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# Using analytic network process and turbo particle swarm optimization algorithm for non-balanced supply chain planning considering supplier relationship management

**ZH Che[1], Tzu-An Chiang[2] and Zhen-Guo Che[3]**

**Abstract**

Supply chain planning has been regarded as a key strategic decision-making activity for the enterprises under the current business circumstances. From the point of supply chain planning, the important issues are to find suitable and quality partners and to decide upon an appropriate production–distribution plan. In this study, hence, we address to develop a decision methodology for supply chain planning in multi-echelon non-balanced supply chain system, taking into account such four criteria as cost, quality, delivery and supplier relationship management and considering quantity discount and capacity constraints. The proposed methodology is based on the analytic network process and turbo particle swarm optimization (TPSO), to evaluate partners and to determine an optimal supply chain network pattern and production–distribution mode. Finally, to demonstrate the performance of the proposed TPSO algorithm, comparative numerical experiments are performed by TPSO, particle swarm optimization (PSO) and genetic algorithm (GA). Empirical analysis results demonstrate that TPSO can outperform PSO and GA in non-balanced supply chain planning problems.

**Keywords**

Analytic network process, non-balanced supply chain, particle swarm optimization, supplier relationship management, supply chain planning

## Introduction

Emerging in the late 1980s, the concepts of supply chain have been widely used in manufacturing management. Some world-renowned companies, such as Dell, IBM and HP, had gained profound benefits from supply chain management (SCM). To supply chain planning, selection of suitable suppliers/partners not only means a basis, but also a critical step. Selection of suppliers has been referenced in a lot of research, such as Sha and Che (2005, 2006), Choi and Chang (2006), Huang and Keskar (2007), Wang and Che (2007), Che and Wang (2008), Ha and Krishnan (2008), Kheljani et al. (2009) and Yue et al. (2010), and cost, quality and delivery are always the most frequently used criteria for selecting suppliers (Dahel, 2003; Liao and Rittscher, 2007; Wadhwa and Ravindran, 2007; Wang and Che, 2008); quantity discount should also be taken into account for costs (Dahel, 2003; Darwish, 2009; Li and Liu, 2006; Xia and Wu, 2007; Xie et al., 2010).

According to Herrmann and Hodgson (2001), supplier relationship management (SRM) is a process of managing suppliers, where cost reduction, experience sharing and procurement co-ordination are achieved through partnership, to offer an integrated management tool. As suggested by David and Stuart (2001), in addition, the relationship between two business partners has changed from an antagonistic one to a symbiotic one, where the stress is placed on mutual reliance and technical co-operation so that the partners can reach an agreement. With respect with the trends of SRM and the effects incurred on supply chains, SRM is taken into account in this study, in conjunction with cost, quality and delivery as criteria for partner selection. For this, we have adopted an analytic network process (ANP) approach to evaluate the weight of each criterion for partner performance evaluation in supply chain system.

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In real-life production systems, there are many uncertainties (Lee and Rosenblatt, 1986; Xu et al., 2006), and hence production characteristics of individual members within a system should be taken into account before planning and construction of supply chain systems to ensure the fulfilment of production goals. In that, supply chains that involve production loss are called non-balanced supply chain system as shown in Figure 1. Assimilation of such system may bring our research closer to real-life production practices.

As in the above statement, in this study, we emphasizes a multi-echelon non-balanced supply chain planning for choosing the suitable partners from a number of potential participators to become involved in the system, and to make the optimal production–distribution planning decisions. Gen and Cheng (1997) pointed out that the multi-stage logistic problem is like the combination of the multiple-choice Knapspack problem with the capacitated location–allocation problem as an NP-hard problem. In our study, the capacity, production and transportation losses, and quantity discount are considered, and hence our problem becomes even more difficult. In addition, in the optimization processes of common particle swarm optimization (PSO), more infeasible solutions may be created after particle position and velocity updating. A novel PSO approach, hence, called the turbo particle swarm optimization (TPSO) for supply chain planning is presented for solving the proposed problem in this paper. The TPSO adopts the stepwise approach to check and adjust the solutions based on a variable-demand dependency mechanism, which can avoid producing the repeated infeasible solutions in updating processes.

Therefore, there are five major study purposes:

1. Developing the partner relationship assessment procedure for SRM that includes partner relationship (PR) and information technology (IT) criteria. As we know, so far, there has never been any procedure proposed that performs the PR evaluation in a supply chain system.
2. Building an ANP procedure for appraising the relative weights among criteria for partner evaluation.
3. Proposing a multiple objective optimization model, and its objectives taken into account include: minimum cost, minimum quality (defective rate), maximum delivery (on-time delivery rate), and maximum PR coefficient (PRC).
4. Applying a variable-demand dependency mechanism to develop a TPSO and applying the TPSO to solve the multiple objective optimization model.
5. Comparing the solving performance of TPSO, PSO and genetic algorithm (GA; Sha and Che, 2006) to verify that TPSO has excellent capabilities for solving the problems defined in this study. The criteria for the performance comparison are the objective value and the convergence time.

The rest of this paper is organized as follows. Section 2 is the literature review about SCM, SRM, ANP and PSO. Section 3 gives a framework to explain this study, and establishes the PR assessment procedure, ANP procedure, optimization mathematical model and TPSO solving model. Section 4 presents a numerical example to illustrate the application of TPSO for obtaining optimal strategies. The results thus obtained are also compared with those of PSO and GA to validate the efficiency of the proposed algorithm. Conclusions are shown in Section 5.

## Literature review

### *Supply chain management and supplier relationship management*

The concept of SCM was first proposed by Houlihan (1984), which was an important advancement in logistics. In the early stages, the concepts and techniques from industry dynamics were utilized to deal with physical distribution and transportation operations. Then, some scholars described it as an integrated activity covering the entire series of logistic operations and categories running from suppliers down to end-users.

Choi and Hartley (1996) held that businesses hoped to quicken distribution, shorten delay, reduce cost and improve quality through managing suppliers in the supply chain. Moreover, the supply chain is dedicated to maximizing the value produced by an entire supply chain, and SCM is intended to gain maximum benefit from a supply chain through the integrated management of logistics, flow of

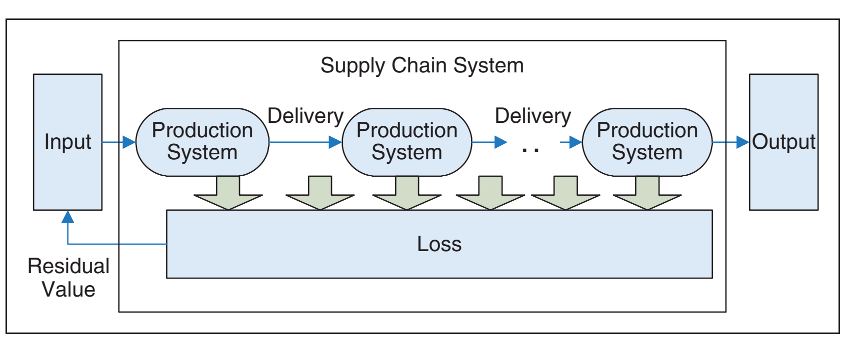


**Figure 1** Non-balanced supply chain system.

cash, business and information. Some reviews about the concept for supply chain planning are available in the literature, such as Che and Wang (2008), Ha and Krishnan (2008), Che (2010), Kheljani et al. (2009), Yue et al. (2010) and Arora et al. (2010).

From the above discussions, we can see that supply chain planning is intended to integrate suppliers, manufacturers, logistic firms and vendors in order to effectively run a supply chain under low cost and high quality, and improve competence for the chain. Corbett et al. (1999) stated that a company allies closely with upstream and downstream suppliers/partners to create a highly competitive supply chain; then members of the supply chain can share market, reduce investment, improve transport services and shorten time-to-market. Hence, the relationship between two business partners has changed from an antagonistic one to a symbiotic one. For this, SRM seems especially important in supply chain planning.

According to Gulledge (2002), SRM refers to the automated accomplishment of a series of processes between companies and suppliers, including planning, scheduling, delivery and payment, which is an integration and exchange of data and processes between companies and suppliers. Most applications of SRM for companies focus on e-Procurement at present, in that it is hoped that more transparent upstream and downstream requirements planning can be secured through the functions of e-Procurement to achieve collaborative supply. Many businesses work on SRM software, including i2 Technologies, Oracle, SAP, PeopleSoft and SAS. Although the SRM applications provided by the developers differ in function, with the advancement in the Internet, the entire SRM IT has been made more convenient, and one can enjoy information sharing once linked up with the Internet.

From the definitions and development for SRM, we can know that the core values affecting SRM lie in long-term PR and IT. Janz et al. (1997) suggested that partners might come to know each other and reach an agreement through interactive information sharing. Information is the most significant strategic sourcing for companies; it is a fixed trend that organizations learn from partnerships through strategic alliance and then develop new capabilities (Simonin, 1999).

Many SCM papers have discussed the importance of PR and IT, such as Prahinski and Benton (2004), Kulp et al. (2004), Benton and Maloni (2005), Kannan and Tan (2005), and Narasimhan and Nair (2005). Hence, the two factors, PR and IT, were taken into account under SRM as impact factors for evaluation and selection of partners.

## The concept of analytic network process

ANP was evolved from an analytic hierarchy process. At the beginning of ANP execution, a problem is resolved into different clusters, which incorporate many elements, and a network graph is constructed to present the interplay between clusters and elements according to the definitions and requirements from decision makers. Saaty (1996) thought that the dependent interplay between clusters and elements could be analysed with graphs, where every element in a graph was connected with each other so that the graph could not be divided into two or more disconnected graphs. Clusters in the graph were used to represent system structure framework, where the elements referred to impact factors in the system, and interplay might exit within every cluster or between elements.

According to Huang et al. (2005), ANP is applicable in quantitative and qualitative data analysis as well as in solving the dependence and feedback relationships between elements. Also, Ravi et al. (2005), Agarwal et al. (2006), Gencer and Gürpinar (2007), and Tseng et al. (2009) pointed out ANP is one of the most widely used multiple criteria decision-making methods and has been proved to be useful for selection problems such as strategy selection, supplier selection and location selection. Hence, in this study, ANP was used to determine the relative weights of the criteria for the evaluation and selection of partners.

## The concept of particle swarm optimization

Proposed by Kennedy and Eberhart (1995), PSO is an optimization tool in evolutionary computation inspired by the collective intelligence of bird flocks and the explorative and exploitative features of particle swarms, and improvement has been made to it by many scholars. Sivanandam and Visalakshi (2009) developed a parallel orthogonal PSO to schedule heterogeneous tasks dynamically on to heterogeneous processors in a distributed setup. Arumugam et al. (2009) presented three PSO algorithms to solve the optimal control problem for the two-stage steel annealing processes and analysed the efficacy, efficacy and validity of each algorithm. Zhang and Qiu (2010) proposed a hybrid PSO approach to solve the travelling salesman problem based on cluster analysis on the swarm with the *k*-centres method. Zhang and Cai (2010) presented a novel hybrid PSO algorithm with dynamic inertial weight and chaotic search to solve the economic load dispatch problem, and results show that the proposed PSO algorithm can save considerable cost of economic load dispatch. In addition, Agrawal et al. (2008b) used PSO to solve the highly constrained multi-objective environmental/economic dispatch problem and the results show it able to provide a satisfactory compromise solution in almost all the trials. Agrawal et al. (2008a) used an interactive PSO in multiple objective problems, and the results show that the PSO intends to find a compromise solution along with a set of Pareto optimal solutions having a higher utility.

Chau (2006) stated that the PSO is based on a set of presumed latent solutions, which are continuously updated to obtain the optimal value. Li et al. (2006) stated that PSO has constructive co-operation between particles, i.e. particles in the swarm share their information. Han and Ling (2008) mentioned that PSO has memory, i.e. the knowledge of good solutions is retained by all particles. Yang et al. (2007) denoted that PSO is rapidly converging towards an optimum, simple to compute, easy to implement and free from the complex computation in GA. Also, Zhang et al. (2006) and Zhang and Cai (2010) applied both PSO and GA on limited resource programming, and the results suggested that the performance of PSO is better than that of GA. There are still many other

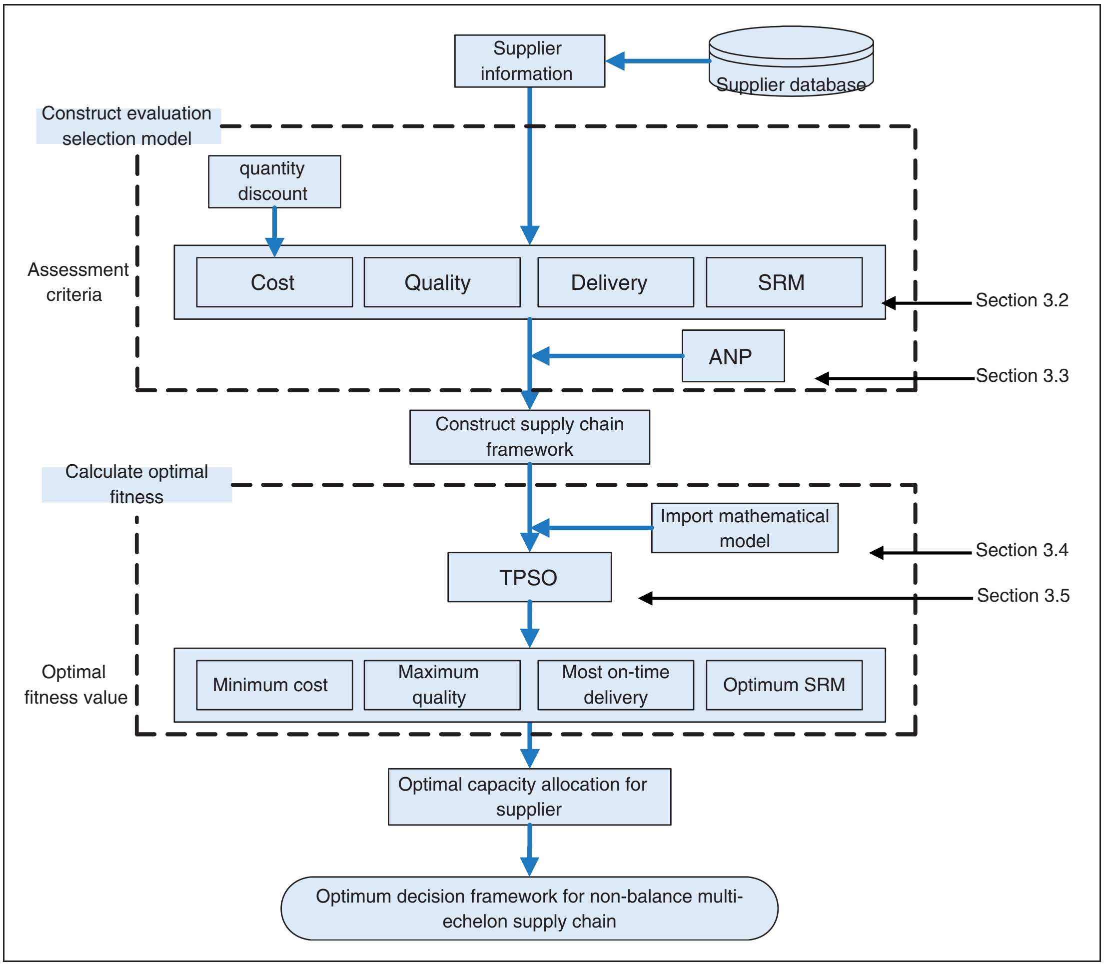


**Figure 2** Research framework. SRM, supplier relationship management; ANP, analytic network process; TPSO, turbo particle swarm optimization.

variants of PSO (Abraham et al., 2010; Deng et al., 2010; Jain et al., 2010; Lu et al., 2010; Singh et al., 2010); for more details please refer to the corresponding references. Since the operating efficiency of PSO is better than that of GA, the proposed solving approach TPSO, in this study, is based on PSO.

## Research framework and problem formulation

### *Research framework*

The numbers of upstream and downstream partners associate closely with each other to form a supply chain. Therefore, in this study, we will gather the information on each partner and assess the relative weight of each criterion by ANP. Then, an optimization mathematical model is constructed, taking into account the relevant costs (production cost, transportation cost, etc.) and capacity constraints. The TPSO is applied in minimization of the overall supply chain cost to find decision results satisfying the constraints and an optimal production decision-making system is developed for decision makers. The research framework is presented in Figure 2, and the developments of PR assessment, ANP procedure, mathematical model and TPSO solution model for this study are to be laid out in following sub-sections.

### *Partner relationship assessment procedure for supplier relationship management*

The following procedure is adopted to derive a PRC for each partner.

- Step 1: Complete PR and IT coefficient assessment tables, as shown in Table 1. Item *1* and Item *2* are factors affecting PR and IT, respectively $I$ and $K$ items in total. The degree to which item $i$ and $k$ respectively in $PR_{ij}$ and $IT_{kj}$ affect PR and IT of partner $j$ is measured in high, medium and low instead of 3, 2 and 1 score. PR relative weight $W_{PR_j}$ and IT relative weight $W_{IT_j}$ for the partner $j$ is to be calculated with the following formula:

$$W_{PR_j} = \frac{\sum_{i=1}^{I} PR_{ij}}{3I}, \quad W_{IT_j} = \frac{\sum_{k=1}^{K} IT_{kj}}{3K}$$

**Table 1** Partner relationship (PR) and information technology (IT) coefficient assessment

| PR | | | | | IT | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Item | 1 | 2 | ... | J | 1 | 2 | ... | J | Item |
| 1 | $PR_{11}$ | $PR_{12}$ | ... | $PR_{1J}$ | $IT_{11}$ | $IT_{12}$ | ... | $IT_{1J}$ | 1 |
| 2 | $PR_{21}$ | : | ... | : | $IT_{21}$ | : | ... | : | 2 |
| : | : | : | ... | : | : | : | ... | : | : |
| I | $PR_{I1}$ | : | ... | $PR_{IJ}$ | $IT_{K1}$ | : | ... | $IT_{KJ}$ | K |
| $W_{PR}$ | $W_{PR_1}$ | $W_{PR_2}$ | ... | $W_{PR_J}$ | $W_{IT_1}$ | $W_{IT_2}$ | ... | $W_{IT_J}$ | $W_{IT}$ |

**Table 2** Partner relationship coefficient (PRC) index

| $W_{PRCj}$ | 0.0–0.2* | 0.2–0.4* | 0.4–0.6* | 0.6–0.8* | 0.8–1.0 |
|---|---|---|---|---|---|
| PRC*j* | 1 | 2 | 3 | 4 | 5 |

*Value is not included.

**Table 3** Partner relationship coefficient (PRC) value

| | Partner | | | |
|---|---|---|---|---|
| | 1 | 2 | ... | J |
| $W_{PRC}$ | $W_{PRC_1}$ | $W_{PRC_2}$ | ... | $W_{PRC_J}$ |
| PRC | $X_1$ | $X_2$ | ... | $X_J$ |

$X_j \in \{1,2,3,4,5\}$, $j = 1,2,\ldots,J$.

- Step 2: Calculate the relative weight $W_{PRC_j}$ of partner $j$ with the following formula:

$$W_{PRC_j} = sw_1\, W_{PR_j} + sw_2\, W_{IT_j}$$

$$sw_u: \text{ Weight, } sw_u > 0 \text{ and } \sum_{u=1}^{2} sw_u = 1,\ for\ u = 1, 2$$

- Step 3: Find PRC for each partner according to PRC index table as shown in Table 2.
- Step 4: Complete partner PRC table for each firm in supply chain system as presented in Table 3.

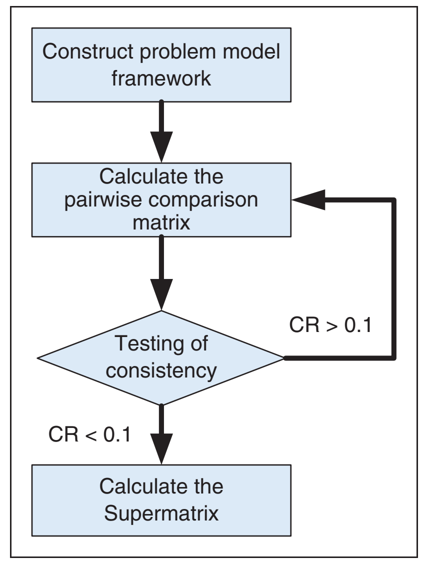


**Figure 3** Relative weights of criteria for analytic network process partner evaluation. CR, crossover rate.

### *Analytic network process for partner evaluation*

This section presents an ANP procedure, proposed by Meade and Sarkis (1998), for evaluating the partners in the supply chain system. Its procedure is shown in Figure 3 and described step-by-step as follows.

- Step 1: Construct the model framework. The first step is to construct a model framework for the problem being solved as shown in Figure 4. We can see clearly the evaluation criteria (dimensions) and subcriteria (performance indices) in the figure, and we should consider whether there is independence or feedback residing in that.
- Step 2: Calculate the pairwise comparison matrix. Pair up the evaluation criteria (dimension) and the subcriteria (performance index) to make matrix computations to evaluate the independence and feedback properties between them, as shown in matrix A,

$$\mathrm{A} = [a_{ij}] = \begin{bmatrix} 1 & a_{12} & \cdots & a_{1n} \\ a_{21} & 1 & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \cdots & 1 \end{bmatrix}, \text{ where } a_{ij} = \frac{1}{a_{ji}};\ i, j = 1, 2 \ldots, n.$$

The assessment coefficients ($a_{ij}$) are obtained through expert questionnaire surveys or major decision makers in each departments based on the measurement scales suggested by Saaty (1996), where pairwise comparisons were classified into nine levels of importance, as presented in Table 4.

- After all the pairwise comparisons are finished, the two-stage algorithm created by Meade and Sarkis (1998) is used to find the row and column mean of the matrix

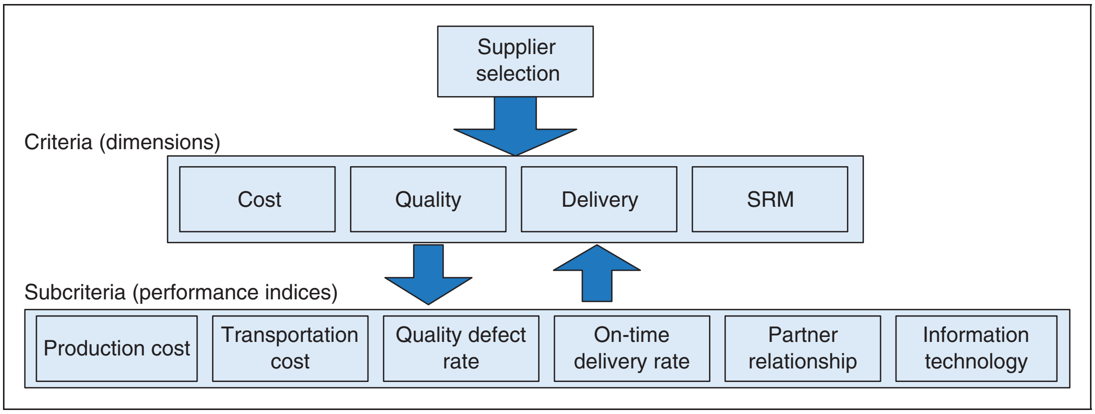


**Figure 4** Model framework for partner assessment criteria. SRM, supplier relationship management.

**Table 4** Pairwise comparison scale for analytic network process preferences

| Numerical rating | Verbal judgments of preferences |
|---|---|
| 1 | Equal importance |
| 3 | Moderate importance |
| 5 | Strong importance |
| 7 | Very strong or demonstrated importance |
| 9 | Extreme importance |
| 2, 4, 6, 8 | Intermediate values |

with the approximate eigenvector $W$; the equation is presented as follows:

$$W_i = \sum_{j=1}^{J} \left( a_{ij} / \sum_{i=1}^{I} a_{ij} \right) / J$$

where $W_i$ is the relative weight of evaluation criterion (dimension) and subcriterion (performance index) $i$. $J$ is the total number of columns in matrix. $I$ is the total number of rows in matrix.

- Step 3: Test the consistency. According to Saaty (1996), $CR < 0.1$ means that in a comparison matrix, the deviation for factor weight assessment is acceptable, and thus there is consistency, otherwise re-examination must be made and assessments of the pairwise comparisons must be modified; detailed formula and specifications are as follows: CR = CI/RI, where CR (Consistency Ratio) indicates consistency, CI (Consistency Index) indicates consistency index, and there is $\mathrm{CI} = \frac{\lambda_{\max} - n}{n-1}$, where $\lambda_{\max}$ denotes a maximum eigenvector in a pairwise comparison matrix, and $n$ is the number of comparative factors. $RI$ denotes random index.
- Step 4: Calculate the Supermatrix. As an important feature for ANP, the Supermatrix is used to represent relationship between elements and their strength; according to the weights for each feasible solution and the relative weights between the criteria, the overall weight for each solution can be found.

As suggested by Saaty (1996), the supermatrix is a complete comprehensive matrix consisting of multiple submatrices with clusters and elements included in clusters respectively distributed on the right and upper side of the matrix, where the submatrices are formed based on the eigenvectors ($W$ in this case) from pairwise element comparisons. A blank or 0 means that the clusters and elements are independent of each other without dependence, yet if the matrix elements are dependent on each other, after a certain number of multiplication operations, the matrix may converge to a fixed extreme value, then the weight can be obtained through $\lim_{i\to\infty} T^{2i+1}$. Figure 5 presents the matrix pattern for the supermatrix.

Matrix A is created by matching each criteria with the indices, matrix B is created by matching each index with the criteria, and matrices C and D are created by matching the criteria and indices respectively; last of all, they aggregate into a supermatrix.

### *Optimization mathematical model for solving supply chain planning problems*

Find the quota for various partners to minimize total cost in the supply chain using cost, quality, delivery and SRM as criteria, and taking customer requirements, partner production capacity limit, production and transportation loss rates into account. It is a multi-echelon, single-product supply chain framework with multi-level partners and multiple customer requirements. Assumptions of the mathematical model are: 1) all customer demands are known; 2) no shortage is allowable; 3) the order quantity is subject to maximum and minimum production capacity; 4) the quantity discount from supply members in respect to order handling is taken into consideration; 5) transportation costs are calculated on a unit basis, and do not change with quantity; and 6) production and transportation loss rates are taken into consideration at the same time, which means a non-balanced supply chain system.

The optimization mathematical model is as follows.

*Objective function.* The four criteria – cost, quality, delivery and SRM – are taken into consideration, and the relative weight for each criterion was found through ANP; then multi-objective mathematical programming approach is

$$\begin{array}{ccc} & \text{criteria} & \text{indices} \\ \text{criteria} & \multicolumn{2}{c}{\left[\begin{array}{c:c} C & B \\ \hdashline A & D \end{array}\right]} \\ \text{indices} & & \end{array}$$

**Figure 5** Matrix model of supermatrix relationships.

incorporated to select the best partners and production quota for them.

1. Cost model $Z_1$ has two parts, production cost $C_1$ and transportation cost $C_2$, where quantity, production loss rate and fixed cost are taken into account; to find minimum cost, the objective function is as follows:

$$Min\, Z_1 = C_1 + C_2$$

$$C_1 = \sum_{i=1}^{I-1} \sum_{j=1}^{J} \sum_{z=1}^{Z} d_{i,j}^{Z}(Q) PC_{i,j} \left[ \frac{\sum_{k=1}^{K} Q_{(i,j)(i+1,k)}}{1 - PDR_{i,j}} \right] + \sum_{i=1}^{I-1} \sum_{j=1}^{J} SO_{i,j} F_{i,j}$$

$$C_2 = \sum_{i=1}^{I-1} \sum_{j=1}^{J} \sum_{k=1}^{K} TC_{(i,j)(i+1,k)} \left[ \frac{Q_{(i,j)(i+1,k)}}{1 - TDR_{(i,j)(i+1,k)}} \right]$$

2. As to quality model $Z_2$, it is hoped that partners minimize their defective rate through continuous improvement on quality; the objective function is as follows:

$$Min\; Z_2 = \sum_{i=1}^{I-1} \sum_{j=1}^{J} QDR_{i,j} \sum_{k=1}^{K} Q_{(i,j)(i+1,k)}$$

3. For delivery model $Z_3$, it is expected that partners maximize their on-time delivery rate to ensure sufficient supply and prevent shortage:

$$Max\; Z_3 = \sum_{i=1}^{I-1} \sum_{j=1}^{J} DR_{i,j} \sum_{k=1}^{K} Q_{(i,j)(i+1,k)}$$

4. In the SRM model $Z_4$, it could be known that PRC is composed of PR and IT from the above PRC inferences, only a long-term relationship can enrich the overall competence for the supply chain under shared information and technologies, and superior IT may provide more transparent upstream and downstream sourcing schemes for collaborative works. Hence, PRC maximization may provide quick response to supply chain failure; the objective function is as follows:

$$Max\, Z_4 = \sum_{i=1}^{I-1} \sum_{j=1}^{J} SR_{i,j} \sum_{k=1}^{K} Q_{(i,j)(i+1,k)}$$

5. As the four criteria in this case are in different units, standardization (Ng, 2007) and *T*-score conversion are necessary (Wang and Che, 2007); together with ANP relative weight, a multi-objective mathematical model ($Z_T$) for total minimization can be found, and the objective function is as follows:

$$Min\; Z_T = (W_1 Z_1 + W_2 Z_2 - W_3 Z_3 - W_4 Z_4)$$

***Constraints.*** Limits on quantity discount, partner production capacity and demand quantity under production and transportation losses are taken into account; the models are detailed as follows.

The discount changes with quantity and is group-based for each partner, and the equations are

$$\text{Let } Q = Q_{(i,j)(i+1,k)},\, d_{i,j}^{Z}(Q) = \begin{cases} d_{i,j}^{0}, & Q < Y_1 \\ d_{i,j}^{1}, & Y_1 \le Q < Y_2 \\ \vdots & \vdots \\ d_{i,j}^{n-1}, & Y_{n-1} \le Q < Y_n \\ d_{i,j}^{n}, & Y_n \le Q \end{cases}$$

$$d_{i,j}^{0} = 1 > d_{i,j}^{1} > d_{i,j}^{2} > \ldots > d_{i,j}^{n} > 0,\; for\, i = 1,2\ldots,I;\, j = 1,2,\ldots,j$$

$$Y_n > Y_{n-1} > \cdots > Y_2 > Y_1 > 0$$

$$Q_{(i,j)(i+1,k)} \geqslant 0\, and \in\; Integer\, for\; all\; i,j,k$$

The total transportation quantity that partner of each echelon and level received should be in compliance with the upper and lower capacity limits with production and transportation costs taken into consideration; the equations are

$$L_{i,j} \le \sum_{k=1}^{K} \left[ \frac{Q_{(i,j)(i+1,k)}}{1 - PDR_{i,j}} \right] \le U_{i,j},$$

$$for\; i = 1,2\ldots,I-1;\, j = 1,2,\ldots,J$$

$$L_{i,k} \le \sum_{j=1}^{J} \left[ Q_{(i-1,j)(i,k)} \left( 1 - TDR_{(i-1,j)(i,k)} \right) \right] \le U_{i,k},$$

$$for\; i = 2,3\ldots,I;\, k = 1,2,\ldots,K$$

With production and transportation cost taken into consideration, the total transportation quantity that partner of each echelon and level received should be in compliance with the quantity demanded, and finally in compliance with customer demand, and the equations are

$$\sum_{j=1}^{J} \left[ Q_{(i-1,j)(i,k)} \left( 1 - TDR_{(i-1,j)(i,k)} \right) \left( 1 - PDR_{i,j} \right) \right] = D_{i,k},$$

$$for\, i = 2,3\ldots,I-1;\, k = 1,2,\ldots,K$$

$$\sum_{j=1}^{J} \left[ Q_{(i-1,j)(i,k)} \left( 1 - TDR_{(i-1,j)(i,k)} \right) \right] = D_{I,k},$$

$$for\, i = I;\, k = 1,2,\ldots,K$$

The binary constrained variables and the relative weights for each criterion add up to 1, and the variable should not be negative, and the equations are

$$SO_{i,j} \in (0,1),\; for\, i = 1,2\ldots,I-1;\, j = 1,2,\ldots,J$$

$$W_t > 0\; and \sum_{t=1}^{4} W_t = 1,\; for\; t = 1,2,3,4$$

## *Turbo particle swarm optimization solving model for the mathematical model*

Many new methods for particle and velocity updating had been proposed, and our study is based on the population rule proposed by Shi and Eberhart (1998), where a computation acceleration technique was used to improve the computation efficiency for PSO – the approach is termed TPSO. Figure 6 shows the computation processes for TPSO, and following are the solution steps.

- Step 1: Set number of particles and epoch, inertia weight and maximum velocity, where number of particles is representative of search points, and a larger epoch would mean a larger number of evolutional searches for all particles, as well as longer time spent. The convergence rate for fitness is dependent on the weight, an optimum weight may be acquired through experimental design and the maximum velocity refers to the maximum scope of movement for particle.
- Step 2: Randomly generate an initial velocity and position for each particle, where velocity ranges between 0 and 1, but the position variable should be generated under the conditions that multi-period customer demand, capacity limit and integer requirement are met. Consider the proposed problem in which the supply chain system with $I$ echelons and $J_i$ members of echelon $i$, and then we can set up a search space of $\sum_{i=1}^{I-1}(J_i \times J_{i+1})$ dimensions. Every particle is composed of $\sum_{i=1}^{I-1}(J_i \times J_{i+1})$ discrete points. The value of each discrete point is restricted within the upper and lower capacity limits, and it represents that the quantity of product is transported from the corresponding upstream partner to the relevant downstream partner. The position of each particle indicates the apropos pattern of the products shipped from each upstream partner to the downstream partner.
- Step 3: Begin iteration from 1.
- Step 4: Calculate fitness function value for each particle according to the specified objective function $Z_T$, and the resulting fitness (objective solution) value varies with particle position. In the multi-echelon non-balanced supply chain planning problem, the objective is to minimize the integrated criterion, which integrates cost, quality, delivery and PRC. Then the following equation is adopted as fitness function in the light of the description in Section 3.4 and the particle with the minimal fitness value should be reserved during the computation processes.

$$\textit{Fitness function} = Z_T = (W_1 Z_1 + W_2 Z_2 - W_3 Z_3 - W_4 Z_4)$$

- Step 5: Record pbest (the best solution that the particle has obtained at the current iteration) and gbest (the best solution obtained from the population); if pbest is better than gbest, then revise gbest in memory, at the

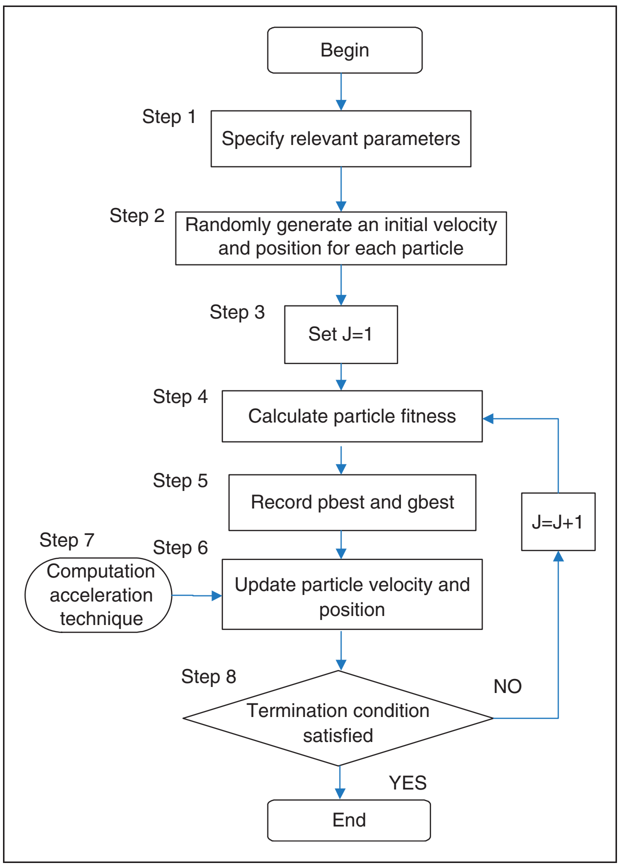


**Figure 6** Turbo particle swarm optimization procedure.

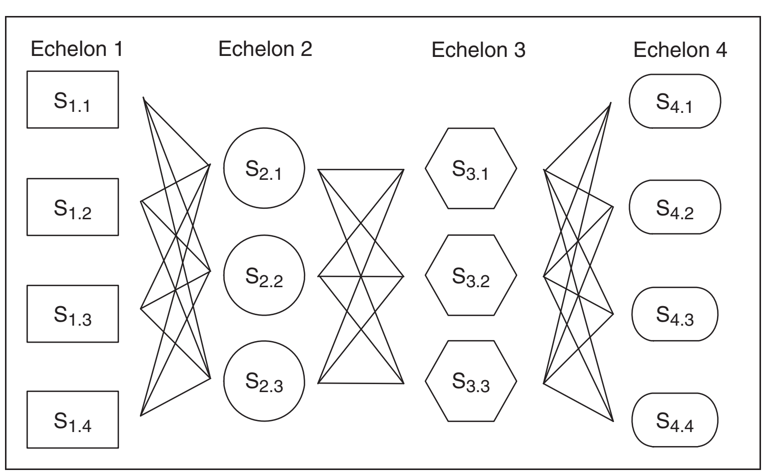


**Figure 7** Supply chain framework.

**Table 5** Related data

| | PC | TC | QD | DR | PRC | PDR | TDR | U | L |
|---|---|---|---|---|---|---|---|---|---|
| Echelon 1 | | | | | | | | | |
| $S_{1.1}$ | 10 | 2 | 0.15 | 0.85 | 5 | 0.001 | 0.002 | 1000 | 100 |
| $S_{1.2}$ | 12 | 1 | 0.02 | 0.99 | 5 | 0.003 | 0.001 | 1000 | 100 |
| $S_{1.3}$ | 10 | 2 | 0.01 | 0.88 | 4 | 0.001 | 0.002 | 1000 | 100 |
| $S_{1.4}$ | 8 | 1 | 0.18 | 0.99 | 4 | 0.002 | 0.001 | 1000 | 100 |
| Echelon 2 | | | | | | | | | |
| $S_{2.1}$ | 10 | 2 | 0.02 | 0.9 | 4 | 0.001 | 0.002 | 1000 | 100 |
| $S_{2.2}$ | 12 | 1 | 0.2 | 0.95 | 4 | 0.002 | 0.001 | 1000 | 100 |
| $S_{2.3}$ | 8 | 2 | 0.03 | 0.97 | 3 | 0.001 | 0.003 | 1000 | 100 |
| Echelon 3 | | | | | | | | | |
| $S_{3.1}$ | 8 | 2 | 0.01 | 0.98 | 3 | 0.001 | 0.002 | 1000 | 100 |
| $S_{3.2}$ | 10 | 1 | 0.01 | 0.96 | 4 | 0.002 | 0.001 | 1000 | 100 |
| $S_{3.3}$ | 12 | 1 | 0.02 | 0.95 | 5 | 0.003 | 0.001 | 1000 | 100 |
| Echelon 4 | | | | | | | | | |
| | Demand | | | | | | | | |
| Period | 1 | 2 | 3 | | | | | | |
| $S_{4.1}$ | 300 | 200 | 100 | | | | | | |
| $S_{4.2}$ | 200 | 300 | 500 | | | | | | |
| $S_{4.3}$ | 300 | 100 | 200 | | | | | | |
| $S_{4.4}$ | 200 | 400 | 200 | | | | | | |

PC, production cost; TC, transportation cost; QD, quality defect rate; DR, on-time delivery rate; PRC, partner relationship coefficient; PDR, production loss rate; TDR, transportation loss rate; U, maximum production limit; L, minimum production limit.

**Table 6** Quantity discount

| Section | Interval | Discount rate |
|---|---|---|
| 1 | 0 to under 400 | 1 |
| 2 | 400 to under 700 | 0.9 |
| 3 | 700 and over | 0.8 |

same time. Each particle modifies the particle velocity for next search according to gbest, which means storage of optimal feasible solutions from particles of various generations.

- Step 6: Update the current position and velocity of each particle by the following formula.

$$v_i^{new} = wv_i^{old} + c_1 rand_1 (x_i^p - x_i^{old}) + c_2 rand_2 (x^g - x_i^{old})$$
$$x_i^{new} = Int[x_i^{old} + v_i^{new}]$$

$v_i^{new}$ and $v_i^{old}$ are the new/old velocities of particle $i$. $x_i^{new}$ and $x_i^{old}$ are the new/old positions of particle $i$. $c_1$ and $c_2$ cognition and social learning factors. $x_i^p$ is the best solution that particle $i$ has obtained at the current iteration. $x_i^g$ is the best solution obtained from $x_i^p$ in the population. $w$ is the inertia weight. $rand_1$ and $rand_2$ are random numbers within [0,1]. $Int[x_i^{old} + v_i^{new}]$ is the integer value of $x_i^{old} + v_i^{new}$.

- Step 7: Find feasible values of variables which satisfy the constraints in a stepwise way based on variable-demand dependency after updating the particle position and velocity with a computation acceleration technique, and those repetitive updating calculations can be reduced.

The computation procedure can be algorithmically stated as follows.

*For each* $j \in (1 \ldots n)$
*when* $i = 1$
*If* $X_{ij} \geq d_j$ *then*
$X_{ij} = d_j$, *other variables equal 0*
*If* $X_{ij} + X_{(i+1)} j \geq d_j$ *then*
$X_{(i+1)j} = d_j - X_{ij}$, *other variables equal 0*
:
*If* $X_{ij} + X_{(i+1)j} + \ldots + X_{(m-1)j} \geq d_j$ *then*
$X_{(m-1)j} = d_j - \{X_{ij} + X_{(i+1)j} + \ldots + X_{(m-2)j}\}$,
*other variables equal 0*
*If* $X_{ij} + X_{(i+1)j} + \ldots + X_{(m-1)j} < d_j$ *then*
$X_{mj} = d_j - \{X_{ij} + X_{(i+1)j} + \ldots + X_{(m-1)j}\}$
*Endfor*
---
*Combinations of* $X_{ij}$ *variables create* $d_j$ *demands under n limit conditions, where*
$i \in (1 \ldots m)$ *and* $j \in (1 \ldots n)$.
*combinations of* $X_{ij}$ *variables* $\rightarrow d_j$
$X_{11} + X_{21} + \ldots + X_{m1} \rightarrow d_1$
$X_{12} + X_{22} + \ldots + X_{m2} \rightarrow d_2$
: :
$X_{1n} + X_{2n} + \ldots + X_{mn} \rightarrow d_n$

- Step 8: Obtain the optimal result of supply chain planning when the termination condition is specified as maximum epoch number. If the condition has not been met, then repeat Step 4.

**Table 7** Partner relationship (PR) and information technology (IT) coefficient assessment for each partner

| PR | | | | | IT | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | Partner | | | | Partner | | | | |
| Item 1 | 1 | 2 | 3 | 4 | 1 | 2 | 3 | 4 | Item 2 |
| 1. Mutual trust | High | Middle | High | Middle | Middle | High | Middle | High | 1. Information science |
| 2. Profit sharing | Middle | High | High | Middle | High | Middle | Middle | Low | 2. Information sharing |
| 3. Jointly forge long-term competitive advantages | High | Middle | Middle | Low | High | Middle | Low | High | 3. Information resource integration capability |
| 4. Risk sharing | High | High | Middle | High | | | | | |
| $W_{PR}$ | 0.92 | 0.83 | 0.83 | 0.67 | 0.89 | 0.78 | 0.56 | 0.78 | $W_{IT}$ |

**Table 8** Partner relationship coefficient (PRC) value of each partner

| | Partner | | | |
|---|---|---|---|---|
| | 1 | 2 | 3 | 4 |
| $W_{PRC}$ | 0.903 | 0.806 | 0.694 | 0.722 |
| PRC | 5 | 5 | 4 | 4 |

**Table 9** Comparison matrix for the importance of criteria and indices

| A matrix | Cost | Quality | Delivery | SRM |
|---|---|---|---|---|
| PC | 0.3767 | 0.1623 | 0.1322 | 0.0662 |
| TC | 0.2993 | 0.0999 | 0.0823 | 0.0511 |
| QD | 0.0677 | 0.184 | 0.0638 | 0.1015 |
| DR | 0.0525 | 0.1239 | 0.441 | 0.0829 |
| PR | 0.1128 | 0.2546 | 0.1655 | 0.3892 |
| IT | 0.091 | 0.1754 | 0.1151 | 0.3091 |

SRM, supplier relationship management; PC, production cost; TC, transportation cost; QD, quality defect rate; DR, on-time delivery rate; PR, partner relationship; IT, information technology.

## Numerical examples and comparison results

We would like to use a 4–3–3–4 supply chain network framework to validate the method proposed here, as shown in Figure 7. The numbers 4, 3, 3, 4 respectively represent the number of partners for echelon 1 to 4, and total market demand is divided into three periods; there are 1000 units for each period. Factors, such as costs (production, transportation) and capacity limits, are different for each member in the supply chain, as shown in Table 5. Assume that all partners use the same conditions for quantity discount as shown in Table 6, and the fixed cost is set at 3000 for all of them. The framework considers a single-product, three-period demand, where products are manufactured under the same framework and distributed to different members on the supply chain, thus the total cost for the supply chain can be minimized through differentiated quantity quota. $S_{1.1}$ on echelon 1 is used as an example to derive the PRC value.

Complete the PR and IT coefficient assessment table, as shown in Table 7. High, medium and low are substituted for 3, 2 and 1 score, then calculate PR and IT for the first partner as $W_{PR_1} = (3+2+3+3)/3(4) = 0.917$ and $W_{IT_1} = (2+3+3)/3(3) = 0.889$. Assuming $sw_1 = sw_2 = 0.5$, we can find that $W_{PRC_1} = 0.5(0.917) + 0.5(0.889) = 0.903$, and $PRC_1 = 5$ can be obtained from Table 1. $PRC_2$, $PRC_3$ and $PRC_4$ are also figured out in the same way as $PRC_1$; then the partner PRC table would be completed and shown in Table 8.

There are four criteria (dimensions) taken into account: cost, quality, delivery and SRM, and there are six subcriteria (performance indices) taken into consideration: production cost, transportation cost, quality loss rate, one-time delivery rate, PR and IT. Figure 2 presents the dependence and feedback relationship between them. Then the four criteria and six indices are paired for comparison matrix computation, and each criterion is matched with the indices to form a $6 \times 4$ matrix A as shown in Table 9. Each index is matched with the criteria to form a $4 \times 6$ matrix B as shown in Table 10. Similarly, a $4 \times 4$ matrix C and a $6 \times 6$ matrix D are also created. Assume that there are consistent among all pairwise comparison matrices and there is no significant correlation between them. Hence, matrices C and D are 0, and those plus the previous matrices A and B, and a $10 \times 10$ supermatrix come into being as presented in Table 11. Then matrix multiplication operations are performed, and thus a stable extreme value is obtained at $T^{16}$ as presented in Table 12. The results indicate that the weights of cost, quality, delivery and SRM are respectively $W_1 = 0.2978$, $W_2 = 0.1634$, $W_3 = 0.1839$ and $W_4 = 0.3549$.

Optimization for the multi-objective programming model here is solved with TPSO, and the period 1 demand in Table 5 is taken as an example. The optimum parameter design suggested by Shi and Eberhart (1998) is taken into account, where 16 ($2 \times 2 \times 2 \times 2$) combinations were obtained from the number of particle ($P = 10$ and 20), number of epoch ($E = 500$ and 1000), weight ($W = 0.9$ and 1.2) and maximum velocity ($V_{\max} = 10$ and 50). Then optimum parameter combination is obtained through experimental design as shown in Table 13 to find the best fitness function. As to the computation of time, a Pentium(R)4 CPU 3.00 GHz, 512 MB is used jointly with Windows XP, and epoch number is mainly used as termination condition for TPSO. The data of $T$-score and

**Table 10** Comparison matrix for the importance of indices and criteria

| B matrix | PC | TC | QD | DR | PR | IT |
|---|---|---|---|---|---|---|
| Cost | 0.5308 | 0.5902 | 0.1758 | 0.1758 | 0.1758 | 0.1664 |
| Quality | 0.148 | 0.1305 | 0.6069 | 0.0888 | 0.1285 | 0.0744 |
| Delivery | 0.1035 | 0.0908 | 0.0888 | 0.6069 | 0.0888 | 0.1757 |
| SRM | 0.2177 | 0.1884 | 0.1285 | 0.1285 | 0.6069 | 0.5834 |

PC, production cost; TC, transportation cost; QD, quality defect rate; DR, on-time delivery rate; PR, partner relationship; IT, information technology; SRM, supplier relationship management.

**Table 11** Initial supermatrix

| Super matrix | Cost | Quality | Delivery | SRM | TC | PC | QD | DR | PR | IT |
|---|---|---|---|---|---|---|---|---|---|---|
| Cost | 0 | 0 | 0 | 0 | 0.5308 | 0.5902 | 0.1758 | 0.1758 | 0.1758 | 0.1664 |
| Quality | 0 | 0 | 0 | 0 | 0.148 | 0.1305 | 0.6069 | 0.0888 | 0.1285 | 0.0744 |
| Delivery | 0 | 0 | 0 | 0 | 0.1035 | 0.0908 | 0.0888 | 0.6069 | 0.0888 | 0.1757 |
| SRM | 0 | 0 | 0 | 0 | 0.2177 | 0.1884 | 0.1285 | 0.1285 | 0.6069 | 0.5834 |
| TC | 0.3767 | 0.1623 | 0.1322 | 0.0662 | 0 | 0 | 0 | 0 | 0 | 0 |
| PC | 0.2993 | 0.0999 | 0.0823 | 0.0511 | 0 | 0 | 0 | 0 | 0 | 0 |
| QD | 0.0677 | 0.184 | 0.0638 | 0.1015 | 0 | 0 | 0 | 0 | 0 | 0 |
| DR | 0.0525 | 0.1239 | 0.441 | 0.0829 | 0 | 0 | 0 | 0 | 0 | 0 |
| PR | 0.1128 | 0.2546 | 0.1655 | 0.3892 | 0 | 0 | 0 | 0 | 0 | 0 |
| IT | 0.091 | 0.1754 | 0.1151 | 0.3091 | 0 | 0 | 0 | 0 | 0 | 0 |

SRM, supplier relationship management; TC, transportation cost; PC, production cost; QD, quality defect rate; DR, on-time delivery rate; PR, partner relationship; IT, information technology.

**Table 12** Supermatrix converged at $T^{16}$

| Super matrix | Cost | Quality | Delivery | SRM | PC | TC | QD | DR | PR | IT |
|---|---|---|---|---|---|---|---|---|---|---|
| Cost | 0 | 0 | 0 | 0 | 0.2977 | 0.2977 | 0.2977 | 0.2977 | 0.2977 | 0.2977 |
| Quality | 0 | 0 | 0 | 0 | 0.1634 | 0.1634 | 0.1634 | 0.1634 | 0.1634 | 0.1634 |
| Delivery | 0 | 0 | 0 | 0 | 0.1839 | 0.1839 | 0.1839 | 0.1839 | 0.1839 | 0.1839 |
| SRM | 0 | 0 | 0 | 0 | 0.355 | 0.355 | 0.355 | 0.355 | 0.355 | 0.355 |
| PC | 0.1865 | 0.1865 | 0.1865 | 0.1865 | 0 | 0 | 0 | 0 | 0 | 0 |
| TC | 0.1387 | 0.1387 | 0.1387 | 0.1387 | 0 | 0 | 0 | 0 | 0 | 0 |
| QD | 0.098 | 0.098 | 0.098 | 0.098 | 0 | 0 | 0 | 0 | 0 | 0 |
| DR | 0.1464 | 0.1464 | 0.1464 | 0.1464 | 0 | 0 | 0 | 0 | 0 | 0 |
| PR | 0.2438 | 0.2438 | 0.2438 | 0.2438 | 0 | 0 | 0 | 0 | 0 | 0 |
| IT | 0.1866 | 0.1866 | 0.1866 | 0.1866 | 0 | 0 | 0 | 0 | 0 | 0 |

SRM, supplier relationship management; PC, production cost; TC, transportation cost; QD, quality defect rate; DR, on-time delivery rate;; PR, partner relationship; IT, information technology.

time for each experiment is got through 10 tests, where the mean of the tests is used. The results show 28618.62 will be the optimal $T$-score with a computation time of 1.83 s, and the parameter combination is: $E = 1000$, $P = 20$, $W = 1.2$, and $V_{\max} = 50$.

The GA optimum parameter design is as shown in Table 14 (Wang and Che, 2007), epoch number $(E) = 500$ and 1000, crossover rate $(\mathrm{CR}) = 0.3$ and 0.6, and mutation rate $(\mathrm{MR}) = 0.03$ and 0.05. Finally, we have the optimum combination: $E = 1000$, $\mathrm{PO} = 20$, $\mathrm{CR} = 0.5$ and $\mathrm{MR} = 0.06$.

$T$-score for the three periods of demand is derived through optimum parameter designs for TPSO, PSO and GA; 20 tests are ran to take the mean, and the results are compared in Table 15. The purpose of this experiment is to validate the optimization of the fitness function found with TPSO. We can gain a clear understanding from Tables 16 and 17 that the TPSO demands for various periods and $t$-test for both PSO and GA all reject $H_0$ at the 95% confidence level, which indicate that the average $T$-score and time for TPSO are superior to those for PSO and GA. In other words, the results validate

**Table 13** *T*-score combinations for turbo particle swarm optimization (TPSO) parameter experimental design

| | *E* | 500 | | 1000 | |
|---|---|---|---|---|---|
| *W* | $V_{max}$ | $p = 10$ | $p = 20$ | $p = 10$ | $p = 20$ |
| 0.9 | 10 | 33949.69 (0.39a) | 34497.05 (0.65) | 34188.41 (0.71) | 33005.87 (1.48) |
| | 50 | 31527.40 (0.43) | 31230.82 (0.85) | 31156.71 (1.04) | 30997.55 (1.90) |
| 1.2 | 10 | 34524.42 (0.37) | 34020.07 (0.72) | 34239.18 (0.76) | 34076.00 (1.27) |
| | 50 | 30460.81 (0.50) | 28929.61 (0.81) | 29759.48 (0.84) | 28618.62 (1.83) |

a, time (s).

**Table 14** *T*-score combinations for genetic algorithm (GA) parameter experimental design

| | *E* | 500 | | 1000 | |
|---|---|---|---|---|---|
| CR | MR | po = 10 | po = 20 | po = 10 | po = 20 |
| 0.3 | 0.03 | 37308.51 (47.44a) | 37169.66 (102.25) | 37088.33 (104.45) | 36996.91 (213.45) |
| | 0.05 | 37286.27 (60.77) | 37063.52 (125.17) | 37190.22 (119.27) | 36873.39 (256.53) |
| 0.6 | 0.03 | 37312.48 (55.39) | 37084.11 (111.97) | 36958.80 (112.75) | 36795.62 (239.99) |
| | 0.05 | 37258.01 (66.88) | 36887.92 (136.47) | 36802.43 (128.66) | 36316.68 (274.86) |

a, time (s).

**Table 15** Turbo particle swarm optimization (TPSO), particle swarm optimization (PSO) and genetic algorithm (GA) comparisons

| | TPSO | | | PSO | | GA | |
|---|---|---|---|---|---|---|---|
| Period | tpb | tpm | tpm′ | pm | pm′ | gm | gm′ |
| 1 | 26467.67 | 28517.75 | 1.73 | 29837.64 | 79.54 | 36603.79 | 279.31 |
| 2 | 26482.63 | 28741.27 | 1.40 | 29742.32 | 91.30 | 36999.57 | 265.86 |
| 3 | 26120.61 | 28119.64 | 1.45 | 29095.97 | 103.21 | 35839.82 | 285.85 |

tpb, best of *T*-score of TPSO; tpm, mean of *T*-score of TPSO; tpm′, mean of time of TPSO; pm, mean of *T*-score of PSO; pm′, mean of time of PSO; gm, mean of *T*-score of GA; gm′, mean of time of GA.

**Table 16** Turbo particle swarm optimization (TPSO) and particle swarm optimization (PSO) comparisons

| | TPSO | | | | PSO | | | |
|---|---|---|---|---|---|---|---|---|
| Period | tpm | tpm′ | tps | tps′ | pm | pm′ | ps | ps′ |
| 1 | 28517.75 | 1.73 | 672.83 | 0.33 | 29837.64 | 79.54 | 1448.83 | 34.22 |
| 2 | 28741.27 | 1.40 | 1594.91 | 0.39 | 29742.32 | 91.30 | 1097.48 | 29.18 |
| 3 | 28119.64 | 1.45 | 1797.50 | 0.41 | 29095.97 | 103.21 | 1495.19 | 34.38 |
| | *t*-Test ($\alpha = 0.05$) | | | *t*-Statistic | | *P*-value | Decision | |
| 1 | $H_0$: $\mu_{tpm} \geq \mu_{pm}$ | | | −3.48 | | 0.001 | Reject $H_0$ | |
| | $H_0$: $\mu_{tpm'} \geq \mu_{pm'}$ | | | −10.17 | | 1E-12 | Reject $H_0$ | |
| 2 | $H_0$: $\mu_{tpm} \geq \mu_{pm}$ | | | −2.33 | | 0.013 | Reject $H_0$ | |
| | $H_0$: $\mu_{tpm'} \geq \mu_{pm'}$ | | | −13.78 | | 1E-16 | Reject $H_0$ | |
| 3 | $H_0$: $\mu_{tpm} \geq \mu_{pm}$ | | | −1.99 | | 0.027 | Reject $H_0$ | |
| | $H_0$: $\mu_{tpm'} \geq \mu_{pm'}$ | | | −13.23 | | 4E-16 | Reject $H_0$ | |

tpm, mean of *T*-score of TPSO; tpm′, mean of time of TPSO; tps, Std. of *T*-score of TPSO; tps′, Std. of time of TPSO; pm, mean of *T*-score of PSO; pm′, mean of time of PSO; ps, Std. of *T*-score of PSO; ps′, Std. of time of PSO.

**Table 17** Turbo particle swarm optimization (TPSO) and genetic algorithm (GA) comparisons

| Period | TPSO | | | | GA | | | |
|---|---|---|---|---|---|---|---|---|
| | tpm | tpm′ | tps | tps′ | gm | gm′ | gs | gs′ |
| 1 | 28517.75 | 1.73 | 672.83 | 0.33 | 36603.79 | 279.31 | 212.84 | 18.83 |
| 2 | 28741.27 | 1.40 | 1594.91 | 0.39 | 36999.57 | 265.86 | 248.96 | 4.71 |
| 3 | 28119.64 | 1.45 | 1797.50 | 0.41 | 35839.82 | 285.85 | 477.40 | 12.33 |
| | *t*-Test ($\alpha = 0.05$) | | | *t*-Statistic | | *P*-value | Decision | |
| 1 | H0: $\mu$tpm $\geq$ $\mu$gm | | | −25.92 | | 8E-19 | Reject H0 | |
| | H0: $\mu$tpm′ $\geq$ $\mu$gm′ | | | −70.63 | | 1E-28 | Reject H0 | |
| 2 | H0: $\mu$tpm $\geq$ $\mu$gm | | | −11.38 | | 3E-11 | Reject H0 | |
| | H0: $\mu$tpm′ $\geq$ $\mu$gm′ | | | −264.93 | | 7E-42 | Reject H0 | |
| 3 | H0: $\mu$tpm $\geq$ $\mu$gm | | | −9.46 | | 1E-09 | Reject H0 | |
| | H0: $\mu$tpm′ $\geq$ $\mu$gm′ | | | −110.31 | | 4E-33 | Reject H0 | |

tpm, mean of *T*-score of TPSO; tpm′, mean of time of TPSO; tps, Std. of *T*-score of TPSO; tps′, Std. of time of TPSO; gm, mean of *T*-score of GA; gm′, mean of time of GA; gs, Std. of *T*-score of GA; gs′, Std. of time of GA.

**Table 18** Results of non-balanced supply chain planning by turbo particle swarm optimization (TPSO)

| | From/To | S2.1 | S2.2 | S2.3 | |
|---|---|---|---|---|---|
| Echelon 1 | S1.1 [1a, 1b, 1c] | 103d, 105e, 105f (1g, 1h, 1i) | – | – | |
| | S1.2 [3, 3, 3] | – | 913, 910, 910 (0, 1, 1) | – | |
| | S1.3 | – | – | – | |
| | S1.4 | – | – | – | |
| | From/To | S3.1 | S3.2 | S3.3 | |
| Echelon 2 | S2.1 [1, 1, 1] | 0, 0, 103 (0, 0, 1) | 101, 103, 0 (1, 1, 0) | – | |
| | S2.2 [2, 2, 2] | – | – | 910, 907, 907 (1, 1, 1) | |
| | S2.3 | – | – | – | |
| | From/To | S4.1 | S4.2 | S4.3 | S4.4 |
| Echelon 3 | S3.1 [0, 0, 1] | 0, 0, 101 (0, 0, 1) | – | – | – |
| | S3.2 [1, 1, 0] | – | 99, 0, 0 (1, 0, 0) | 0, 101, 0 (0, 1, 0) | – |
| | S3.3 [3, 3, 3] | 301, 201, 0 (1, 1, 0) | 103, 301, 501 (1, 1, 1) | 301, 0, 201 (1, 0, 1) | 201, 401, 201 (1, 1, 1) |

a, period-1 production loss of s (PL); b, period-2 PL; c, period-3 PL; d, period-1 transportation quantity between s (TQ); e, period-2 TQ; f, period-3 TQ; g, period-1 transportation loss between s (TL); h, period-2 TL; i, period-3 TL; –, out of operation.

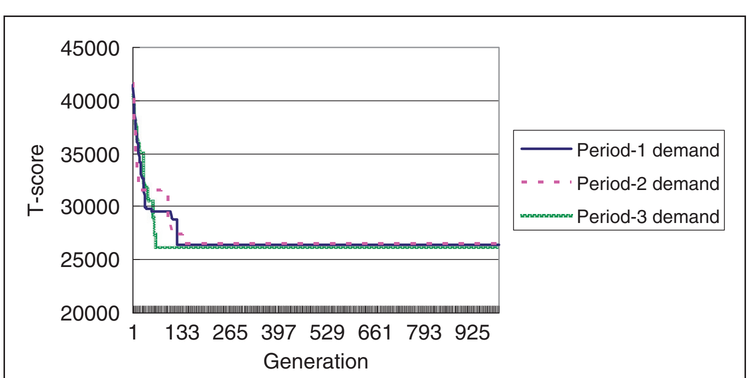


**Figure 8** Convergence graph for optimum turbo particle swarm optimization parameter combination.

the stability and reliability of TPSO in this study. In addition, we found the optimum supply chain network and transportation quantity quota between the partners from the experimental results in Table 18, where production loss and transportation loss are included. Taking period-1 demand for example, from the fact that $S_{1.3}$, $S_{1.4}$, $S_{2.3}$ and $S_{3.1}$ are out of operation, we find the optimum supply chain network {2–2–2–4}, and $S_{1.1}$ transports 103 units to $S_{2.1}$, where one unit of transportation loss is deducted and one unit of production loss is also deducted from $S_{2.1}$. Those add up to 101 units, which are transported to $S_{3.2}$, then one unit of transportation loss is deducted and one unit of production loss is deducted from $S_{3.2}$; those add up to 99 units, which are transported to $S_{4.2}$. Similarly, we can find that on echelon 1, $S_{1.1}$ and $S_{1.2}$ should input 103+1+913+3 = 1020 units, after deducting production and transportation loss for various echelons. The total demand 1000 on echelon 4 can be finally met, where the 1000 come from $S_{4.1} = 300$, $S_{4.2} = 200$, $S_{4.3} = 300$ and $S_{4.4} = 200$. TPSO demand convergence for various periods in this experiment is presented in Figure 8.

## Conclusions

In this study, we propose a multi-echelon, single-product and multi-period non-balance supply chain planning decision support methodology. Based on that, optimum supply chain structure and production–distribution decisions are derived, under the condition that customer demand can be met. The total cost for the supply chain is minimized through differentiated quantity quota, and based on this system, companies can effectively pick out suitable supply chain partners and optimal production resource allocation, as well as help decision makers find optimal plans and make an assessment.

In the methods proposed in this study, production and transportation losses are taken into account, and the required quantity of production predicted by upstream partners in advance is incorporated in SRM as criteria for partner evaluation to perfect the evaluation model. ANP technique is also used to handle subjectively the relative weights between criteria. Finally, TPSO algorithm is utilized to solve the multi-objective optimization mathematical model, and then the supply chain network structure and production–distribution plan are determined. A case study with a 4–3–3–4 supply chain framework is used to demonstrate the application of this model. The analysis of the results indicate that the model is capable of quickly and effectively constructing a supply chain structure by selecting the suitable supply chain partners and figuring out the optimal production–distribution quantity. Moreover, comparisons between PSO and GA algorithms are made to validate the optimization performance of the TPSO model proposed in this study. We find from the comparisons that the approach created in this study is more stable and reliable.

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## Nomenclature

Notations for the optimization mathematical model development for non-balanced supply chain planning problems in Section 3.4 are as follows.

| | |
|---|---|
| i | Echelon index for supply chain system, $i = 1,2,3 \ldots I$ |
| I | Total number of echelons |
| j,k | Partner index, $j = 1,2,3 \ldots J$; $k = 1,2,3 \ldots K$ |
| J,K | Number of partners |
| $Q_{(i,j)(i+1,k)}$ | Quantity of product is transported from partner $j$ of echelon $i$ to partner $k$ of echelon $i+1$ |
| $U_{i,j}$ | Maximum production limit for partner $j$ of echelon $i$ |
| $L_{i,j}$ | Minimum production limit for partner $j$ of echelon $i$ |
| $d^z_{i,j}(\mathrm{Q})$ | $d^z_{i,j}$ is a function of $Q$, indicating discount from partner $j$ of echelon $i$ at stage $z$ |
| $TC_{(i,j)(i+1,k)}$ | Unit transportation cost for transit from partner $j$ of echelon $i$ to partner $k$ of echelon $i+1$ |
| $TDR_{(i,j)(i+1,k)}$ | Transportation loss rate for transit from partner $j$ of echelon $i$ to partner $k$ of echelon $i+1$ |
| $PDR_{i,j}$ | Production loss rate for partner $j$ of echelon $i$ |
| $\mathrm{PC}_{i,j}$ | Production cost for partner $j$ of echelon $i$ |
| $SO_{i,j}$ | $\begin{cases} 1 & \text{Operation ongoing for partner } j \text{ of echelon } i \\ 0 & \text{Otherwise} \end{cases}$ |
| $F_{i,j}$ | Fixed cost for partner $j$ of echelon $i$ |
| $D_{i,j}$ | Demand quantity for partner $j$ of echelon $i$ |
| $QDR_{i,j}$ | Defective rate for partner $j$ of echelon $i$ |
| $DR_{i,j}$ | On-time delivery rate for partner $j$ of echelon $i$ |
| $PRC_{i,j}$ | Partner relationship assessment coefficient for partner $j$ of echelon $i$ |
| $W_t$ | Weight of criterion $t$ |
| [X] | Integer value of X |

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