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Research Article

Modeling Multilevel Supplier Selection Problem Based on Weighted-Directed Network and Its Solution

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With the rapid development of economy, the supplier network is becoming more and more complicated. It is important to choose the right suppliers for improving the efficiency of the supply chain, so how to choose the right ones is one of the important research directions of supply chain management. This paper studies the partner selection problem from the perspective of supplier network global optimization. Firstly, this paper discusses and forms the evaluation system to estimate the supplier from the two indicators of risk and greenness and then applies the value as the weight of the network between two nodes to build a weighted-directed supplier network; secondly, the study establishes the optimal combination model of supplier selection based on the global network perspective and solves the model by the dynamic programming-tabu search algorithm and the improved ant colony algorithm, respectively; finally, different scale simulation examples are given to testify the efficiency of the two algorithms. The results show that the ant colony algorithm is superior to the tabu search one as a whole, but the latter is slightly better than the former when network scale is small.

1. Introduction

With the development of supply chain management, agile supply chains have stronger flexibility and better ability to resist the risk. However, they mainly rely on the close cooperation of suppliers at all levels. Thus, how to select suitable supplier partners and how to combine suppliers are very important in supply chain management. From the previous study, researches on supplier partner selection mainly focused on the studies of supplier evaluation index systems and the selection of evaluation methods [1]. For the former, the current research results do not combine with the new requirements of enterprise development. And the old index system cannot evaluate the enterprises objectively and accurately in the new market environments. As for the latter, it mainly concentrated in the local optimization selection; that is, it only considered the effects from associated enterprises and did not consider the impact on the node enterprise from the entire supplier network when selecting vendors. In fact, supply chain management is overall and systematic, and the selection of a supplier will affect the efficiency of an entire supply chain. Thus, it is necessary to choose the best combination of supplier partners and optimize the supplier network from a global perspective supplier partner selection problem.

Aiming at the problems existing in the current related researches, this paper transforms the supplier partner selection problem into network shortest path problem, takes the relationship weight coefficient between the upstream and downstream suppliers as the edge weight of the weighted-directed network to build a supply chain weighted-directed network, and establishes an optimization problem with the goal of minimizing the path. Then dynamic programming-tabu search algorithm and ant colony one are used to solve and analyze different simulation examples so as to test the efficiency of solution.

In a theoretical sense, on the one hand, supplier networks become increasingly complex with the growing scale and current academic study of supplier network is less. Therefore, in-depth exploration of the problems in the supplier network can further expand and improve supplier network theory and also help to improve the scientific and systematic research of the entire supply chain network. On the other hand, from a practical sense, supplier network is a critical part of the supply chain network. How to establish a stable supplier network is the key influencing factors of stability throughout the supply chain network. By establishing the best vendor partner selection model, it is easy to find out a stable supplier network structure and avoid potential risks.

2. Literature Review

Currently, the extant literatures have studies supplier selection from two aspects: one is the evaluation criteria and index system and the other is the methods models to evaluate suppliers.

On the evaluation criteria and index system, the early works on supplier selection identified over twenty supplier attributes which manager trade off when choosing a supplier [2]. After that, a number of ideal studies mentioned about supplier selection have been addressed [3]. For example, Choy and Lee [4] studied the problem of evaluating and selecting the outsourcing of suppliers in the manufacturing industry and chose manufacturing capacity, product price, delivery time, shipping quality, product development, process improvement, sales performance, marketing objectives, quality planning as the evaluation attributes to select the manufacturing outsourcing suppliers. Similarly, Patton [5] proposed a system of supplier evaluation with Willis using price, quality, delivery time, sales support, equipment and technology, order situation, and financial health. Chen [6] proposed a structured methodology for supplier selection and evaluation based on the supply chain integration architecture. In developing the methodology for supplier selection and evaluation in a supply chain, enterprise competitive strategy was first identified using strengths, weaknesses, opportunities, and threats (SWOT) analysis. Based on the competitive strategy, the criteria and indicators of supplier selection were chosen to establish the supplier selection framework. Subsequently, potential suppliers were screened through data envelopment analysis. Mukherjee and Kar [7] presented a new fuzzy preference degree between two triangular fuzzy numbers and considered the weights of the decision-makers. Moreover, a unique process of classifying the suppliers in different groups was proposed. Luthra et al. [8] identified 22 sustainable supplier selection criteria and three dimensions of criteria (economic, environmental, and social) through literature and experts' opinions for sustainable supplier selection and evaluation in supply chains.

On the methods' models to evaluate suppliers, research has proposed various evaluation schemes. These may be classified into two categories, namely, (1) individual approach and (2) integrated approach. The adopted individual approaches for supplier selection are multicriteria decision-making (MCDM), mathematical programming (MP), and artificial intelligence (AI), whereas integrated approach comprises the analytic hierarchy process (AHP), data envelopment analysis (DEA), and grey relational analysis (GRA), among others. On the MCDM, Karsak and Dursun [9] propose a fuzzy MCDM approach based on the quality function deployment (QFD) methodology, fusion of fuzzy information, and 2-tuple linguistic representation model for supplier selection and the proposed methodology sought to establish the relevant supplier assessment criteria while also considering the impacts of inner dependence among them. Büyüközkan and Göçer [10] introduced a new integrated methodology that was used for the first time in the literature. This approach consisted of intuitionistic fuzzy analytic hierarchy process (IFAHP), an MCDM technique, for determining the weights of supplier evaluation criteria and the concept of intuitionistic fuzzy axiomatic design (IFAD) principles for ranking competing supplier alternatives with respect to their overall performance. On the MP, some typical articles addressed multiobjective decision-making. For example, Bilsel and Ravindran [11] aimed at formulating a multiobjective optimization model to mitigate disruption risks while simultaneously addressing operational risks as well. The model's solution was a mitigation plan, through backup suppliers, that would be used when the supply chain faced a disruption and a supplier-order assignment matrix that optimized the multiple objectives of the model. Jadidi et al. [12] formulated a single product supplier selection problem as a multiobjective optimization model with three minimization objectives: price, rejects, and lead-time and a new multichoice goal programming (MCGP) approach was proposed. On the AI, Tsai et al. [13] developed an approach based on the attribute-based ant colony system (AACS) to construct a platform to examine the critical factors for decision-making in a dynamic business environment in order to select the appropriate suppliers. Kuo et al. [14] developed an intelligent supplier decision support system which was able to consider both the quantitative and qualitative factors. It was composed of (1) the collection of quantitative data such as profit and productivity, (2) a particle swarm optimization- (PSO-) based fuzzy neural network (FNN) to derive the rules for qualitative data, and (3) a decision integration model for integrating both the quantitative data and fuzzy knowledge decision to achieve the optimal decision. On the AHP and DEA, Zeydan et al. [15] introduced a new methodology and this one was realized in two steps. In the first stage, qualitative performance evaluation was performed by using fuzzy AHP in finding criteria weights. In the second stage, DEA was performed with one dummy input and four output variables, namely, quality management system audit, warranty cost ratio, defect ratio, and quality management. Jain et al. [16] presented a Carbon Market Sensitive (CMS) and a green decision-making approach based on DEA called CMS-GDEA. It is built on an existing Green DEA model and they modified it to include a carbon market model. On the GRA, Chen and Zou [17] developed generalized intuitionistic fuzzy soft set (GIFSS) combined with extending grey relational analysis (GRA) method to select an appropriate supplier from the perspective of risk aversion in group decision-making environment. The proposed approach consisted of two phases. In the first phase, the weights of decision-makers were determined by using an extended GRA method with intuitionistic fuzzy soft set (IFSS). In the next phase, to eliminate the bias of decision-makers in the choice of supplier and rule out

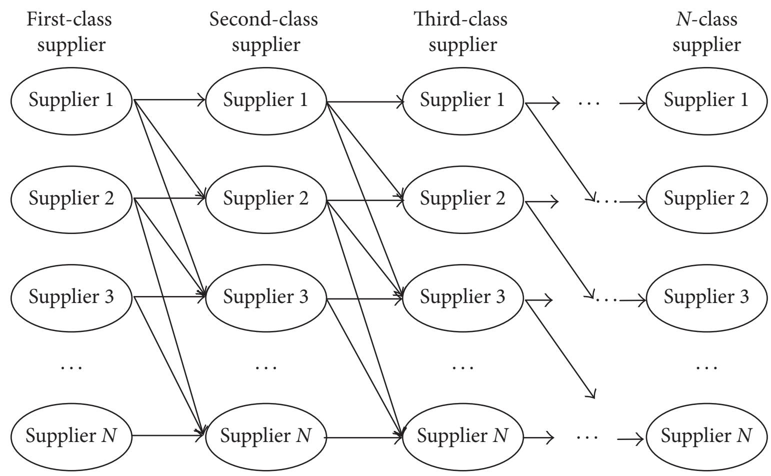

Figure 1: Supplier network structure.

the possibility of errors occurring in the evaluation of alternatives, the general manager would further validate it by utilizing the GIFSS. Rao et al. [18] investigated the problem of supplier selection under multisource procurement for a type of divisible goods (such as coal, oil, and natural gas). By considering both the risk attributes and the attributes under a commercial criterion, they designed a new two-stage compound mechanism for supplier selection based on multiattribute auction and supply chain risk management. In the first stage, a multiauction mechanism was established to determine the shortlist among all qualified suppliers based on four attributes (quality, price, quantity flexibility, and delivery time reliability) under a commercial criterion. In the second stage, seven risk attributes against the shortlisted suppliers were further considered, and a new ranking method based on grey correlation degree of mixed sequence was proposed to rank the finalists and to select the final winners. Ehsan et al. [19] developed a multiobjective fuzzy linear programming model for a GSS problem, including 17 criteria, formed into 5 clusters, while a hybrid fuzzy multiobjective decision-making (MODM) was employed to solve it. The aim of this paper was to select the best set of suppliers regarding optimal allocation of order quantities while demand and supplier's capacity are restricted. In addition, Miah and Huth [20] developed a web-based group decision support system (GDSS) to solve the supplier selection problem by using an AHP model. The GDSS provided a flexible and dynamic environment which enabled the participation of several parties with the use of advanced web technologies to cope with the complexities of the supplier selection problem.

To sum up, although there are many supplier evaluation indicators in present studies, with the changes in market economy environment and customer demand, most of the previous evaluation indexes have been gradually not adapt to the supplier evaluation at this stage. Thus, it is necessary to update and improve the index system. Secondly, most of the current supplier selection evaluation processes combine qualitative method with the quantitative one. To some extent, it can enhance the objectivity of evaluation value of enterprise supplier. But it only took the adjacent enterprise into consideration. So it is evaluated from a local perspective rather than from the perspective of global supplier network to evaluate the nodes of supply chain. Based on this, this paper takes the new requirements and goals of enterprise development as the evaluation indicators to measure supplier selection, from the supplier network global optimal perspective, to study the multinodes cooperation partner selection problem of the whole supplier network, of which the essence is to find the best partners for establishing an efficient supply chain.

3. The Problems Analysis and Model Establishment

3.1. Problems Analysis. The supplier network structure is a whole functional network chain structure composed of each node defined by rules in a logical order [21]. These activities or tasks and their operation logic relationships can be presented by a directed graph formed by directed connection arcs, as shown in Figure 1.

In the supply chain partner selection problem, the supplier network is composed of many upstream and downstream enterprises; thus it can be abstracted into a weighted-directed graph [22]. And V presents the set of nodes; E presents the set of edges; the number of nodes is n; the number of edges is m; the set $E = \bigcup_{i=1}^{n} E_i$ presents the available node supplier enterprises on supplier network and presents the set of edges [23]. Based on this, the supply chain directed weighted network is defined as follows.

(1) When $E_i, E_j \in E$ and $j - i = 1$, $V_{ij} \in V$, the relationship between node enterprises i and j is upstream and downstream. The node i is the antecedent node of node j, and node j is the successor of node i.

(2) e_{ij} is the edge weight between node i and node j. In this paper, e_{ij} presents the cooperative value between adjacent supplier node enterprises, which can be obtained through the downstream node by relevant index system. The main indexes considered in the paper are the risk index R and green index G. And the risk index is composed of internal risk index r_1

and external risk index r_2. The internal risks mainly come from the enterprise's own risk factors, such as the operation scale, the credit, the quality of the staff, and the quality cost of product. And the external risks mainly include customer risk, industry operation risk, competitor risk, and the whole market environment risk. The green index also includes two aspects. One is the enterprise's hardware facility g_1, which contains that whether the construction facilities meet the requirements of green environmental protection, whether the transportation facilities meet the requirements of green environmental protection, whether the materials used in the process of office meet the requirements of green environmental protection, and so on. The other is the enterprise's operation management process g_2, which contains the utilization and turnover rate of equipment, recycling rate of waste, the popularity rate of safe and environmental production management concept, and so on.

(3) p_{ij} is defined as a 0-1 Boolean variable which can reflect the links between upstream and downstream enterprises. That is, if there exists cooperation between upstream and downstream enterprises, the variable value is 1; otherwise the variable value is 0.

(4) The supplier network is divided into k phases, each of which is defined as a set. And the process of supplier partner selection is as follows: start from the upstream supplier stage u_1, and then turn back successively to go through the stage u_k of each downstream supplier in the direction of the directed arcs, according to the adjacent combination rule and the maximum cooperative value between enterprises to select the optimal subsequent node enterprises and build multistage portfolio of optimal supplier partners.

3.2. Model Establishment. We need to find the multistage portfolio of optimal supplier partners in this paper; that is, we need to find the best supplier partner chain in the complex supplier network. The parameters involved in the model are as follows:

Z: the weight of cooperation between node enterprises, that is, the weight of the weighted network

R_i: the evaluation value of risk index of node i

G_i: the evaluation value of green index of node i

e_{ij}: the weight of cooperation between node i and node j, that is, the evaluation value of index

w: the index weight coefficient

r_1: the evaluation value of internal risk index

r_2: the evaluation value of external risk index

g_1: the green index evaluation value of enterprise's hardware facility

g_2: the green index evaluation value of enterprise's operation management process

$C_f(i)$: the degree of importance of node i in the entire supplier network

λ: the eigenvalue of network adjacency matrix

f_j: f being the corresponding feature vector of λ and j the ordinal number of the feature vector

N: the number of network nodes

S_i: the point weight of node i

S_i^{in}: the sum of edge weights of all arcs with node i as end point

S_i^{out}: the sum of edge weights of all arcs with node i as start point

p_{ij}: 0-1 Boolean variable, used to judge whether there exists any connection between upstream and downstream node enterprises.

The objective function of the model is to maximize edge weight and node weight between adjacent nodes, which is presented in the following formula:

$$Z_k = \max \sum_{i=1}^{k} C_e(i)\left[z(R_i, G_i) + S_i\right], \tag{1}$$

where $z(R_i, G_i)$ is the edge weight value between adjacent nodes, which is determined by the evaluation value of associated nodes and the 0-1 variable p_{ij} used to judge whether the two nodes are connected, which is expressed as follows:

$$z(R_i, G_i) = p_{ij} \times e_{ij}. \tag{2}$$

In this model, the evaluation value of edge weight is determined by two indexes, risk index and green index. And the risk index is determined by the internal risk index r_1 and external risk index r_2. The green index is determined by the green degree of enterprise's hardware facility g_1 and the green degree of enterprise's operation management process g_2. On the basis of enterprise types, the relevant experts determine the weight values of indexes with certain evaluation methods. Thus, the formula of calculating the edge weight is as follows:

$$e_{ij} = w * R(r_1, r_2) + (1 - w) * G(g_1, g_2). \tag{3}$$

p_{ij} is a 0-1 variable used to judge whether the two nodes are connected and can be described:

$$p_{ij} = \begin{cases} 0, & \text{no connection between } i \text{ and } j \\ 1, & \text{have connection between } i \text{ and } j. \end{cases} \tag{4}$$

The degree of importance of node i in the entire supplier network $C_f(i)$ is also taken into consideration in this model. There is a linear relationship between the eigenvector centrality of node and the centrality of its neighbor node. And when a node is connected to another node with higher degree of importance, its influence power also changes. Therefore, the eigenvector method can be used to indirectly measure the importance degree of node in the network [24]. Supposing that A presents the adjacency matrix of supplier network, $\lambda_1, \lambda_2, \ldots, \lambda_N$ are the characteristic values of adjacency matrix A, so the feature vector of λ is $(f_1, f_2, \ldots, f_N)$. According to the formula of feature vector $\lambda f_i = \sum_{j=1}^{N} p_{ij} f_j$, the solution formula of the degree of importance of node i can be deduced as follows:

$$C_f(i) = \lambda^{-1} \sum_{j=1}^{N} p_{ij} f_j. \tag{5}$$

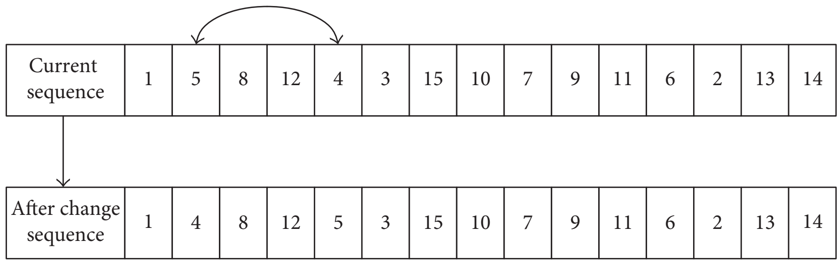

Figure 2: The interchange rules of tabu search algorithm.

In addition, the value of point weight S_i is determined by edge weight, that is, the sum of the in-out degree of the node. And the formula is as follows:

$$\begin{aligned} S_i &= S_i^{\text{in}} + S_i^{\text{out}}, \\ S_i^{\text{in}} &= \sum_{j=1}^{n} p_{ji} e_{ji}, \\ S_i^{\text{out}} &= \sum_{j=1}^{n} p_{ij} e_{ij}. \end{aligned} \tag{6}$$

In this model, not only the supplier network edge weight, but also the point weight of each node, which can make the evaluation of nodes more globally, is taken into consideration when selecting. Moreover, the degree of importance of node i in the entire supplier network is included in this model, which reflects the evaluation and selection from the supplier's global network perspective.

4. Problem-Solving Algorithms

4.1. Algorithm Analysis. The solution for supplier network partner selection problem is to seek the shortest path of the network, which belongs to combinatorial optimization decision problem [25]. Two intelligent heuristic algorithms including dynamic programming-tabu search algorithm and ant colony algorithm are selected here to solve it, where the tabu search algorithm is a dynamic neighborhood search algorithm with strong hill-climbing ability, and it can jump out of the local optimization to find the global optimal solution. At present, combinatorial optimization problem is one of the most widely used fields of tabu search algorithm, and permutation problem is a typical representation of combinatorial optimization problems [26]. The selection of optimal supplier partners in this paper is a kind of typical replacement combinatorial optimization problems, so the method is selected to solve the problem. Usually, the speed and quality of solution in the algorithm is dependent on the initial solution; thus a set of feasible solutions should be found by using dynamic programming method as the initial solution of tabu search algorithm so as to speed up the convergence speed of the algorithm. In addition, the ant colony algorithm is a kind of probabilistic intelligent algorithms, with some characteristics such as distributed computing, positive feedback, and heuristic search. It is widely used in various combinatorial optimization problems. Although both are representative intelligent algorithms when solving combinatorial optimization problems, there are some differences between them. Ant colony algorithm belongs to one of bionic intelligent algorithms, while tabu search is one of general heuristic intelligent algorithms developed from local neighborhood. This paper selects the two mentioned above in order to explore the effectiveness of problem-solving using different methods.

4.2. Dynamic Programming-Tabu Search Algorithm. In the paper, the dynamic programming-tabu search algorithm is used to find the global optimal solution in supplier network. Dynamic programming is an accurate local optimization method, and tabu search algorithm is a global optimization algorithm. In general, the speed and quality of solution are of great relevance to the initial solution in tabu search algorithm. A good initial solution can help to find the optimal solution fast. Therefore, the dynamic programming combined with tabu search algorithm is considered in the paper to obtain the initial solution of tabu search algorithm. The implementations of the algorithm are as follows.

(1) Initial Solution. The initial solution is obtained by dynamic programming, and it is a local optimal solution. The objective function is the maximum value of point weight and edge weight from the global perspective. The weights of edges are bordered by the evaluation of downstream suppliers on upstream suppliers. And the point weight S_i is decided by edge weight, and it is the sum of out-in weight. Through solving the equation, the optimal node path can be obtained as the initial solution.

(2) Neighborhood Search Transformation Rules. In tabu search algorithm, the neighborhood structure transformation determines the quality and distribution of neighborhood solutions, and the selection of transform rules affects not only the hill-climbing ability of algorithm but also its ability to jump out of the local solution. Therefore, the neighborhood transformation rules are an important factor affecting the quality and efficiency of tabu search. At present, the neighborhood search rules include interchangeable, insert, reverse, and some other methods. The interchange rules of nodes are applied in this paper to transform the nodes in the supply chain with current solution, and the operation process is shown in Figure 2.

(3) Taboo Objects and Tabu List. The taboo object represents a set of feasible solutions. The tabu list used in this algorithm is a FIFO queue; that is, when its length exceeds the limitation, the taboo object entering into the tabu list firstly will be cleared out firstly. And the tabu length is an important factor that affects the quality of the tabu search algorithm. As for different data, if the tabu lengths are the same, the result quality may vary greatly. For the selection of tabu length, there will be a better numerical value in the following case calculation.

(4) Fitness Function. The fitness function is the objective function of the dynamic programming model. That is, the sum of point weights and edge weights of supply chain network nodes, Z_k.

(5) Aspiration Criterion. The aspiration criterion used in the paper is based on the fitness value. When the fitness value of a candidate solution is better than a solution in a "best-so-far" condition, the former will replace the latter; that is, the former solution is in a "best-so-far" condition. And when a better objective value is obtained, it will replace the current solution.

(6) Stop Criterion. When the number of iterations is greater than a preset value, the search process will stop and the algorithm is finished.

The specific processes are as follows.

Step 1. Initialize algorithm and set parameters, including taboo length, candidate set length, and the maximum number of iterations.

Step 2. Find the optimal initial solution with dynamic programming method and set the tabu list empty.

Step 3. According to the neighborhood search strategy mentioned above, generate the neighborhood and select some components from the neighborhood to composite candidate set.

Step 4. According to the fitness function, select the local optimal solution that is not limited by the tabu list from the candidate set.

Step 5. Update tabu list and candidate solution set.

Step 6. Judge if the termination condition is satisfied; that is, the maximum number of iterations preset; if so, output the optimal solution and the algorithm is terminated; otherwise, the current local optimal solution is taken as the starting point of the next iteration, and then go to Step 3.

The flow of the algorithm is shown in Figure 3.

4.3. Ant Colony Algorithm. The ant colony algorithm is a bionic heuristic algorithm based on multiagent, and its basic idea is that ant can leave pheromone on its path in the process of movement and can know the existence and intensity of pheromone [27, 28]. In addition, the ants tend to move to the direction of high concentration. If the amount of information left on the shorter path is more than the others in equal time, the ants that select the shorter path will increase. Therefore, the pheromone-updating rule is one of the factors determining the convergence rate of the algorithm [29]. The strategies used to solve the problem with ant colony algorithm in this paper mainly include two aspects: one is the transition probability rule of nodes and the other is the update rule of information. The specific process is as follows.

(1) The Transition Probability Rule of Nodes. The ant K ($K = 1, 2, \ldots, m$) decides its transfer direction based on the amount of information on each path in the process of movement. In this paper, the tabu list tabu_k ($K = 1, 2, \ldots, m$) is used to record all the paths of ant K and this set is adjusted accordingly. In the searching process, the ant will calculate the node transition probability according to the amount of information on each path and heuristic information and then select the next node connected to it. ${p_{ij}}^k(t)$ presents the node transition probability from node i to node j at the moment t. And its formula is as follows:

$$p_{ij}^{k}(t) = \begin{cases} \dfrac{\left[\gamma_{ij}(t)\right]^{\alpha} \bullet \left[\eta_{ik}(t)\right]^{\beta}}{\sum_{s \subset \text{allowed}_k} \left[\gamma_{is}(t)\right]^{\alpha} \bullet \left[\eta_{is}(t)\right]^{\beta}}, & \text{if } j \in \text{allowed}_k \\ 0, & \text{others}, \end{cases} \quad (7)$$

where allowed_k is the nodes outside the tabu list, which presents the nodes selected by the ant k in the next step. α is an information elicitation factor, which presents the relative importance of trajectory. It reflects the effect of the information accumulated by the ants in the process of their movements. The greater the value, the more likely of the path of other ants selected by the ant k, that means the stronger cooperation between ants. β is an expected heuristic factor representing the relative importance of visibility. It reflects the degree of importance of heuristic information in path selection in the process of movement. The greater the value, the transition probability is closer to the greedy rule. $\eta_{ij}(t)$ is a heuristic function and its expression is $\eta_{ij}(t) = 1/d_{ij}$. d_{ij} presents the distance between two adjacent nodes, that is the possibility of cooperation among node enterprises of suppliers. For the ant k, the shorter the distance between two nodes is, the greater the values of $\eta_{ij}(t)$ and transition probability ${p_{ij}}^k(t)$ are [30].

(2) The Update Rule of Information. In order to avoid the bionic heuristic information submerged by too much residual information, the residual information must be updated after each ant taking a step or completing the traversal of n nodes. The update strategy adopted here is that the impressive memory is easy to stay for a long time while the less impressive memory is easy to be forgotten. The pheromone residual coefficient is set as the transition probability of node, ${p_{ij}}^k(t)$. That is to say, the greater the transition probability, the greater the likelihood that the information will remain as time

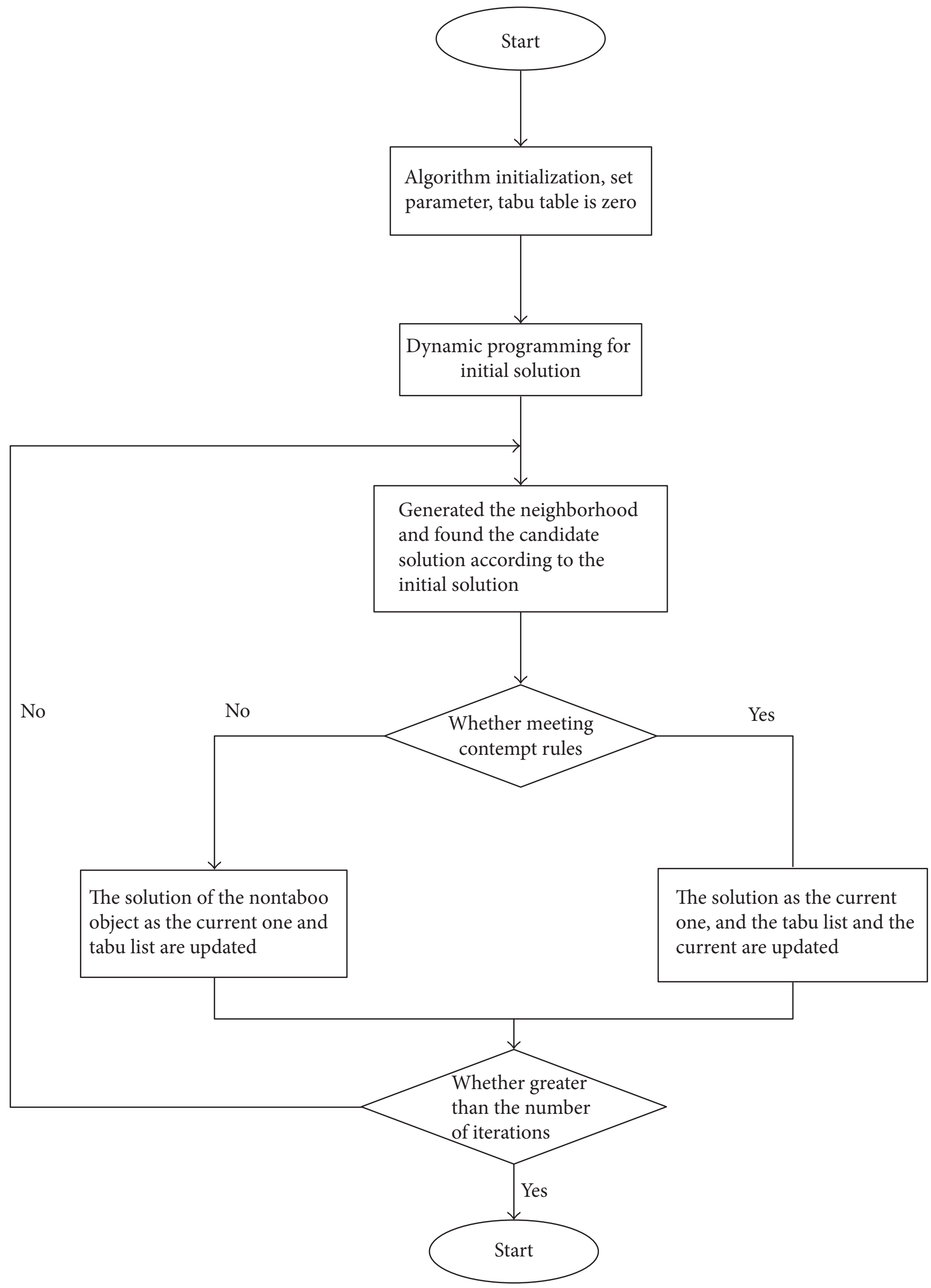

Figure 3: The flow of the tabu search algorithm.

goes on. Thus, the information updating adjusts according to formula (8) shown as follows:

$$\gamma_{ij}(t+n) = p_{ij}{}^{k} * \gamma_{ij}(t) + \Delta\gamma_{ij}(t)$$
$$\Delta\gamma_{ij}(t) = \sum_{k=1}^{m} \Delta\gamma_{ij}{}^{k}(t), \tag{8}$$

where $\Delta\gamma_{ij}(t)$ presents the information increment on the path (i, j). The update rule of information is closely related to the strategy of information updating. And the update rule of information is to figure out the information increment on the path after the first circulation of ant k. The formula is as follows:

$$\Delta\gamma_{ij}^{k}(t) = \begin{cases} \dfrac{Q}{L_k}, & t \text{ if the the } k\text{th ant pass through } (i,j) \\ 0, & \text{others}, \end{cases} \tag{9}$$

where Q is the pheromone intensity, and it affects the speed of convergence to a certain extent. L_k is the total length of the paths that the ant k walks in this cycle. It presents the overall information applied so as to avoid the algorithm trapped into the local optimum.

The specific process of the ant colony algorithm is as follows.

Step 1 (initialization). Set the maximum number of iterations.

Step 2. Place each ant on a starting node and put its current position in the tabu list to avoid the revisit.

Step 3. Build a solution for each ant by using one transfer rule and update the rule with local information.

Step 4. Calculate the value of objective function of each ant.

Step 5. Calculate the value of objective function until all the ants find a complete supply chain.

Step 6. According to predetermined update formula to modify the trajectory intensity by applying global pheromone update rule.

Step 7. If the number of iterations runs is less than the scheduled maximum number of iterations and there is no degradation behavior, then turn to Step 2 until satisfying the condition.

The flow of the algorithm is shown in Figure 4.

In this algorithm, the transfer rule applied by each ant is roulette method; that is to say, the transfer direction is determined by the pheromone left on the path. Through this method, the node with maximum amount of individual information outside the taboo can be selected as the next node to be connected.

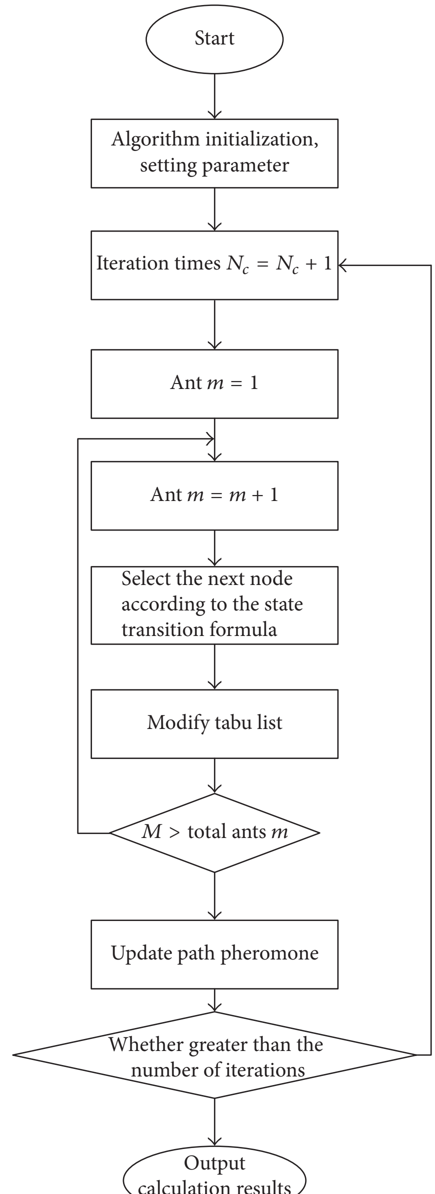

Figure 4: The flow of the ant colony algorithm.

5. Simulation Example

5.1. Background. The aim of this paper was to model the supplier network and realize problem-solving. Therefore, the simulation example did not use the actual data, but only randomly selected data generated in computer for simulation problem of different sizes. In doing so, the effectiveness of the method and the efficiency of the algorithms are both verified.

In this section, different scales of the problem are discussed. The multilevel supply network is composed of 16, 30, 50, 60, 70, 80, 90, and 100 nodes, respectively. We assume that the edge weight of the weighted-directed network is determined by the value obtained through a certain evaluation method of the cooperation between the associated node enterprises. In order to study the solving ability of the two algorithms, some matrixes are randomly generated as the edge weight matrixes, $16 * 16$, $30 * 30$, $50 * 50$, $60 * 60$, $70 * 70$, $80 * 80$, $90 * 90$, and $100 * 100$, respectively. Their unit values are the cooperation evaluation values of node enterprises to adjacent nodes. Besides, the tabu length selected in the tabu search algorithm is the number of nodes N. And in ant colony algorithm, the parameters involved are the number of ants that is equal to the number of nodes, that is, $m = N$, the degree of importance of information $\alpha = 1$, the importance degree of heuristic function $\beta = 5$, the information residual factor is Rho $= {p_{ij}}^k(t)$, and the constant coefficient set as $Q = 1$. In the experiment, the network scale T determines the number of iterations N. We set $T = 30 * N$.

5.2. Analysis and Discussion

(1) Performance Comparison of Two Algorithms. In order to compare the solution-abilities of the two algorithms and find the most appropriate method to solve different scale problems of supplier partners, this paper, through more than 10 simulations running to the problem with different scales, and the calculation of the average number of the results, the shortest path running results, and time of two algorithms in searching different scale node networks are shown in Table 1.

Some results can be drawn from Table 1.

Table 1: The simulation results for different scale problems.

		The average values of 10 experiments				
Network scale	Algorithm	Minimum	Maximum	Average	Variance	Convergence frequency
16 nodes	Ant colony	74.43	80.81	74.54	0.48	207.08
	Tabu search	74.08	104.70	80.20	3.18	515.00
30 nodes	Ant colony	425.8	491.48	426.44	2.6956	530
	Tabu search	436.5	532.2	481	19.39	375.00
50 nodes	Ant colony	7560.50	9041.10	7609.10	105.79	910.00
	Tabu search	8238.20	9187.80	8641.20	154.64	44.00
60 nodes	Ant colony	62.72	71.90	62.78	0.31	150.00
	Tabu search	73.93	89.98	80.88	2.55	243.33
70 nodes	Ant colony	68.35	87.12	68.52	0.51	700.00
	Tabu search	71.58	87.53	82.24	2.38	16.67
80 nodes	Ant colony	69.22	83.71	69.52	0.78	900.00
	Tabu search	83.94	95.17	90.06	91.06	92.06
90 nodes	Ant colony	82.32	101.20	83.05	0.74	1966.67
	Tabu search	90.74	104.30	97.97	2.23	750.00
100 nodes	Ant colony	81.38	101.55	81.71	0.57	1340.00
	Tabu search	89.26	106.90	100.10	0.39	1900.00

Table 2: The solutions of tabu search algorithm before and after improvement.

Network scale	Algorithm	Minimum	Maximum	Average	Variance	Convergence frequency
30 nodes	Tabu search	443.43	554.3	505.46	48.88	375.00
	Dynamic programming- tabu search	436.5	532.2	481	19.39	375.00

Firstly, from the trend of algorithm results, in each running, the variance of ant colony algorithm is smaller, which means that the ant colony algorithm is stable. While the variance of tabu search algorithm is larger, its stability is weaker than ant colony algorithm.

Secondly, from the scale of the problem, tabu search algorithm is more suitable for solving small-scale network problems. We can see from Table 1 that only when the scale of nodes is 16, the solution of tabu search algorithm is slightly better than ant colony algorithm. With the increasing of network scale, the difference between the tabu search algorithm and ant colony algorithm is more and more obvious. In addition, for different problem scales, the solving ability of ant colony algorithm is relatively stable, and it has higher efficiency and stability than the tabu search algorithm.

From the above analysis, we can find that because of its stability and solving ability, ant colony algorithm is better than dynamic programming-tabu search algorithm. It is more suitable for solving the large or medium scale problems of suppliers and partner selection

(2) Analysis of Improved Algorithm. In this section, we take the network scale problem with 30 nodes as an example to test the differences before and after improvement of the two algorithms, respectively.

(i) Comparative Analysis of Improved Tabu Search Algorithm. The initial solution of tabu search algorithm in this paper is

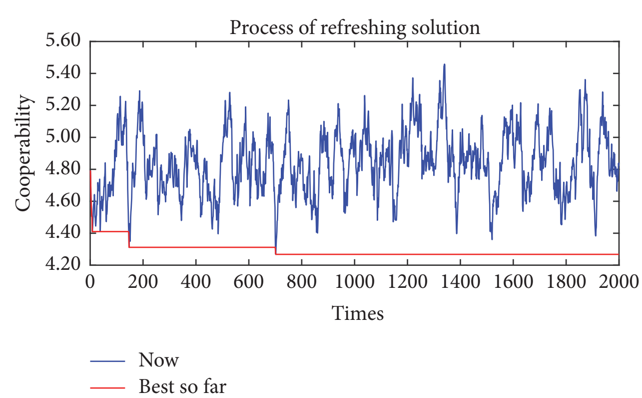

Figure 5: The search process of dynamic programming-tabu search.

the shortest path obtained through the dynamic programming method. The tabu search algorithm depends on the quality of the initial solution and, so in the experiment, compares the improved initial solution with the initial solution generated randomly and analyzes if the improved algorithm is effective. The number of iterations is set as 2000, the distance matrix is the same as the distance matrix of 30-node scale network mentioned in the experiment above, and the average values of the 10 experiments are shown in Table 2.

The search processes are shown in Figures 5 and 6.

Table 3: The solutions of ant colony algorithm before and after improvement.

Network scale	Algorithm	Minimum	Maximum	Average	Variance	Convergence frequency
30 nodes	Ant colony	426.42	497.13	427.04	3.03	340.00
	Improved ant colony	425.8	491.48	426.44	2.6956	530

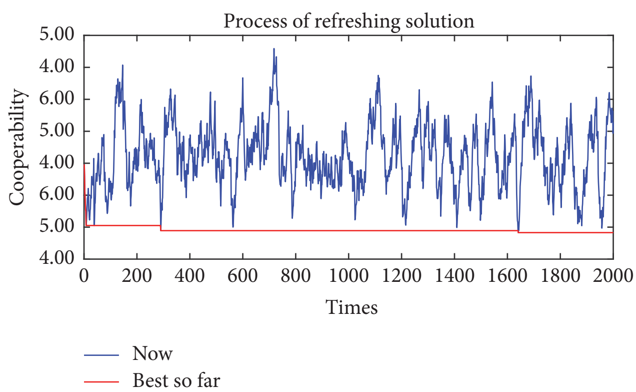

Figure 6: The search process of tabu search.

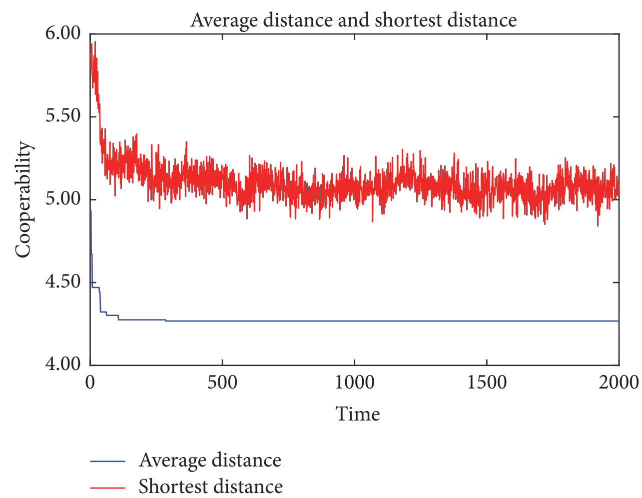

Figure 7: The search process of ant colony.

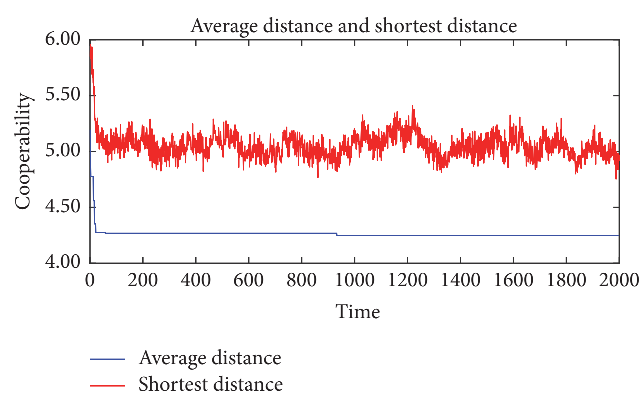

Figure 8: The search process of improved ant colony.

From the comparison of the search processes shown in Figure 5 and Figure 6, it can be seen that, through the improvement of initial solution, not only is the optimal solution of the algorithm improved, but also its variance is relatively small; that is, the improvement of initial solution can enhance the solving ability of the algorithm and can also make it more stable.

(ii) Comparative Analysis of Improved Ant Colony Algorithm. The improvement on ant colony algorithm in the paper is the change of residual information factor from a constant to a variable. Based on the memory, the impressive one can be kept for a long time while the plain one is easy to be forgotten. And according to this characteristic, the pheromone residual coefficient is set as the transfer probability of the nodes ${p_{ij}}^k(t)$. The ant colony algorithm is improved through the change of this parameter and compare with the original ant colony algorithm through experiments. The parameters are set the same as the 30-node scale network mentioned in the experiment above, the number of iteration is set as 2000, and the average values of the 10 experiments are shown in Table 3.

The search processes are shown in Figures 7 and 8.

From the search process shown in Figures 7 and 8, it can be seen that through the improvement of residual factor, the result of the algorithm changes from 426.42 to 425.8, that is to say, the algorithm is improved to some extent. And its average value and variance both decrease. Thus, the improvement of residual factor can enhance the solving ability of the algorithm and can make it more stable.

As to the shortest path optimization of supplier network in the paper, on the whole, the ant colony algorithm is better than the tabu search algorithm. When the scale of the network is small, the tabu search algorithm can be used. However, for the large-scale supplier network selection problem, the ant colony algorithm is more appropriate.

6. Conclusions and Future Work

This paper discusses the evaluation of supplier from two indexes, risk index and green index. And the evaluation value is set as the edge weight of supplier network in order to construct the weighted-directed supplier network. The partner selection is analyzed from the perspective of global network. The simulation is carried through dynamic programming-tabu search and ant colony algorithm and the solving efficiency of the two algorithms for different scale problems is also compared. It is easy to see from the experimental results that the ant colony algorithm is more suitable for the problem, because it is not only better than the tabu search algorithm on the speed of solving problem and efficiency but also more stable through the test of many experiments. This paper considers the problem of supplier selection of partners from a new perspective, but there are still many limitations. First of all, because of the limited conditions, no actual data obtained from green enterprises and risk data of the actual supplier network is studied. As a result, the further application analysis should be explored. Secondly, in this paper, two typical algorithms, named tabu search algorithm and ant colony algorithm, are used to solve supplier network selection problems. However, due to length limitation of the paper, we do not discuss the parameters of algorithms related to the efficiency. In the future, the risk evolution and immunization strategy will be introduced into the paper to continually discuss the supplier network stability problems.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

Acknowledgments

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References

[1] X. Fu and T. Chen, "Supply Chain Network Optimization Based on Fuzzy Multiobjective Centralized Decision-Making Model," *Mathematical Problems in Engineering*, vol. 2017, Article ID 5825912, 2017.

[2] G. W. Dickson, "An Analysis Of Vendor Selection Systems And Decisions," *Journal of Purchasing*, vol. 2, no. 1, pp. 5–17, 1966.

[3] T. Y. Choi and J. L. Hartley, "An exploration of supplier selection practices across the supply chain," *Journal of Operations Management*, vol. 14, no. 4, pp. 333–343, 1996.

[4] K. L. Choy and W. B. Lee, "A generic supplier management tool for outsourcing manufacturing," *Supply Chain Management Review*, vol. 8, no. 2, pp. 140–154, 2003.

[5] W. E. Patton III, "Use of human judgment models in industrial buyers' vendor selection decisions," *Industrial Marketing Management*, vol. 25, no. 2, pp. 135–149, 1996.

[6] Y.-J. Chen, "Structured methodology for supplier selection and evaluation in a supply chain," *Information Sciences*, vol. 181, no. 9, pp. 1651–1670, 2011.

[7] S. Mukherjee and S. Kar, "A three phase supplier selection method based on fuzzy preference degree," *Journal of King Saud University - Computer and Information Sciences*, vol. 25, no. 2, pp. 173–185, 2013.

[8] S. Luthra, K. Govindan, D. Kannan, S. K. Mangla, and C. P. Garg, "An integrated framework for sustainable supplier selection and evaluation in supply chains," *Journal of Cleaner Production*, vol. 140, pp. 1686–1698, 2017.

[9] E. E. Karsak and M. Dursun, "An integrated fuzzy MCDM approach for supplier evaluation and selection," *Computers & Industrial Engineering*, vol. 82, pp. 82–93, 2015.

[10] G. Büyüközkan and F. Göçer, "Application of a new combined intuitionistic fuzzy MCDM approach based on axiomatic design methodology for the supplier selection problem," *Applied Soft Computing*, vol. 52, pp. 1222–1238, 2017.

[11] R. U. Bilsel and A. Ravindran, "A multiobjective chance constrained programming model for supplier selection under uncertainty," *Transportation Researcht B: Methodological*, vol. 45, no. 8, pp. 1284–1300, 2011.

[12] O. Jadidi, S. Cavalieri, and S. Zolfaghari, "An improved multichoice goal programming approach for supplier selection problems," *Applied Mathematical Modelling*, vol. 39, no. 14, pp. 4213–4222, 2015.

[13] Y. L. Tsai, Y. J. Yang, and C.-H. Lin, "A dynamic decision approach for supplier selection using ant colony system," *Expert Systems with Applications*, vol. 37, no. 12, pp. 8313–8321, 2010.

[14] R. J. Kuo, S. Y. Hong, and Y. C. Huang, "Integration of particle swarm optimization-based fuzzy neural network and artificial neural network for supplier selection," *Applied Mathematical Modelling*, vol. 34, no. 12, pp. 3976–3990, 2010.

[15] M. Zeydan, C. Çolpan, and C. Çobanoglu, "A combined methodology for supplier selection and performance evaluation," *Expert Systems with Applications*, vol. 38, no. 3, pp. 2741–2751, 2011.

[16] V. Jain, S. Kumar, A. Kumar, and C. Chandra, "An integrated buyer initiated decision-making process for green supplier selection," *Journal of Manufacturing Systems*, vol. 41, pp. 256–265, 2016.

[17] W. Chen and Y. Zou, "An integrated method for supplier selection from the perspective of risk aversion," *Applied Soft Computing*, vol. 54, pp. 449–455, 2017.

[18] C. Rao, X. Xiao, M. Goh, J. Zheng, and J. Wen, "Compound mechanism design of supplier selection based on multiattribute auction and risk management of supply chain," *Computers & Industrial Engineering*, vol. 105, pp. 63–75, 2017.

[19] A. Ehsan, A. Alireza, A. Mohammad, S. Javad, and A. Mostafa, "Evaluating a green supplier selection problem using a hybrid MODM algorithm," *Journal of Intelligent Manufacturing*, vol. 28, no. 4, pp. 913–927, 2017.

[20] S. Miah and M. Huth, "Cross-functional decision support systems for a supplier selection problem," *International Journal of Management and Decision Making*, vol. 11, no. 3-4, pp. 217–230, 2017.

[21] E. Xie and J. Liang, "Partner selection strategies, control mechanisms, and supplier network governance," *Soft Science*, vol. 10, no. 6, pp. 57–61, 2016.

[22] C. Ju, G. Zhou, and T. Chen, "Disruption management for vehicle routing problem with time-window changes," *International Journal of Shipping and Transport Logistics*, vol. 9, no. 1, pp. 4–28, 2017.

[23] Z. G. Lu and K. Shen, "A hybrid algorithm of particle swarm and ant colony for partner selection in supply chain," *Computer Engineering and Science*, vol. 11, no. 05, pp. 946–953, 2016.

[24] R. Ren, *Research on mining important nodes in software execution network based on cascading failure*, Yanshan University, 2015.

[25] W.-C. Yeh and M.-C. Chuang, "Using multi-objective genetic algorithm for partner selection in green supply chain problems," *Expert Systems with Applications*, vol. 38, no. 4, pp. 4244–4253, 2011.

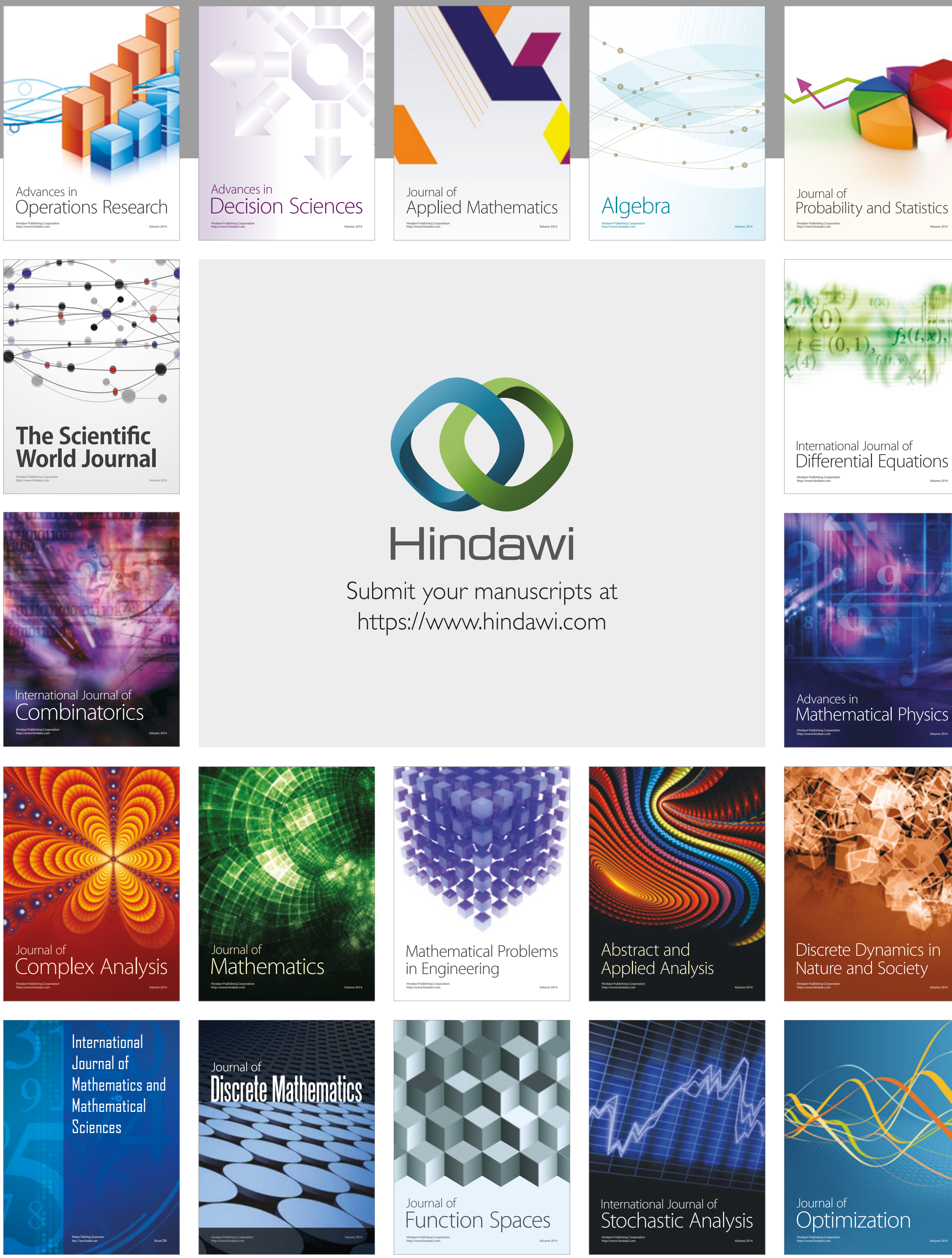
[26] G. Y. Liu, Y. He, and C. H. Wen, *Tabu search algorithm and its application*, Science Press, Beijing, China, 2014.

[27] L. Zhang, Y. Wang, T. Fei, and H. Ren, "The research on low carbon logistics routing optimization based on DNA-ant colony algorithm," *Discrete Dynamics in Nature and Society*, vol. 2014, Article ID 893851, 2014.

[28] J. Ma and G. Sun, "Mutation ant colony algorithm of milk-run vehicle routing problem with fastest completion time based on dynamic optimization," *Discrete Dynamics in Nature and Society*, vol. 2013, Article ID 418436, 2013.

[29] J. F. Yang, *Ant colony algorithm and its application research*, Zhejiang University, 2015.

[30] H. B. Duan, X. Zhang, and C. F. Y, *Bionic intelligent computing*, Science Press, Beijing, China, 2011.



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