9

Engineering Value Chain Modelling and Optimization

Lina Zhou and Xiaofei Xu

1 Background

The aim of this chapter is to introduce the modelling and optimization methods in engineering value chain decision-making and show the effectiveness and advances of solving management problems by information technologies. Decision-making is a very important part of engineering value chain management. There are many critical problems, such as selecting one among a number of suppliers, determining the order quantities of individual items in the next period, choosing the appropriate locations to set up the warehouses, allocating the product inventory among different distribution centres, deciding which route to take for the

L. Zhou (✉) · X. Xu
School of Computer Science and Technology,
Harbin Institute of Technology, Harbin, China
e-mail: zln@hit.edu.cn

X. Xu
e-mail: xiaofei@hit.edu.cn

Y. Zhang and M. Gregory (eds.), *Value Creation through Engineering Excellence*,
https://doi.org/10.1007/978-3-319-56336-7_9

transportation vehicle and so on and so forth. Based on the characters of a specific problem, different decision methods are developed and applied.

In this chapter, we summarize several typical value chain decision problems and related decision methods and introduce the popular decision-making methods based on mathematic model and optimization algorithms. We then investigate an engineering value chain construction decision problem, develop a multi-objective model, and propose the genetic algorithm-based solution procedure. Finally, numerical experiment and discussion are conducted to demonstrate the benefit of the method. Further trends of development in engineering value chain modelling and optimization will be illustrated.

2 Engineering Value Chain Decision-Making Problems and Methods

Problem solving is an essential skill for business and life. As an important problem-solving activity, the role of decision-making is to identify and choose alternatives based on the values and preferences of the decision-makers. The most popular decision-making problems in engineering value chain management can be categorized into four broad classes: partner selection, location-allocation, inventory decision, and vehicle routing.

1. Partner selection problem

The right partners must be selected to be involved in the value chain according to certain criteria. Partner selection is one of the key factors influencing the strategic alliance's performance, and the success of a value chain depends on the selection of the right partners (Beamish 1987). Developing appropriate criteria to evaluate the alternatives and select the right ones are the crux of partner selection. Many methods have been proposed and applied to different partner selection problem in the literature (Boer 2001; Chai 2013; Govindan 2015).

2. Location-allocation problem

Proposed by Cooper (1963), this location-allocation problem concerns the location and relation of a set of facilities that will provide homogeneous services. In engineering value chain management, the "facilities" could be plants, warehouses, distribution centres, service centres and any other nodes of an EVC. Location-allocation decision plays a very important role in the strategic design of value chain networks. Its decision object is to decide the best number and location of the facilities subject to certain constrains. Snyder (2006), Melo (2009), and Farahani (2012) reviewed the location-allocation decision problems from different perspectives.

3. Inventory decision problem

Inventory is the quantity of goods or materials in stock. As buffers to balance supply and demand, most of the nodes of the engineering value chain need to carry inventories. Inventory management is a very important part of core operations activities and will affect the performance of the value chain. The management of inventory requires a number of decisions. When to replenish stock, and how much to order are the two basic decisions in inventory management, which is the so-called inventory policy. Generally, the objective of inventory decisions is to decide the inventory policy that minimizes the total inventory cost, which include the ordering cost, carrying cost, and shortage cost. Uncertainty, revenue, and deterioration should also be considered in practical inventory decision problems (Bakker 2012; Horenbeek 2013).

4. Vehicle routing problem

One of the most important factors in implementing engineering value chain management is to efficiently control the physical flow of the material and goods. Vehicle routing decisions concern physical flows, which focus on how to effectively transport the materials and the products while minimizing the total cost. For example, how to transport the products to the final customers via the plants, warehouses, and distribution centres using group of vehicles. As a generalization of the travelling salesman problem, the vehicle routing formulation was first introduced by Dantzig and Ramser (1959). Beyond the classical formulation, a number of variants have been studied. Beyond this classical formulation, a number of variants have been proposed. Eksioglu (2009) presents a methodology for classifying the literature of the vehicle routing problem. Pillac (2013) gave a good survey of the dynamic vehicle routing problem. Lin (2014) reviewed the popular green vehicle routing problems.

The aforementioned problems are the most typical and popular decision problems in engineering value chain management, which have been hot topics in both academe and industry, and are receiving increasing attention. Based on the characters of specific decision problem, different kinds of decision methods are developed. Multi-criteria decision aid method, data mining technology-based method and optimization model-based method are the three commonly used methods in engineering value chain decision-making.

1. Multi-criteria decision-making methods

Multi-criteria decision-making methods are generally realized in the following paradigm: a decision-maker considers a set of alternatives and seeks to take an "optimal" decision considering all the factors that are relevant to the analysis. Developed to standardize the complex decision process and based on the alternatives evaluation theory, multi-criteria decision methods are very efficient in dealing with decision problems in which alternatives form a finite discrete set, typically consisting of a small number of elements, in which each alternative is fully known in complete detail, and any one of them can be selected as the decision. However, in many decision cases, the alternatives are complex, infinite, and not given in advance.

2. Data mining technology-based methods

Data mining is the computational process of discovering patterns in LARGE datasets involving methods at the intersection of artificial intelligence, machine learning, statistics, and database systems. The overall goal of the data mining process is to extract information from a data set and transform it into an understandable structure for further use. Discovering hidden knowledge from huge amounts of data will strongly improve the decision quality. For example, mining customer data can predict future demand and thus aid the production, inventory, and delivery decisions. Collecting large amounts of business data along an EVC, developing appropriate data cleaning and mining algorithms are key issues in applying data mining technology in decision-making.

3. Optimization model-based methods

Originated and defined in mathematics, an optimization problem concerns finding the best solution from all feasible solutions. It is applied to a widening array of contexts, including machine learning and information retrieval, engineering design, economics, finance, and management. Optimization model-based methods are very efficient in dealing with the complex constrained decision problems with infinite and unknown alternatives. Optimization model-based methods can identify the set of all possible alternatives and provide the optimal solutions for the decision-makers.

3 Decision-Making Based on Optimization Model and Algorithms

The standard form of an optimization model is formulated as follows (Boyd 2004):

$$\begin{aligned} &Minimize\, f(x) \\ &subject\ to \\ &\qquad g_i(x) \leq 0,\ i = 1, 2, \ldots, m \\ &\qquad h_i(x) = 0,\ i = 1, 2, \ldots, n \end{aligned} \tag{1}$$

where $f(x)$ is the objective function to be minimized over the variable x, $g_i(x) \leq 0$ are called inequality constraints, and $h_i(x) = 0$ are called equality constraints.

As shown in Fig. 1, the parameters represent the decision environment, the variables represent the candidate alternatives, the objective function(s) is (are) the criterion(s); the constraints are the requirements on the alternatives.

According to the number of the objectives, the optimization models can be divided into two categories: single-objective models and multi-objective models. The goal of single-objective models is to find out the best solution, which will lead to the minimum (maximum) value of the single-objective function. Cost is usually formulated as the single objective in many value chain management decision problems. Examples include Gumus (2009), Monteiro (2010), Başligil (2011), Creazza (2012), and Lee (2014). Depending on the form and functional description of the optimization problem, different optimization techniques can be used for the solution, linear programming, nonlinear programming, discrete optimization, etc. (Nemhauser 1989).

However, almost every real-world problem involves simultaneous optimization of several incommensurable and even competing objectives. In multi-objective optimizations, the various objective functions conflict with each other (i.e. optimizing one of them usually tends to move another towards undesirable values) and the aim is to simultaneously optimize a group of conflicting objectives. The interaction among

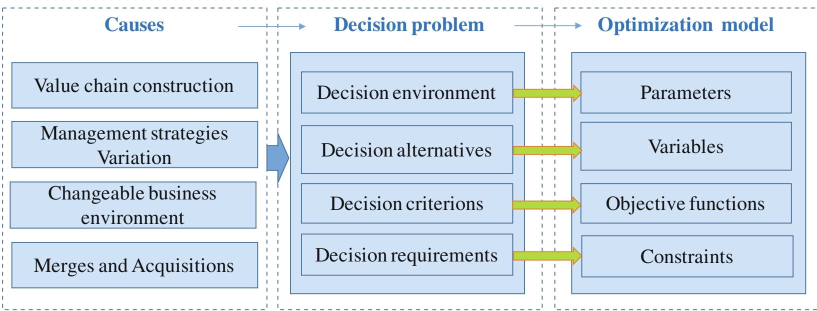

Fig. 1 Relationship between the decision problem and the optimization model

different objectives gives rise to a set of compromised solutions, largely known as the trade-off, non-dominated, non-inferior, or Pareto-optimal solutions. For multi-objective decision problems, there is no single optimal solution, but a set of alternative solutions. Pareto-optimality is expected to provide flexibility for the decision-makers.

Traditionally, there are several popular methods available in the operational research literature for solving multi-objective programming models, such as goal programming (Charnes 1957), goal attainment (Kiresuk 1968) and weighted sum method (Turban 1998). Due to the fact that multi-objective optimization problems are usually NP-hard, evolutionary algorithms are found efficient for solving multi-objective models (Zitzler 1999). Originated in the late 1950s, the term evolutionary algorithm stands for a class of stochastic optimization methods that simulate the process of natural evolution. Some famous evolutionary algorithms for multi-objective decision problems include vector evaluated genetic algorithm (VEGA) (Schaffer 1985), multi-objective genetic algorithm (MOGA) (Fonseca 1993), niched Pareto-genetic algorithm (NPGA) (Horn 1994), strength Pareto-evolutionary algorithm (SPEA) (Zitzler 1999), non-dominated sorting genetic algorithms (NSGA) (Srinivas 1994), Pareto-archived evolution strategy (PAES) (Knowles 1999), etc.

Efficient in handling alternative large search spaces and generating multiple alternative trade-offs, evolutionary algorithms are widely applied in solving multi-objective decision problems. Today, multi-objective decision is evolving towards the application of computer algorithms to solve mathematical models on computers.

4 Engineering Value Chain Configuration Model

In high value engineering industry (such as the aerospace industry), product design and fabrication is a long-term process and contains complex subprocesses that usually need the combined efforts of numerous organizations, ranging from very small enterprises to large corporations. Such value networks are usually very complex as they are composed of many nodes to handle many kinds of tasks. Thus, value network design and optimization is very complicated and hard to complete manually in high value engineering industry.

To interpret the decision process based on an optimization model and algorithm in detail, an engineering value chain construction problem is investigated, belonging to the location-allocation decision category and involves two companies—A and B. Suppose company A is an aerospace manufacturing company and has a mature supply network which is composed of the internal and external suppliers, warehouses, and assembly plants. Company B is a supplier of hardware and related components to aerospace original equipment manufacturers and their subcontractors and has its own distribution network composed of the plants and the regional warehouses, distributing the components to the customers.

The supply relationship before the acquisition is shown in Fig. 2. BP_p are the plants of company B, and BW_i represent its regional warehouses. S_s are the suppliers of company A (including both internal and external suppliers, indicated by different colours). AW_j represent company A's regional warehouses. C_k are company B's general customers, while AP_q are the assembly plants of company A, which are also customers of company B. M types of products are produced in company B's plants

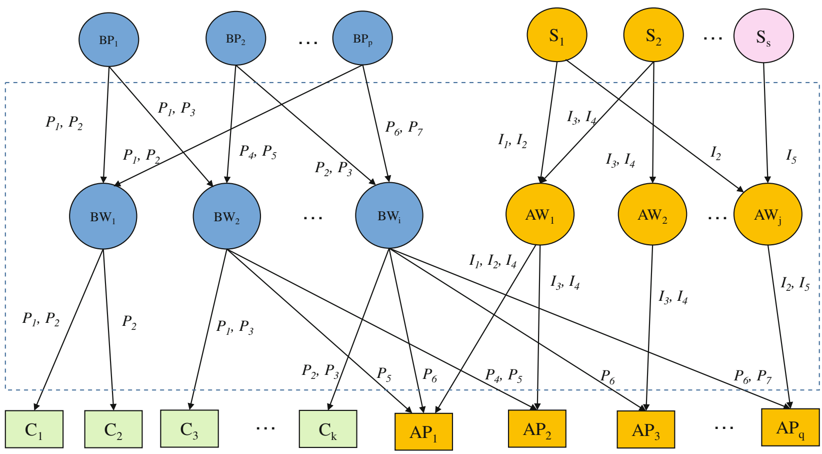

Fig. 2 Two value chain networks prior to acquisition

(BP_p) and distributed to the regional warehouses BW_i. Then, BW_i serve the customers (C_k and AP_q). Company A's suppliers (S_s) supply n types of items to company A's regional warehouses (AW_j), which distribute them to the right assembly plants (AP_q). The assembly plants integrate the parts and components supplied by company B and the suppliers into modules, subassemblies, and finally, aircrafts.

Before the acquisition, company B has to rent the warehouses (BW_i) and maintain its own distribution channel, which is a massive and costly process in order to satisfy the customers' (C_k and AP_q) requirements. It is obvious that company A's mature supply network can be utilized to distribute company B's products to the customers' (C_k and AP_q) after the acquisition. Thus, how to integrate the two multi-item value chain networks is a critical issue. The required network integration decisions include: (1) assessing whether to retain or eliminate company B's specific warehouses (BW_i); (2) warehouse expansion strategy and the new capacities of each warehouse (BW_i and AW_j); (3) supply links between the facilities; (4) the quantity of items shipped among the facilities.

A mathematical model will be developed to solve the network integration problem. The proposed model is based on the following assumptions:

1. Company A's suppliers (including internal and external suppliers) and company B's plants are retained, and their production capacities remain unchanged after the acquisition.
2. Company B's general customers are retained and their future product requirements are estimated based on the history business data.
3. All the requirement of company A's assembly factories must be satisfied.
4. Each regional warehouse of company B can be eliminated with a certain penalty cost.
5. Each regional warehouse of company B and A can be expanded with a certain cost.
6. Some important items must be stored in the appointed regional warehouses.

Consider that the new value chain network will distribute different kinds of items to different customers (general customers and company A's assembly plants) and the decision-makers generally compromise incompatible objectives to achieve adequate economic profits. We formulate the network integration problem as a multi-objective programming model with three objectives: (1) minimization of total integration cost, which consists of the costs of closing former warehouses, and adjusting the capacities of existing warehouses. (2) Minimization of total operation cost, including the annual fixed cost of warehouse operation, as well as the variable costs such as transportation cost. (3) Maximization of the general customer satisfaction rate, which is calculated by the weighted sum of each general customer's customer satisfaction rate.

Sets and indices

I Index set of items; $i \in I$

S Index set of the first-layer facilities (including firm B's plants and firm A's suppliers); $s \in S$

W Index set of the second-layer facilities (including firm B's existing warehouse and firm A's existing warehouse); $j \in W$

C Index set of the general customers; $k \in C$

P Index set of firm A's assembly plants; $p \in P$

M Index set for capacity levels available to existing warehouses; $m \in M$, in which $m = 0$ means that the warehouse is closed

Model parameters

SC_{isj} Unit transportation cost of item i from S_s to $W_j s$

TC_{ijn} Unit transportation cost of item i from W_j to C_n or P_n; $n \in C \cup P$

FC_{jm} Fixed cost of operating W_j with capacity level m

AC_{jlm} Cost of adjusting W_j capacity level from l to m; $l, m \in M$, in which $AC_{jl0} (l \neq 0)$ is the penalty cost of closing W_j with capacity level l, while $l = m$, $AC_{jlm} = 0$

CR_{ik} Demand for item i of C_k

PR_{ip} Demand for item i of AP_p

C_{is} Production capacity of item i for S_s; in which $C_{is} = 0$, while S_s does not produce item i

G_{jm} Capacity with level m for existing W_j

λ_n The relative importance of general customer; $n \in C$ and $\sum \lambda_n = 1$

α_{ij} The appointed storage relationship for item i; $\alpha_{ij} = 0$ or 1

Model variables

$$X_{jlm} = \begin{cases} 1 & \text{if the capacity level of } W_j \text{ is adjusted form } l \text{ to } m \\ 0 & \text{otherwise} \end{cases}$$

Particularly, W_{jll}= $1(l \neq 0)$ indicates the unchanged W_j capacity level, and W_{jl0}= $1(l \neq 0)$ indicates closure of an existing W_j with capacity level l.

Y_{isj} Amount of item i shipped from S_s to W_j

Z_{ijn} Amount of item i shipped from W_j to C_n or P_n; $n \in C \cup P$

With the above notation, the value chain network integration problem is formulated as follows:

$$\text{Min Cost}_I = \sum_{j \in W} \sum_{l \in M} \sum_{m \in M} AC_{jlm} X_{jlm} \tag{2}$$

$$\text{Min Cost}_O = \sum_{j \in W} \sum_{m \in M} FC_{jm} \sum_{l \in M} X_{jlm} + \sum_{i \in I} \sum_{s \in S} \sum_{j \in W} Y_{isj} SC_{isj} + \sum_{i \in I} \sum_{j \in W} \sum_{n \in C \cup P} Z_{ijn} TC_{ijn} \tag{3}$$

$$\text{Max PDC} = \sum_{n \in C} \lambda_n \left(\sum_{i \in I} \left(\left(\sum_{j \in W} Z_{ijn} \right) \Big/ CR_{in} \right) \right) \tag{4}$$

Subject to:

$$\sum_{l,m \in M} X_{jlm} \leq 1, \forall j \in W \tag{5}$$

$$\sum_{s \in S} Y_{isj} = \sum_{n \in C \cup P} Z_{ijn}, \forall i \in I, j \in W \tag{6}$$

$$\sum_{j \in W} Y_{isj} \leq C_{is}, \forall i \in I, s \in S \tag{7}$$

$$\sum_{n \in C \cup P} \sum_{i \in I} Z_{ijn} \leq \sum_{l,m \in m; m \neq 0} G_{jm} X_{ilm}, \forall j \in W \tag{8}$$

$$\sum_{j \in W} Z_{ijp} \geq PR_{ip}, \forall i \in I, p \in P \tag{9}$$

$$Y_{isj} \leq \alpha_{ij} \cdot Y_{isj}, \forall i \in I, j \in W, s \in S \tag{10}$$

$$X_{jlm} \in (0, 1), \forall j \in W, l, m \in M \tag{11}$$

$$Y_{isj} \geq 0, \forall i \in I, s \in S, j \in W \tag{12}$$

$$Z_{ijn} \geq 0, \forall i \in I, j \in W, n \in C \cup P \tag{13}$$

In the above formulation, the objective functions maximize the percentage of satisfied demand of the general customers, while minimizing the integration cost Cost_I and the operation cost Cost_O. The integration cost Cost_I consists of the costs of closing former warehouses, and adjusting the capacities of existing warehouses. The operation cost Cost_O of the new value chain network includes the annual fixed cost of warehouse operation, as well as the variable transportation cost from the first layer to the third layer through warehouses. The percentage of satisfied demand PDC is the weighted sum of each general customer's satisfied percentage. Constraint (5) ensures that at most one capacity level is assigned to each warehouse. Constraint(6) makes the incoming and outgoing flows equal at each warehouse. Constraint (7) guarantees that the item quantity transported between the first layer and the second layer does not exceed the suppliers' production capacity. Constraint (8) guarantees that the item quantity transported between second layer and the third layer does not exceed the warehouses' capacities. Constraint (9) ensures all the requirement of the assembly plants must be satisfied. Constraint (10) ensures the appointed storage relationship. Constraint (11) ensures the integrality restriction on the variables, whereas Constraint (12)/(13) enforce the non-negativity restriction on all other decision variables.

5 Engineering Value Chain Configuration Optimization Algorithm

Several conflicting objective functions must be simultaneously optimized in the multi-objective problems. Due to the conflicting nature of the objectives, it is impossible to achieve an ideal solution in which each objective obtains its optimal value. To that end, Swiss economist Pareto introduced the concept of Pareto-optimality for multi-objective optimization. A solution of a multi-objective optimization problem is Pareto-optimal if and only if it is impossible to make at least one objective better without making anyone else worse. The set of Pareto-optimal solutions of a multi-objective optimization problem consists of all decision vectors for which the corresponding objective vectors cannot be improved in a given dimension without worsening another, and the set of all the corresponding objective vectors is called the Pareto-front. The objective of multi-objective optimization is to find its Pareto-optimal solution set and corresponding Pareto-front.

In the literature, many researchers have successfully applied genetic algorithms (GAs) to solve value chain optimization problems. As a population-based approach, genetic algorithm (GA) is appropriate in solving complex multi-objective problems. Many multi-objective GAs have been proposed, and NSGAII (Deb 2002) is one of the best multi-objective genetic algorithms as evident from the existing literature. Thus in this study, NSGAII algorithm is adopted to solve the value chain network integration model, and the detailed steps of NSGAII are shown in Fig. 3.

The whole process is repeated until the stopping criterion is met and the individuals with rank 1 in the last generation are reported. The termination criterion is usually characterized by the number of generations. The output of the algorithm is a set of non-dominated Pareto-optimal solutions, as all the solutions are the best in a sense of multi-objective optimization. In the following account, the key components of the proposed multi-objective solution procedure will be described in detail.

5.1 Problem Representation and Initialization

Choosing a good representation scheme for the construction of the genotype is one of the critical issues in using GA to solve optimization problems. In the value chain network integration problem, the network handles n types of items and each type of item has an independent two-stage logistics network (from the first-layer facilities to the second-layer facilities and from the second-layer facilities to the customer and plants). The whole value chain network can be seen as a superposition of the logistic networks of each type of item. Since a single-stage logistics network can be represented by a spanning tree (Gen 2000) and be encoded using a determinant code (Abuali 1995). We can encode the solutions of the value chain network integration problem based on tree structure. The chromosome structure is designed as shown in Fig. 4.

As shown in Fig. 4, the chromosome includes two parts, the first part represents the DC capacity levels with M integers between 0 and m, where “0” means the warehouse is closed. The second part corresponds to the logistics networks of K items. Each item has two determinant codes, representing the spanning tree of the first and second stages, respectively. The determinant code D_T for a spanning tree $T(V, E)$ is defined as follows (Abuali 1995):

$$\mathrm{D}_T = (x_2, x_3, \cdots, x_n) | (x_i, i) \in E, \mathit{for}\ i{=}2\ \mathit{to}\ n$$

where x_i is an integer between 1 and n.

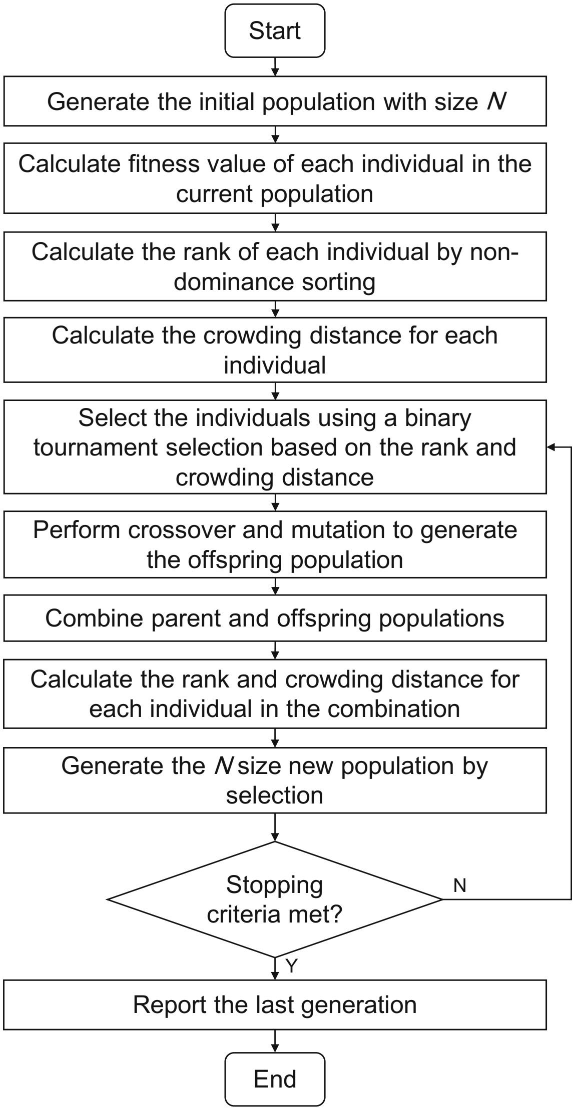

Fig. 3 NSGAII-based solution procedure

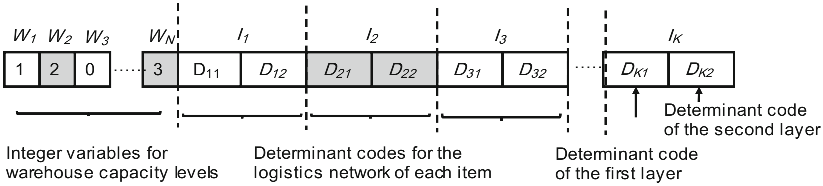

Fig. 4 Representation of chromosome

D_T has n-1 digits, and the i-1 position in D_T represents the direct connecting node of node i. For example, the determinant code for the spanning tree in Fig. 5 is (6 6 9 1 2 2 3 1). The first digit "6" means that Nodes 2 and 6 are connected in the spanning tree. The decoding flow chart of the determinant code is shown in Fig. 6.

Using the structure shown in Fig. 4, each chromosome corresponds to a value chain network and the related logistics relationships. All the decision variables can be achieved by decoding the chromosome. The decoding algorithm flow chart is shown in Fig. 7.

As previously defined, the chromosome has (1 + K) parts. The first substring consists of N integers representing the capacity levels of the warehouses. The last K substrings are determinant codes representing two-stage logistics network of K items. When decoding the chromosome,

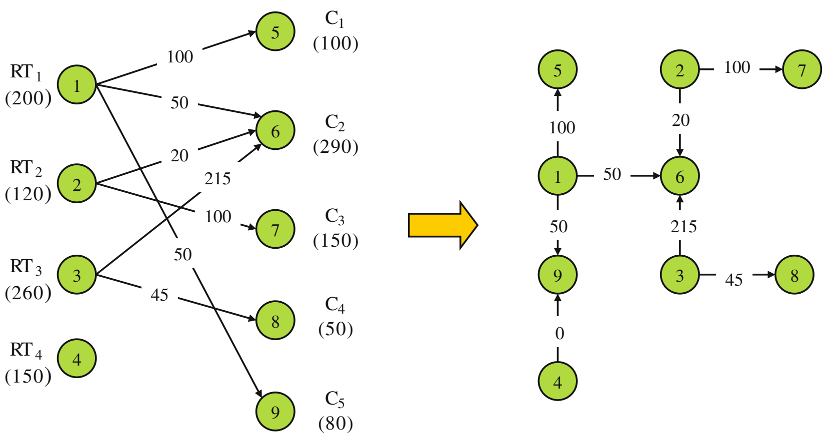

Fig. 5 Spanning tree of a single-stage logistics network

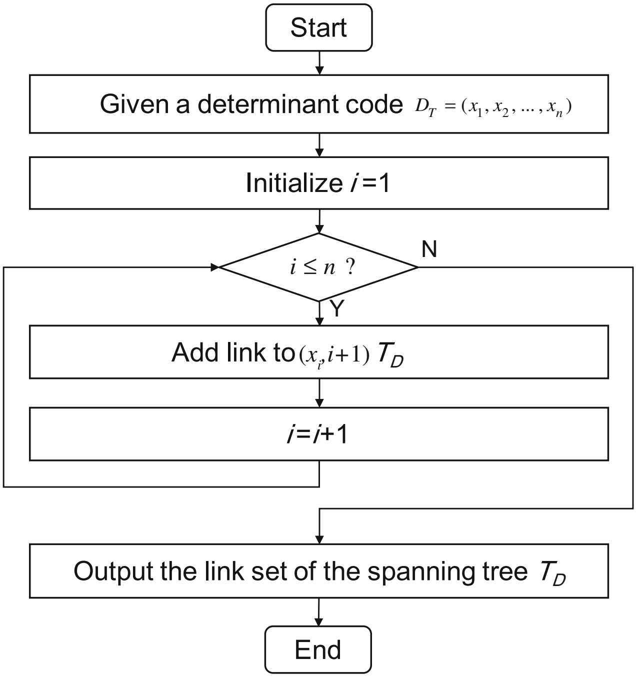

Fig. 6 Determinant decoding flow chart

the first N digitals are decoded firstly to achieve the capacity of each warehouse (if the capacity is "0" the warehouse is not included in the network). Then, the logistics network of each item is decoded successively. The chromosome substring of each item consists of two determinant codes, namely D_{k1} and D_{k2}. D_{k1} corresponds to the first stage, whereas D_{k2} corresponds to the second stage. For a certain item, the decoding process is backwards and can be divided into three steps: (1) decode D_{k2} firstly to achieve the subnetwork and supply amounts between the second layer and the third layer; (2) decode D_{k1} to achieve the subnetwork and supply amounts between the first layer and the second layer; and (3) check whether the equal flows constraints are satisfied and otherwise rearrange the supply amounts between the second layer and the third layer. In step (1), the determinant code D_{k2} is decoded first to achieve the supply links between the warehouse and the

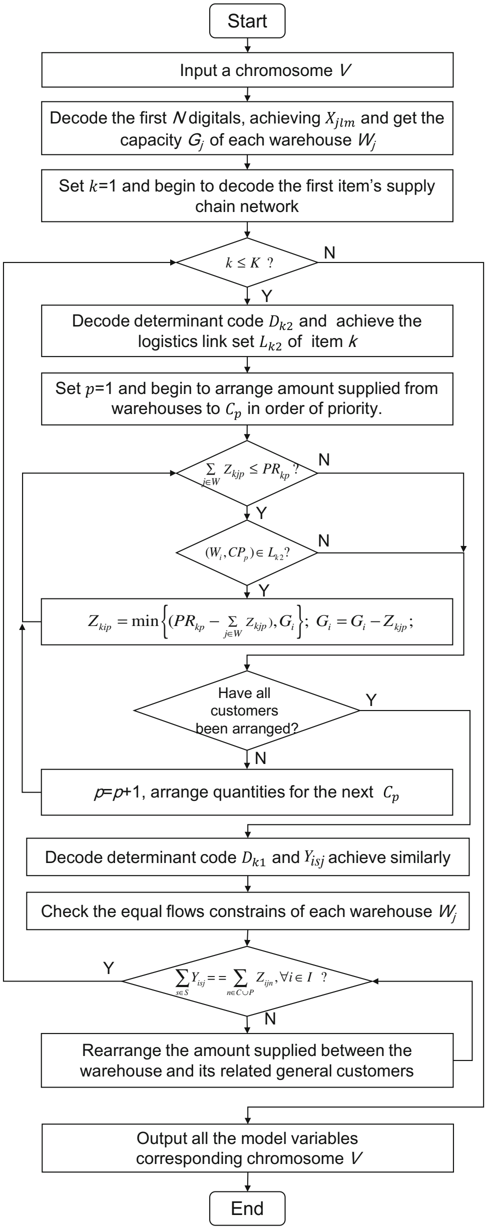

Fig. 7 Decoding algorithm

customers (including general customer and assembly plants). Due to the capacity constraints, the warehouses may not satisfy or the customers; however, according to the constraints that all the requirement of the assembly plants must be satisfied, thus the assembly plants are satisfied prior to the general customer, and furthermore, the general customers are also queued in a priority-descending order. In step (3), the rearrangements also follow the same allocation principle and the chromosome that cannot satisfy the assembly plants' requirements will be abandoned. With the above three steps, the value chain network corresponds to a certain item and the related variables are achieved. Conducting the decoding procedure on the items one by one, all the single-item value chain networks will be achieved and then the whole value chain network can be determined.

5.2 Crossover and Mutation

Based on the encoding structure, we employ two-cut-point crossover and segment-based mutation operations (Altiparmak 2009). Figure 8 shows a simple illustration of the crossover operation. Two random positions are generated as the head and tail, respectively, and alleles from the head to the tail are exchanged between parents.

A mutation is then applied to the generated offspring according to a mutation rate. As previously defined, the chromosome can be divided

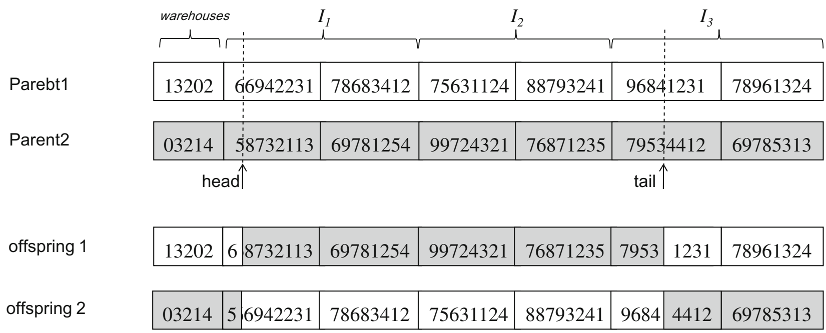

Fig. 8 Illustration of crossover operator

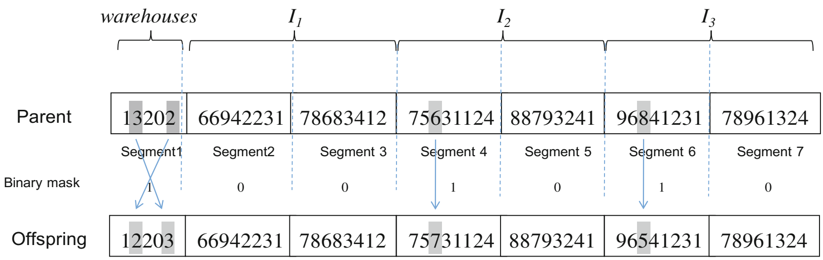

Fig. 9 Illustration of mutation operation

into (1 + K) segments, where K is the number of items. The first segments are integers representing the capacity levels of each warehouse. The last K segments are determinant codes representing the logistics network of K items. The mutation is based on the chromosome segments. Figure 9 illustrates the mutation operation.

The binary mask indicates the segments to be mutated. If the first two segments are selected, an exchange mutation operator is employed within the segment. If the last K segments are selected, the value of a randomly selected gene is replaced with a new one, ranging from one to the number of corresponding nodes.

5.3 Repair Mechanism

During determinant codes generation, chromosome crossover and mutation, infeasible codes that cannot be adapted to generate the transportation tree may be obtained. Thus, a repair mechanism is needed in the whole evolution process to check and repair the illegal determinant codes.

A spanning tree may be illegal due to three reasons: "missing Node 1"; "cycle"; and "self-loop" (Abuali 1995) ;(Chou 2001). "Cycle" and "self-loop" can be avoided in the initialization through a restriction on the encoding range of genes: in concrete terms, suppliers are numbered from 1 to M and demanders are numbered from M + 1 to M + N. According to the determinant decoding method, nodes corresponding to the first (M−1) genes connect to nodes indexed from 2 to M, which are supplier nodes. Therefore, the first (M−1) genes must correspond to the demander nodes, and the value range of the first (M − 1) genes is restricted to [M + 1, M + N]. Similarly, the value range of the last (N + 1) genes is restricted to [1, M], ensuring connection of demand nodes to supplier nodes. Such restrictions on the value range effectively prevent "self-loops" and "cycles".

Thus, only "missing Node 1" may occur in our problem, and the repair mechanism is as follows: Given a determinant encoding substring, an initial scan determines if Node 1 is missing. If yes, find the lowest-cost node connected to Node "1" based on the cost matrix, and assign 1 to the corresponding position. In case of a tie, randomly select a position. After this repair procedure, all the determinant codes can be decoded into spanning trees, and the distribution patterns in each stage can be determined.

6 Numerical Example and Discussion

The proposed model and solution procedure are tested with a network integration problem with three types of items: 100 first-layer facilities, 15 warehouse and 50 end customers. The algorithm was implemented using MATLAB programming language and was executed on a Pentium Dual E2200 processor (2.2 GHz clock) with 2 GB memory. The parameters were determined as: population size = 300; maximum number of generations = 300; crossover probability = 0.7; mutation probability = 0.3. Figure 10 shows the Pareto-front, and Table 1 shows part of the Pareto-optimal solutions.

The Pareto-optimal solutions represent the trade-off among the three objectives, validating the fact that the three objectives are incompatible, and that a perfect value chain network is unreachable. For example, achieving higher customer service level would require higher operation cost. Result No.1 shows that more cost is incurred to ensure that all general customer demands are satisfied. However, the general customer demand quantities are predicted based on the history of business data and market research; thus, increasing the investment to reach customer service level "1" is unadvisable. Particularly, result No.10–12 show that

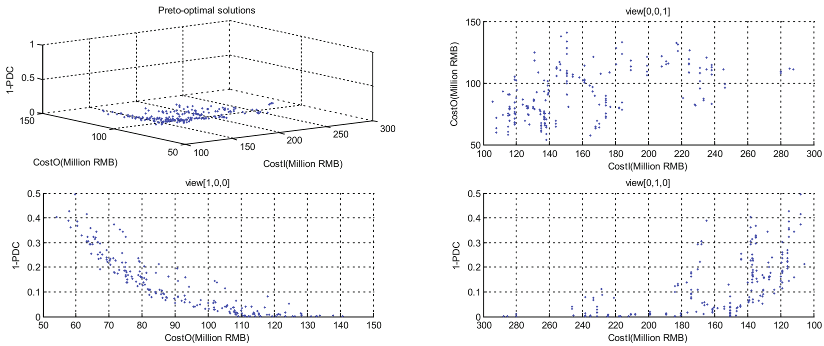

Fig. 10 The Pareto-front of the value chain network construction problem

Table 1 Part of the Pareto-optimal solutions

No.	*PDC*	Cost_I	Cost_o	*First part of the chromosome*
1	1.0000	117.35	164.52	121101020002200
2	0.9796	93.22	149.45	021100202002200
3	0.9573	85.17	134.32	220100221002200
4	0.9443	74.34	156.23	121100201002200
5	0.9339	81.88	130.34	122100220002200
6	0.9322	82.34	125.60	120100220002200
7	0.9262	78.95	135.72	202000220002200
8	0.9250	75.71	141.89	022100201002200
9	0.9004	65.33	149.24	120100221002200
10	1.0000	0	382.78	121121111211111
11	0.9321	0	317.53	121121111211111
12	0.9145	0	300.21	121121111211111

to achieve the same standard service level, the operation cost ($Cost_o$) will be very high if the two networks are not integrated and optimization ($Cost_I = 0$).

7 Summary

Decision-making is a very important part of engineering value chain management. In this chapter, four popular decision-making problems (partner selection, location-allocation, inventory decision, and vehicle routing) and three decision-making methods (multi-criteria decision aid method, data mining technology-based method, and optimization model-based method) are introduced firstly. Then, the optimization model-based methods are emphasized. To interpret the decision process using optimization model-based method in detail, a complex value network integration and optimization problem is investigated as an example, a multi-objective optimization model is developed, and the genetic algorithm-based solution procedure is proposed to achieve the network integration and optimization solutions. Finally, numerical experiment and discussion are conducted to demonstrate the benefit of integration and optimization. The decision example shows the effectiveness and advances of solving management problems by information technologies. How to formulate a realistic decision problem and develop appropriate optimization algorithm are the crux and difficulty of the optimization model-based decision method. A stochastic or fuzzy model would be more realistic, but increasingly complex. Future work can focus on formulating the stochastic model and developing an effective solution algorithm.

References

Abuali, F. N., Wainwright, R. L., & Schoenefeld, D. A. (1995, July). Determinant factorization: A new encoding scheme for spanning trees applied to the probabilistic minimum spanning tree problem. *Proceedings of the Sixth International Conference on Genetic Algorithms*, (pp. 470–477).

Altiparmak, F., Gen, M., Lin, L., & Karaoglan, I. (2009). A steady-state genetic algorithm for multi-product supply chain network design. *Computers & Industrial Engineering, 56*(2), 521–537.

Bakker, M., Riezebos, J., & Teunter, R. H. (2012). Review of inventory systems with deterioration since 2001. *European Journal of Operational Research, 221* (2), 275–284.

Başligil, H., Kara, S. S., Alcan, P., Özkan, B., & Çağlar, E. G. (2011). A distribution network optimization problem for third party logistics service providers. *Expert Systems with Applications, 38*(10), 12730–12738.

Beamish, P. W. (1987). Joint ventures in LDCs: Partner selection and performance. *Management International Review*, 23–37.

Boer, L. D., Labro, E., & Morlacchi, P. (2001). A review of methods supporting supplier selection. *European Journal of Purchasing & Supply Management, 7* (2), 75–89.

Boyd, S., & Vandenberghe, L. (2004). *Convex optimization*. Cambridge: Cambridge University Press.

Chai, J., Liu, J. N., & Ngai, E. W. (2013). Application of decision-making techniques in supplier selection: A systematic review of literature. *Expert Systems with Applications, 40*(10), 3872–3885.

Charnes, A., & Cooper, W. W. (1957). Management models and industrial applications of linear programming. *Management Science, 4*(1), 38–91.

Chou, H., Premkumar, G., & Chu, C. H. (2001). Genetic algorithms for communications network design-an empirical study of the factors that influence performance. *IEEE Transactions on Evolutionary Computation, 5*(3), 236–249.

Cooper, L. (1963). Location-allocation problems. *Operations Research, 11*(3), 331–343.

Creazza, A., Dallari, F., & Rossi, T. (2012). Applying an integrated logistics network design and optimisation model: The pirelli tyre case. *International Journal of Production Research, 50*(11), 3021–3038.

Dantzig, G. B., & Ramser, J. H. (1959). The truck dispatching problem. *Management Science, 6*(1), 80–91.

Deb, K., Pratap, A., Agarwal, S., & Meyarivan, T. (2002). A fast and elitist multiobjective genetic algorithm: NSGA-II. *IEEE Transactions on Evolutionary Computation, 6*(2), 182–197.

Eksioglu, B., Vural, A. V., & Reisman, A. (2009). The vehicle routing problem: A taxonomic review. *Computers & Industrial Engineering, 57*(4), 1472–1483.

Farahani, R. Z., Asgari, N., Heidari, N., Hosseininia, M., & Goh, M. (2012). Covering problems in facility location: A review. *Computers & Industrial Engineering, 62*(1), 368–407.

Fonseca, C. M., & Fleming, P. J. (1993, June). Genetic algorithms for multiobjective optimization: Formulation discussion and generalization. *Proceedings of the Fifth International Conference on Genetic Algorithms,* (pp. 416–423).

Gen, M., & Cheng, R. (2000). *Genetic algorithms and engineering optimization*, Vol. 7. Wiley.

Govindan, K., Rajendran, S., Sarkis, J., & Murugesan, P. (2015). Multi criteria decision making approaches for green supplier evaluation and selection: A literature review. *Journal of Cleaner Production, 98,* 66–83.

Gumus, A. T., Guneri, A. F., & Keles, S. (2009). Supply chain network design using an integrated neuro-fuzzy and MILP approach: A comparative design study. *Expert Systems with Applications, 36*(10), 12570–12577.

Horenbeek, A. V., Buré, J., Cattrysse, D., Pintelon, L., & Vansteenwegen, P. (2013). Joint maintenance and inventory optimization systems: A review. *International Journal of Production Economics, 143*(2), 499–508.

Horn, J., Nafpliotis, N., & Goldberg, D. (1994, June). A niched pareto genetic algorithm for multiobjective optimization.In *Proceedings of the First IEEE Conference on Evolutionary Computation. IEEE World Congress on Computational Intelligence*, (pp. 82–87).

Kiresuk, T. J., & Sherman, M. R. E. (1968). Goal attainment scaling: A general method for evaluating comprehensive community mental health programs. *Community Mental Health Journal, 4*(6), 443–453.

Knowles, J., & Corne, D. (1999, July). The pareto archived evolution strategy: A new baseline algorithm for paretomultiobjective optimisation. In *Proceedings of the 1999 Congress on Evolutionary Computation*.

Lee, J. H. (2014). Energy supply planning and supply chain optimization under uncertainty. *Journal of Process Control, 24*(2), 323–331.

Lin, C., Choy, K. L., Ho, G. T., Chung, S. H., & Lam, H. Y. (2014). Survey of green vehicle routing problem: Past and future trends. *Expert Systems with Applications, 41*(4), 1118–1138.

Melo, M. T., Nickel, S., & Saldanha-da-Gama, F. (2009). Facility location and supply chain management—A review. *European Journal of Operational Research, 196*(2), 401–412.

Monteiro, M. M., Leal, J. E., & Raupp, F. M. P. (2010). A four-type decision-variable MINLP model for a supply chain network design. *Mathematical Problems in Engineering, 2010*.

Nemhauser, G. L. (1989). *Handbook in Operations Research and Management Science*. North-Holland.

Pillac, V., Gendreau, M., Guéret, C., & Medaglia, A. L. (2013). A review of dynamic vehicle routing problems. *European Journal of Operational Research, 225*(1), 1–11.

Schaffer, J. D. (1985, July). Multiple objective optimization with vector evaluated genetic algorithms. In *Proceedings of the First International Conference on Genetic Algorithms* , (pp. 93–100).

Snyder, L. V. (2006). Facility location under uncertainty: A review. *IIE Transactions, 38*(7), 547–564.

Srinivas, N., & Deb, K. (1994). Muiltiobjective optimization using nondominated sorting in genetic algorithms. *Evolutionary Computation, 2*(3), 221–248.

Turban, E., & Meredith, J. R. (1998). *Fundamentals of management science*.New york: McGraw-Hill College.

Zitzler, E., & Thiele, L. (1999). Multiobjective evolutionary algorithms: A comparative case study and the strength Pareto approach. *IEEE Transactions on Evolutionary Computation, 3*(4), 257–271.

Authors' Biography

Lina Zhou is a Lecturer at the School of Computer Science and Technology of Harbin Institute of Technology, China. She has extensive experience in industry information management system development. Her research interests include supply chain management and optimisation, service engineering, machine learning and intelligent decision-making.

Xiaofei Xu is professor of Computer Science and Technology at Harbin Institute of Technology, China. He is President of Harbin Institute of Technology (Weihai). He chairs the Technical Committee on Service Computing of China Computer Federation.