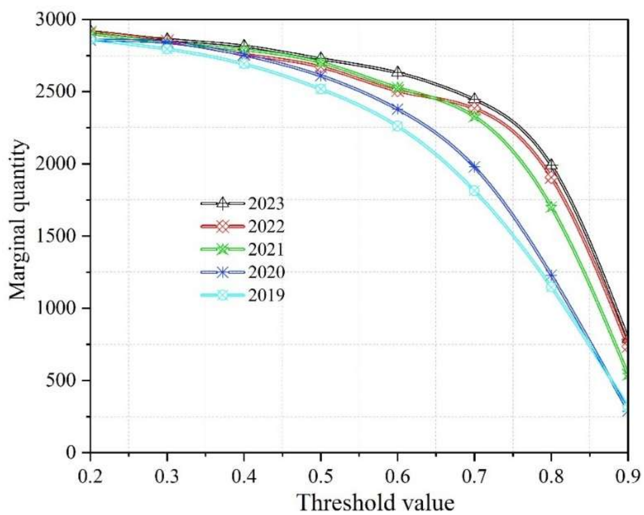

Fig. 4. The number of stocks on the different threshars of 2019-2023

The average weightedness for 2019-2023 under different thresholds is shown in Figure 5. The results show that when the threshold value is less than 0.65, the average weighting degree changes gently and the slope tends to be consistent. When the threshold value > 0.65, the average weighted degree of the network decreases rapidly and the slope increases sharply can be proved, which is highly related to the change of the number of nodes and edges. When the similarity is low, the number of financial risks and the number of connected edges in the network are stable, and the change in the average weighted degree is small. When the similarity is higher, there are only a few financial risks with high financial structure similarity and the number of edges decreases very fast, so the average weighted degree decreases linearly.

On the one hand, it shows that the current energy financial market is improving, the financial indicators are becoming more and more harmonized and standardized, and the financial system is becoming more and more sophisticated, thus there are more and more similarities in the financial structure. On the other hand, the increasing convergence of financial indicator structures has led to similarity and homogenization of development models, reduced individualization of the entire energy industry, and a lack of dynamism and innovation.

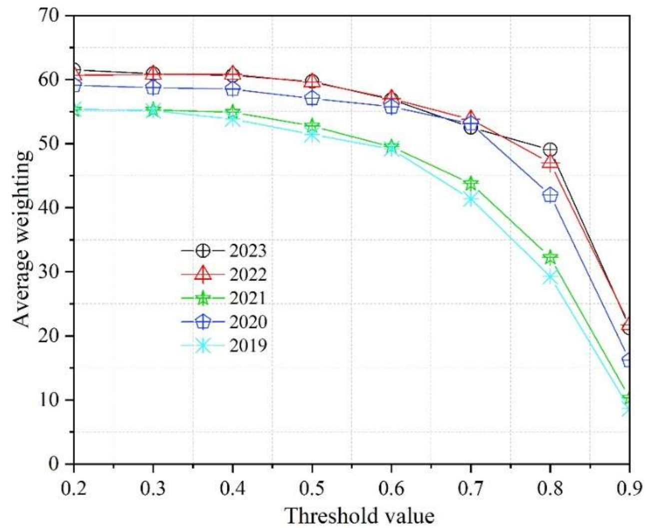

Fig. 5. The average weighting of 2019-2023

4.1.2. Closeness of similarity of financial risks. The average path lengths for 2019-2023 under different thresholds are shown in Table 5; the network diameters for 2019-2023 under different thresholds are shown in Table 6. The results show that when r<0.6, the average path length is below 1.156, the network diameter is all less than 2.9956, and the change of both is small, which indicates that the tightness of financial risks with similar financial structures in the whole network is high, and they can directly establish a connecting edge with the financial risks with the existence of similar financial structures. r⩾0.6, the average path length increases rapidly by 0.22% -4.97%, and the network diameter also fluctuates to increase by 2.34%-30.57%, which indicates that the aggregation degree of some nodes decreases, and they can only relate to other financial risks through intermediate financial risks, which are indirectly connected. As a result, the degree of closeness between financial risk nodes with similar financial structures decreases and the network tends to be more decentralized.

Looking at the time scale, the average path length and network diameter of the network are found to be decreasing overall. This suggests that the energy financial risk market has developed more maturely in recent years, and that most energy listed companies behind financial risks have well-established financial indicators and more closely related financial structures.

Table 5. The average path length of 2019-2023 under different thresholds

Threshold value	2023	2022	2021	2020	2019
0.2	1.0147	1.0123	1.0363	1.0099	1.0147
0.3	1.0194	1.0075	1.0194	1.0099	1.0194
0.4	1.0289	1.0313	1.0459	1.0313	1.0459
0.5	1.0507	1.0554	1.0986	1.0268	1.1128
0.6	1.0938	1.0578	1.1560	1.0602	1.1465
0.7	1.0578	1.3552	1.2589	1.1394	1.3262
0.8	1.2110	1.8417	1.4221	1.2087	1.5971
0.9	1.7337	1.0147	2.0358	1.7313	2.3885

Table 6. The network diameter of 2019-2023 under different thresholds

Threshold value	2023	2022	2021	2020	2019
0.2	2.0079	1.9570	1.9468	1.9438	1.9774
0.3	1.9672	1.9774	1.9468	1.9367	1.9367
0.4	1.9672	1.9367	1.9044	1.9468	1.9367
0.5	2.0079	2.9138	3.0141	1.9146	2.6447
0.6	2.8920	2.9836	3.2225	3.0566	2.9836
0.7	2.0181	3.9389	3.9389	3.9287	3.0040
0.8	2.9734	3.9915	2.9836	2.9734	4.0933
0.9	4.0322	3.9813	4.9672	5.1318	6.0464

4.2. Characterization of the evolution of the network at specific thresholds

4.2.1. Similar scope and intensity of financial risks. The frequency of degree distribution of the nodes is shown in Table 7. Firstly, the degree values were divided into 8 stages. The degree distribution is fluctuating upward trend. The degree value is extremely variable at 70. This indicates that financial risk nodes with small degree values have decreased in recent years, and more and more structural similarities between financial risks have appeared, the connecting edges have been established, and the scope of influence of financial risks has increased. This is very useful for understanding the similarity influence range of the current energy financial risks, and discovering the impact that financial risks with changed financial structure may have on their associated financial risks.2022, with the concept of the new energy revolution, energy companies make corresponding policies and financial adjustments. When facing similar external environments and external demands, listed companies with highly similar financial structures will adopt similar financial policies in order to gain access to resources, opportunities and profitability.

Table 7. The degree of distribution of nodes

Node degree	Frequency [0, 1]				
	2023	2022	2021	2020	2019
10	0.0111	0.0152	0.0466	0.0480	0.0523
20	0.0016	0.0206	0.0084	0.0084	0.0206
30	0.0057	0.0124	0.0247	0.0084	0.0672
40	0.0111	0.0070	0.0796	0.0070	0.0550
50	0.0097	0.0276	0.1152	0.0111	0.1536
60	0.0276	0.1179	0.2152	0.0453	0.2509
70	0.5932	0.7317	0.4878	0.0769	0.3878
80	0.3371	0.0563	—	—	—

4.2.2. Cohesive intensity of financial risk. The average weighted agglomeration coefficients at different point intensities for 2019-2023 are shown in Table 8. The agglomeration coefficient measures the cohesion of associations within a small localized area centered on a node, reflecting the nature of the grouping among the first-level immediate neighbors of that vertex; the more connected the immediate neighbors are, the higher the agglomeration coefficient of that vertex. The point strength was categorized into eight stages. Overall, the cohesion coefficient gradually decreases with the increase of point strength, indicating that the network as a whole exhibits that the neighbor nodes of nodes with low point strengths are highly cohesive, while the neighbor nodes of nodes with high point strengths are less cohesive. It implies that the stronger the similarity between the financial structure of a particular financial risk and other connected financial risks, the local cohesive feature decreases. In terms of time scale, the trend is similar in 2019-2023, both of which show a decreasing trend. And with the increase of time, the average cohesion coefficient decreases slightly as a whole, indicating that the trend of network wholeness increases and the association decreases, which indicates that the network of energy-based financial risk linkages exhibits the characteristic of global cohesion.

Table 8. Average weighted concentration coefficient under different intensity

Point strength	Average weighted aggregate coefficient[0, 2.5]				
	2023	2022	2021	2020	2019
10	1.9096	2.3932	2.1663	2.1451	2.1451
20	0.0601	1.7598	1.7902	0.1032	1.7682
30	1.4904	1.5844	1.6099	1.5505	1.5971
40	1.3617	1.3787	1.4048	1.3702	1.4006
50	1.1736	1.2507	1.2804	1.2804	1.3059
60	1.0704	1.1263	1.1821	1.1736	1.1991
70	1.0619	1.0831	—	—	—

5. Conclusion

Based on complex network theory, this paper combines topological computation optimization method and principal component analysis to construct a network model oriented to the optimization of enterprise financial risk transmission and efficiency, which provides theoretical support and practical guidance for the financial risk management of complex enterprises. The main conclusions are as follows:

1) The average degree value of the network shows that financial risk information can be directly transmitted to another 7.1933 financial risk indicators. The degree centrality of the gearing ratio, quick ratio and other indicators are all >50%, which shows that most of the financial risk indicators of the enterprise have strong correlation. The values of "current asset turnover ratio, interest coverage multiple, net profit growth rate" indicators with degree centrality, intermediary centrality and near centrality are all higher, which shows that they can play the role of intermediary and bridge. In addition, there is a significant risk transmission effect among the four indicators.

2) The topological characteristics of the network under different thresholds show that the size of the network decreases with the increase of the threshold, and the overall number of nodes and edges decreases slowly with the increase of time. The results of the average path length and network diameter of the network indicate that the threshold value of 0.65 is a watershed for the change of the financial structure of the enterprise, and the network tends to be more decentralized when the degree of closeness between the nodes of financial risk with similar financial structure decreases. And with the increase of time, the two overall decrease year by year.

3) The results of the frequency of node degree value distribution show that the frequency of degree value at 70 is the most frequent, and thus most financial risks in the network have a high degree of financial structure similarity. The point intensity and average agglomeration coefficient show that the agglomeration coefficient gradually decreases with the increase of point intensity, which shows that the two have negative correlation characteristics. And the average agglomeration coefficient overall decreases slightly with the increase of time.

Acknowledgements

This work was supported by 2022 Scientific Research Preparation Plan Project of Anhui Province (Project approval number: 2022AH051850) and 2022 New Professional Quality Improvement Project of Anhui Province (Project approval number: 2022xjzlts013).

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