Hindawi
Discrete Dynamics in Nature and Society
Volume 2022, Article ID 9605189, 13 pages
https://doi.org/10.1155/2022/9605189

Research Article

Heuristic Algorithm for Cross-Platform Credit Risk Transmission Based on Hybrid Strategies

Zhang Xiaodong,[1] **Shen Hong**,[1] **Wang Tao**,[2] **and Li Yazhi**[3]

[1]*School of Information and Engineering, Nanjing Audit University, Nanjing 211185, Jiangsu, China*
[2]*Jusfoun Big Data Information Group Co., Ltd, Beijing 211185, China*
[3]*School of Software Engineering, Jinling Institute of Technology, NanJing 211169, Jiangsu, China*

Correspondence should be addressed to Shen Hong; shenhong@nau.edu.cn

Received 8 March 2022; Revised 1 April 2022; Accepted 7 April 2022; Published 25 May 2022

Academic Editor: Xueyi Wang

Credit risk transmission between cross-platforms is an important issue in the construction of a credit service system. The effect of credit risk transmission between credit entities (nodes) is analyzed in this paper. A heuristic algorithm based on hybrid strategies (HAHS) is proposed to find risk transmission paths and calculate the influence of nodes. Besides, a novel community model is applied to predict the credit risk areas in advance. In detail, the mathematical association structure between credit entities is firstly given in the algorithm, and the breadth first search algorithm is used to find the hierarchical nodes on the credit risk transmission paths. Then, the characteristics of credit risk transmission are analyzed, and the calculation methods of single-path and multipath influence are proposed. Finally, the credit entities are divided into communities based on a greedy strategy considering the characteristics of the credit entity association structure. The threshold control strategy is adopted to find global key nodes among all of the entities and local key nodes in communities, respectively, so as to realize the early warning of credit risk.

1. Introduction

In recent years, with the development of cloud computing and big data technology, online service has become the mainstream operation mode in all walks of life. With the convenient service of the Internet, all kinds of cross-platform users can obtain various production and operation services through a simple application process anytime and anywhere. However, credit risk is everywhere due to the virtuality of the network, the complexity of the production and operation process, and the dynamic change of user credit evaluation in the time interval. In fact, credit risk does not exist in isolation. The credit entity (node) changes under the influence of macroeconomics, market investment, financing environment, and other macro factors, which may lead to credit risk. On the other hand, the economic connection between enterprises caused by production cooperation and equity relationship may lead to risk transmission. The correlation between credit entities reflects the transmission mode and path of credit risk [1]. The description of the correlation between credit entities should reflect the complex connections between credit entities in social production and life. The transmission of credit risk is mainly related to the association structure and the correlation strength between credit entities. Many researchers have discussed this work from the perspective of theoretical and empirical analysis.

Daily banking practice shows that there may be contagion effects between portfolios, which has been clearly recognized through current supervision. Literature [2] describes a model that distinguishes default behavior in each portfolio and allows credit risk contagion between portfolios, including macroeconomic and financial factors. In addition, it also stimulates the multivariable scenario of portfolio credit risk. Literature [3] constructs the unconditional correlation network between listed financial institutions and comprehensively deconstructs the overall correlation of financial networks and the correlation characteristics within and between departments through network analysis. Literature [4] analyzes the complex network theory and epidemiological thought to study the infection of the financial crisis on the global stock market. Through the causality method, the asymmetric impact between different markets can be reflected. Literature [5] applied the Diebold Yilmaz connectivity method to sovereign credit default swaps (SCDSs) to estimate the global network structure of sovereign credit risk. Literature [6] uses a factor model and elastic net shrinkage to model a high-dimensional network of European credit default swap (CDS) spreads. It also provides dynamic estimates of risk transmission, which is a useful tool for systemic risk monitoring. Literature [7] proposed a multilayer network model for credit risk assessment. The model takes into account the multiple connections between borrowers (such as geographical location and economic activities), allows explicit modeling of the interaction between related borrowers, and develops a multilayer personalized PageRank algorithm. Literature [8] constructs a network model of credit risk contagion in the interbank lending market based on time series. By the theoretical deduction and simulation method, how the contagion effects of credit risk accumulate and spread in the interbank market network is studied. In addition, it studies the evolution characteristics of credit risk contagion caused by the initial default of debt banks in the interbank market. In literature [9], many data samples are used to build an early warning model of Internet credit risk. The constructed model is trained and tested by BP neural network algorithm, and the genetic algorithm (GA) is used to optimize the neural network to improve the accuracy of early warning.

For the business activities of enterprises, literature [10] constructs a credit default estimation model for micro and small enterprises (MSEs) under the condition of changing information asymmetry. By relaxing the assumption that the bank can fully observe the customer's initial information, it constructs a theoretical model with practical application value. The model can accurately estimate the default probability of MSEs by quantitatively modeling the mechanism of default risk management and control. Literature [11] proposed an e-commerce credit risk evaluation method based on the language consensus model and established individual consensus measurement and group consensus measurement planning models to improve the consensus level of decision-making groups. Literature [12] studies the in-depth application of financial technology, which will reconstruct the internal relationship of enterprises in the supply chain, truly integrate small and medium-density enterprises into the network system of the supply chain, and turn the business behavior data of small and medium-density enterprises in the whole industrial chain ecology into "evaluable credit." Literature [13] studies credit risk contagion among affiliated enterprises by constructing the Markov chain and believes that credit risk contagion is the main cause of cluster default. Literature [14] considers that credit risk contagion between banks and firms is one of the important triggers of the financial crisis, and the credit linkage network is the way of systemic risk contagion triggered by external shocks. Literature [15] constructs a two-layer network model of credit risk contagion between the bank and corporate counterparties from the perspective that banks do not withdraw loans from enterprises by considering the influence of corporate credit defaults on their counterparties under the credit linkage. Literature [16] analyzes the contagion path of credit risk in Internet P2P lending. Based on complex network theory and the theory of infectious disease dynamics, the characteristics of Internet P2P lending development are combined to construct a SEIR model of credit risk transmission among Internet P2P lending platforms with a time lag, and the robustness of the model is analyzed and proven. Literature [17] proposes a two-stage hybrid model, credit data high-dimensional transformation model and graph-based neural network model, to enhance the prediction performance of credit risk. Literature [18] first analyzes the main factors affecting the performance of BSO and then proposes an orthogonal learning framework to improve its learning mechanism. In addition, a set of auxiliary transmission vectors with different characteristics are balanced through OD decision mechanism. Finally, the algorithm is verified on a set of benchmark tests and is used to solve the problem of quantitative association rule mining considering support, confidence, understandability, and netconf. For large-scale multiobjective optimization problems, an adaptive local decision variable analysis method based on decomposition is proposed in [19]. In this method, the guidance of the reference vector is incorporated into the analysis of control variables, and the adaptive strategy is used to optimize the decision variables.

In the current credit service mode of cross-platform, cross-domain, and cross-ecological, the sources of credit information are uneven, and credit risks are everywhere. There is no effective scheme for the transmission mode and influence calculating of credit risk between credit entities to meet the requirements of high real-time. To solve this problem, this paper analyzes the characteristics of credit risk transmission between cross-platform credit entities. Based on hybrid strategies, a heuristic algorithm is proposed. It finds the credit transmission path, constructs influence calculation models for both single-path and multipath transmission, and uses a greedy strategy to divide the credit entities into communities. In addition, threshold control strategies are applied to find global and local key nodes which can have a great impact on the associated credit entities and give the credit risk area in advance.

2. Problem Description

The cross-platform credit risk transmission problem considered in this paper is to find the credit risk transmission paths, compute the influence of credit risk on entities, and search for the key node sets from a set of n interrelated credit entities. The problem is analyzed for the purpose of improving the efficiency of credit risk prevention and reducing the possible risks caused by credit risk transmission.

This section firstly studies the association structure of credit entities and the credit risk transmission model, then gives the influence calculation method when credit risk is transmitted through the associated entities, and finally puts forward the rules of community division.

2.1. Credit Entity Association Structure and Risk Transmission Model. As shown in Figure 1, in the complex credit entity association structure model, the importance of each credit entity (i.e., node) is related to the structure of the model and the correlation strength of the adjacency relationship between nodes. It is difficult to accurately measure the importance of nodes by a single factor.

In order to study the credit risk transmission path and influence on credit entities, n nodes in the association structure are transformed into a directed graph $G=(V,E)$, where V represents the set of nodes and E represents the set of edges. Each node in set V represents a credit entity, and each edge in set E represents the relationship between credit entities (such as parent-child relationship, equity relationship, supply relationship). The mathematical model of a given credit entity association structure is an n-order square matrix M which is composed of elements shown in the following formula:

$$d_{ij} = \begin{cases} w_{i,j} < i, j > \in E, \\ 0 < i, j > \notin E. \end{cases} \tag{1}$$

The weight $w_{i,j}\,(0 < w_{i,j} < 1)$ of each edge represents the correlation strength, and the value is given by experience according to the type of relationship between credit entities. Hence, the matrix M is shown in the following formula:

$$M = \begin{pmatrix} d_{11} & d_{12} & \cdots & d_{1N} \\ d_{21} & d_{22} & \cdots & d_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ d_{N1} & d_{N2} & \cdots & d_{NN} \end{pmatrix}. \tag{2}$$

Existing empirical studies in credit-related fields have shown that the transmission of credit risk is mainly related to the association structure of credit entities and the correlation strength between credit entities. Based on the credit entity association structure model and some research conclusions from the existing literature on the social relationship network, this section models the credit risk transmission problem according to the following principle and method:

(1) Three-degree influence principle:

Fowler et al. [20] put forward the principle of three degrees of influence: nodes can not only affect neighbor nodes (one degree) but also affect neighbor nodes (two degrees) of neighbor nodes and even affect neighbor nodes (three degrees) of neighbor nodes. As long as they belong to a strong connection within three degrees, they are likely to cause risk transmission. If it is more than three degrees, the influence between nodes will be weakened to negligible or even disappear.

(2) Measurement method based on degree-centrality of topological network:

The problem of node centralization aims to study the centrality of nodes in the graph [21]. That is, the more frequently and closely connected with other nodes, the higher the centralization index, and nodes close to others with higher indexes generally have higher centralization indexes. The degree-centrality of the node reflects the influence of the current node in the whole credit entity association structure. This paper adopts the outdegree of node i to measure its degree centrality. The reason is that the higher the output degree of a node, the more nodes it affects and the greater its influence. This measurement strategy is also used to reduce the complexity of the algorithm.

2.2. Influence Calculation Method. When credit risk occurs to a credit entity, the transmission modes are mainly described as follows.

2.2.1. Single Path Transmission. This transmission mode reflects the multilevel transmission of credit risk among credit entities. Assuming that credit risk occurs to node i (called source node), its influence on itself is $\rho_{i,i} = 1$, and the transfer path from node i to node j is, $i \longrightarrow s_1 \longrightarrow s_2 \longrightarrow \cdots \longrightarrow s_k \longrightarrow j$, then the single-path influence calculation expression of node i on node j is shown as the following equation:

$$\rho_{i,j} = \rho_{i,i} \times w_{i,s_1} \times \cdots \times w_{s_{k-1},s_k} \times w_{s_k,j}. \tag{3}$$

Obviously, formula (2) ensures that the influence of credit risk on the transmission path is continuously reduced and reflects the buffer ability of each credit entity to credit risk. On the other hand, it also meets that the impact on the end node and the initial node of the path is positive correlation. As shown in Figure 2, the influence of nodes 1 on 2 is $\rho_{1,2} = 1 \times 0.3 = 0.3$, the influence on node 3 is $\rho_{1,3} = 1 \times 0.3 \times 0.4 = 0.12$, and the influence on node 4 is $\rho_{1,4} = 1 \times 0.3 \times 0.4 \times 0.3 = 0.036$.

2.2.2. Multipath Transmission. When credit risk occurs to the source node, it will be passed to the successor nodes through multiple paths, and some of these successor nodes may be affected by multiple predecessors at the same time. As shown in Figure 3, node 6 is affected by both nodes 3 and 5. It is assumed that the influence of node 3 on 6 is $\rho_{3,6}$, and the influence of node 5 on 6 is $\rho_{5,6}$. For node 6, in order to ensure that the influence of multipath transfer superposition is not lower than any influence of single-path, and the influence is less than or equal to 1, the calculation formula of multipath composite influence is shown as follows: $\rho_{*,6} = 1 - (1 - \rho_{3,6}) \times (1 - \rho_{5,6})$. Especially, $1 - \rho_{3,6}$ represents the degree of uncorrelation of node 3 on 6, and the similar to $1 - \rho_{5,6}$. The composite uncorrelation degree is obtained by multiplying, and the composite influence of multipath credit risk transmission is calculated.

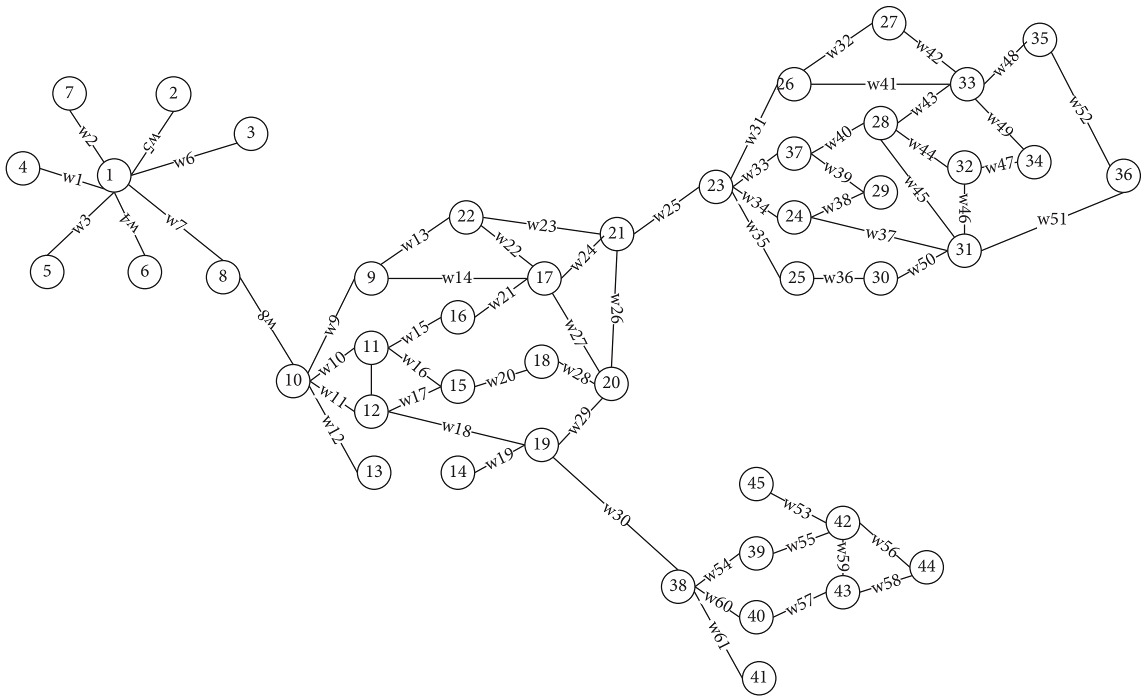

Figure 1: Credit entity association structure model.

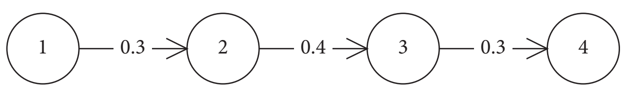

Figure 2: Continuous influence.

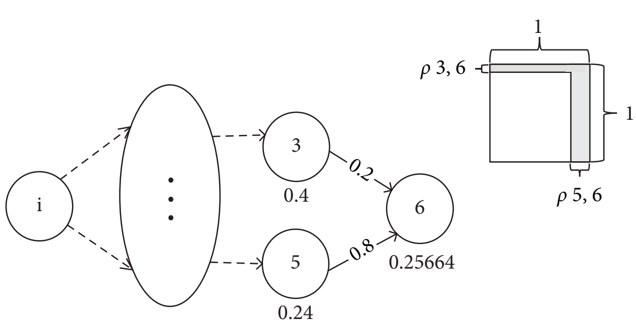

Figure 3: Influence superposition.

It can be seen from Figure 3, the value of $\rho_{i,3}$ is 0.4, and the value of $\rho_{i,5}$ is 0.24; thus, the influence of the source node i on node 6 through node 3 is $\rho_{3,6} = 0.4 \times 0.2 = 0.08$, and the influence on node 6 through node 5 is $\rho_{5,6} = 0.24 \times 0.8 = 0.192$. Therefore, the composite influence is obtained as follows: : $\rho_{*,6} = 1 - 1 - \rho_{3,6} \times 1 - \rho_{5,6} = 1 - (1 - 0.08) \times (1 - 0.192) = 0.25664$.

Based on the above description, the composite influence calculation model under multipath transmission is proposed. It can be described as follows, with the given credit entity association structure, if credit risk occurs to node *i*, it will pass through multiple-path to node *j*. The multipath composite influence calculation expression on node *j* is shown as follows:

$$\rho_{i,j} = 1 - \prod_{\forall<pre,j>\in E} 1 - \rho_{i,pre} \times w_{pre,j}, \tag{4}$$

where pre is any direct predecessor node of j, $\rho_{i,\mathrm{pre}}$ is the influence of the source node i on node pre, and $w_{\mathrm{pre},j}$ is the correlation strength from node pre to node j.

2.2.3. Circular Transmission. In the complex credit entity correlation structure, there may be a ring structure between many closely related entities. The transmission of credit risk is circular transmission in the ring structure, resulting in the circular calculation of influence. Therefore, this structure should be avoided. When calculating the influence of multipath credit risk transmission, this paper adopts the following preprocessing strategies to avoid the emergence of the ring: along with the direction of influence transmission, expand the successor adj of the current node i layer by layer according to the hierarchical structure. In the expansion process, if the node adj has appeared in the upper layer, it indicates that the node has already been affected at a higher level. According to the three-degree influence principle, the lower the level, the weaker the influence of the node. Therefore, the influence of the current node i on its successor adj can be ignored. Repeat the above layer-by-layer expansion operation until all nodes are traversed. Applying this strategy can avoid the ring on the delivery path in advance.

As the example shown in Figure 4, assuming that the source node with credit risk is node 1, it can be seen that nodes 3, 4, and 5 will form a ring structure. However, using the above strategy, when the influence is transmitted layer by layer, node 1 first affects nodes 2 and 4, node 2 then affects

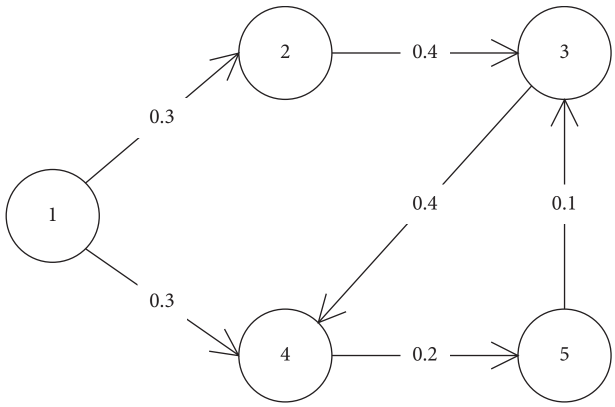

Figure 4: Circular transmission (before treatment).

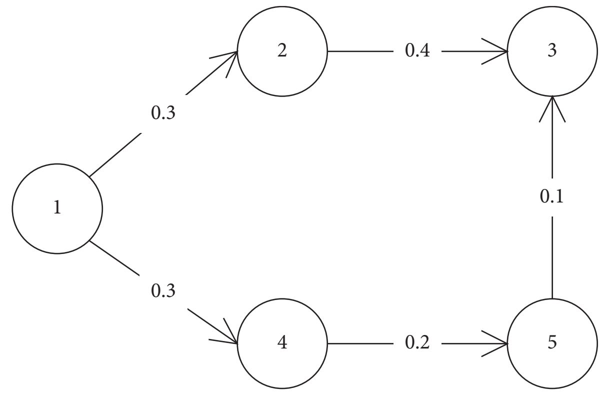

Figure 5: Circular transmission (after treatment).

node 3. Since node 4 has been affected by node 1, when node 3 is affected by node 2, the influence will no longer be transmitted to node 4. By applying this strategy to solve the credit risk transmission path of this example, the result is shown in Figure 5, which avoids the emergence of the ring structure mentioned above.

2.3. Division of Community. In the credit entity association structure, the correlation strength between nodes is determined by the relationship category between credit entities, and the subset of nodes with a strong association relationship may constitute a community. The internal connection of the community is close and influential, while the connection with external nodes is low-density. There may be multiple communities composed of different credit entities from the node set V. One node may form a special community, called an isolated community, which has a weak association with other communities.

One of the objectives of this paper is to find out the node sets from all of the credit entities. By forming different communities, the efficiency of credit risk supervision can be improved, and the possible harm of credit risk can be reduced. The method of community division in this paper is described as follows:

(1) Initial set P with all the nodes in V, t = 0

(2) If node set $P \neq \varnothing$, select node i with the maximal degree-centrality from P to establish a new community $C_{t+1} = \{i\}$, and remove node i from P

(3) For each successor adj of node i, if the degree-centrality of node adj is greater than or equal to the mean degree-centrality of node i and all its successors, thus $C_{t+1} = C_{t+1} \cup \{adj\}$, and remove adj from P

(4) Repeat (2)-(3) until $P = \varnothing$

3. Heuristic Algorithm Based on Hybrid Strategies

In this section, a heuristic algorithm based on a hybrid strategy (HAHS) is proposed for the considered problem. It aims to search the credit transmission paths, calculate the influence of nodes on the credit risk paths, divide credit entities into different communities, and find key nodes for each community. The proposed heuristic algorithm is depicted in Algorithm 1.

It mainly contains 6 steps with 4 subalgorithms. First, the credit entity association data is inputted and the mathematical model of the association structure is constructed. Next, a breadth first search algorithm (BFS) is used to search the credit risk transmission paths when the risk occurs to a credit entity. The influence calculation algorithm (Cal) is suggested to calculate the credit risk transmission impact through not only single-path but also multipaths. Global search algorithm (GS) is proposed to find global key nodes of the whole association structure. Last, the Community division and local key nodes searching algorithm (CDLS) is used to divide all of the credit entities into communities and find the local key nodes of each community.

The time complexity of the HAHS algorithm is $O(n^3)$, and the detailed analysis is given in Sections 3.1 to 3.4.

3.1. Breadth First Search Algorithm for Transmission Paths. In the credit entity association structure, when credit risk occurs to a node, it will be transmitted to the node's associated nodes, but the influence cannot be transmitted back. Otherwise, a ring will be generated. Meanwhile, the successors that the node can influence are its subordinate nodes. Thus, the credit risk transmission mode has the following characteristics:

(1) The impact of credit risk is a one-way transmission. That is, only the nodes at the upper level can affect the nodes at the lower level.

(2) The node at the lower level may be affected by one or more nodes at the upper level.

(3) There are no isolated nodes that neither affect nor be affected by other nodes.

As credit risk is transmitted layer by layer, the breadth first search algorithm is proposed for the transmission paths shown in Algorithm 2. It should be noted that the maximum value of the affected layer is 3 based on the three-degree influence principle, so the variable lev in algorithm 2 is less than 3.

```
    Input: Credit entity association data
    Output: 0
(1) Input the credit entity association data
(2) Construct the mathematical model of association structure: n-order square matrix M
(3) Cal BFS () to find the credit risk transmission path
(4) Cal Cal () to calculate influence for each node
(5) Cal GS () to find global key nodes in all of the credit entities
(6) Cal CDLS () to divide all of the credit entities into communities and find the local key nodes in each community
(7) Return 0
```

Algorithm 1: Heuristic Algorithm based on Hybrid Strategy (HAHS).

```
    Input: n-order square matrix M, Credit risk source node i, Θ = {i}
    Output:Affected node set Θ
(1) start = 0, end = |Θ|, lev = 0
(2) While lev < 3
          For i = start to end
             Set current node a as the i th element in set Θ
             For j = a to n
                If d_aj ≠ 0 and j ∉ Θ
                   Θ = Θ ∪ j
             Endif
          Endfor
       Endfor
    lev = lev + 1, start = end, end = |Θ|
    Endwhile
(3) Return Θ
```

Algorithm 2: Breadth first search algorithm (BFS).

The time cost of BFS algorithm is mainly in Step 2, and its time complexity is O (n^2), so the time complexity of the BFS algorithm is O (n^2).

3.2. Influence Calculation Method. When the transmission paths are obtained by algorithm 2, the influence of each node in the path is then to be calculated. As shown in section 2.2, the ring of credit risk transmission no longer exists. There are only two situations to be considered: single-path transmission and multipath transmission. For the single-path transmission, the influence of each node is calculated by the single-path influence calculation expression described in formula (2). For the multipath transmission, the influence of each node is calculated by the multipath composite influence calculation expression described in formula (3). The implementation of the influence calculation is shown in Algorithm 3. If the influence of a credit entity exceeds the credit change threshold "T" which is set by the service supervision platform, the platform needs to change the entity's credit.

The time cost of the Cal algorithm is mainly in Step 2, and its time complexity is O (n^2); thus, the time complexity of the Cal algorithm is O (n^2).

3.3. Searching for Global Key Nodes. If a node has a great impact on other nodes in the whole domain, it is called a global key node. In order to give early warning to other nodes in advance to reduce the impact of credit risk, it is necessary to search for the global key nodes. A greedy strategy is given to select global key nodes among all of the credit entities. The basic idea of this method is to calculate the total influence of each node on other nodes and the number of nodes affected by the node and take those nodes that meet the defined threshold θ as global key nodes. The specific implementation is depicted in algorithm 4.

The time cost of GS algorithm is mainly in Step 2 and Step 3, and its time complexity is O (n), so the time complexity of the GS algorithm is O (n).

3.4. Community Division and Local Key Nodes Searching. The idea of finding the local key nodes in communities is similar to that of finding global key nodes among all of the credit entities. The difference is that all of the credit entities should first be divided into communities as described in Section 2.3, and then the key nodes in each community, i.e., local key nodes, are to be found. The specific implementation is shown in Algorithm 5. It produces a set S composed of several communities and a set Z containing sets of local key nodes for the communities.

```
    Input: n − ordermatrixM, creditrisksourcenodei, affectednodesetΘ
    Output: Ω = {⟨node, influence⟩}
(1)   Ω = φ
(2)   For each node a ∈ Θ
          If ρ_{i,a} ≠ 0
             continue;
          Endif
          Ψ = φ
          For j = 1 to a − 1
             If d_{j,a} ≠ 0
                Ψ = Ψ ∪ j
             Endif
          Endfor
          For each node p ∈ Ψ
             Recursively call this algorithm to calculate the influence of node p
          Endfor
          If |Ψ| = 1
             ρ_{i,a} = ρ_{i,pre} × w_{pre,a}
          Else
             ρ_{i,a} = 1 − ∏_{∀<pre,a>∈E} 1 − ρ_{i,pre} × w_{pre,a}
          Endif
          Ω = Ω ∪ {⟨a, ρ_{i,a}⟩}
       Endfor
(3)   Return Ω
```

Algorithm 3: Influence calculation method (Cal).

```
    Input: n − ordermatrixM, thesetofΩ
    Output: T = {global key nodes}
(1)   T = φ
(2)   For each node i in node set V
          Find the sum of influence Sum_i obtained by Algorithm 2
          Endfor
(3)   For each node i in node set V
             If Sum_i ≤ θ and deg_i ≤ θ
                T = T ∪ {i}
             Endif
          Endfor
(4)   Return T
```

Algorithm 4: Global Search (GS).

The time cost of the CDLS algorithm is mainly in Step 4, and its time complexity is O (n^3), so the time complexity of the CDLS algorithm is O (n^3).

4. Experiment

The proposed HAHS algorithm is written in Java language and runs on Intel (*R*) core (TM) i5-5200U CPU@ 2.2 GHz, 2.19 GHz, 8 GB RAM personal computer and MS Windows 10 operating system. The simulation experiment of credit risk transmission is first carried out, then a large number of instances with different sizes are tested and compared.

4.1. Simulation Experiment. This section takes the association structure with 20 credit entities as an example to conduct the simulation experiment of credit risk transmission.

After inputting the credit entity association data, the 20-order square matrix M is generated in the second step, and the result is shown in Table 1.

Assuming that credit risk occurs to node 1, i.e., node 1 is the source node. After the BFS algorithm is applied in the third step, the results of the credit risk transmission paths are obtained, shown in Figure 6. In this figure, it shows that the transmission paths of credit risk are expanded layer by layer. The first layer contains nodes 2, 3, 4, 5, 6, 8, and 10, the second layer contains nodes 7, 9, 11, 12, 13, 14, 15, 16, 17, and 18, the third layer is composed of nodes 19 and 20.

In Step 4, the Cal algorithm is used to compute the influence of each node on the above paths. The resulting key value pairs $\langle i, \rho_{1,i} \rangle$ of the influence are as follows:

Input: $G = (V, E)$, n – ordermatrix M,{<node, influence>}
Output: Community set S, $Z = \{O_1, O_2, \ldots\}$ where O_i = {key nodes set for community i}
(1) $S = \varnothing$, $Z = \phi$
(2) For each node i in node set V
  Calculate the centrality of node idepictedasdeg$_i$
 endfor
(3) Repeat
   Select the node i with the largest degree of centrality
   $C_i = \phi$, $C_i = C_i \cup \{i\}$
   For each node j and $d_{ij} \neq 0$
    If $\deg_j \geq \deg_i$ and $\deg_j \geq \overline{\sum_{\forall k, d_{ik} \neq 0} \deg_k}$
    $C_i = C_i \cup \{j\}$
   Endif
  Endfor
  $S = S + C_i$
 Until nodes in node set V are all divided
(4) For each community C_i
   For each node j in community set C_i
  Find the sum of influence (sum$_i$) generated by node j obtained by algorithm 2
  Endfor
  For each node j in community set C_i
   If $\text{sum}_j \leq \theta$ and $\deg_j \leq \theta$
    $O_i = O_i \cup \{j\}$
    Endif
  Endfor
  $Z = Z + O_i$
 Endfor
(5) Return S, Z;

Algorithm 5: Community division and local key nodes searching (CDLS).

Table 1: An instance with 20 nodes.

Number	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	0	0.62	0.62	0.56	0.59	0.45	0	0.54	0	0.57	0	0	0	0	0	0	0	0	0	0
2	0	0	0.56	0.52	0.54	0.43	0	0	0.4	0.4	0.61	0	0	0	0	0	0	0	0	0
3	0	0	0	0.35	0	0.63	0.46	0.54	0.45	0	0.43	0.43	0	0	0	0	0	0	0	0
4	0	0	0	0	0.51	0.52	0.62	0	0.42	0.52	0	0	0.62	0.64	0	0	0	0	0	0
5	0	0	0	0	0	0	0.36	0	0	0.57	0.39	0.59	0.53	0.64	0	0.6	0	0	0	0
6	0	0	0	0	0	0	0.51	0.42	0	0.59	0.61	0	0.63	0	0	0.6	0.33	0	0	0
7	0	0	0	0	0	0	0	0.36	0.41	0.47	0	0	0.33	0	0.58	0	0.5	0	0.39	0
8	0	0	0	0	0	0	0	0	0.51	0.42	0	0.45	0.51	0.52	0.42	0	0	0.61	0	0
9	0	0	0	0	0	0	0	0	0	0.65	0.48	0.59	0.41	0.39	0	0.41	0	0.36	0	0
10	0	0	0	0	0	0	0	0	0	0	0.34	0.36	0	0.48	0.41	0.58	0	0	0	0
11	0	0	0	0	0	0	0	0	0	0	0	0.65	0.59	0.43	0.33	0.46	0.52	0.65	0	0
12	0	0	0	0	0	0	0	0	0	0	0	0	0	0.52	0.38	0.38	0.59	0.42	0.59	0
13	0	0	0	0	0	0	0	0	0	0	0	0	0	0.35	0.61	0.62	0.44	0.45	0	0.62
14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.5	0.5	0.57
15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.61	0.5	0.6	0.42	0
16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.39	0.52	0	0.65
17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.58	0.43
18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.55
19	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.33
20	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

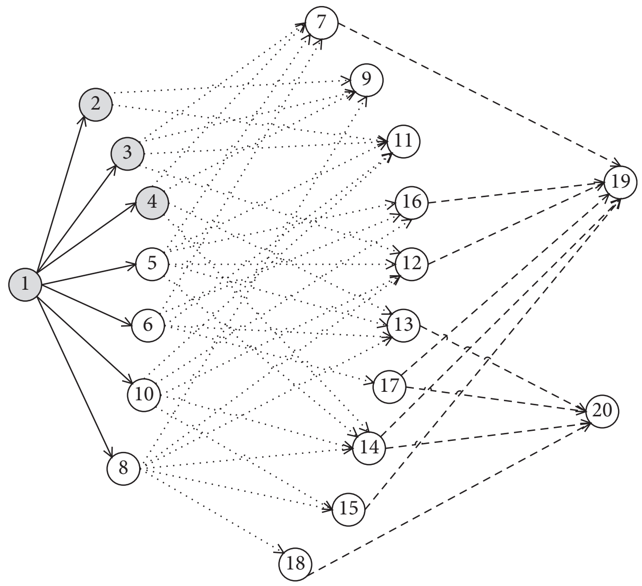

Figure 6: The transmission path of credit risk.

(1) The first layer: {<2,0.62>, <3,0.62>, <4, 0.56>, <5, 0.59>, <6, 0.45>, <8, 0.54>, <10, 0.57>}

(2) The second layer: {<7,0.717>, <9,0.700>, <11,0.795>, <12,0.712>, <13,0.767>, <14,0.791>, <15,0.407>, <16,0.684>, <17, 0.148>, <18,0.329>}

(3) The third layer: {<19, 0.809>, <20, 0.910>}

According to the GS algorithm in Step 5, the global key nodes are found, and these nodes include nodes 1, 2, 3, and 4. Once credit risk occurs to any of these nodes, it will have a significant impact on other nodes in the credit entity association structure.

Figure 7 shows the community division result based on the CDLS algorithm. It can be seen that the 20 credit entities are divided into five communities: A, B, C, *D*, and E. There are 12 nodes in community A, and nodes 1, 2, and 3 are the local key nodes of community A. There are 4 nodes in community B, and node 10 is the local key node of community B. There are 2 nodes in Community C, and node 17 is the local key node of community C. For the local key nodes of each community, once credit risk occurs to any one of these nodes, it will have an important impact on other nodes in its community. As nodes 18 and 20 have a weak influence on other nodes, each of them forms a community independently; i.e., they are isolated communities.

Through the above simulation experiment, the following conclusions can be obtained:

(1) Credit risk transmission is transmitted from near to far by layer diffusion

(2) Under the multipath composite influence, the influence of credit risk on a node does not consequentially weaken with the increase of hierarchy, and some outer nodes may be greatly influenced, leading to credit changes

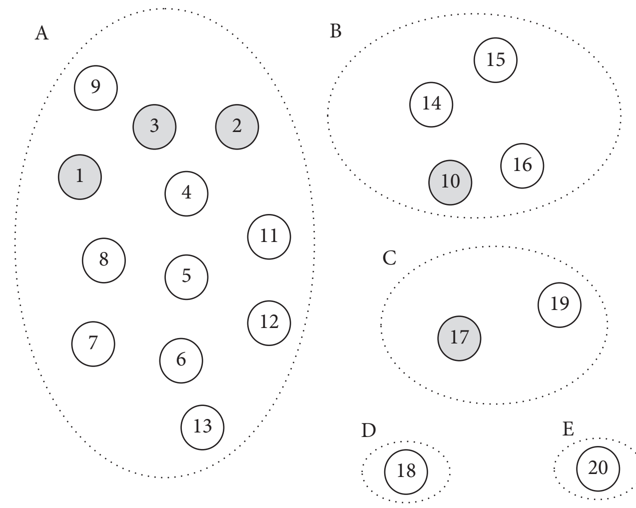

Figure 7: Division of community.

(3) Through the comparison between the global key nodes and the local key nodes, it can be found that a global key node is not necessarily a local key node and vice versa

4.2. Comparable Experiment. This section gives more comparative tests for node sets with different sizes and correlation densities.

4.2.1. Parameter Setting. In the credit entity association structure, if the nodes are closely related, that is, the number of associated nodes is much larger than the number of nonassociated nodes. The matrix M of the association structure is a high-density matrix; otherwise is a low-density matrix. In order to verify whether the algorithm has a significant impact on the node-set with different densities or not, this paper sets the association density property as 0.25, 0.45, and 0.65, which correspond to the low-density matrix, medium-density matrix, and high-density matrix, respectively.

In the following experiments, there are two factors, i.e., the sum influence of a node on its successors and the number of successors affected by the node, to determine whether a node can become a key node or not. Theoretically, if the sum influence of a node on its successors and the number of successors affected by the node are both greater than other nodes', the node can be taken as a key node. In the actual environment, the more key nodes, the greater the load of the service platform. Otherwise, if there are few key nodes, it is difficult to find the entities with credit risk in time. Experiments show that if the nodes with influence greater than the mean are taken as key nodes, the number of them accounts for about 30% of the total number of nodes. According to the Pareto principle, this paper finally selects the intersection of 20% of the nodes that meet the above two factors, respectively, as key nodes. Therefore, the threshold $''\theta''$ in this study is set to 0.2.

Table 2: Experimental results (low-density matrix).

Problem size ∗ number of instances	Number of global key nodes	Total number of local key nodes	Number of communities	Number of isolated communities
60 ∗ 10	10.6	13.5	11.2	6.1
90 ∗ 10	16.6	20.6	11.1	5.2
120 ∗ 10	21.7	26	11.7	6.1
150 ∗ 10	27	31.7	13.1	7.6
180 ∗ 10	32.1	38.5	12.7	6.3
210 ∗ 10	37.8	44.5	12.9	6.4
240 ∗ 10	43.5	51.4	12.3	5.3

Table 3: Experimental results (medium-density matrix).

Problem size∗number of instances	Number of global key nodes	Total number of local key nodes	Number of communities	Number of isolated communities
60 ∗ 10	10.8	14.1	7.9	3.1
90 ∗ 10	17.2	20.3	8.4	3.2
120 ∗ 10	23.2	26.6	9.2	3.7
150 ∗ 10	29.2	32.5	9.9	4.2
180 ∗ 10	34.9	38.7	9.4	3.4
210 ∗ 10	41	45	10.3	3.9
240 ∗ 10	46	51.6	10.7	3.5

Table 4: Experimental results (high-density matrix).

Problem size ∗ number of instances	Number of global key nodes	Total number of local key nodes	Number of communities	Number of isolated communities
60 ∗ 10	11.8	14	7.5	2.9
90 ∗ 10	17.5	20.7	7.9	2.5
120 ∗ 10	23.3	26.8	8.8	2.8
150 ∗ 10	29.5	32.8	9.3	3.2
180 ∗ 10	35.5	39	8.6	2.4
210 ∗ 10	41.4	45.6	9.3	2.4
240 ∗ 10	47.4	51.8	9.5	2.2

4.2.2. Experimental Results and Conclusions. This section randomly generates instances using the method of literature [22]. For each kind of density, the test data is divided into 7 groups, the problem size in each group are 60, 90, 120, 150, 180, 210, and 240, respectively, and each group generates 10 instances.

The experimental results of association structure with the low-density matrix are shown in Table 2.

The experimental results of association structure with the medium-density matrix are shown in Table 3.

The experimental results of association structure with the high-density matrix are shown in Table 4.

From the above experimental results, some characteristics of the considered problem can be concluded.

(1) For any instance, the total number of local key nodes is greater than the number of global key nodes. This is because the significance of local key nodes is that when credit risk occurs to a credit entity, its impact will spread violently within the community. In the global scope, the influence of a key node in one community is relatively weak or even has no influence on nodes in other communities. Therefore, the total number of local key nodes is greater than that of global key nodes.

(2) For instances with the same density, although the node size is increasing, the number of communities and isolated communities is growing slowly. This is because although the number of nodes has increased, the number of nodes in each community has also increased due to the improvement of the degree of association between nodes rather than forming more communities. Similarly, the number of isolated nodes increases slowly due to the improvement of the degree of association between nodes.

(3) For instances with different densities, it can be seen from the comparison of the above three tables: with the increase of matrix density, i.e., node correlation, the number of communities and the average number of isolated communities gradually decrease. This is because the closer the degree of association, the closer the relationship between nodes, and with a higher degree of mutual influence, the number of communities decreases gradually, and the

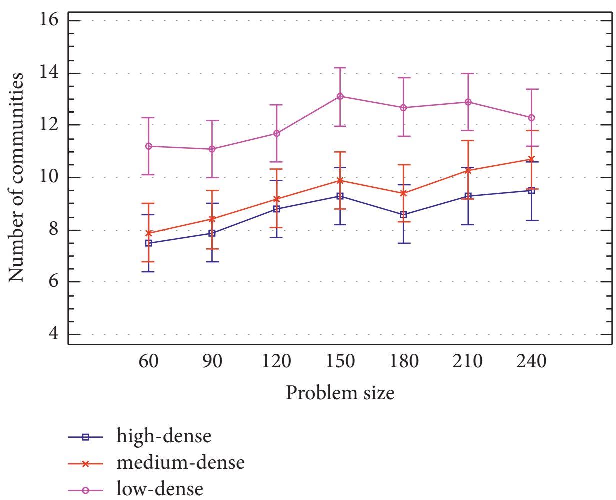

FIGURE 8: Comparison of the number of communities in the 95% Tukey HSD confidence interval.

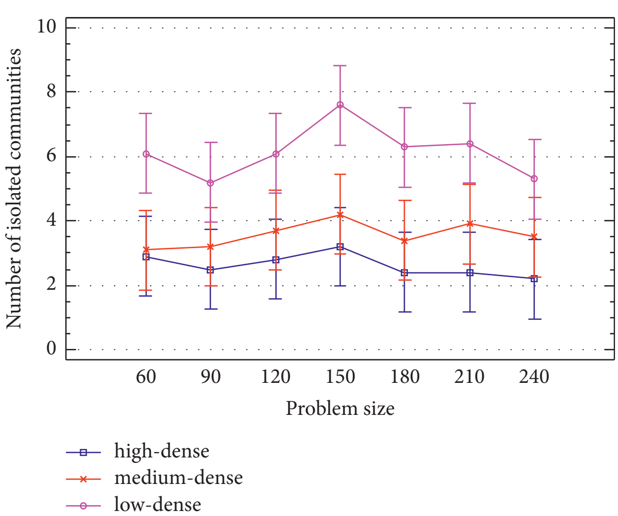

FIGURE 9: Comparison of the number of isolated communities in the 95% Tukey HSD confidence interval.

probability of forming isolated nodes also decreases gradually.

4.2.3. Further Analysis and Discussion. In order to better analyze the effectiveness of the algorithm, this section uses StatGraphics to statistically analyze the experimental results generated in the previous section. As mentioned in the above section, the experimental results come from 210 instances, which, respectively, describe the association structure matrix obtained under different problem sizes and different densities. The statistical analysis of the experimental results contains the number of communities, the number of isolated communities, the number of global key nodes, and the total number of community key nodes, as shown in Figure 8 to Figure 11.

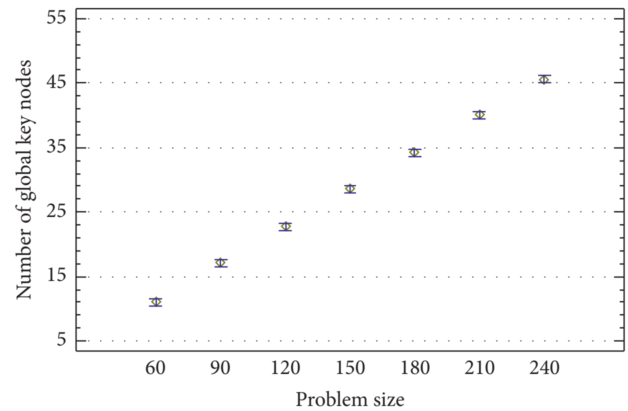

FIGURE 10: Comparison of the number of global key nodes in 95% Tukey HSD confidence interval.

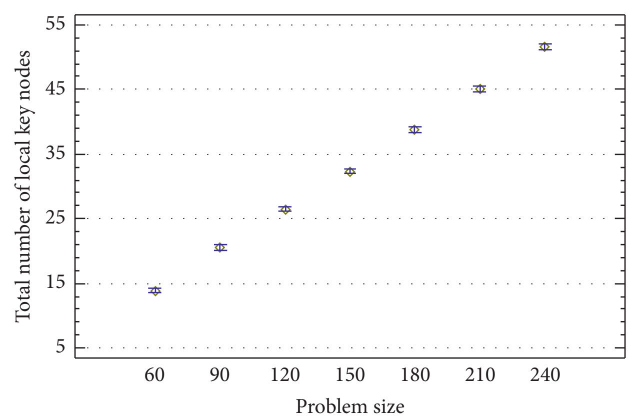

FIGURE 11: Comparison of the total number of local key nodes in 95% Tukey HSD confidence interval.

As shown in Figure 8, with the increase in the size of the problem, the total number of communities found shows a slow upward trend in the 95% Tukey HSD confidence interval, which is consistent with the second conclusion in the previous section. In addition, the higher the association density, the fewer communities are found, and vice versa. The reason is that the higher the association density is, the closer the credit entities are connected, and these closely connected credit entities are put into the same community, so fewer communities are obtained.

As shown in Figure 9, with the increase in the problem size, the total number of isolated communities found fluctuated up and down within the 95% Tukey HSD confidence interval, and there was no obvious upward trend. This statistical result is similar to the third conclusion in the previous section. Besides, the lower the association density, the more isolated communities are found, and vice versa. This is because the lower the association density, the more sparse the connections between credit entities, and these credit entities are more likely to form isolated communities.

In order to better realize the early warning of credit risk, this paper sets 20% as a threshold to select the qualified credit entities as the key nodes, so the number of these key nodes increases linearly with the problem size. It can also be seen from Figures 10 and 11 that, with the increase of the problem size, the number of global key nodes found by the GS algorithm shows an obvious upward trend, so as to the number of local key nodes in the community found by CDLS algorithm.

5. Conclusion

This paper studies credit risk transmission of cross-platform credit services. Aiming at the considered problem, a heuristic algorithm based on hybrid strategies named HAHS is proposed. After modeling the association structure of credit entities, the characteristics of credit risk transmission are analyzed, and influence calculation methods of credit risk are proposed for single-path and multipath transmission. Finally, a greedy strategy is used for community division, and a threshold control strategy is applied to find global and local key nodes. The results of the simulation experiment show the effectiveness of the algorithm. Through comparative experiments, the characteristics of credit risk transmission are concluded, which further shows the algorithm can be used to solve the problem of cross-platform credit risk transmission.

Abbreviations

HAHS: Heuristic algorithm based on hybrid strategy
BFS: Breadth first search algorithm
Cal: Influence calculation algorithm
GS: Global search
CDLS: Community division and local key nodes searching.

Data Availability

No datasets were generated or analyzed during the current study.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

This work was supported by the National Key R&D Program of China (Grant no. 2019YFB1404602) and Open Project for Young Teachers in School of Information Engineering, Nanjing Audit University (Grant no. XG202102). The authors would like to thank Jiangsu Key Laboratory of Audit Information Engineering for their support and anyone who supported the publication of this paper.

References

[1] F. X. Diebold and K. Yılmaz, "On the network topology of variance decompositions: measuring the connectedness of financial firms," *Journal of Econometrics*, vol. 182, no. 1, pp. 119–134, 2014.
[2] A. Uquillas and R. Tonato, "Inter-portfolio credit risk contagion including macroeconomic and financial factors: a case study for Ecuador," *Economic Analysis and Policy*, vol. 73, pp. 299–320, 2022.
[3] Z. Li, Q. Liang, and X. F. Tu, "Research on the relevance of listed financial institutions in China -- based on network analysis," *Journal of Financial Research*, vol. 8, pp. 95–110, 2016.
[4] K. D. Wang, X. B. Pang, and S. S. Wang, "Research on the contagion of financial crisis to global stock market: based on complex network analysis method," *World Economy Studies*, vol. 4, pp. 28–39, 2018.
[5] G. Bostanci and K. Yilmaz, "How connected is the global sovereign credit risk network?" *Journal of Banking & Finance*, vol. 113, Article ID 105761, 2020.
[6] C. Gross and P. L. Siklos, "Analyzing credit risk transmission to the nonfinancial sector in Europe: a network approach," *Journal of Applied Econometrics*, vol. 35, no. 1, pp. 61–81, 2020.
[7] M. Óskarsdóttir and C. Bravo, "Multilayer network analysis for improved credit risk prediction," *Omega*, vol. 105, Article ID 102520, 2021.
[8] T. Chen, Y. Wang, Q. Zeng, and J. Luo, "Network model of credit risk contagion in the interbank market by considering bank runs and the fire sale of external assets," *Physica A: Statistical Mechanics and its Applications*, vol. 542, Article ID 123006, 2020.
[9] G. Du, Z. Liu, and H. Lu, "Application of innovative risk early warning mode under big data technology in Internet credit financial risk assessment," *Journal of Computational and Applied Mathematics*, vol. 386, Article ID 113260, 2021.
[10] T. Chen and S. Wang, "Incomplete information model of credit default of micro and small enterprises," *International Journal of Finance & Economics*, pp. 1–19, 2021.
[11] P. Wu, L. G. Zhou, and H. Y. Chen, "E-commerce credit risk evaluation method based on language consensus model," *Control and Decision*, vol. 36, pp. 1465–1471, 2021.
[12] K. S. Leung and Y. K. Kwok, "Counterparty risk for credit default swaps: Markov chain interacting intensities model with stochastic intensity," *Asia-Pacific Financial Markets*, vol. 16, no. 3, pp. 169–181, 2009.
[13] D. Petrone and V. Latora, "A dynamic approach merging network theory and credit risk techniques to assess systemic risk in financial networks," *Scientific Reports*, vol. 8, no. 1, pp. 5561–61, 2018.
[14] P. Mu, T. Chen, K. Pan, and M. Liu, "A network evolution model of credit risk contagion between banks and enterprises based on agent-based model," *Journal of Mathematics*, vol. 2021, pp. 1–12, Article ID 6593218, 2021.
[15] T. Chen, Q. Yang, Y. Wang, and S. Wang, "Double-layer network model of bank-enterprise counterparty credit risk contagion," *Complexity*, vol. 2020, Article ID 3690848, 25 pages, 2020.
[16] C. Zhao, M. Li, J. Wang, and S. Ma, "The mechanism of credit risk contagion among internet p2p lending platforms based on a SEIR model with time-lag," *Research in International Business and Finance*, vol. 57, Article ID 101407, 2021.
[17] J. Liu, S. Zhang, and H. Fan, "A two-stage hybrid credit risk prediction model based on XGBoost and graph-based deep neural network," *Expert Systems with Applications*, vol. 195, Article ID 116624, 2022.
[18] L. Ma, S. Cheng, and Y. Shi, "Enhancing learning efficiency of brain storm optimization via orthogonal learning design," *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, vol. 51, no. 11, pp. 6723–6742, 2021.
[19] L. Ma, M. Huang, S. Yang, R. Wang, and X. Wang, "An adaptive localized decision variable analysis approach to

large-scale multiobjective and many-objective optimization," *IEEE Transactions on Cybernetics*, vol. 99, pp. 1–13, 2021.

[20] J. H. Fowler and N. A. Christakis, "Dynamic spread of happiness in a large social network: longitudinal analysis over 20 years in the framingham heart study," *British Medical Journal*, vol. 3, pp. 1–31, 2009.

[21] L. Wang and Q. Q. Zhang, "Centralization of complex networks," *Complex Systems and Complexity Science*, vol. 3, no. 1, pp. 13–20, 2006.

[22] E. Demeulemeester, M. Vanhoucke, and W. Herroelen, "Rangen: a random activity-on-the-node network generator," *Journal of Scheduling*, vol. 6, no. 1, pp. 17–38, 2003.