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Innovation and Prediction Methods for Collaborative Optimization of Enterprise Supply Chain Network from the Perspective of Accounting Information Disclosure

Jun Wang*

Yiwu Industrial & Commercial College, China

ywiccwj@163.com

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Abstract. The rapid development of the Internet is constantly changing the structure and internal operation mode of supply chain network. The research on supply chain network optimization and its innovative application has become the focus of academic research. Many scholars have explored from the perspectives of supply chain network structure design, network hierarchy, distribution mode, inventory control and so on. From the perspective of accounting information disclosure, this paper analyzes the collaborative optimization of supply chain network and the innovative application of enterprises in optimization, uses the improved particle swarm algorithm to solve it, and proposes the corresponding link prediction method combined with the topological update strategy and individual learning strategy. This paper compares and analyzes the proposed algorithm using multiple real enterprise supply chain data sets, and finds that the proposed Enterprise supply chain Network Collaborative Optimization and Prediction Algorithm (OP-SCN) has higher accuracy and efficiency than the classical algorithm.

Keywords: disclosure of accounting information, enterprise supply chain network, collaborative optimization model, prediction algorithm

1 Introduction

The supply chain network facilitates cooperative partnerships among enterprises, forming alliances based on demand. These interdependent enterprises impact the overall performance of the supply chain. However, inconsistencies in goals, asymmetric information, or external uncertainties can lead to issues like the bullwhip effect, preventing the network from maximizing its overall benefits [1]. Achieving "synchronization" among enterprises in the supply chain is crucial for improving overall efficiency. In a dynamic demand market, close cooperation is essential for enterprises to adjust strategic plans in response to uncertainties. This requires seamless connections and real-time collaboration across all links to ensure coordination and synchronization [2, 3].

The "synchronization" of the supply chain network can not only make the entire supply chain network run in a coordinated and efficient manner, but more importantly, it can improve the market response ability and flexibility of the entire supply chain, and minimize the phenomenon of network uncoordinated [4]. The cooperative and synchronous operation state of the supply chain network is that the real-time production level of each enterprise on the supply chain network is carried out in accordance with the quantity proportion of the product structure chart, the product inventory level is stored in accordance with the quantity proportion of the product structure chart, the procurement level of each raw material is also consistent with the proportion of the product structure chart, and the production level of the enterprise is consistent with the market demand level. Such a state can be regarded as the cooperative synchronization state of supply chain operation [5].

The existing research on supply chain management mainly focuses on the following aspects; The first is supply chain risk management. This paper addresses supply chain risks from two angles: the types of risks (operational and interruption risks) and strategies for mitigation through supply, demand, product, and information management. Operational risk includes daily operational issues like equipment failures and human errors, which can be mitigated by optimizing processes and enhancing employee quality. Interruption risk arises from supply or demand disruptions due to events like natural disasters or supplier bankruptcies, necessitating a flexible supply chain network and alternative suppliers for quick responses and reduced impact. By managing supply and

* Corresponding Author

demand, enterprises can better adapt to market changes, while effective product management ensures quality and cost control, minimizing product-related risks [6]. Second, by incorporating environmental factors into the supply chain process, the main factors and components that affect the management mode of green supply chain, such as product life cycle, operation life cycle, performance measures and enterprise policies, are studied, and the relationships among these factors are analyzed to investigate the impact of green supply chain on enterprise performance [7, 8]. Third, the scientific relationship between green supply chain management and informatization lies in the integration and utilization of advanced technologies to realize the sustainability and efficiency of the supply chain. By using informatization, organizations can improve the transparency, traceability and efficiency of the supply chain, and can also achieve real-time monitoring and decision-making [9].

The multivariate optimization algorithm mainly releases the implicit parallelism ability based on overall search in a multitask environment to take advantage of the potential complementarity between different tasks to improve the performance of each task optimization and accelerate the convergence of each task so that the final result of each task can reach the overall optimal state [10, 11]. Combining multi-task evolutionary algorithms can achieve optimal results that individual algorithms may not reach. The supply chain network is an integrated system of suppliers, manufacturers, customers, and distribution channels. Through organized selection, it efficiently manages raw material acquisition, production, distribution center location, transportation channel selection, and ensures timely delivery of products to customer nodes in the right quantities, ultimately minimizing total costs [12, 13].

From the perspective of the specific organizational structure and operation mode of cyberspace, its entities are mainly enterprises [14]. The main body of an enterprise consists of two existing real organizational forms and network virtual forms. Different corporate bodies are distributed in different geographical and cyberspace locations, independent of each other's economies, and have different organizational culture forms [15, 16]. The basic organizational structure of the network space cluster must be based on the third-party network platform, which mainly includes the network payment transaction guarantee platform, financial service institutions, network service providers and so on. After finding opportunities, business brokers in cyberspace clusters will find suitable partners through network virtual clusters and form a complete industrial chain [17, 18].

With the continuous adjustment of business strategy, enterprises have different requirements for information and data. Therefore, the accounting information system must be continuously reformed and developed to meet the needs of enterprise development as much as possible [19]. If an enterprise wants to gain an advantage in the competition, the first thing to do is to strengthen the cooperation between enterprises and obtain the highest interests by improving the integrity of the supply chain. In this regard, supply marketing needs to adjust the internal and external resources of the enterprise to achieve the development goal of the enterprise [20]. It can be said that the supply chain is the virtual sector of the enterprise. This virtual economy presents a dynamic change and will be constantly adjusted with the market demand. Different from other departments of enterprises, accounting department is more dependent on the support of information system [21]. Accounting information disclosure provides essential data for supply chain managers to monitor and evaluate performance. It enables enterprises to understand costs, revenues, and profits across the supply chain. By transparently sharing financial data, companies can enhance trust among partners, promote cooperation, and facilitate information sharing. An effective disclosure system fosters stable, efficient supply chain relationships, improving overall operational efficiency and competitiveness.

The algorithm proposed in this paper integrates financial data from accounting information disclosure with supply chain management to more accurately predict operations and trends within the supply chain network. This approach helps enterprises timely adjust their strategies, reduce operational risks, and enhance efficiency, providing comprehensive decision-making support. Additionally, the improved particle swarm optimization algorithm demonstrates better adaptability and convergence speed for collaborative optimization and prediction, increasing overall algorithm efficiency. This research also contributes to the understanding of supply chains from the perspective of accounting information disclosure, supporting future studies.

2 Literature Review

The supply chain is characterized by its network structure, with multiple interconnected supply chains forming a supply chain network that significantly impacts enterprise performance [22]. Multinational companies leverage these networks to strengthen connections and achieve substantial profits globally, enhancing competitiveness. Enterprises within the supply chain collaborate to produce and transport goods to distributors, ultimately reach-ing consumers [23, 24]. Research has evolved from single-chain studies to examining networks of multiple supply chains, constructing basic models of complex networks based on enterprise data to analyze their effectiveness and impact on businesses [25, 26]. Additionally, digital supply chains offer strategies for resource reconfiguration and high-quality development, providing new options for global manufacturing firms in supply chain risk management, while also improving risk resistance and optimizing operations across all parties involved [27, 28].

Supply chain optimization is a decision-making framework for enterprises operating under constraints, serving as the core goal of supply chain management [29]. It involves decision variables, objective functions, and constraints [30]. Decision variables include factors like ordering times and quantities, production scheduling, and delivery timings [31]. Objective functions represent goals such as maximizing profit, minimizing costs and cycle times, ensuring high customer service quality, and meeting customer demands. Constraints are the necessary conditions for decision-making, including supplier production capabilities and production line capacity. Some researchers propose a green supply chain optimization framework using a two-stage heuristic algorithm, which aids in modeling and optimizing green supply chains by efficiently determining urgent deadlines and transportation plans, ultimately supporting decision-makers in maximizing benefits [32]. As modern logistics and technology evolve, factors like globalization, customer customization, outsourcing, mergers, agile manufacturing, and the rise of third-party logistics contribute to the increasing complexity of supply chain development [33].

Supply chain management aims to enhance the long-term performance of individual organizations and the entire supply chain by optimizing the flow of goods and information. This optimization reduces costs, improves customer satisfaction, and enables a more effective response to market demand, thereby developing core competitiveness and positively impacting enterprise performance [34, 35]. Additionally, supply chain management increases enterprise value, with technological innovation and supply chain concentration influencing risk levels and further enhancing value [36]. Previous research has examined factors affecting supply chain management, emphasizing that intra- and inter-company activities and process structures are vital for achieving competitiveness and profitability. The integration of supply chain practices with innovative product development encompasses both the tangible flow of resources and the intangible flow of knowledge. Effectively incorporating knowledge management into supplier management and new product development can significantly boost enterprise performance [37].

Due to the complexity and diversity of supply chain data, various clustering methods have been proposed by scholars to meet specific problem needs, with the choice of method depending on factors like data type, clustering purpose, and application area [38, 39]. Current clustering methods are primarily categorized into several types: partition-based, hierarchical, density-based, grid-based, and statistical learning methods [40]. Hierarchical and partition-based algorithms rely on distance to measure data similarity, making them suitable for spherical clusters but limited for non-spherical ones [41]. To overcome this limitation, density-based clustering algorithms were developed, which focus on data distribution density, filter low-density areas, connect dense regions, and identify clusters of arbitrary shapes while effectively managing outliers.

3 Model Construction

3.1 Construction of the Basic Network Model

From the perspective of accounting information disclosure, consider a directed network composed of n nodes, and the directed graph $\mathcal{G}(\mathcal{V}, \mathcal{E})$ is used to describe its supply chain network topology structure. At each moment $k\in[T]$, each node $i\in\mathcal{V}$ makes a decision $x_i(k)$ from the constraint set $\Omega\in\mathbb{R}^m$, and then the local cost function $f_{i,k}$: $\mathbb{R}^m\to\mathbb{R}$ which is not known to node $i\in\mathcal{V}$ is exposed to node $i\in\mathcal{V}$ and produces a cost of size $f_{i,k}(x_i, k)$). Therefore, the cost at time $k \geq 0$ can be expressed as the sum of the local costs for all nodes at that time $\sum_{i=1}^{n} f_{i,k}(x)$.

Each node can only contact the cost function value of its own generation, and the global cost function f_k cannot be contacted by any single node, so each node needs to communicate with its neighbors to cooperatively optimize the global cost function. Moreover, the value of each local cost function is revealed to each node after each node makes the decision at the current moment, that is to say, each node cannot know the local cost function value at the current moment before making the decision.

Since the cost function is time-varying, a distributed algorithm needs to be designed for the time window $T\geq 0$, reducing the difference between the total cost generated by the algorithm and the total cost of the best fixed decision when all the information is known. On the other hand, due to the concern of privacy leakage, the nodes in the network pass the decision value of the injected noise through a random mechanism, so as to protect the privacy information of the nodes. With $\mathcal{F}$ represents the σ^{-} domain generated by the stochastic algorithm from the initial time to time $k \geq 0$. In this problem framework, the goal of the distributed online optimization algorithm is to reduce the total cost of the network in a finite time window based on local information interaction and local computation. Each node communicates with its neighbor node, and at each moment makes its own decisions based on what decisions it "thinks" that the entire network will make. Thus, the static form of the node $j \in \mathcal{V}$ can be expressed as shown in Equation (1).

$$\mathbb{E}(\cdot)=\sum_{t=1}^{T}\mathbb{E}\left[f_k\left(x_j\left(k\right)\right)\right]-\sum_{k=1}^{T}f_k\left(\arg\min_{x\in\Omega}\sum_{k=1}^{T}f_k\left(x\right)\right) \tag{1}$$

Represents the best fixed decision when all information is available. If the average of the static state defined above converges to the time window for a given time window T, then the designed distributed online optimization algorithm is effective. The adjacency matrix corresponding to the directed graph $\mathcal{G}$, $\mathcal{A} = [a_{ij}]_{n\times n}$ is a row random matrix and has $a_{ii} > 0$ for any node $i\in\mathcal{V}$. Design a distributed collaborative optimization method based on differential algorithm, where each node $i\in\mathcal{V}$ at each moment $k\in\mathbb{N}$ maintains $x_i(k)\in\mathbb{R}^m$ and $z_i(k)\in\mathbb{R}^n$ two variables. At each moment $k\in[T]$, where $[T] = \{1, ..., T\}$, each node $i\in\mathcal{V}$ generates a random noise vector, $\eta_i(k)$, $x_i(k)$ perturbbed using noise $\eta_i(k)$, each node $i\in\mathcal{V}$ passes its own state $y_i(k)$ after being perturbed by the noise to its neighbor node $j\in\mathcal{N}_i^{out}$ out. Then update its own status according to the following rules as shown in equation (2).

$$x_i\left(k+1\right)=\sum_{j=1}^{n}a_{ij}y_j\left(k\right)-\alpha\left(k\right)\frac{g_{i,k}}{z_{ii}\left(k\right)} \tag{2}$$

Where, $g_{i,k}$ represents the local cost function $f_{i,k}$ subgradient at $x_i(k)$, $\alpha(k)$ represents the step size of the algorithm, $A_i(k)$ represents the i th element of the vector $A_i(k)$, and the vector $A_i(k)$ is dynamically updated as in Equation (3).

$$A_i\left(k\right)=\sum_{j=1}^{n}a_{ij}A_j\left(k\right) \tag{3}$$

Algorithm 1. Network collaborative model design based on differential method

Import: $\mathcal{G}$, i, j
Export: $z_i(k+1)$, $x_i(T)$
01. define $[T] = \{1, ..., T\}$, $k = \{0, 1, 2, ..., T\}$, $i = \{1, 2, ..., n\}$
02. Generate noise $\eta_i(k)\sim Lap(\sigma(k))$
03. The $y_i(k)$ is obtained by perturbating the $x_i(k)$ with the generated noise $\eta_i(k)$
04. Node $i\in\mathcal{V}$ passes the intermediate variables $y_i(k)$ and $z_i(k)$ to its neighbor $j\in\mathcal{N}_i^{out}(k)$;
05. The node $i\in\mathcal{V}$ updates its own state variable $x_i(k)$ by the following equation
06. for the intermediate variable $z_i(k)$ is updated according to the initial value α of the set weighted matrix
07. While the objective function does not converge and the maximum number of iterations is γ
08. End for
09. Return $z_i(k+1)$, $x_i(T)$

When the local cost function is a general convex function, the $\mathbb{E}$, $\mathbb{E}[f_{i,k}(x) - f_{i,k}(x_i(k))]$ term appear coefficient $\frac{\pi_i}{z_{ii}(k)}$ due to the presence of Laplace noise, so the term is divided into two parts. It can be seen that the introduced intermediate variable $z_{ii}(k)$ plays an important role in the treatment of the network imbalance process.

3.2 Solution Method

The dynamic evolution process of supply chain network topology is one of the important research contents of network dynamics. Link prediction is a powerful tool used to study the dynamic evolution of the topological structure of supply chain networks. The basic idea is to use some information about the current network topology to construct the corresponding indicators, and use these indicators to predict the possible connected edges in the future.

This study defines whether there is a relationship of mutual learning between different particles, i. e., whether the two nodes are connected, so that the corresponding topological network is an undirected network. The topology G of an undirected network can be represented by G The number of neighbors of node x is called the degree of node x and is expressed by $k(x) = |\Gamma(x)|$. If a node is connected to node x by an intermediate node, then this node is called the 3rd order neighbor of node x and is represented by $\Gamma_3(x)$. $|\Gamma_3(x)|$ Represents the number of order 3 neighbors of the node x. By analogy, one can define the higher-order neighbors of the node x. If the number of nodes in a network is N, the network has $N(N-1)/2$ node pairs.

According to the definition of the connection matrix, it is easy to know that the number of common neighbors of node i and node j can be calculated from the connection matrix according to equation (4). $(A^2)_{ij}$ represents the elements of row i and column j of the matrix A^2.

$$\left|\Gamma(i) \cap \Gamma(j)\right| = \sum_{k=1}^{N} a_{ik} \cdot a_{kj} = \left(A^2\right)_{ij} \tag{4}$$

By introducing the concept of fitness-based edge weight, the connection matrix A_w with weight information is established. Furthermore, $S_w = A_w^2 + A_w^3$ is used to calculate the weighted local path link prediction index to solve the problem of not effectively distinguish the particle fitness in the existing link prediction methods. It is known that in the connection matrix A_w with weight information, good quality particle information has more weight. When performing network topology updates based on link predictions, edges with greater weights have a more connected chance. Therefore, the particles with better fitness can affect more particles and can transfer their information to other particles in the neighborhood faster, thus improving the search and optimization ability of the particle swarm algorithm.

And use the basic operation of the genetic algorithm to improve the performance of the particle swarm algorithm to accelerate the convergence rate. First randomly initiate the N subgroups and remember them as GA_i. Each subgroup runs its own genetic algorithm independently, and after a certain number of generations, the respective optimal individual is taken out of the elite group forming the upper layer, and denoted as the particle group. The particle group algorithm is used to evolve the elite group. After a certain algebra, the stopping criterion is satisfied. If so, the output result and the algorithm stops. Otherwise, each genetic subgroup randomly obtains the individual extremums of k particles from the upper elite group, randomly replacing its own k individuals. N subgroup resumes the genetic algorithms operation and cycles until the stopping criterion is met. Classical genetic algorithms can converge to the global optimal solution as long as they contain the historical optimal solution in each generation of the population, whether before or after the operator, which is called the optimal retention strategy.In this paper, the genetic algorithm of evolving the underlying subgroup adopts the optimal retention strategy, finds the historical optimal solution before selecting the operator, and randomly replaces anyone in the current population if it is not in the current population. Thus the genetic algorithm used by the underlying subgroup has a global convergence. In particle swarm optimization, assuming that $p_{ib}(t)$ and $p_{gb}(t)$ remain unchanged in evolution, the $x_i(t)$ of the particle swarm algorithm converges to $p_{ib}(t)$, and the weighted center of $p_{gb}(t)$ is shown in Equation (5).

$$x_i(t) \to \frac{\varphi_1 p_{ib}(t) + \varphi_2 p_{gb}(t)}{\varphi} \tag{5}$$

Consider that the global optimal position is p_{gbest}, because the genetic algorithm of the underlying subgroup has global convergence. When the underlying subgroup converges to the global optimal solution, all the particles in the upper elite group will be in the global optimal position, and the individual extreme values are the same and remain unchanged in the evolutionary process, both are p_{gbest}. Therefore, when the underlying subgroup evolves with a genetic algorithm with an optimal retention strategy, the algorithm has global convergence, as shown in

Algorithm 2.

Algorithm 2. Improved particle swarm solution method of fusion genetic algorithm and neural network

Import: s, $T(t)$, $D(t)$, $I(t)$
Export: $p_{ib}(t)$, p_{gbest}, $\boldsymbol{F}_{\mathrm{best}}$
Remember the individual as $x_i (i = 0, 1, ..., n - 1)$
  Middle n individuals were selected by using the unbiased selection method
    if $f_i \le f_k \rightarrow x_i^{'} = x_i$
  A new generation of individuals is fully crossed for intermediate individuals
    $x_i = rand1 * x_i^{'} + (1 - rand2) * x_{i+1}^{'}$
  Non-consistent variation was used for each dimensional component by probability P_m for all individuals
    if rand $\le 5 \rightarrow x_j = \boldsymbol{x}_i + \Delta(t, U_{max}^{j} - x_j)$
      Individual fitness values were calculated
      Find out the optimal individual in the current generation, and update the historical optimal individual I_{best} and its fitness value F_{best}
  end if
Return $p_{ib}(t)$, p_{gbest}, $\boldsymbol{F}_{\mathrm{best}}$

4 Algorithm Design

4.1 Wavelet Denoising Method

The defined background noise signal P_n and the multipath effect X_σ can be used as noise. Thus, a decomposition of the stochastic part of the SNR can be seen as a denoising of the SNR time series. The wavelet denoising algorithm has the advantages of maximizing fidelity, maximizing edge descent, and retaining more feature information, which can decompose the random part in the time series. There are three main steps, namely wavelet decomposition, denoising and wavelet reconstruction.

The raw SNR time series is decomposed by the discrete wavelet transform, which is represented by low-pass filters and high-pass filters. The low-pass filter extracts the approximation coefficient A_j, and the high-pass filter extracts the detail coefficient D_j, where j = 1, 2, ..., and j represents the DWT level. The denoising soft threshold is applied to the detail coefficient D_j of all layers to suppress the noise component of the high frequency part. The threshold $\overline{\mathrm{d}} = \sqrt{2\log(\mathrm{N})}$ is determined by the universal threshold widely adopted in wavelet denoising. The soft function can be expressed as shown in Equation (6).

$$d_T = sign(d)\left(|d| - \overline{d}\right) \tag{6}$$

Finally, the wavelet reconstruction is performed, using the new detail coefficient $D_j^{'}$ and the original approximate coefficient A_j, to reconstruct the denoised SNR time series, which is treated as the deterministic part and expressed as $S^{'}$. Then the filtered noise time series (expressed as R) is used as random part and the formula is $R = S - S^{'}$.

4.2 Supply Chain Network Collaborative Optimization and Prediction Algorithm

Through the optimization characteristics of enterprise accounting information disclosure and the introduction of learning rate parameters, LM algorithm can ensure the positive shape of Hessian matrix to a certain extent. However, when the number of training samples is large, the storage and calculation of Jacobian matrix is still a key factor restricting the application of LM algorithm. To solve these problems, an improved second-order learning algorithm is introduced. When the performance evaluation index function approaches the minimum value, the elements in the matrix S become very small and negligible, so the Hessian-like matrix can be defined as shown in Equation (7).

$$\theta_{k+1} = \theta_k - \left(Q_k + \mu_k I\right)^{-1} g_k \tag{7}$$

In order to reduce the spatial complexity and time complexity of the Jacobi matrix calculation process, the sum of the Heissen-like matrix into multiple Heisen-like submatrices is $\sum_{p=1}^{p} q_p$. For the Heissen-like sub-matrices q_p of the p training sample can be obtained by the corresponding Jacobi vector j_p calculation, class The Heisen matrix can be defined as $j_p^T j_p$. After being converted into a Heisen-like sub-matrice, the calculation of Jacobi vector is only related to the current sample and the parameters to be adjusted, so the storage space required for the Jacobi matrix is greatly reduced. Similarly, the calculation of the gradient vector g can be transformed into the summation definition of the gradient sub-vector as shown in the Equation (8).

$$g(\cdot) = \sum_{p=1}^{p} j_p^T * e_p \tag{8}$$

Therefore, from the perspective of accounting information disclosure, the introduction of learning rate parameters, the conversion of Heissen-like matrix and gradient vector method can avoid the pathological solution of the traditional Newton algorithm and the lack of large computational complexity to a certain extent. When the RBF neural network is trained with an improved second-order learning algorithm, the parameters that need to be adjusted include the center of the implicit layer neuron, the radial action range, and the connection weight of the implicit layer to the output layer. Starting from the characteristics of RBF neurons, this study uses a growth structure design algorithm based on error compensation to determine the initial parameters of the network while the structure is growing, and then adjusts the network parameters with an improved second-order learning algorithm to establish a generalized regression neural network structure based on the improved error compensation algorithm. The pre-method to optimize the supply chain network collaboration model from the perspective of information disclosure, and the transfer function can be expressed as shown in Equation (9).

$$p_i = exp\left[-\frac{\left(X - X_i\right)^T \left(X - X_i\right)}{2\sigma^2}\right] \tag{9}$$

Among them, X means the input learning sample; X_i is the training sample; p_i is the sum of the Euclidean distance squares between the learning sample and the training sample; and σ is the standard deviation of the Gaussian function. The output sample of the output layer is $Y = [y_1, y_2, ..., y_n]$, and the output of neurons in the output layer can be expressed as shown in Equation (10).

$$y_j = \frac{\sum_{i=1}^{n} P_i}{\sum_{i=1}^{n} y_{ij} P_i}, j = 1, 2, \cdots, k \tag{10}$$

Among them, Pi is the output of neurons in each pattern layer; S_{Nj} , S_D are the summation result of the two types of neurons in the summation layer; y_{ij} is the j th element of Y_i . Because the generalized regression neural network has a flexible network structure, high fault tolerance and robustness, it can get a good prediction and recommendation effect in the supply chain network environment for the problem of few samples and poor data accuracy of some samples. Reasonable volume attenuation coefficient and search frequency can effectively balance the optimization accuracy and convergence speed of the algorithm. In the algorithm simulation, it is necessary to constantly adjust the volume attenuation coefficient and search frequency. For the given input vector x, assuming that the estimated function is continuous and smooth, the expected value of the estimated y is as shown in Equation (11).

$$E\left[y\middle|x\right]=\frac{\int_{-\infty}^{\infty}v\left(2\pi\right)^{\frac{p+1}{2}}\sigma^{(p+1)}dv}{\int_{-\infty}^{+\infty}f\left(x,y\right)dy} \quad \textbf{(11)}$$

Where f(x, y) is a continuous probability density function. x_i, y_i are the ith sample value of the random variables x and y respectively. σ is the smooth parameter, p is the dimension of the random variable x, and k is the number of samples. In the topology of a generalized regression neural network, there are network structures such as input layer, pattern layer, summation layer and output layer. In this study, the sample is entered into the input layer. The number of nodes in the input layer is equal to the dimension p of the input vector, and then the elements of the input vector are then transmitted to the mode layer. Let the schema layer transfer function as shown in Equation (12).

$$t_i=\exp\left(-\frac{D_i^2}{2\sigma^2}\right) \quad \textbf{(12)}$$

Topology update interval will have a certain impact on the performance of the algorithm. Too small an update interval, that is, if the topology is updated frequently, does not guarantee sufficient search under the current topology. However, a large update interval can not obtain the dynamic evolution information of the population in time, and is not conducive to maintaining the diversity of the population. Based on the analysis of topology update strategy and individual learning strategy based on link prediction, algorithm 3 is defined. The proposed method in this study is defined as the Enterprise supply chain Network Collaborative Optimization and Prediction Algorithm (OP-SCN) from the perspective of accounting disclosure.

Algorithm 3. Supply chain network link prediction method based on topology update strategy and individual learning strategy

Input: Particle position *x*, particle velocity *v*
Output: Global optimal solution gbest and corresponding fitness value
01: Evaluate the fitness and transfer function of the initial population, and determine the individual pbest, nbest and population gbest of the initial particle
02: Ream $i = i + 1$, calculate the inertial weight ω_L of each iteration *i*
03: Calculate the weighted local path link predictor $\boldsymbol{S}_w$
04: Update the neighborhood topology, update the speed and position of particles in the population
05: Determine the learning object *fi*(*d*) of pbest according to the neighborhood topology, and determine nbest according to the neighborhood topology
06: Calculate the fitness value of each particle after update, update pbest, nbest and gbest
07: Output the global optimal solution gbest and the corresponding fitness value
08: Returns gbest

5 Numerical Example

5.1 Experimental Design

From the perspective of accounting information disclosure, to study the impact of the initial load adjustment parameter θ on the underload failure, it is necessary to adopt the control variable method to fix other parameters of the underload failure model and change the initial load adjustment parameter θ. Considering the local and global importance of the node, this experiment adopts a comprehensive index combining node degree and node intermediate number to allocate the initial load of the node. The on-line adjustment parameter of load capacity in the underload failure model is set to δ, the lower limit of load capacity adjustment parameter σ, and the correlation intensity adjustment parameter α are set to 1.4, 0.8 and 0 respectively. The MonteCarlo simulation method is used to calculate the corresponding network efficiency under 1,000 random fault events.

The results of comprehensive experiments on the real enterprise supply chain network show that the algorithm is better than other recommended methods. The comparison methods are as follows: (1) Linear Threshold Model (LT) [16], (2) Independent Cascade Model (IC) [16], (3) Greedy Algorithm (GA) [24], (4) Neighborhood Recommendation Method Based on Differential Privacy Protection (DPKNN) [16], (5) Average Prediction Method (IA) [21], (6) Basic Neighborhood-based Recommendation Algorithm (BasicKNN) [23], (7) Neighborhood-Based Recommendation Algorithm with bias terms (BiasedKNN) [16]. Combined with the literature [31], two precision functions are used: Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). The reason why MonteCarlo simulation method is superior to these algorithms is that, first of all, in terms of randomness and statistics, MonteCarlo algorithm is a numerical calculation method based on random sampling, which simulates and solves problems by generating random numbers or pseudorandom numbers. This method enables the MonteCarlo algorithm to deal with complex and uncertain problems, especially when the analytical solution of the problem is obtained, compared with the above methods may be more focused on deterministic or structured solutions, and the processing ability of complex and uncertain problems is relatively weak. The MonteCarlo algorithm is more adaptable, especially when dealing with high-dimensional data and complex systems. Secondly, in terms of efficiency and scalability, Monte Carlo algorithms usually have high computational efficiency, especially in parallel computing and distributed computing environments. By increasing computing resources, the running speed and problem-solving ability of the algorithm can be significantly improved. In addition, the Monte Carlo algorithm has good scalability and can adapt to problems of different sizes and complexity. Finally, in uncertainty analysis, Monte Carlo algorithm obtains the approximate solution of the problem through random simulation, so the result itself contains a certain degree of uncertainty. This uncertainty analysis helps us to understand more fully the nature of the problem and the potential risks. In contrast, other algorithms may focus more on obtaining deterministic solutions to problems, while ignoring the importance of uncertainty analysis. The specific calculation methods are shown in formula (13) and formula (14) respectively.

$$MAE = \frac{1}{N}\sum\nolimits_{i=1}^{N}\left|f_i - y_i\right| \tag{13}$$

$$RMSE = \sqrt{\frac{1}{N}\sum\nolimits_{i=1}^{N}\left(observed_i - predicted_i\right)^2} \tag{14}$$

It is evaluated based on two indicators, namely, Area Under the Receiver Operating Characteristics curve (AUROC) [2] and Average Precision (AP) [5]. The ROC curve is a curve between the real case rate (sensitivity) on the Y-axis and the false regularity rate (1-specificity) on the X-axis. A single-point summary statistics with an area of [0,1] under the ROC curve can be calculated using the trapezoid rule, which adds all trapezoids under the curve. The AUROC value of the link prediction method should be greater than 0.5. The higher the AUROC value, the better the performance of the link prediction method. The average accuracy is a single-point summary value calculated based on different recall thresholds, which is the average accuracy value of the interval [0,1] recall value. The details are shown in the formula (15). Among them, p represents the accuracy rate under the r threshold of different recall rates, and R is the set of different thresholds.

$$AP = \sum_{k=1}^{R} p(k) * \Delta r(k) \tag{15}$$

In the practice of reference [27], three real supply chain network data sets were used in the experiment (as shown in Table 1). This article uses the supply chain data set of listed companies, the supply chain data set of non-listed companies and the supply chain data set of listed companies as the basic data of experimental simulation (the crawling or acquisition time is from February 13, 2023 to November 3, 2023). Take each enterprise as a node, and use the edges between nodes to represent the relationship between enterprises. A list of 20 enterprises with strong influence and their partners was selected as the initial node of the supply chain network to generate a simple supply chain network. The team used Tensorflow 1.5.1 to implement the algorithms proposed in this article and the relevant algorithms for comparison. The experimental process is carried out in groups, and the data is divided into 10 groups. Cross-validation is adopted, that is, the data set is divided into 10 equal parts. Each time a set of data is selected as the test set, and the other groups are selected as the training set, and the average value is finally taken. And save all data in CSV format in MySQL database for data processing. For each supply chain network data set, use the Rapidminer data mining tool to randomly select 10% of the rating data of each user as the test set, and use the remaining 90% of the user data as the training set. The experiment is implemented under the Python framework. In view of the network community query problems in this article, this article uses the query algorithm BasicSCS based on edge density, Index Tree-based query algorithm IndexBasedSCS and improved index tree-based query algorithm EnIndex BasedSC. The experimental hardware environment is InterCorei7-10510U, the main frequency is 1.8Hz, the memory is 12GB, the graphics card is Nvidia 3070, and the experimental software environment is Windows10 64-bit operating system.

Table 1. Accounting information disclosure and supply chain network data set used in the experiment

Network serial number	Network name	Type	Number of nodes	Number of node boundaries	Average degree	Average path of nodes	Clustering coefficient
1	Supply Chain Network of Listed Companies	Directed	224123	4284923	42.14	5.35	0.131
2	Supply Chain Network of Unlisted Companies	Directed	3602389	29389120	67.12	5.42	0.245
3	American Public Company Supply Chain Network	Directed	418293	7400282	41.90	6.77	0.152

This article uses WebCrawler to download the annual report and detailed text. In this chapter, the Python language based Scrapy framework crawls the annual reports disclosed by listed companies and the specific information of non-listed companies. Since the announcements disclosed by listed companies include a large amount of text information, it is necessary to further screen the obtained text information to ensure the accuracy and effectiveness of the captured information. The final amount of data captured is shown in Table 1.

Algorithm 4. Improve the LDA algorithm

Input: Enterprise Corpus
Output: Document topic emotion score
for theme z, emotion m
Extract multinomial distribution $\varnothing_{z,m}$
for document d, emotion j
Extract multinomial distribution φ_d, θ_{dj}
for each sentence s in the sentence s, word $w_{d,n}$
Extract binomial distribution m_s, π_{n-1}
    if $x_n = 0$
Extract multiple variable topics Z_n and words w_n
    else if $x_n = 1$
Extract the theme Z_{n-1} and the word w_{n-1} from the LDA distribution with a parameter δ
    end if
    end for
  end for
end for
Return to theme emotion score

The text sentiment analysis of accounting information disclosure can be used to estimate the temotion of accounting information in time. In this study, we construct emotion lexemes, polarity lexemes and negative lexemes respectively, and use the improved LDA algorithm as shown in algorithm 1 to adjust the emotion data of accounting information of the above enterprises. The sentiment thesaurus is based on the Detailed Explanation Dictionary of Commonly used commendatory and derogatory Words, the commendatory Dictionary and the derogatory word Dictionary, and the emotion words with low frequency are deleted, and the network and oral emotion words are added, including 3587 commendatory words and 4152 derogatory words. Secondly, a polar lexicon (that is, words containing some emotional words with very strong polarity) is marked out in the emotional lexicon, especially some derogatory words. In the identification of opinion sentences, as long as the above words appear, the polarity of the opinion sentence is judged to be the polarity of the word (negative sentence pattern is the opposite). In order to distinguish the large emotion lexeme, this kind of lexeme is called polar lexeme, which contains 158 positive words and 281 negative words.

5.2 Experimental Results

Table 2 presents a comparison of RMSE, MAE, and AUROC indicators between the OP-SCN method and classical algorithms using real enterprise supply chain network data. The results show that the OP-SCN method exhibits more stable and scientifically sound performance compared to traditional supply chain collaborative optimization and prediction algorithms, effectively addressing collaborative optimization and prediction challenges in real supply chain environments with higher accuracy.

Table 2. Comparison results of real social e-commerce data set in different link prediction methods

Network name	Indicator name	LT	IC	GA	DPKNN	IA	BasicKNN	BasicKNN	OP-SCN
Public Company Supply Chain Network	RMSE	0.9685	0.8476	0.8018	0.7591	0.5876	0.5698	0.5595	0.2526
	MAE	0.8309	0.8601	0.8091	0.7403	0.6939	0.6984	0.5356	0.3184
	AUROC	0.2412	0.3496	0.3214	0.6228	0.6385	0.6591	0.6822	0.7593
Unlisted Company Supply Chain Network	RMSE	0.8382	0.7693	0.7293	0.7342	0.6342	0.5425	0.5429	0.2755
	MAE	0.8433	0.7352	0.7541	0.7251	0.6820	0.5592	0.5421	0.2935
	AUROC	0.1422	0.2465	0.3498	0.3098	0.3924	0.5494	0.5283	0.8391
US Public Company Supply Chain Network	RMSE	0.8394	0.8472	0.8102	0.6948	0.5391	0.4582	0.4791	0.2487
	MAE	0.7334	0.6983	0.6983	0.6823	0.5928	0.5702	0.4395	0.2387
	AUROC	0.2547	0.3263	0.4655	0.4372	0.5516	0.6544	0.6930	0.8402

Note: The values shown in bold all indicate that the corresponding algorithm performs well.

This study further compares algorithms using precision, recall, and F1 score calculations. True Positive (TP) indicates correctly predicted links, True Negative (TN) reflects correctly predicted non-links, False Positive (FP) denotes incorrectly predicted links, and False Negative (FN) indicates missed links. Experimental results in Table 3 show that the OP-SCN method outperforms other algorithms in accuracy. Table 4 reveals that the coefficient of determination for the OP-SCN method is generally superior to others. Additionally, as shown in Table 5, the OP-SCN method excels due to its quick response capability and real-time adjustments to optimize the supply chain network, minimizing total cooperation losses among nodes.

Table 3. Precision analysis of real supply chain network data set in different link prediction methods

Network name	Indicator name	LT	IC	GA	DPKNN	IA	BasicKNN	BasicKNN	OP-SCN
Public Company Supply Chain Network	Precision	0.4232	0.3643	0.3252	0.4563	0.4266	0.5734	0.5124	0.7243
	Recall rate	0.3422	0.3390	0.3634	0.4233	0.5636	0.5396	0.5881	0.7467
	F1 value	0.4537	0.4261	0.3690	0.4512	0.5313	0.5543	0.6474	0.7973

Unlisted Company Supply Chain Network	Precision	0.2415	0.2452	0.2462	0.3606	0.5203	0.4652	0.5246	0.7939
	Recall rate	0.2451	0.2583	0.2663	0.3295	0.5320	0.5293	0.5645	0.7631
	F1 value	0.2423	0.2970	0.2753	0.4102	0.4954	0.5361	0.5960	0.8545
US Public Company Supply Chain Network	Precision	0.2325	0.3522	0.3353	0.4494	0.5919	0.5838	0.6149	0.8492
	Recall rate	0.2917	0.2830	0.3596	0.4192	0.5543	0.5454	0.5930	0.8876
	F1 value	0.2846	0.2359	0.3674	0.4594	0.5737	0.6102	0.6983	0.7681

Note: The values shown in bold all indicate that the algorithm they correspond to performs well.

Table 4. Comparison results of algorithm determination coefficients (R2) in different supply chain network datasets

Name of data set	LT	IC	GA	DPKNN
Supply Chain Network Of Listed Companies	0.3942	0.4021	0.3849	0.1924
Unlisted Company Supply Chain Network	0.2412	0.2812	0.3574	0.1823
US Public Company Supply Chain Network	0.3195	0.4982	0.3485	0.1921
Data set name	IA	BasicKNN	BasicKNN	OP-SCN
Public Company Supply Chain Network	0.2541	0.3812	0.5445	**0.7391**
Unlisted Company Supply Chain Network	0.3844	0.4381	0.6934	**0.8852**
US Public Company Supply Chain Network	0.3491	0.4855	0.5820	**0.7495**

Note: The values shown in bold all indicate that the algorithm they correspond to performs well.

Table 5. Results of algorithm running time comparison in different supply chain network datasets

Data set Name	LT	IC	GA	DPKNN
Public Company Supply Chain Network	2422.321	819.849	492.193	849.232
Supply Chain Network For Unlisted Companies	3244.831	1079.124	979.124	1109.753
US Public Company Supply Chain Network	7491.293	793.351	692.429	1032.23
Data set name	IA	BasicKNN	BasicKNN	OP-SCN
Public Company Supply Chain Network	1423.244	242.402	435.317	120.439
Unlisted Company Supply Chain Network	1592.890	310.985	782.295	142.795
US Public Company Supply Chain Network	1230.402	248.312	591.940	125.951

Note: The values shown in bold all indicate that the algorithm to which they correspond performs well.

6 Conclusions

This paper examines the collaborative optimization of enterprise supply chain networks through the lens of accounting information disclosure, utilizing an improved particle swarm optimization algorithm and proposing link prediction methods. To validate the algorithm's performance, several real enterprise supply chain datasets were analyzed, demonstrating that the OP-SCN algorithm offers faster response times and higher accuracy compared to traditional methods. However, limitations exist, such as the algorithm's inability to fully account for external factors like market demand fluctuations, which may lead to unstable predictions. Additionally, the complexity of the supply chain network and its numerous participants may necessitate intricate models, increasing the algorithm's complexity. This study highlights the critical role of supply chain management in global competition and aims to enhance the efficiency and accuracy of collaborative optimization. The OP-SCN algorithm effectively manages accounting information disclosure and considers the influence of external stakeholders, particularly suppliers and customers, on innovation behavior. By innovatively analyzing supply chain optimization from the accounting perspective, this research provides a fresh viewpoint in the field. Future work will focus on improving data collection and analysis accuracy through big data and AI technologies to support real-time collaborative optimization. The study will also expand to include other enterprise departments, such as procurement and sales, integrating cross-departmental data to enhance overall supply chain network efficiency and effectiveness.

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