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A decision method for supplier selection in multi-service outsourcing

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ABSTRACT

Although supplier selection in multi-service outsourcing is a very important decision problem, research concerning this issue is still relatively scarce. This paper proposes a decision method for selecting a pool of suppliers for the provision of different service process/product elements. It pioneers the use of collaborative utility between partner firms for supplier selection. A multi-objective model is built to select desired suppliers. This model is proved to be NP-hard, so we develop a multi-objective algorithm based on Tabu search for solving it. We then use an example to show the applicability of the proposed model and algorithm. Extensive computational experiments are also conducted to further test the performance of the proposed algorithm.

1. Introduction

In today's global service outsourcing arena, increasing numbers of firms adopt multi-service outsourcing; that is, they combine service process/product elements (SPEs) from multiple providers (Levina and Su, 2008). For example, Chinamobile provides M-zone business services, including music online, mobile purse, color ring and mobile news, through service providers (SPs). Multi-service outsourcing has become an important business approach since it can significantly decrease service price, shorten waiting time, improve customer satisfaction and enhance the firm's core competence (McCarthy and Anagnostou, 2004; Antelo and Bru, 2010). As for the process of multi-service outsourcing, a service process/product disaggregation is first conducted to pinpoint the SPEs that need to be outsourced. SPEs imply sub-services or products that combine to form a whole service process/product. A pool of appropriate suppliers is then selected for providing specific SPEs (Stratman, 2008). The outsourcing firm selects the most appropriate suppliers by considering service price, waiting time or service capacity, and builds long-term and profitable relationships with them (Wang and Yang, 2009; Qi, 2011). Supplier selection, orienting long-term collaborative relationships in multi-service outsourcing, is a very important decision problem (Lee, 2009; Nordin, 2008; Levina and Su, 2008; Bustinza et al., 2010).

As for multi-service outsourcing, the collaboration between the outsourcing firm and the potential suppliers as well as between the potential suppliers (partner firms for conciseness, hereafter) is an important underlying factor for the development of long-term collaborative relationships, which has been of particular interest (Lee, 2009; Büyüközkan et al., 2009). The outsourcing firm develops mutually beneficial relationships with their key suppliers so that the suppliers are more willing to invest in skills or technologies that are specific to it (McCutcheon and Stuart, 2000). An outsourcing firm and its suppliers may broaden their contact and share business or technology information. Suppliers may expand their roles to provide related supports beyond traditional outsourcing transactions, such as participating in the outsourcing firm's research and development (R&D) activities or providing technology supports and training by virtue of their areas of expertise (McCutcheon and Stuart, 2000; Guo et al., 2010). Suppliers may share their service facilities or processes with each other to exploit pooling benefits (Allon and Federgruen, 2009). Particularly, suppliers in service industries need more collaboration than those in manufacturing industries because they perform different activities consecutively in a whole service process and in order to impress customers consistently, they have to employ compatible interface management. Indeed, collaborative utility between partners has gained an increasing attention in some latest research on collaborative organizations, such as alliances (Ding and Liang, 2005; Emden et al., 2006), bilateral collaboration innovation networks (Cowan et al., 2007), interfirm collaboration networks (Schilling and Phelps, 2007), virtual network organizations (Lavrač et al., 2007), and teams (Fan et al., 2009; Feng et al., 2010a, b). The collaborative utility between partner firms is a valuable input for decision-making. Thus, it is necessary to consider the collaborative utility between partner firms for supplier selection in multi-service outsourcing.

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In the last two decades, various decision-making methods have been proposed to tackle the problem of supplier evaluation and selection; please refer to a recent review by Ho et al. (2010). However, the vast majority of the published works deal with supplier selection in manufacturing industries and few of them address such a problem in service industries. And usually the individual utility of a single supplier is considered, such as financial stability, business track record, technical expertise, market knowledge and managerial experience (Büyüközkan et al., 2008), while the collaborative utility between pairwise suppliers is seldom involved. Moreover, the criteria (or objectives) focused in service supplier selection differ from those for manufacturing supplier selection. Revenue, cost or the number of suppliers is usually considered in manufacturing supplier selection. However, service price and waiting time are the two most important and irreplaceable objectives for supplier selection in multi-service outsourcing (Allon and Federgruen, 2009). Finally, unlike part or product purchasing, service outsourcing is ordinarily conducted by a long-term contract, not by repeated orders. The outsourcing cost does not contain ordering, transportation, inspection and storage costs. Therefore, the existing decision methods cannot be directly used to solve the problem of supplier selection in multi-service outsourcing. Clearly, there is a need for a straightforward and routine decision method for solving the multi-service outsourcing problem.

In this paper, we propose a model and algorithm, which pioneer the use of collaborative utility between partner firms, for supplier selection in multi-service outsourcing. A multi-objective 0–1 programming model involving three objectives, collaborative utility, service outsourcing cost and service waiting time, is built for selecting a pool of desired suppliers for the provision of different SPEs. To solve this multi-objective model, we develop a multi-objective algorithm based on Tabu search (TS). We then use an example to show the applicability and necessity of the suggested model and algorithm. In addition, extensive computational experiments are conducted to show the efficiency and effectiveness of the algorithm.

The organization of this paper is as follows. In Section 2, the literature on supplier selection is reviewed. In particular, the existing mathematical programming models for supplier selection are listed. Section 3 builds a model for supplier selection for the provision of different SPEs in multi-service outsourcing. Section 4 develops a multi-objective algorithm based on TS for solving this model. An example and computational experiments are reported in Section 5 to show the effectiveness of the proposed model and algorithm. Section 6 contains some conclusions and suggests future work.

2. Literature review

So far, research on supplier selection in multi-service outsourcing is limited, so the broad and indirect literature on supplier selection is reviewed.

Supplier selection is one of the most widely researched areas in purchasing with methodologies ranging from conceptual to empirical and modeling streams. A series of literature surveys have been made to summarize the criteria and decision methods involved in papers starting from the mid-1960s. See, for example, surveys provided by Moore and Fearon (1973), Kingsman (1986), Holt (1998), De Boer et al. (2001), Aissaoui et al. (2007) and Ho et al. (2010). According to recent research work of Wang and Yang (2009), the quantitative decision methods for solving the supplier selection problem can be classified into three categories: (1) multi-attribute decision-making, (2) mathematical programming models and (3) intelligent approaches. Furthermore, in the latest literature survey by Ho et al. (2010), the mathematical programming models are grouped into the following five categories: (1) linear programming, (2) integer linear programming, (3) integer non-linear programming, (4) goal programming and (5) multi-objective programming. Table 1 summarizes the optimization models for supplier selection involved in the literature published since 2000.

3. Model for supplier selection in multi-service outsourcing

In this section, we formulate a mathematical model for supplier selection in multi-service outsourcing. First, notations used for problem description are defined. Then, a multi-objective 0–1 programming model for supplier selection considering collaborative utility, outsourcing cost and waiting time is built.

Table 1
Research on mathematical programming models for supplier selection.

Model	Objective function	Constraint	Author
Linear programming	Max (overall performance) Min (overall performance)	Productivity score based on the best measures, efficiency score of each vendor	Talluri and Narasimhan (2003)
	Max (overall performance)	Attribute weights	Ng (2008)
	Max (total value of purchasing)	Demand, quality, budgeting and suppliers' capacity	Guneri et al. (2009)
Integer linear programming	Min (number of suppliers)	Efficiency of suppliers, amount order from vendor, buyer's demand requirement, capacity of vendor, and minimum order quantity requirement of vendor	Talluri (2002)
	Max (revenue)	Purchasing demand in meaningful purchasing unit, supplier's potential system constraints and purchaser's policy constraints, number of suppliers, minimization of the supplier number and changing cost	Hong et al. (2005)
	Min (purchasing cost)	Order quantity, quality rate, late delivery rate and number of suppliers	Choi and Chang (2006)
Integer non-linear programming	Min (total annual purchasing cost)	Vendor's capacity, buyer's demand and purchased volume	Ghodsypour and O'Brien (2001)
Goal programming	Min (annual product cost)	Quality of castings purchased, delivery reliability of castings purchased, capacities of each supplier and demand	Karpak et al. (2001)
Multi-objective programming	Min (cost, scrap ratios, tardy-delivery fraction)	Purchasing budget, buyer's demand, inventory capacity and supplier's capacity	Gao and Tang (2003)
	Min (price, lead-time, quality)	Vendor's maximum capacity, product demand, maximum number of vendors and price discounts	Wadhwa and Ravindran (2007)

3.1. Notations

The following indices, parameters and variables are used to build the model for supplier selection in multi-service outsourcing:

i,j	index of suppliers, $i,j=1,\ldots,m$
s	index of SPEs, $s=1,\ldots,n$
k	index of collaborative criteria, $k=1,\ldots,l$
I	set of candidate suppliers, $I=\{1,\ldots,m\}$
S	set of SPEs, $S=\{1,\ldots,n\}$
C	set of collaborative criteria, $C=\{1,\ldots,l\}$
p_{is}	unit price of SPEs that supplier i charges the outsourcing firm
t_{is}	average waiting time of SPEs if it is supplied by supplier i
d_s	demand quantity of SPEs
u_{ijk}	collaborative utility between suppliers i and j concerning criterion k for $i\neq j$; collaborative utility between the outsourcing firm and supplier i concerning criterion k for $i=j$
w_k	weight of collaborative criterion k
p_s^A	the highest acceptable price of SPEs
t_s^A	the longest acceptable waiting time of SPEs

$$x_{is}=\begin{cases}1 & \text{supplier } i \text{ is selected for SPEs}\\ 0 & \text{otherwise}\end{cases}$$

3.2. Presentation of the decision problem

The decision problem addressed in this paper is to select a pool of desired suppliers from pre-determined candidate suppliers for the provision of different SPEs to achieve multi-service outsourcing. Suppose that the decision maker (DM) is going to select n suppliers from m candidate suppliers for providing n SPEs, $2\leq n\leq m$. We assume that a SPE is outsourced to a supplier. The assumption origins from the fact that allowing a supplier to provide more than one service will enhance its bargaining power in long-term, and as a result, the outsourcing firm will face higher risks of service delay and bad performance. Simultaneously, the existing literature on outsourcing and supply chain management has identified critical tradeoffs involved in increasing the number of suppliers and has strongly recommended focusing on a handful of strategic partners to balance these tradeoffs (Levina and Su, 2008). In addition, the case that one supplier is allowed to provide more than one service can be easily handled by creating multiple copies of the supplier, each bidding only for one SPE. Furthermore, in the decision process, acceptable service price and acceptable waiting time should be considered with regard to each SPE. The combination of desired suppliers should have the optimal collaborative utility, outsourcing cost and waiting time.

The decision-making problem discussed above can be generalized by Fig. 1. In Fig. 1, the region circled by dashed lines presents collaborative utilities between suppliers ($i\neq j$), and between the outsourcing firm and suppliers ($i=j$). The region with single lines shows the decision data of service price and waiting time of each supplier for each SPE. The acceptable price and acceptable waiting time for each SPE, as well as the demand quantity for each SPE are shown in the region marked with double lines.

3.3. Decision model

The collaborative utility can be measured by collaborative criteria such as service system sharing (Allon and Federgruen, 2009), interface management compatibility (Fan et al., 2009), mutual technology supports (McCutcheon and Stuart, 2000), resource complementarity (Emden et al., 2006), overlapping knowledge bases (Emden et al., 2006), motivation correspondence (Emden et al., 2006), goal correspondence (Emden et al., 2006), compatible cultures (Emden et al., 2006), etc. Different types of firms may employ different collaborative criteria for supplier selection in multi-service outsourcing. For example, a knowledge-intensive service firm may focus on interface management compatibility, mutual technology supports, overlapping knowledge bases, goal correspondence and compatible cultures for supplier selection. Thus, the DM can finalize the collaborative criteria in light of the real requirements of multi-service outsourcing.

As for the collaborative criteria, diverse types of utility scales often are involved. For example, goal correspondence may be a score of 1–10, while relationship-specific investments may be a numerical value with the unit of million USD. To deal with the commensurability between various collaborative criteria for measuring collaborative utility, we adopt the normalization of

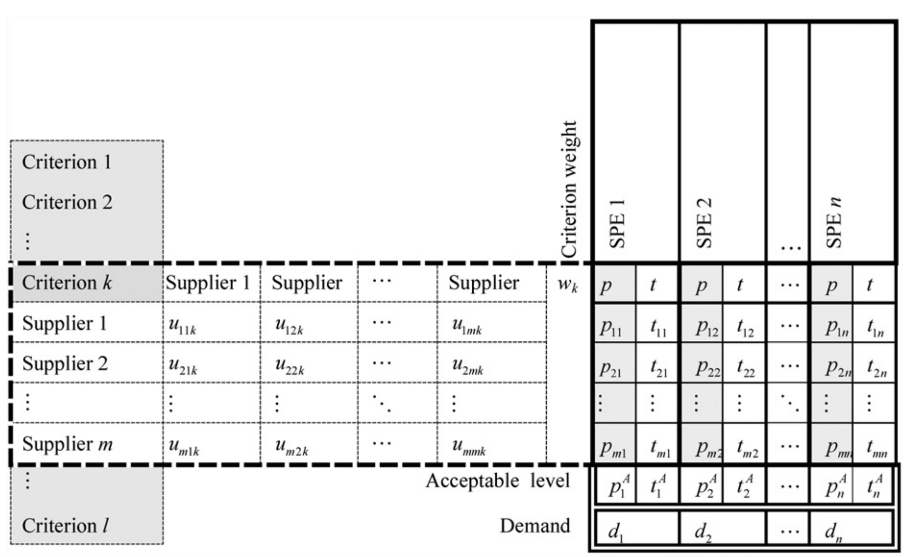

Fig. 1. Supplier selection in multi-service outsourcing.

criterion values. According to the approach provided by Hwang and Yoon (1981), u_{ijk} is normalized using the following formula:

$$u'_{ijk} = \frac{u_{ijk} - u_k^{min}}{u_k^{max} - u_k^{min}}, \quad i,j = 1,\ldots,m; \quad k = 1,\ldots,l \quad \text{for benefit criteria,} \tag{1}$$

$$u'_{ijk} = \frac{u_k^{max} - u_{ijk}}{u_k^{max} - u_k^{min}}, \quad i,j = 1,\ldots,m; \quad k = 1,\ldots,l \quad \text{for cost criteria,} \tag{2}$$

$$u_k^{max} = \max\{u_{ijk} | i,j = 1,\ldots,m\}, \quad k = 1,\ldots,l, \tag{3}$$

$$u_k^{min} = \min\{u_{ijk} | i,j = 1,\ldots,m\}, \quad k = 1,\ldots,l. \tag{4}$$

Suppose the DM provides criterion weights w_k, $k = 1,\ldots,l$, by direct assignment or using AHP (see Saaty, 1980). Then, using the simple additive weighting method (Hwang and Yoon, 1981), the overall value of collaborative utility between partner firms can be expressed as

$$u_{ij} = \sum_{k=1}^{l} w_k u'_{ijk}, \quad i,\ j = 1,\ldots,m. \tag{5}$$

Based on the above analysis, the following decision model is built for supplier selection in multi-service outsourcing:

$$\text{Minimize } Z_1 = \sum_{i=1}^{m} \sum_{s=1}^{n} p_{is} d_s x_{is}, \tag{6}$$

$$\text{Minimize } Z_2 = \sum_{i=1}^{m} \sum_{s=1}^{n} t_{is} x_{is}, \tag{7}$$

$$\text{Maximize } Z_3 = \sum_{i=1}^{m} \sum_{j=1}^{m} u_{ij} \sum_{s=1}^{n} x_{is} \sum_{s=1}^{n} x_{js}, \tag{8}$$

subject to,

$$\sum_{s=1}^{n} x_{is} \le 1, \quad i = 1,\ldots,m, \tag{9}$$

$$\sum_{i=1}^{m} x_{is} = 1, \quad s = 1,..,n \tag{10}$$

$$\sum_{i=1}^{m} p_{is} x_{is} \le p_s^A, \quad s = 1,..,n, \tag{11}$$

$$\sum_{i=1}^{m} t_{is} x_{is} \le t_s^A, \quad s = 1,..,n, \tag{12}$$

$$x_{is} \in \{0,\ 1\}, \quad i = 1,\ldots,m; \quad s = 1,\ldots n. \tag{13}$$

In models (6)–(13), objective function (6) presents the minimization of total service outsourcing cost. Objective function (7) shows the minimization of service waiting time. Objective function (8) shows the maximization of collaborative utility between partner firms. Constraint (9) restricts that one supplier can provide at most one service. Constraint (10) confines that each SPE is assigned to exactly one supplier. Constraint function (11) ensures that the service price promised by the supplier is lower than or equal to the acceptable level. Constraint function (12) ensures that the service waiting time promised by the supplier is shorter than or equal to the acceptable level.

Models (6)–(13) is a basic model for supplier selection in multi-service outsourcing. Objectives and constrains could be added or changed according to specific applications. For example, the DM could add the objective of maximization of customers' satisfaction, or the constraint of a minimum number of suppliers.

We provide the analysis on the computation complexity of models (6)–(13) below. Kuo et al. (1993) have proved that the maximum diversity problem (MDP) defined by the following model is NP-hard:

$$\text{Maximize } z = \sum_{i<j} u_{ij} x_i x_j \tag{14}$$

subject to,

$$\sum_{i=1}^{m} x_i = n, \tag{15}$$

$$x_i \in \{0,1\}, \quad i = 1,\ldots,m, \tag{16}$$

where u_{ij} is the distance between elements i and j; m is the number of elements in the candidate set and $n < m$ is the desired size of the selected set. For models (6)–(13), if we ignore the first two objectives and only look at objective Z_3, we can then easily verify that the maximum diversity problem is its special case. The original problem (6)–(13), however, is more difficult since it is a multi-objective optimization problem.

As for models (6)–(13), such a multi-objective problem can be solved using three approaches. First, a multi-objective problem can be converted to a single objective problem by a variety of methods, including the weighted objective method, goal programming method or compromise programming method. Second, a multi-objective problem can be transformed into multiple single objective problems by using methods including the layered sorting method, key objective method, and grouped sorting method. Third, a multi-objective problem can be solved directly using a multi-objective intelligent algorithm. In the two former cases, only weakly effective solutions can be obtained, whereas effective solutions (or Pareto-optimal solutions) can be obtained in the third case. Based on the above analysis, we therefore propose a multi-objective heuristic algorithm for solving models (6)−(13) in the next section.

4. A multi-objective algorithm based on TS

In this section, we suggest a multi-objective algorithm based on TS for solving models (6)–(13) to achieve supplier selection in multi-service outsourcing.

4.1. Description of the proposed algorithm

According to Glover (1989, 1990), TS borrows some of its concepts from the artificial intelligence field such as the notion of memory, moves, neighborhood, and descent procedure, all of which are the basic concepts of this local search approach. TS is used extensively for solving the problems of scheduling the activities, progressive resource allocation, etc. (Belfares et al., 2007). Some effective mechanisms are used in TS, such as successive searching in the neighborhood, the type of move, as well as intensification and diversification. In addition, the flexibility of TS enables us to perform a search guided in a multi-objective space where an interesting search direction can be determined by more than one function.

The procedure of the proposed algorithm is inspired by a progressive resource allocation algorithm proposed by Belfares et al. (2007). It has made significant contributions to solving multi-objective resource-constrained project-scheduling resource allocation with time window constraints. The algorithm proposed in this paper starts with an initial feasible solution. Local potentially efficient solutions are then generated by using a multi-objective Pareto-based optimization technique. The optimization method is based on a posteriori preference articulation approach.

The goal is to find the largest number of well diversified efficient solutions. An interactive multi-objective filtering approach is used to eliminate the dominated solutions and local improvement is conducted to obtain a set of rich and diversified solutions. The main mechanisms used in the suggested algorithm are presented below.

First, the proposed algorithm uses a non-dominance concept. Every neighbor candidate generated from the current solution is evaluated using the dominance rule presented as follows:

Consider a decision problem with λ objectives to be minimized. Dominance relationships between two solutions x_1 and x_2 are defined as follows:

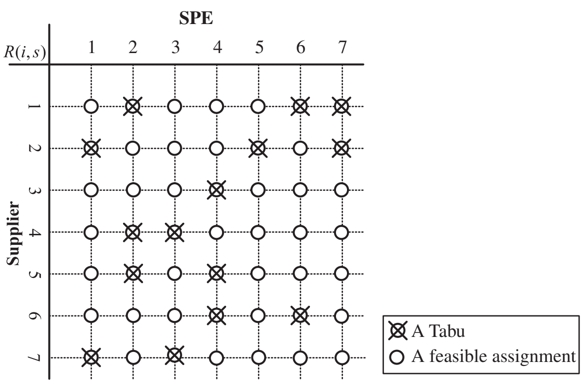

Fig. 2. An illustration of Tabulist.

(i) x_1 absolutely dominates x_2 denoted $(x_1 D^a x_2) \Leftrightarrow Z_r(x_1) < Z_r(x_2)$ for $r = 1,2,\ldots,\lambda$;
(ii) x_1 strictly dominates x_2 denoted $(x_1 D^s x_2) \Leftrightarrow Z_r(x_1) \leq Z_r(x_2)$ for $r = 1,2,\ldots,\lambda$, and $\exists h$ where $Z_h(x_1) < Z_h(x_2)$;
(iii) x_1 weakly dominates x_2 denoted $(x_1 D^w x_2) \Leftrightarrow Z_r(x_1) \geq Z_r(x_2)$ for $r = 1,2,\ldots,\lambda$ and
(iv) x_1 and x_2 are incomparable if neither $x_1(D^a \cup D^s \cup D^w)x_2$ nor $x_2(D^a \cup D^s \cup D^w)x_1$.

We have $D^a \subseteq D^s \subseteq D^w$. In this paper, the weak dominance rule is employed during the search process because it allows more solutions to be reached from the existing ones with regard to the connectedness of the search space.

Second, a multi-objective filtering approach (Belfares et al., 2007) is used. When several non-dominated neighbors are generated, a multi-criteria filtering approach is adopted to filter these solutions. Suppose that F^T be a threshold value vector on all objectives. F^T can be computed dynamically by a dichotomous method between $F^- = \{F_1^-, F_2^-, \ldots, F_\lambda^-\}$ and $F^+ = \{F_1^+, F_2^+, \ldots, F_\lambda^+\}$, where F^- and F^+ are the anti-ideal points and ideal points of a sub-set of non-dominated solutions (denoted by O), respectively. Here, a minimization problem is considered and a transformation should be conducted when a maximization problem is required. This multi-objective filtering approach consists of disjunction and conjunction. In disjunction, solutions are retained by improving at least one objective. Disjunction retains the solutions that score a minimal value on at least one objective. If the number of retained solutions is lower than $C(O)$, then conjunction is used to reach this number, where $C(O)$ is the

Initialization

B^F : a feasible solution, $B^F = \varnothing$,

I : set of candidate supplier,

I^α : set of selected supplier,

S : set of SPEs,

O_z : set of objective functions,

$R(i,s)$: an assignment between supplier i and SPE s,

B^N : set of new solutions.

B^P : set of Pareto-optimal solutions, $B^P = \varnothing$.

Step 1. Choose randomly a candidate supplier i^* from I, $I = I \setminus \{i^*\}$. Check if $i^* \in I^\alpha$, if yes go to **Step 4**;

Step 2. Choose randomly a supplier $i \in I^\alpha$, $R(i,s) \in B^F$;

Step 3. Check whether $R(i^*,s)$ is Tabu? If yes go to **Step 2**;

Step 4. Remove x_{is} from the current solution, $B^F = B^F \setminus R(i,s)$, and add x_{i^*s} to the current solution $B^F = B^F \bigcup R(i^*,s)$;

Step 5. Choose objective Z_r from O_z. $O_z = O_z \setminus \{Z_r\}$. Construct a new solution accordingly;

Step 6. Check whether all the objectives are performed $O_z = \varnothing$? Otherwise return to **Step 5**;

Step 7. Check whether all the candidate suppliers are changed: $I = \varnothing$.

Fig. 3. Steps of the proposed multi-objective algorithm based on TS.

cardinality of set O. In this step, a sub-set of non-dominated solutions that improves all the objectives is selected. The solutions are selected if all objectives achieve thresholds.

Third, management of a Tabulist is involved in the proposed algorithm. We define *Tabu SPE* and *Tabu assignment* lists. For instance, the assignment $R(i,s)$ is forbidden if this combination is presented in a dominated assignment solution. Such a restriction avoids the cycling phenomenon in the solving process. A Tabulist is vividly shown in Fig. 2.

Fourthly, the proposed algorithm starts from an initial feasible solution and generates a set of rich and diversified solutions by local improvements. In the algorithm, the improvement is conducted based on each objective in turn to escape local optima, and only non-dominated solutions are retained at each step. The local search in the neighborhood consists of a succession of intensification and diversification phases.

The intensification phase generates the extreme solutions by improving only one objective (D_r). The diversification phase generates best compromise solutions by investigating the multi-objective search space at each level. This is done by improving a direction D_r, a solution already optimized on $D_f\,(f \neq r)$ at the present level. The advantage of this approach is to generate, at each level, both extreme solutions and best compromise solutions.

4.2. Steps of the proposed algorithm

The proposed algorithm consists of seven steps. Step 1 contains a random selection of a candidate supplier. Steps 2 – 4 involve the withdrawing of a substituted supplier and the updating of the current solution. Step 5 consists of iterations for searching for better assignments between suppliers and SPEs. Step 6 checks whether all the objectives are considered and the last step checks whether all the candidate suppliers are considered. We present the steps of the proposed multi-objective algorithm based on TS in Fig. 3. The sub-steps of step 5 are also shown in detail in Fig. 4.

5. An example and computational experiments

In this section, we present an example of the supplier selection in multi-service outsourcing of CSA company. In addition, extensive computational experiments are conducted to further test the effectiveness of the suggested algorithm.

CSA is a main air transportation firm of China. It has 14 branches, 5 holding subsidiaries and 53 international offices located in major metropolitan markets around the world. CSA operates the largest and most technologically advanced airline fleet, as well as the most extensive domestic air network in China. Currently, CSA serves 844 cities in 169 countries, covering all of China and radiating throughout Asia with convenient connections to all the main cities in the world via close cooperation with allied members.

CSA attaches key importance to its branded product strategy, offering a host of reliable and convenient on-time services. The airline currently has a frequent flyer club with more than 8 million members. CSA was honored with the "*Five Star Diamond Award*" by the American Academy of the Hospitality Sciences in 2004.

Step 5.1. Initialize $B^N = \varnothing$;

Step 5.2. Select a supplier i from I^α;

Step 5.3. Select a SPE s from S;

Step 5.4. Check whether $R(i,s)$ is Tabu? If yes, then return to **Step 5.3**;

Step 5.5. Assign supplier i to SPE s, $B^N = B^N \cup R(i,j)$, $I^\alpha = I^\alpha \setminus (i)$, $S = S \setminus (s)$;

Step 5.6. Check $S = \varnothing$? if not return to **Step 5.2**;

Step 5.7. Evaluate new solution B^N and compare to concurrent solution B^F. If the new solution is dominated, then forbid new solution: $R(i,s)$ Tabu and go to **Step 5.2**;

Step 5.8. Record the new solution and replace the concurrent solution with the new solution: $B^P = B^P \cup B^N$, $B^F = B^N$.

Fig. 4. The sub-steps of step 5 of the proposed multi-objective algorithm based on TS.

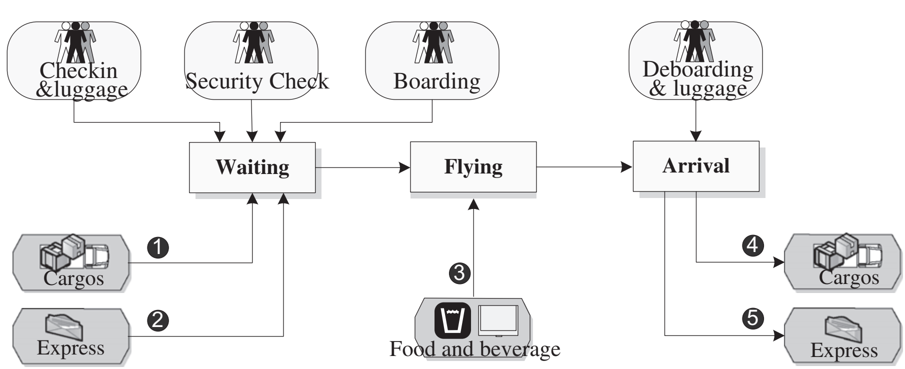

Fig. 5. The SPEs involved in a flight.

However, with the increasing competition in the travel market, CSA plans to outsource a portion of its services so that it can focus on its core business service as well as balance its costs and benefits. To achieve multi-service outsourcing, a disaggregation of service processes associated with a flight is conducted, as shown in Fig. 5. This process involves two parts of the business service, passenger transportation and cargo traffic, and it comprises three key sub-processes, *waiting*, *flying* and *arrival*. Five SPEs of a flight service need to be provided by suppliers, i.e., (i) sorting the cargoes that are consolidated by freight forwarders (S_1); (ii) pickup and sorting real-time small parcels and mails that are carried by a latest flight (S_2); (iii) serving passengers food and beverages (S_3); (iv) sorting the cargoes from service (i) (S_4) and (v) sorting and delivering the express from service (ii) (S_5). Simultaneously, other SPEs that are involved in this process are provided by the local airport. For analytical tractability, we mark the order numbers of the five SPEs in Fig. 5.

As a strategic goal, CSA will build long-term collaborative relationships with its potential suppliers. Five suppliers need to be selected from twenty potential collaborators to achieve such a multi-service outsourcing. The DM firstly conducts a screen to determine the feasible candidate suppliers by using the constraints of acceptable levels p_s^A and t_s^A. Fifteen feasible candidates are picked out from the 20 potential collaborators. The decision model and algorithm proposed in Sections 3 and 4 are employed to select a desired pool of supplies. Three objectives are considered by the DM for supplier selection, i.e., collaborative utility, outsourcing cost and waiting time. The decision data of service price and waiting time of each feasible candidate, the acceptable levels concerning the two criteria as well as the expected demand for each SPE are shown in Table 2. In Table 2, the units of p and t are *RMB per kilogram* and *hour*, respectively. $M >> 0$ is a real number and it implies that candidate supplier i cannot provide SPEs, $i=1,\ldots,m$; $s=1,\ldots n$.

To measure the collaboration utility between partner firms, three collaborative criteria are employed, namely, *interface management compatibility* (C_1), *service system sharing* (C_2) and *mutual technology supports* (C_3), as shown in Table 3. The DM regards the importance weights of the three criteria to be equal, i.e., $w_1=w_2=w_3=1/3$. Furthermore, it is obvious that the three criteria are qualitative and the subjective assessment (or judgment) of DM is more suitable to deal with this situation. The DM expresses his/her preference on the collaborative utility between candidates and between candidates and CSA using the scale of scores of 1–10 (1: definitely low; 10: definitely high; others: the intermediate levels), and the assessment data on collaborative utility is shown in Tables 4–6. In Tables 4–6, the principal diagonal elements are the data of collaborative utility between CSA and candidates. The non-principal-diagonal elements are the data of collaborative utility between candidates. Normalization of the collaborative criterion data is not required since they have the

Table 3
Collaborative criteria.

Criterion	Definition
Interface management compatibleness (C_1)	Partner firms have the consistent management style and regulations, as well as compatible cultures
Service system sharing (C_2)	Partner firms could share the stevedores, vehicles or equipments
Mutual technology supports (C_3)	Partner firms could use information technologies to share the data stored in enterprise information systems with each other

Table 4
The original assessment data concerning collaborative criterion C_1.

	P_1	P_2	P_3	P_4	P_5	P_6	P_7	P_8	P_9	P_{10}	P_{11}	P_{12}	P_{13}	P_{14}	P_{15}
P_1	**8**	6	5	7	7	9	7	8	5	3	4	7	3	5	9
P_2	6	**7**	5	6	3	7	7	5	6	6	7	6	5	6	8
P_3	5	5	**6**	5	6	6	8	6	5	5	9	3	5	5	5
P_4	7	6	5	**6**	5	6	5	5	5	7	6	5	4	5	6
P_5	7	3	6	5	**7**	4	5	8	4	6	7	6	6	4	9
P_6	9	7	6	6	4	**4**	4	7	5	5	4	6	6	7	6
P_7	7	7	8	5	5	4	**5**	8	5	5	6	5	6	6	5
P_8	8	5	6	5	8	7	8	**10**	6	7	5	10	5	7	8
P_9	5	6	5	5	4	5	5	6	**4**	6	6	4	6	5	3
P_{10}	3	6	5	7	6	5	5	7	6	**3**	3	4	7	4	7
P_{11}	4	7	9	6	7	4	6	5	6	3	**7**	7	4	6	5
P_{12}	7	6	3	5	6	6	5	10	4	4	7	**7**	5	5	9
P_{13}	3	5	5	4	6	6	6	5	6	7	4	5	**5**	3	9
P_{14}	5	6	5	5	4	7	6	7	5	4	6	5	3	**6**	6
P_{15}	9	8	5	6	9	6	5	8	3	7	5	9	9	6	**8**

Table 2
The decision date of service price and waiting time.

Feasible candidate	SPE									
	S_1		S_2		S_3		S_4		S_5	
	p_{i1}	t_{i1}	p_{i2}	t_{i2}	p_{i3}	t_{i3}	p_{i4}	t_{i4}	p_{i5}	t_{i5}
P_1	0.600	1.200	7.200	0.900	M	M	M	M	M	M
P_2	0.800	1.100	8.200	0.700	M	M	M	M	M	M
P_3	1.100	1.400	7.100	0.700	M	M	M	M	M	M
P_4	1.000	3.200	6.400	0.800	M	M	M	M	M	M
P_5	1.200	1.700	6.000	0.700	M	M	M	M	M	M
P_6	1.500	2.800	7.100	0.500	M	M	M	M	M	M
P_7	M	M	M	M	10.500	0.500	M	M	M	M
P_8	M	M	M	M	9.500	0.300	M	M	M	M
P_9	M	M	M	M	12.000	0.600	M	M	M	M
P_{10}	M	M	M	M	M	M	1.200	1.400	8.100	9.400
P_{11}	M	M	M	M	M	M	1.200	1.600	7.200	7.600
P_{12}	M	M	M	M	M	M	0.700	1.200	8.500	6.800
P_{13}	M	M	M	M	M	M	1.000	1.000	8.200	5.400
P_{14}	M	M	M	M	M	M	1.400	1.500	8.500	4.300
P_{15}	M	M	M	M	M	M	1.000	1.500	6.500	3.400
$\boldsymbol{p_s^A, t_s^A}$	**1.500**	**3.200**	**8.500**	**1.500**	**12.000**	**0.500**	**1.500**	**3.200**	**8.500**	**10.000**
$\boldsymbol{d_s}$	**10.000** (tonne)		**0.100** (tonne)		**200.000** (set)		**10.000** (tonne)		**0.100** (tonne)	

same unit. The assessment data of overall collaborative utility between partner firms, u_{ij}, $i,j=1,2,\ldots,m$, is then obtained using Eq. (5), and is shown in Table 7.

Using models (6)–(13), the model for supplier selection discussed in the example can be formed as follows:

$$\text{Minimize } Z_1 = 0.6x_{11}+7.2x_{12}+0.8x_{21}+8.2x_{22}+\cdots +1.4x_{1,4}+8.5x_{14,5}+x_{15,4}+6.5x_{15,5},$$

$$\text{Minimize } Z_2 = 1.2x_{11}+0.9x_{12}+1.1x_{21}+0.7x_{22}+\cdots +1.5x_{14,4}+4.3x_{14,5}+1.5x_{15,4}+3.4x_{15,5},$$

Table 5
The original assessment data concerning collaborative criterion C_2.

	P_1	P_2	P_3	P_4	P_5	P_6	P_7	P_8	P_9	P_{10}	P_{11}	P_{12}	P_{13}	P_{14}	P_{15}
P_1	**7**	4	5	5	9	7	6	9	6	5	6	8	9	6	7
P_2	4	**5**	6	4	3	8	6	8	4	5	6	6	5	6	5
P_3	5	6	**5**	4	5	6	4	7	7	4	4	5	4	7	7
P_4	5	4	4	**7**	5	6	5	6	6	4	7	5	9	5	6
P_5	9	3	5	5	**8**	6	7	9	5	5	4	7	7	5	8
P_6	7	8	6	6	6	**6**	8	6	4	5	7	5	6	8	5
P_7	6	6	4	5	7	8	**6**	5	6	6	4	5	5	6	5
P_8	9	8	7	6	9	6	5	**6**	7	7	5	10	6	5	7
P_9	6	4	7	6	5	4	6	7	**10**	6	6	4	6	7	5
P_{10}	5	5	4	4	5	5	6	7	6	**7**	3	5	3	5	6
P_{11}	6	6	4	7	4	7	4	5	6	3	**8**	3	6	4	6
P_{12}	8	6	5	5	7	5	5	10	4	5	3	**8**	5	6	7
P_{13}	9	5	4	9	7	6	5	6	6	3	6	5	**4**	7	6
P_{14}	6	6	7	5	5	8	6	5	7	5	4	6	7	**5**	8
P_{15}	7	5	7	6	8	5	5	7	5	6	6	7	6	8	**10**

Table 6
The original assessment data concerning collaborative criterion C_3.

	P_1	P_2	P_3	P_4	P_5	P_6	P_7	P_8	P_9	P_{10}	P_{11}	P_{12}	P_{13}	P_{14}	P_{15}
P_1	**9**	5	4	4	7	3	7	8	8	5	4	7	6	5	9
P_2	5	**6**	5	6	5	7	5	8	5	4	6	5	6	4	6
P_3	4	5	**6**	7	5	4	5	6	4	6	6	5	7	5	4
P_4	4	6	7	**5**	6	3	6	6	6	3	5	7	5	4	7
P_5	7	5	5	6	**10**	5	3	10	6	10	5	6	6	5	7
P_6	3	7	4	3	5	**7**	5	7	6	6	4	3	6	5	6
P_7	7	5	5	6	3	5	**6**	5	5	6	4	4	5	7	8
P_8	8	8	6	6	10	7	5	**9**	6	10	5	7	5	6	9
P_9	8	5	4	6	6	6	5	6	**7**	5	5	6	7	4	6
P_{10}	5	4	6	3	10	6	6	10	5	**8**	5	5	7	7	4
P_{11}	4	6	6	5	5	4	4	5	5	5	**7**	7	6	5	5
P_{12}	7	5	5	7	6	3	4	7	6	5	7	**6**	5	6	6
P_{13}	6	6	7	5	6	6	5	5	7	7	6	5	**10**	5	7
P_{14}	5	4	5	4	5	5	7	6	4	7	5	6	5	**5**	6
P_{15}	9	6	4	7	7	6	8	9	6	4	5	6	7	6	**10**

$$\text{Maximize } Z_3 = 8(x_{11}+x_{12}+\cdots x_{15})(x_{11}+x_{21}+\cdots x_{15}) +5(x_{11}+x_{12}+\cdots x_{15})(x_{21}+x_{22}+\cdots x_{25}) +\cdots+9.333(x_{15,1}+x_{15,2}+\cdots x_{15,5})(x_{15,1}+x_{15,2}+\cdots x_{15,5}),$$

subject to,

$$\sum_{s=1}^{5} x_{1s} \le 1,$$

$$\sum_{s=1}^{5} x_{2s} \le 1,$$

$$\vdots$$

$$\sum_{s=1}^{5} x_{15s} \le 1,$$

$$\sum_{i=1}^{15} x_{i1} = 1,$$

$$\sum_{i=1}^{15} x_{i2} = 1,$$

$$\vdots$$

$$\sum_{i=1}^{15} x_{i5} = 1,$$

$$x_{is} \in \{0,\ 1\}, \quad i,=1,2,\ldots,15; \quad s=1,2,\ldots,15.$$

The multi-objective algorithm based on TS proposed in Section 4 was employed to solve the above model. The proposed algorithm was coded in MATLAB 8.0 and run on a PC with an Intel Core2 1.66 GHz CPU and 1 Gbytes RAM. We set $M=10{,}000$ and ran the algorithm three times. The average runtime was 0.7672 s. A Pareto-optimal solution set was obtained, as shown in Table 8. The DM could select a pool of desired suppliers according to his/her preference on the importance of the three decision objectives.

In addition, we can observe from Table 8 that the focus of collaborative utility will affect the final decision for the DM. If we ignore the objective of collaborative utility, then the third solution dominates the fifth one. In this case, the combination of suppliers P_1, P_6, P_8, P_{13} and P_{15} would be considered better than that of suppliers P_1, P_6, P_8, P_{12} and P_{15}. In reality, however, the DM ordinarily prefers the fifth solution to the third one because the fifth solution can achieve higher collaborative untidily and better performance balance among the three objectives. The computational results show that the proposed model and algorithm can support satisfactory supplier selection in multi-service outsourcing.

Extensive computational experiments were conducted to further test the efficiency of the proposed algorithm. We designed

Table 7
The derived data concerning overall collaborative utility.

	P_1	P_2	P_3	P_4	P_5	P_6	P_7	P_8	P_9	P_{10}	P_{11}	P_{12}	P_{13}	P_{14}	P_{15}
P_1	**8.000**	5.000	4.667	5.333	7.667	6.333	6.667	8.333	6.333	4.333	4.667	7.333	6.000	5.333	8.333
P_2	5.000	**6.000**	5.333	5.333	3.667	7.333	6.000	7.000	5.000	5.000	6.333	5.667	5.333	5.333	6.333
P_3	4.667	5.333	**5.667**	5.333	5.333	5.333	5.667	6.333	5.333	5.000	6.333	4.333	5.333	5.667	5.333
P_4	5.333	5.333	5.333	**6.000**	5.333	5.000	5.333	5.667	5.667	4.667	6.000	5.667	6.000	4.667	6.333
P_5	7.667	3.667	5.333	5.333	**8.333**	5.000	5.000	9.000	5.000	7.000	5.333	6.333	6.333	4.667	8.000
P_6	6.333	7.333	5.333	5.000	5.000	**5.667**	5.667	6.667	5.000	5.333	5.000	4.667	6.000	6.667	5.667
P_7	6.667	6.000	5.667	5.333	5.000	5.667	**5.667**	6.000	5.333	5.667	4.667	4.667	5.333	6.333	6.000
P_8	8.333	7.000	6.333	5.667	9.000	6.667	6.000	**8.333**	6.333	8.000	5.000	9.000	5.333	6.000	8.000
P_9	6.333	5.000	5.333	5.667	5.000	5.000	5.333	6.333	**7.000**	5.667	5.667	4.667	6.333	5.333	4.667
P_{10}	4.333	5.000	5.000	4.667	7.000	5.333	5.667	8.000	5.667	**6.000**	3.667	4.667	5.667	5.333	5.667
P_{11}	4.667	6.333	6.333	6.000	5.333	5.000	4.667	5.000	5.667	3.667	**7.333**	5.667	5.333	5.000	5.333
P_{12}	7.333	5.667	4.333	5.667	6.333	4.667	4.667	9.000	4.667	4.667	5.667	**7.000**	5.000	5.667	7.333
P_{13}	6.000	5.333	5.333	6.000	6.333	6.000	5.333	5.333	6.333	5.667	5.333	5.000	**6.333**	5.000	7.333
P_{14}	5.333	5.333	5.667	4.667	4.667	6.667	6.333	6.000	5.333	5.333	5.000	5.667	5.000	**5.333**	6.667
P_{15}	8.333	6.333	5.333	6.333	8.000	5.667	6.000	8.000	4.667	5.667	5.333	7.333	7.333	6.667	**9.333**

Table 8
Pareto-optimal solution set of the example.

Code	Pareto-optimal solution	Optimal objective function value		
1	$P_1\to S_1$, $P_5\to S_2$, $P_8\to S_3$, $P_{12}\to S_4$, $P_{15}\to S_5$	$Z_1=1907.250$	$Z_2=6.800$	$Z_3=199.667$
2	$P_2\to S_1$, $P_6\to S_2$, $P_8\to S_3$, $P_{13}\to S_4$, $P_{15}\to S_5$	$Z_1=1919.360$	$Z_2=6.300$	$Z_3=164.333$
3	$P_1\to S_1$, $P_6\to S_2$, $P_8\to S_3$, $P_{13}\to S_4$, $P_{15}\to S_5$	$Z_1=1916.250$	$Z_2=6.400$	$Z_3=172.333$
4	$P_2\to S_1$, $P_5\to S_2$, $P_8\to S_3$, $P_{12}\to S_4$, $P_{15}\to S_5$	$Z_1=1914.360$	$Z_2=6.700$	$Z_3=179.667$
5	$P_1\to S_1$, $P_6\to S_2$, $P_8\to S_3$, $P_{12}\to S_4$, $P_{15}\to S_5$	$Z_1=1917.360$	$Z_2=6.600$	$Z_3=181.667$

Table 9
Eight middle and large-scale experimental problems.

No.	m	n	$\bar{t}$ (s)
1	50	5	1.3987
2	100	5	2.2561
3	100	10	2.4135
4	150	10	4.1891
5	150	15	6.3236
6	200	20	11.6822
7	200	25	32.1105
8	300	30	49.1618

Table 10
Eight experimental problems with varied numbers of objective functions.

No.	$C(O)$	m	n	$\bar{t}$ (s)
1	4	50	5	1.6732
2	4	100	10	2.7941
3	6	50	5	3.8346
4	6	100	10	4.7360
5	8	50	5	6.6194
6	8	100	10	7.0367
7	10	50	5	15.4528
8	10	100	10	16.2939

eight middle and large-scale experimental problems, as shown in Table 9. In the eight experimental problems, the parameters p_{is}, t_{is}, u_{ij} were generated using random numbers from the uniform distribution $N(1, 10)$, i.e., p_{is}, t_{is}, $u_{ij}\in N(1,10)$. We set perimeters $p_s^A=8$, $t_s^A=8$, $d_{is}=10$ and took an equal number of candidate suppliers for each SPE. We ran the developed algorithm ten times for each experimental problem and the computational results are shown in Table 9. In addition, we included more objectives in the decision model to test the efficiency of the suggested multi-objective TS (MOTS). The involved objectives contain both the linear or non-linear forms and we set two different scales for each test problem. The computational time varies between 1.6732 s for problem no. 1 to 16.2329 s for problem no. 8 when we increase the numbers of objective functions from 3 to 10 (see Table 10). Thus, the above results show that the suggested multi-objective TS is robust to the scale of problems and the number of objective functions.

Moreover, we compared MOTS with the other two leading multi-objective meta-heuristics, MOGA-II (Deb et al., 2002) and AMOSA (Bandyopadhyay et al., 2008). Deb et al. (2002) developed a set of nine test problems to compare MOGA-II with other excellent MOGAs, which is extensively used in the comparisons among algorithms (see, for example, Bandyopadhyay et al., 2008; Jaeggi et al., 2004, 2005, 2008). We used the nine test problems as benchmark problems because our focus for developing our MOTS is not absolute performance on a set of benchmark problems but solution for the real-world problems.

We coded MOTS, MOGA-II and AMOSA algorithms in MATLAB 8.0 in real-coded manner and run on a PC with an Intel Core2 1.66 GHz CPU and 1 Gbytes RAM. Table 11 shows the parameter settings for each algorithm. Each algorithm was run 10 times on each test problem and the non-dominated solution sets derived after 10,000 function evaluations were used to generate the performance measures. We chose the convergence (Υ), diversity (Δ) and time (t) as the performance metrics to compare the effectiveness and efficiency among the three algorithms. The former two indicators are taken from Deb et al. (2002), and the smaller Υ and Δ are, the more ideal a Pareto-optimal solution set is.

Table 12–14 show the mean and variance of convergence ($\overline{\Upsilon}$, σ_Υ) and diversity ($\overline{\Delta}$, σ_Δ) and the mean of time ($\bar{t}$). It can be seen from Table 12 that MOTS outperforms NSGA-II and AMOSA on majority of the test problems in the presence of convergence metric. Table 13 indicates that MOTS show worse performance than NSGA-II and slightly better performance than AMOSA with regard to the diversity of Pareto-optimal solutions. Moreover, MOTS is comparable to NSGA-II and AMOSA on time metric and none of them possesses obvious advantage when we set same function evaluations, which can be observed from Table 14. In fact, the execution time for the tree algorithm does not exceed 30 s, which is very acceptable for the real-world problems. In sum, the above analytical results indicate that the developed algorithm can tackle the problems of supplier selection in multi-service outsourcing effectively and efficiently.

6. Conclusion and future work

Supplier selection orienting long-term collaborative relationships in multi-service outsourcing is a very important decision problem. Close collaboration or interaction may occur between partner firms for the purpose of decreasing costs, sharing resources, exploiting capability complementarities or risk reduction. Collaborative utility, which indicates the potential collaborative level between partner firms, is a very important input for decision-making. It deserves much more attention in supplier selection orienting long-term collaborative relationships.

This paper presents a decision method for solving the problem of supplier selection in multi-service outsourcing. A multi-objective 0–1 programming model is built to select a pool of desired suppliers for different SPEs. A multi-objective algorithm based on TS is then developed to solve this model. A Pareto-optimal solution set can be obtained to support the supplier selection decision in multi-service outsourcing. The major contributions of this paper are as follows.

First, this paper considers the collaborative utility between partner firms for supplier selection. It is a new idea to use collaborative utility for selecting a pool of suppliers who will form long-term collaborative relationships. It overcomes the limitation in the existing decision-making methods for supplier selection, which only focus on the individual utilities.

Second, we build a multi-objective 0–1 programming model for selecting a pool of desired suppliers for the provision of different SPEs. Three objectives including collaborative utility, outsourcing cost and waiting time are involved in this decision

Table 11
Parameter settings.

Algorithm	Parameter	Value	Description
MOTS	*n-stm*	20	The last *n-stm visited points are tabu*
	n-region	2	Divide search space into *n_variables***n_regions* regions
	intensify	10	Perform intensify search when *i_local*=*intensify*
	diversify	20	Perform intensify search when *i_local*=*diversify*
	restart	50	Reduce step sizes and restart when *i_local*=*restart*
	SS	10%	Initial step sizes as percentage of variable range
	SSRF	0.5	Step sizes are multiplied by this factor at *restart*
	n_sample	6	Number of points randomly sampled
MOGA-II	*n-pop*	100	Population size
	n_parent	100	Number of parents
	n_child	100	Number of children
	p_m	0.1	Mutation probability
	p_r	0.9	Recombination probability
	n_m	15	Mutation distribution index (for SBX operator)
	n_r	5	Recombination distribution index (for SBX operator)
AMOSA	α	0.8	Cooling rate
	σ	0.1	Mutation probability
	n_archive	100	Archive size

Table 12
Convergence metric (Υ).

Algorithm	Υ	SCH	FON	POL	KUR	ZDT1	ZDT2	ZTD3	ZTD4	ZTD6
MOTS	$\overline{\Upsilon}$	0.00306	0.00077	0.01479	0.02772	0.04077	0.06502	0.01473	0.01131	0.3526
	σ_{Υ}	0	0	0.00052	0.00303	0.00062	0.00113	0.00372	0.00665	0.00728
MOGA-II	$\overline{\Upsilon}$	0.00347	0.00201	0.01561	0.02899	0.03971	0.07398	0.11574	0.02797	0.29821
	σ_{Υ}	0	0	0	0.00005	0.00441	0.02318	0.00691	0.02162	0.01724
AMOSA	$\overline{\Upsilon}$	0.00214	0.00428	0.04070	0.37786	0.01090	0.02829	0.10103	0.04781	0.23285
	σ_{Υ}	0	0	0.00171	0.00427	0.00238	0.08192	0.00389	0.03397	0.01933

Table 13
Diversify metric (Δ).

Algorithm	Δ	SCH	FON	POL	KUR	ZDT1	ZDT2	ZTD3	ZTD4	ZTD6
MOTS	$\overline{\Delta}$	0.37061	0.79283	0.86822	0.87216	0.76579	0.64371	0.90683	0.87972	0.33242
	σ_{Δ}	0.02267	0.03687	0.00391	0.14890	0.06581	0.02067	0.00184	0.00336	0.08650
MOGA-II	$\overline{\Delta}$	0.49782	0.38270	0.54572	0.67210	0.47542	0.68252	0.68747	0.78743	0.68476
	σ_{Δ}	0.00218	0.00056	0.00391	0.00187	0.00098	0.00553	0.00436	0.08892	0.00987
AMOSA	$\overline{\Delta}$	0.37851	0.83260	0.85669	0.88658	0.47487	0.67084	0.91865	0.90681	0.65743
	σ_{Δ}	0.02327	0.00321	0.00547	0.37803	0.07970	0.03749	0.00236	0.04531	0.08691

Table 14
Diversify metric ($\overline{t}$).

Algorithm	SCH	FON	POL	KUR	ZDT1	ZDT2	ZTD3	ZTD4	ZTD6
MOTS	0.37110	1.79615	4.36532	2.7531	18.8002	20.8690	23.97023	12.1632	15.3945
MOGA-II	0.36663	1.76563	4.53026	2.6795	18.9709	20.9701	23.09940	12.0887	14.5632
AMOSA	0.36207	1.77326	5.05740	2.6489	18.8809	21.6811	25.47043	12.5422	14.4426

model. It is also seen that the acceptable levels on price and waiting time of each SPE are taken into consideration. This model lies within a flexible decision framework, and it can be extended or modified to deal with service supplier selection problems in different scenarios by changing objectives and constrains in the light of actual requirements.

Third, we develop a multi-objective algorithm based on TS for solving the multi-objective 0–1 programming model. Several effective mechanisms are employed in this algorithm, such as multi-objective filtering, a succession of intensifications and diversifications for local search and Tabulist management. A Pareto-optimal solution set can be obtained using this algorithm. Extensive computational experiments show the effectiveness and efficiency of the proposed algorithm. The algorithm is universal, and it can be applied to solve other multi-objective assignment problems.

Future work will extend the above model and algorithm to the settings where collaborative utility should be considered, such as application service provider (ASP) selection in IT outsourcing or partner selection for codevelopment alliances. As for different decision problems, the proposed model can be modified by changing objectives or adding constraints before it is applied. Moreover, we intend to develop a decision support system (DSS), in which the proposed model and algorithm will be embedded. The DSS will be universal and convenient for DMs to tackle the complex or complicated decision problems of supplier selection in service outsourcing.

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