Computers & Industrial Engineering 105 (2017) 63–75

Contents lists available at ScienceDirect

Computers & Industrial Engineering

journal homepage: www.elsevier.com/locate/caie

Compound mechanism design of supplier selection based on multi-attribute auction and risk management of supply chain

Congjun Rao [a,b,*], Xinping Xiao [a,b], Mark Goh [c,d], Junjun Zheng [e], Jianghui Wen [a]

[a] School of Science, Wuhan University of Technology, Wuhan 430070, PR China
[b] Hubei Engineering Research Center of RF-Microwave Technology and Application, Wuhan 430070, PR China
[c] The Logistics Institute-Asia Pacific, National University of Singapore, Singapore
[d] School of Business IT and Logistics and Platform Technologies Research Institute, RMIT University, Australia
[e] School of Economics and Management, Wuhan University, Wuhan 430072, PR China

ARTICLE INFO

Article history:
Received 4 December 2015
Received in revised form 28 December 2016
Accepted 30 December 2016
Available online 3 January 2017

Keywords:
Supply chain
Supplier selection
Two-stage compound mechanism
Multi-attribute auction
Risk management
Grey correlation degree

ABSTRACT

The quality of the supplier base affects the competitiveness of firms and the attendant supply chain. The supplier selection decision is key to effective supply chain management. This paper investigates the problem of supplier selection under multi-source procurement for a type of divisible goods (such as coal, oil, and natural gas). By considering both the risk attributes and the attributes under a commercial criterion, we design a new two-stage compound mechanism for supplier selection based on multi-attribute auction and supply chain risk management. In the first stage, a multi-auction mechanism is established to determine the shortlist among all qualified suppliers based on four attributes (quality, price, quantity flexibility, and delivery time reliability) under a commercial criterion. In the second stage, seven risk attributes against the shortlisted suppliers are further considered, and a new ranking method based on grey correlation degree of mixed sequence is proposed to rank the finalists and to select the final winners. Moreover, the implementation, availability, and feasibility of the two-stage compound mechanism are highlighted by using an example of the multi-source procurement of electricity coal. This presented compound mechanism may well improve the procurement efficiency of divisible goods and greatly reduce the procurement risk.

1. Introduction

Suppliers have several roles under supply chain management: to manufacture parts and components for their customers, to ensure product quality and assurance, to indirectly help manage the cost over-runs of their downstream partners in the supply chain. As such, a supplier's production capacity can limit the output level of the entire supply chain. Further, a supplier's quality level determines the quality assurance of the final product, and the supplier's cost control affects the cost control capacity of the entire supply chain, and the supplier's new product development capacity influences the quality and cycle of the new product development. In short, the supplier is the foundation of supply chain operation, and is key to the competitiveness of the supply chain for a focal firm (Adida & DeMiguel, 2011; Azadi, Jafarian, Saen, & Mirhedayatian, 2015; Li, 2013; Rao, Zhao, Zheng, Wang, & Chen, 2016b).

As a supply chain grows in scale and operations, its structure will become more complicated. This then engenders greater supply chain risk (Cárdenas-Barrón, González-Velarde, & Treviño-Garza, 2015; Federgruen & Yang, 2008; Ma, Lin, & Chen, 2000). Thus, in managing this risk, by sharing supply chain information for all members, improving the overall flexibility of the supply chain, and enhancing the competitiveness of supply chain, managers can better assess, control, and act on the risks resident in the chain (Aqlan & Lam, 2015; Ho, Zheng, Yildiz, & Talluri, 2015). In this regard, the evaluation and selection of suppliers are imperative in the risk control of a supply chain. Through better supplier evaluation and selection, we can effectively reduce a chain's operational risk.

The extant literature has studied supplier evaluation and selection, in particular, the design of a system for supplier evaluation and the methods and models of supplier selection (Yu, Kaihara, Fujii, Sun, & Yang, 2015). On the supplier evaluation system, Dickson first proposed 23 attributes such as quality, delivery time,

* Corresponding author at: School of Science, Wuhan University of Technology, Wuhan 430070, PR China.
E-mail address: cjrao@foxmail.com (C. Rao).

http://dx.doi.org/10.1016/j.cie.2016.12.042
0360-8352/

historical performance as the evaluation measures (Dickson, 1966). Then, Weber reviewed, annotated, and classified 74 related articles which have appeared from 1966 to 1990, and ranked all the attributes in these articles. He concluded that price, delivery time, quality, and capacity are the most important evaluation attributes (Weber, Current, & Benton, 1991). Later, Choy and Lee (2003) studied the problem of evaluating and selecting the outsourcing of suppliers in the manufacturing industry, and chose manufacturing capacity, product price, delivery time, shipping quality, product development, process improvement, sales performance, marketing objectives, quality planning as the evaluation attributes to select the manufacturing outsourcing suppliers. Wilson (2006) studied the relative importance of supplier selection criteria, and constructed an index system formed by quality, price, service, technology, finance, location, reputation, and mutual benefits to comprehensively evaluate the suppliers. For firms that rely on a just-in-time production system, Willis, Huston, and Pohlkamp (2005) proposed a supplier evaluation system of 8 attributes (quality, price, order response speed, customer service, inventory planning, delivery time, financial health, and ease of ordering). Similarly, Patton (2008) proposed a system of supplier evaluation with Willis using price, quality, delivery time, sales support, equipment and technology, order situation, and financial health. Yahya and Kingsman (2009) interviewed 16 senior executives and proposed a similar evaluation system to Willis et al. and Patton. Moreover, Patton weighted all the attributes using AHP. Petroni and Braglia (2010) used Principal Components Analysis to construct a system of supplier evaluation from a supply chain perspective. The composition of Bragha's system is similar to the system with Patton, less the attributes of sales support and financial health, but included the attribute of management capacity. Menon, McGinnis, and Ackerman (2008) studied supplier selection for third-party logistics services, and established a supplier evaluation system that included price, delivery punctuality, management efficiency, corporate reputation, financial health, ability to implement the contract and disruption responsiveness, and empirically validated the effectiveness of the selection system. Shemshadi, Shirazi, Toreihi, and Tarokh (2011) chose product quality, effort to establish cooperation, supplier's technical level, supplier's delay on delivery and price/cost to evaluate and rank suppliers. Similarly, Chen and Wu (2013) proposed cost, quality, deliverability, technology, productivity, service to select new suppliers from a supply chain risk's perspective and AHP to determine the weight of each attribute.

On the methods and models to evaluate suppliers, research has proposed various evaluation schemes. These can be divided into three categories. First, the qualitative selection methods (Ma et al., 2000), for example, the judgment method based on direct experience, and the consultation choice method. Qualitative selection methods are simple and practicable, albeit too subjective and lack science and rationality to make choices based on experience or some certainty attributes. Quantitative selection methods, such as linear weighting (Ma et al., 2000), benefit-cost analysis (Federgruen & Yang, 2011; Hammami, Temponi, & Frein, 2014), new normalized goal programming (Jadidi, Zolfaghari, & Cavalieri, 2014), locally linear neuro-fuzzy model (Vahdani, Iranmanesh, Mousavi, & Abdollahzade, 2012), fuzzy integral-based model (Liou, Chuang, & Tzeng, 2014), believable rough set approach (Chai & Liu, 2014), integrated data envelopment analysis (DEA) (Toloo & Nalchigar, 2011), Green DEA (Kumar, Jain, & Kumar, 2014), multi-objective integer linear programming (Choudhary & Shankar, 2014), multi-objective linear programming (Arikan, 2013), mixed integer programming (Rezaei & Davoodi, 2011; Ventura, Valdebenito, & Golany, 2013; Zhang & Chen, 2013), multi-choice goal programming (MCGP) approach (Jadidi, Cavalieri, & Zolfaghari, 2015), Possibilistic programming (Li, 2014), algorithm for linearly constrained C-convex vector optimization (Qu, Goh, Ji, & Robert, 2015), Bayesian network model (Hosseini & Barker, 2016), multi-criteria DC programming (Ji & Goh, 2016), two-stage stochastic mixed-integer programming model (Amorim, Curcio, Almada-Lobo, Barbosa-Póvoa, & Grossmann, 2016), and two-level genetic algorithm (Aliabadi, Kaazemi, & Pourghannad, 2013), are better than the qualitative selection methods, and can solve specific problems under a deterministic environment, but the quantitative selection methods are generally based on deterministic evaluation attributes, and are difficult to quantify some qualitative attributes, and are thus unable to meet all requirements of processing uncertain information in a supply chain environment. The hybrid of quantitative and qualitative methods, such as integrated fuzzy MCDM approach (Karsak & Dursun, 2015), integrated approach based on Weighted Aggregated Sum Product Assessment (WASPAS) method (Ghorabaee, Zavadskas, Amiri, & Esmaeili, 2016), integrated approach including F-AHP and MILP model (Ayhan & Kilic, 2015), clustering method based on interval type-2 fuzzy sets (Heidarzadea, Mahdavi, & Mahdavi-Amiri, 2016), fuzzy AHP (Shawa, Shankar, Yadav, & Thakur, 2012), D-AHP (Deng, Hu, Deng, & Mahadevan, 2014), integrated fuzzy TOPSIS and MCGP (Liao & Kao, 2011), integrated approach including fuzzy techniques for order preferences by similarity to ideal solution (TOPSIS) and a mixed integer linear programming model (Kilic, 2013), parameterized non-linear programming approach (Li & Liu, 2015), Hesitant fuzzy linguistic VIKOR method (Liao, Xu, & Zeng, 2015; Liao, Xu, Zeng, & Xu, 2016), ranking method of fuzzy inference system (Amindousta, Ahmeda, Saghafiniab, & Bahreininejada, 2012) approach based on adaptive neuro-fuzzy inferences (Güneri, Ertay, & Yücel, 2011), method combined grey systems theory and uncertainty theory (Memon, Lee, & Mari, 2015), meta-approach by integrating multi-criteria decision analysis and linear programming (LP) (Sodenkamp, Tavana, & Caprio, 2016), and weighted max–min models (Amid, Ghodsypour, & O'Brien, 2011), however, is better at solving such problems more scientifically and rationally.

From above literature review, we can conclude that the study of supplier evaluation and selection has been a hot research direction of supply chain management, and the recent research has the following characteristics. Firstly, the evaluation criteria and index system gradually become systematic, diverse and comprehensive. The original single evaluation which only considers the production factors such as quality, price and cost is gradually replaced by the comprehensive evaluation by considering many aspects such as production, service, cooperation, and environmental (Hashemi, Karimi, & Tavana, 2015; Orji & Wei, 2015; Rezaei, Nispeling, Sarkis, & Tavasszy, 2016; Yu, Xue, Sun, & Zhang, 2016). So the evaluation index system is more comprehensive, and the evaluation results are more scientific. Secondly, the evaluation methods and models tended to more and more reasonable from the original mainly qualitative judgment, gradually to develop in the direction of the combination of qualitative and quantitative. On model applications, it is from using a single model to evaluate, gradually to develop in the direction of the combination evaluation with multiple models. Thirdly, the evaluation object gradually refined from the original general studies to steer specific industries and specific supplier evaluation. And some studies have proposed different evaluation index system for different industries and suppliers.

However, there are also some disadvantages for existing studies. First, no clear evaluation measurement standards are given for some evaluation indexes. And these index data is rarely combined with enterprise's actual demand, so it is difficult to apply in practice. Secondly, the evaluation index weight determination and the evaluation results are over-reliance on mathematical models, so the limitations of the model itself may affect on the accuracy of the evaluation results. Third, in the supplier evaluation, most of the literature does not consider the risk factors in the supply chain environment (Ho, Xu, & Dey, 2010). Even a few literatures studied on the supplier selection problem in supply chain risk management, but most still remain in the qualitative analysis. They did not really quantify the risk factors and not consider the quantified risk in the overall level of supplier evaluation. Fourthly, for the quantitative evaluation of suppliers in many literatures, the evaluation index values are generally taken to be accurate values. However, in the practical data statistics, due to the complexity of the decision-making system and decision-making environment, and the ambiguity of the human mind, many index values are difficult to count by using the exact numbers such as reputation for suppliers and supplier service level. The evaluation results of these qualitative indexes are given often only in the form of linguistic fuzzy variable (such as better, good, bad or very high, high, low) (Li & Ren, 2015; Rao, Goh, Zhao, & Zheng, 2015; Rao & Peng, 2009; Rao, Zheng, Wang, & Xiao, 2016a; Xu, 1999; Xu & Zhang, 2013). Also, for instance, in the evaluation of technology risk and management risk for the suppliers, the results of risk evaluation are generally given by high risk, low risk, and so on. For the problem of supplier evaluation and selection under mixed data information environment which the real numbers and linguistic fuzzy variable are coexisting, there are few literatures discussed. How to deal with uncertainty under a complex and volatile situation in the supplier selection process is the focus of our study. In addition, the existing procurement mechanisms and evaluation index system are proposed mostly by considering a unique good or multiple indivisible goods. The research on a kind of divisible goods (such as coal, oil, natural gas) with the characteristic of homogeneousness and continuity is few.

Specifically, we study the problem of supplier selection in the procurement of divisible goods which is scant in the literature. A new system for supplier selection is proposed by considering the attributes under a commercial criterion and the supply chain risk attributes. Specifically, a two-stage compound mechanism based on multi-attribute auction and supply chain risk management is designed for selecting the suppliers. This compound mechanism may well improve the procurement efficiency of divisible goods and greatly reduce the procurement risk. In terms of actual application, our compound mechanism will stimulate the suppliers to develop better products and services. This is just the main contribution of the presented decision mechanism in this paper comparing with many existing supplier selection methods.

The rest of this paper is organized as follows. Section 2 proposes an evaluation system for supplier selection. Section 3 designs a two-stage compound mechanism for supplier selection based on the multi-attribute auction and supply chain risk management. Section 4 provides an example on the multi-source procurement of electricity coal. Section 5 concludes the paper.

2. Evaluation system for supplier selection

In this section, an evaluation system for suppliers was established. As risk reduction is critical to good supply chain risk management, supplier selection needs to consider commercial factors such as quality, price and delivery time, albeit cognizant of the risks resident in a supply chain. In this paper, drawing from the existing related research (Aqlan & Lam, 2015; Azadi et al., 2015; Chen & Wu, 2013; Ho et al., 2015; Kumar et al., 2014; Sawik, 2014; Torabi, Baghersad, & Mansouri, 2015), we take into account both the commercial factors and supply chain risks as shown in Table 1.

Each attribute in Table 1 is briefly described as follows.

A_1 Quality refers to the features and characteristics of the product supplied by the suppliers. A high-quality product is key to ensuring the effective functioning of the supply chain as poor quality products lead to waste in capital, poor market acceptance, loss of revenue, and faster exit from the market.

A_2 Price, a core attribute in supplier evaluation, refers to the purchase price for a buyer.

A_3 Quantity is the largest amount that a supplier can supply for a fee and by a certain time.

A_4 Delivery time is the time taken by a supplier to deliver the goods to a buyer under contract. This time can be either early, on-time or late, as it is affected by transportation.

The following attributes A_5 to A_6 are the risk management attributes of supply chain, and their specific meanings and quantitative methods (Cao, 2012; Chen & Wu, 2013; Ho et al., 2015) are given as follows.

A_5 Technology risk. Technology is advancing rapidly. To be competitive, a supplier must quickly absorb new technology and innovate. A supplier's technology risk can be measured by the new product development capability, i.e., being able to present new products to a market. It reflects a supplier's ability to accept new technology and the level of technological innovation. It can be expressed by the percentage of new product sales to total sales, i.e., supplier's new product development capability $a =$ (new product sales/total sales) $\times$ 100%. The greater the value of a, the higher the supplier's technology level, and the lower the supplier's technology risk. Table 2 shows a method to quantify a supplier's technology risk.

A_6 Information risk refers to the risk generated by information distortion, disclosure, and asymmetry during information transmission between the buyer and supplier. This risk will lead to unsuccessful collaboration between buyers and suppliers. The accuracy of information transmission depends on the supplier's information gathering and forecasting capabilities, and on the reliability and information technology of the management information systems (MIS). Inefficient information sharing platforms or weak supplier's information system, and a low level of information security may cause information distortion and information leaks. For example, if the degree of information security is lower, the hackers or criminals will invade the information management system easily to steal or tamper the key data, then we will face the risk of information distortion and information leaks. Table 3 gives the method to quantify a supplier's information risk.

A_7 Management risk. A strong management team and efficient management method are key to the growth and development of a firm. Unqualified managers and inefficient management present management risk to business. Here three main factors are selected to quantify a supplier's management level, i.e., the quality of managers, the order management ability and logistics management ability (Cao, 2012; Chen & Wu, 2013). As the quality of managers is related to the level of education, we use the educational level of the supplier's management personnel to proxy this quality. We select the ratio of graduate managers who obtain the master's

Table 1
Evaluation system for supplier selection.

First level attribute	Second level attribute
Commercial criterion	A_1 Quality
	A_2 Price
	A_3 Quantity
	A_4 Delivery time
Supply chain risk	A_5 Technology risk
	A_6 Information risk
	A_7 Management risk
	A_8 Economic risk
	A_9 Environmental risk
	A_{10} Societal risk
	A_{11} Ethical risk

degree to all managers to quantify the quality of managers, i.e. b_1 = (Number of managers who obtain the master's degree/total number of managers) × 100%. The greater the value of b_1, the better the quality of managers, and the smaller the management risk. The supplier's order management ability can be reflected by the correct handling ratio of orders during a certain period, i.e., b_2 = (Number of error-free order processing /total number of order processing) × 100%. The supplier's logistics management ability can be reflected by the accurate delivery ratio of orders, i.e., b_3 = (number of accurate delivery orders /total number of orders) × 100%, where the accurate delivery orders means the supplier deliver the goods to the procurer in accordance with the time, the location and the quantity prescribed by the purchase contract, and the perfectness ratio of goods is 100%. We denote $b = (b_1 + b_2 + b_3)/3$ as a supplier's management level. The greater the value of b, the lower the supplier's management risk level is. Table 4 gives a method to quantify a supplier's management risk.

A_8 Economic risk has two aspects: risks due to the changes in a supplier's business environment such as financial crisis and stock market fluctuations. These factors affect a supplier's investment and cash flow. The other is the risk due to the changes in a supplier's market such as demand volatility and competitive behavior. These factors affect a supplier's operations and development. Table 5 gives the method to quantify a supplier's economic risk.

A_9 Environmental risk refers to the risks due to natural disasters such as earthquakes. These disasters have a low likelihood of occurrence but the consequences are often dire. This attribute investigates whether there are natural disasters in the supplier locations, as well as whether there are risk prevention measures and contingency plans to respond to these risks. Table 6 shows the method for quantifying a supplier's environmental risk.

A_{10} Societal risk refers to the risk caused by destabilizing factors such as laws and regulations in a supplier's country or region, opaque laws and policies, political instability, and civil conflicts. While such risks are low in probability, business prefers socially stable locations even when the operating cost may be high. Table 7 gives the method to quantify the supplier's societal risk.

A_{11} Ethical risk is the risk caused by asymmetric information and unhonoured contracts. In the procurement process, this risk arises from the bad behavior of suppliers such as fraud, cheating on workmanship and materials, and shoddy goods. Table 8 gives the method to quantify a supplier's ethical risk.

In the above 11 attributes, A_1 and A_3 are benefit type attributes, i.e., the greater the attribute value, the better the corresponding supplier. The rest are cost type attributes, i.e., the smaller the attribute value, the better the corresponding supplier. Further, the attributes can be divided into two types: the attributes of a precise number type and a linguistic fuzzy variable type.

The attributes of a precise number type are: A_1 quality, A_2 price, A_3 quantity and A_4 delivery time. In certain goods procurement, the values of this kind of attribute are submitted directly by the suppliers in their bids, and the values are real numbers. The attribute set formed by the attributes of the precise number type is denoted as $A^1 = \{A_1, A_2, A_3, A_4\}$.

The attributes of a linguistic fuzzy variable type: A_5 technology risk, A_6 information risk, A_7 management risk, A_8 economic risk, A_9 environmental risk, A_{10} societal risk and A_{11} ethical risk. These attributes are somewhat qualitative and fuzzy, and their evaluation values cannot be given precisely, but generally given in the form of "Potential risk, Low Risk, Medium risk and High Risk" by the buyer. The attribute set formed by the attributes of a linguistic fuzzy variable type is denoted as $A^2 = \{A_5, A_6, \ldots, A_{11}\}$.

In the practical evaluation and selection of suppliers, we must perform multi-attribute decision making according to the information of the 11 attributes. The values of the attributes in set A^1 can

Table 2
Method to evaluate supplier's technology risk.

Risk level	Description
Potential	Supplier's new product development capability is very strong. ($a \geqslant 90$)
Low	Supplier's new product development capability is strong. ($70 \leqslant a < 90$)
Medium	Supplier's new product development capability is fair. ($50 \leqslant a < 70$)
High	Supplier's new product development capability is poor. ($a < 50$)

Table 3
Method to evaluate supplier's information risk.

Risk level	Description
Potential	The supplier has an advanced and efficient MIS and perfect information sharing mechanism and has achieved integrated information management
Low	The supplier has a good MIS and information sharing mechanism, and has achieved integrated management of production, finance, and logistics
Medium	The supplier has an MIS and information sharing mechanism, but has not achieved information integration and information sharing
High	The supplier lacks an effective MIS, and no information processing

Table 4
Method to evaluate supplier's management risk.

Risk level	Description
Potential	Supplier's management level is very high. ($b \geqslant 90$)
Low	Supplier's management level is high. ($70 \leqslant b < 90$)
Medium	Supplier's management level is acceptable. ($50 \leqslant b < 70$)
High	Supplier's management level is low. ($b < 50$)

Table 5
Method to evaluate supplier's economic risk.

Risk level	Description
Potential	Economic growth is good, market is mature, infrastructure is good, and development prospect is good
Low	One or two of the above four aspects is weak
Medium	Economic growth is relatively slow, market is immature, but good development potential
High	Economic growth is slow, market is closed, and poor development potential

Table 6
Method to evaluate supplier's nature risk.

Risk level	Description
Potential	There are no major natural disasters in the past three years, and the supplier has detailed prevention and contingency plans
Low	There are no major natural disasters in past year, and the supplier has detailed prevention and contingency plans
Medium	There are major natural disasters recently, and the supplier has simple prevention and emergency measures
High	Natural disasters are frequent but supplier has no prevention and emergency measures

Table 7
Method to evaluate supplier's societal risk.

Risk level	Description
Potential	The supplier's region has an efficient and transparent political system, stable legal policy, and open political and legal environment
Low	The supplier's region has a stable political environment, healthy policy and legal environment, and the legal system is constantly improved
Medium	The political system is relatively stable, policies can be improved, and the legal system is relatively backward
High	The political system is unstable, the policies are unclear, and the legal system is incomplete in the region of the supplier

Table 8
Method to evaluate supplier's ethical risk.

Risk level	Description
Potential	The supplier has good reputation, and he can always fulfill the procurement contract to provide high-quality products within a specified time
Low	The supplier has a good reputation and can fulfill the contract; the defective rate is low, and the delivery time is relatively punctual
Medium	The reputation of the supplier is fair and occasionally breaks contracts
High	The reputation of the supplier is poor, and the supplier often breaks contracts; the defective rate is high, and the delivery is not on time

be given by real numbers, but the values of attributes in set A^2 must be quantified and then can be used for multi-attribute decision making. We now give a method for transforming the linguistic fuzzy variables into interval numbers in Definition 1.

Definition 1. Suppose $F_a = \{f_1, f_2, f_3, f_4\}$ = {Potential risk, Low risk, Medium risk, High risk} is a set formed by the attributes of a linguistic fuzzy variable type, then the corresponding interval number to F_a: $f_1 = [0.9,1]$, $f_2 = [0.7,0.9]$, $f_3 = [0.5,0.7]$, $f_4 = [0.2,0.5]$, where Potential risk ≻ Low Risk ≻ Medium risk ≻ High Risk.Under the above evaluation system, the problem can be described as follows. A buyer wants to procure Q_0 units of divisible goods such as coal, oil, and natural gas. The buyer has m risk neutral suppliers to choose from, and the supplier set is denoted as $M = \{1, 2, \ldots, m\}$, using the 11 attributes given above. The set of weights for the attributes is denoted as $W = \{w_1, w_2, \ldots, w_{11}\}$, with $0 \leqslant w_j \leqslant 1$ and $\sum_{j=1}^{11} w_j = 1$. The values of attribute weights can be determined by Delphi method or Analytic Hierarchy Process method in the practical decision-making of supplier selection.

3. Two-stage compound mechanism design of supplier selection

We now design a two-stage compound mechanism for supplier selection. In the first stage, we design a multi-auction mechanism to determine the shortlist of suppliers by considering the four attributes under a commercial criterion. In the second stage, we further include the seven risk attributes of the shortlist and design a multi-attribute decision making mechanism to select the final supplier (s).

3.1. Stage 1: determine the shortlist by a multi-auction mechanism

Before the suppliers (bidders) submit their bids, the buyer (auctioneer) will announce some basic requirements and the scoring rules for the procurement to all suppliers. Then all suppliers submit sealed bids to the buyer. Within the auction, every supplier has only one chance to submit a bid. When the bidding process is over, the buyer will analyse the bids, and publish the scores and rank order. The buyer will determine the shortlist, according to the scores and his actual procurement amount.

3.1.1. Assumptions and notations

In a multi-auction procurement auction of divisible goods Q_0, a buyer will consider four attributes under a commercial criterion, i.e., A_1 quality, A_2 price, A_3 quantity and A_4 delivery time. Attribute A_1 comprises several sub-attributes. For instance, in electricity coal procurement, these sub-attributes are calorific value, moisture, volatile matter, ash melting point, and sulfur coal classification.

Supplier i's values of attributes A_1, A_2, A_3 and A_4 are denoted by a_i, p_i, q_i, t_i, respectively, $i = 1, 2, \ldots, m$. In the auction, supplier i submits a sealed bid in the form (a_i, p_i, q_i, t_i), where $p_i, q_i, t_i, \in R$ and a_i is an ordered array with $a_i = (a_1, a_2, \ldots, a_s)$, and $a_1, a_2, \ldots, a_s$ are the attribute values of s sub-attributes of quality respectively.

For supplier i, the cost of supplying one unit of good depends on the quality value a_i, and the delivery time t_i. The cost function is denoted as $C_i(a_i, t_i)$, which is increasing in a_i and decreasing in t_i (David, Azoulay-Schwartz, & Kraus, 2006; Rao & Zhao, 2011; Rao, Zhao, & Ma, 2012). Then the utility of supplier i who will supply the buyer with q_i units of goods at unit price p_i can be expressed as $U_{si}(a_i, p_i, q_i, t_i) = q_i[p_i - C_i(a_i, t_i)]$. Clearly, supplier i's total utility increases with the increase in the bid price p_i, and decreases with the increase in a_i.

For the buyer, we assume that the buyer's utility function is additive across the s quality sub-attributes and t_i, and the buyer's revenue function is $u_{ik}(a_{ik})$ on the k^{th} ($k = 1, 2, \ldots, s$) quality sub-attribute value a_{ik}, and the buyer's revenue function on delivery time t_i is denoted as $u_i(t_i)$ (David et al., 2006; Rao & Zhao, 2011; Rao et al., 2012). Then, when supplier i supplies a buyer q_i units of goods at unit price p_i, the buyer's total revenue can be expressed as $U_{bi}(a_{i1}, a_{i2}, \ldots, a_{is}, p_i, q_i, t_i) = q_i[\sum_{k=1}^{s} u_{ik}(a_{ik}) + u_i(t_i) - p_i]$ where $u_{ik}(a_{ik})$ is increasing, concave and twice continuously differentiable in a_{ik}. $u_i(a_i)$ is decreasing in t_i. This is because the delivery time t_i is a cost type attribute for the buyer. A longer delivery time t_i will provide a smaller utility to the buyer.

3.1.2. Bidding and scoring rules

(1) Bidding rules

To ensure that the bids are effective and feasible, the buyer will announce some standards and rules at the beginning of the bidding, for example,

(1) The quality level should not be less than the given reserve value $\underline{a}$, for instance, in electricity coal procurement, the bid values of the six quality sub-attributes in a supplier's bid should not be less than the given reserve values $\underline{a} = (\underline{a}_1, \underline{a}_2, \ldots, \underline{a}_6)$. The detailed reserve values can be based on the quality measures of the national standard GB/T7562-2010 in China.
(2) The price submitted by a supplier should not exceed the reserve price $\bar{p}$, i.e., $p_i \leqslant \bar{p}$.
(3) Each supplier's delivery time cannot exceed the prescribed time limit, i.e., it must satisfy $t_i \leqslant \bar{t}$, where $\bar{t}$ is the longest delivery time.
(4) To let more suppliers have a chance to supply the goods, the buyer will limit the suppliers' maximum supply quantity i.e., $q_i \leqslant \bar{q}$, $i = 1, 2, \ldots, n$, where $\bar{q}$ is the maximum supply quantity for all suppliers.

All submitted bids must meet these standards and rules, or be eliminated from the auction.

(2) Scoring rules for suppliers

The scoring rule (score function) is used to select the optimal bid. The buyer will announce this scoring rule to all suppliers at the beginning of the procurement auction. Thus, the buyer can design the scoring rule from his total utility function $U_{bi}(a_{i1}, a_{i2}, \ldots, a_{is}, p_i, q_i, t_i) = q_i\left[\sum_{k=1}^{s} u_{ik}(a_{ik}) + u_i(t_i) - p_i\right]$. To achieve the goal of maximizing utility, and to induce the suppliers to announce their actual cost truthfully, the buyer can define the scoring function as follows: $S_i = \sum_{k=1}^{s} u_{ik}(a_{ik}) + u_i(t_i) - p_i$.

Clearly, S_i is increasing in a_{ik}, and decreasing in price p_i and delivery time t_i, and the revenue from the goods increases with the increase in S_i. Thus, the buyer will only shortlist suppliers using the higher scores.

(3) Rules for selecting shortlist

As a supplier can only provide a limited number of goods, it is difficult to meet the buyer's every needs within a stipulated time. Hence, the buyer can use a multi-source procurement strategy, i.e., the bid winner is not unique; there can be one or more suppliers chosen. In this stage of the auction, the buyer can rank the suppliers' scores from high to low, and then select l suppliers whose scores in the top l as the shortlist, according to his actual total procurement amount and the suppliers' maximum supply quantity in the bids. The value of l must satisfy the condition $\sum_{i=1}^{l} q_i \geqslant Q_0$, which means that the l suppliers have enough supply capacity.

It is easy to prove that the above auction mechanism has an information incentive, i.e., this mechanism can encourage suppliers to submit actual bid information on quality, price, and delivery time. In fact, under the scoring rule, $S_i = \sum_{k=1}^{s} u_{ik}(a_{ik}) + u_i(t_i) - p_i$. To improve their ideal scores and to stand a better chance to be shortlisted, supplier i will increase the quality value $a_i = (a_{i1}, a_{i2}, \ldots, a_{is})$ within his technical capability and production level as far as possible, and shorten the delivery time t_i and decrease the selling price p_i within his budget. Reporting false information on quality, price, and delivery time will lead to low scores and risk elimination in this auction stage. Thus, the auction mechanism has an information incentive.

3.2. Stage 2: determine winners by multi-attribute decision making

In the second stage, we design a multi-attribute decision making mechanism to select the final supplier(s) from the shortlist. We propose a method based on the grey correlation degree of mixing sequences to evaluate and rank the shortlist under the seven risk attributes and four commercial attributes. The winner(s) will be determined according to the rank results. The specific steps are given as follows.

3.2.1. Data processing

The original decision making matrix formed by the values of the 11 evaluation attributes for the l shortlisted suppliers is denoted as $X = (x_{ij})_{l\times 11}$, $i = 1, 2, \ldots l$, where x_{ij} is the attribute value of finalist i under attribute A_j, j=1, 2, ..., 11. We set $N_1 = \{1,2,3,4\}$, $N_2 = \{5, 6, \ldots, 11\}$. According to the classification information of the attributes in Section 2, if $j \in N_1$, then $x_{ij} \in R$. If $j \in N_2$, then x_{ij} is a linguistic fuzzy variable such as potential, low, moderate, and high risk.

For attribute value x_{ij}, when $j \in N_2$, x_{ij} can be transformed as an interval number. The original decision making matrix $X = (x_{ij})_{l\times 11}$ can then be rewritten as a new decision matrix $Y = (y_{ij})_{l\times 11}$.

The physical dimensions of the 11 attributes are different. To eliminate the influence of the different physical dimensions on the decision result, we normalize the matrix $Y = (y_{ij})_{l\times 11}$. The normalized matrix is denoted as $Z = (z_{ij})_{l\times 11}$, where

$$z_{ij} = \begin{cases} z_{ij} & i = 1, 2, \ldots, l, \quad j \in N_1 \\ \left[z_{ij}^L,\ z_{ij}^U\right] & i = 1, 2, \ldots, l, \quad j \in N_2 \end{cases}.$$

The normalized processing method (Xu, 1999) is given as follows.

(i) When $y_{ij} \in R$, for a benefit type attribute, the normalized processing rule is

$$z_{ij} = \frac{y_{ij} - \min_i y_{ij}}{\max_i y_{ij} - \min_i y_{ij}} \quad i = 1, 2, \ldots, l, \quad j \in N_1 \tag{1}$$

(ii) When $y_{ij} \in R$, for a cost type attribute, the normalized processing rule is

$$z_{ij} = \frac{\max_i y_{ij} - y_{ij}}{\max_i y_{ij} - \min_i y_{ij}} \quad i = 1, 2, \ldots, l, \quad j \in N_1 \tag{2}$$

(iii) When y_{ij} is an interval number, for a benefit type attribute, the normalized processing rule is

$$\begin{cases} z_{ij}^L = \dfrac{y_{ij}^L}{\sqrt{\sum_{i=1}^{l}\left(y_{ij}^U\right)^2}} \\ z_{ij}^U = \dfrac{y_{ij}^U}{\sqrt{\sum_{i=1}^{l}\left(y_{ij}^L\right)^2}} \end{cases} \quad i = 1, 2, \ldots, l, \quad j \in N_2 \tag{3}$$

(iv) When y_{ij} is an interval number, for a cost type attribute, the normalized processing rule is

$$\begin{cases} z_{ij}^L = \dfrac{\frac{1}{y_{ij}^U}}{\sqrt{\sum_{i=1}^{l}\left(\frac{1}{y_{ij}^L}\right)^2}} \\ z_{ij}^U = \dfrac{\frac{1}{y_{ij}^L}}{\sqrt{\sum_{i=1}^{l}\left(\frac{1}{y_{ij}^U}\right)^2}} \end{cases} \quad i = 1, 2, \ldots, l, \quad j \in N_2 \tag{4}$$

3.2.2. Ranking method based on grey correlation degree of mixed sequences

The idea of a ranking method based on the grey correlation degree of mixed sequences is to compare and to rank the alternatives by a grey correlation degree between the compared sequence and the optimal reference sequence, where the compared sequence and the optimal reference sequence are all formed by mixed data (real numbers and interval numbers coexist). The greater the grey correlation degree, the better the corresponding alternative (Rao & Peng, 2009; Rao & Zhao, 2011; Xiao, Song, & Li, 2005). The first step is to determine the reference sequence and compared sequence. The reference sequence is a set of data used to reflect the characteristics of the ideal system. Here we will create an optimal fictional supplier (the best reference object) from the l shortlisted suppliers. The attribute values of this fictional supplier comprise all the optimal values of the shortlisted suppliers under the 11 attributes, and all the optimal values constitute the reference sequence. The values of the 11 attributes for each finalist form a compared sequence. Then we calculate the grey correlation degree between the reference sequence and each compared sequence, and rank the shortlisted suppliers.

Definition 2. z_i is a mixed attribute sequence if in decision matrix $Z = (z_{ij})_{l\times 11}$, the 11 elements of each row form the following sequence

$$z_i = \left(z_{i,1}, z_{i,2}, z_{i,3}, z_{i,4}, \left[z^L_{i,5}, z^U_{i,5}\right], \left[z^L_{i,6}, z^U_{i,6}\right], \ldots, [z^L_{i,11}, z^U_{i,11}], \quad i = 1, 2, \ldots, l \right. \tag{5}$$

For the ranking method based on the grey correlation degree of mixed sequence Z, each mixed attribute sequence z_i is just a compared sequence. Based on the mixed attribute sequences $z_1, z_2, \ldots, z_l$, the definition of a positive ideal is given as follows.

Definition 3. From the mixed attribute sequences $z_1, z_2, \ldots, z_l$ in a normalized decision matrix $Z = (z_{ij})_{l\times 11}$, we set

$$z_0 = (z_{0,1}, z_{0,2}, \ldots, z_{0,11}) = \Big(\max_{1\leqslant i\leqslant l} z_{i,1}, \max_{1\leqslant i\leqslant l} z_{i,2}, \max_{1\leqslant i\leqslant l} z_{i,3}, \max_{1\leqslant i\leqslant l} z_{i,4}, \left[\max_{1\leqslant i\leqslant l} z^L_{i,5}, \max_{1\leqslant i\leqslant l} z^U_{i,5}\right], \left[\max_{1\leqslant i\leqslant l} z^L_{i,6}, \max_{1\leqslant i\leqslant l} z^U_{i,6}\right], \ldots, \left[\max_{1\leqslant i\leqslant l} z^L_{i,11}, \max_{1\leqslant i\leqslant l} z^U_{i,11}\right]\Big) \tag{6}$$

Then z_0 is called a positive ideal.

The positive ideal given in Definition 3 is just the reference sequence in the ranking method based on the grey correlation degree of mixed sequences. The formula of the traditional grey correlation degree only applies to the case when the numbers in the reference sequence and compared sequences are real, but the reference sequence and compared sequence in this paper are mixed sequences where real numbers and interval numbers coexist. So we cannot directly use the expression for the traditional grey correlation degree to calculate the grey correlation degree. Next, we reference the definition of the traditional grey correlation degree and define a grey correlation degree of a mixed sequence.

Definition 4. For the compared sequences given by Eq. (5),

$$z_1 = \left(z_{1,1}, z_{1,2}, z_{1,3}, z_{1,4}, \left[z^L_{1,5}, z^U_{1,5}\right], \left[z^L_{1,6}, z^U_{1,6}\right], \ldots, \left[z^L_{1,11}, z^U_{1,11}\right]\right),$$
$$z_2 = \left(z_{2,1}, z_{2,2}, z_{2,3}, z_{2,4}, \left[z^L_{2,5}, z^U_{2,5}\right], \left[z^L_{2,6}, z^U_{2,6}\right], \ldots, \left[z^L_{2,11}, z^U_{2,11}\right]\right),$$
$$\cdots$$
$$z_l = \left(z_{l,1}, z_{l,2}, z_{l,3}, z_{l,4}, \left[z^L_{l,5}, z^U_{l,5}\right], \left[z^L_{l,6}, z^U_{l,6}\right], \ldots, \left[z^L_{l,11}, z^U_{l,11}\right]\right),$$

and the reference sequence given by Eq. (6)

$$z_0 = (z_{0,1}, z_{0,2}, \ldots, z_{0,11}) = \Big(\max_{1\leqslant i\leqslant l} z_{i,1}, \max_{1\leqslant i\leqslant l} z_{i,2}, \max_{1\leqslant i\leqslant l} z_{i,3}, \max_{1\leqslant i\leqslant l} z_{i,4}, \left[\max_{1\leqslant i\leqslant l} z^L_{i,5}, \max_{1\leqslant i\leqslant l} z^U_{i,5}\right], \left[\max_{1\leqslant i\leqslant l} z^L_{i,6}, \max_{1\leqslant i\leqslant l} z^U_{i,6}\right], \ldots, \left[\max_{1\leqslant i\leqslant l} z^L_{i,11}, \max_{1\leqslant i\leqslant l} z^U_{i,11}\right]\Big),$$

the grey relational coefficient between z_{0j} and z_{ij} is defined as

$$r(z_{0j}, z_{ij}) = \frac{\rho \max_i \max_j D(z_{0j}, z_{ij})}{D(z_{0j}, z_{ij}) + \rho \max_i \max_j D(z_{0j}, z_{ij})}, \tag{7}$$

and the grey correlation degree of mixed sequence between the compared sequence z_i $(i = 1, 2, \ldots, l)$ and the reference sequence z_0 is defined as

$$r(z_0, z_i) = \sum_{j=1}^{11} w_j r(z_{0j}, z_{ij}), \tag{8}$$

where $D(z_{0j}, z_{ij})$ is the distance between z_{0j} and z_{ij}. When $j \in N_1$, i.e., z_{0j} and $z_{ij} \in R$, we have

$$D(z_{0j}, z_{ij}) = \left|\max_{1\leqslant i\leqslant l} z_{ij} - z_{ij}\right|.$$

When $j \in N_2$, i.e., z_{0j} and z_{ij} are all interval numbers, we have

$$D(z_{0j}, z_{ij}) = \frac{\sqrt{2}}{2}\sqrt{\left(\max_{1\leqslant i\leqslant l} z^L_{ij} - z^L_{ij}\right)^2 + \left(\max_{1\leqslant i\leqslant l} z^U_{ij} - z^U_{ij}\right)^2},$$

where ρ is the distinguishing coefficient, $\rho \in (0, 1)$. Generally, we set $\rho = 0.5$; w_j is the weight of the j-th attribute A_j, $j = 1, 2, \ldots, 11$, which satisfies $0 \leqslant w_j \leqslant 1, \sum_{j=1}^{11} w_j = 1$.

Theorem 1. *The grey relational degree of mixed sequences $r(z_0, z_i)$ defined in Definition 4 satisfies the four axioms of grey relational analysis, i.e.,*

(1) *Normality*

$$0 \leqslant r(z_0, z_i) \leqslant 1,$$

$$r(z_0, z_i) = 0 \iff z_0,\ z_i \in \phi \text{ (empty set)},$$

$$r(z_0, z_i) = 1 \iff z_0 = z_i.$$

(2) *Symmetry*

$$r(z_0, z_i) = r(z_i, z_0) \iff X = \{z_0, z_i\}.$$

(3) *Wholeness*

$$z_i, z_j \in X = \{z_s | s = 0, 1, 2, \ldots, l, l \geqslant 2\}, \quad z(x_i, x_j) \neq z(x_j, x_i).$$

(4) *Approachability: The smaller the value of $D(z_{0j}, z_{ij})$, the greater is $r(z_0, z_i)$ where z_0 is the reference sequence, and z_i $(i = 1, 2, \ldots, l)$ is the compared sequence.*

Theorem 1 *is proved by a similar process of the traditional grey correlation degree* (*see* Xiao et al., 2005).

The process of ranking based on the grey correlation degree of a mixed sequence is as follows. For the l finalists, we select 11 maximum values of the 11 attributes to form the positive ideal (reference sequence), then we use the calculation method of grey correlation degree of a mixed sequence given by Definition 4 to calculate the grey correlation degree $r(z_0, z_i)$ between the compared sequence z_i and the reference sequence z_0. $r(z_0, z_i)$ reflects the degree of closeness between shortlisted supplier i and the optimal fictional supplier. The greater the value of $r(z_0, z_i)$, the closer is supplier i to the optimal fictional supplier.

3.2.3. Method of determining winners

In practical procurement, a buyer can use a multi-source procurement strategy, i.e., the final suppliers can be one or more. We now provide a method of determining the winners in the multi-source procurement of divisible goods.

Using the ranking method based on the grey correlation degree of a mixed sequences given in Section 3.2.2, we obtain the grey correlation degree $r(z_0, z_i)$ of the l finalists. We set the ranking order as $r_1 \geqslant r_2 \geqslant \ldots \geqslant r_l$, and the maximum supply quantities in the corresponding finalists' bids in the multi-auction stage as $q_{r_1}, q_{r_2}, \ldots, q_{r_l}$. The rule for determining the winners is that the buyer allocates the goods to the supplier with a greater grey correlation degree $r(z_0, z_i)$. The detailed allocation method is as follows.

(1) The buyer allocates a total amount Q_0 to the supplier with the greatest grey correlation degree r_1. So the supplier with

the greatest grey correlation degree r_1 is allowed a supply quantity $q_1^* = q_{r_1}$.

(2) The buyer allocates the remaining amount $Q_0 - q_{r_1}$ to the supplier with the second greatest grey correlation degree r_2. We discuss it in two different cases as follows.

Case 1: If $q_{r_2} \geqslant Q_0 - q_{r_1}$, then $q_2^* = Q_0 - q_{r_1}$, and $q_3^* = q_4^* = \ldots = q_l^* = 0$, which means that the supplier with the second greatest grey correlation degree r_2 is allocated the remaining amount $Q_0 - q_{r_1}$. The allocation is complete. The two suppliers whose grey correlation degree is in the top 2 ranks are selected.

Case 2: If $q_{r_2} < Q_0 - q_{r_1}$, then $q_2^* = q_{r_2}$, and the residual amount $Q_0 - q_{r_1} - q_{r_2}$ will be allocated to the rest of the suppliers sequentially.

Similarly, for any q_k^*, $k = 3, 4, \ldots, l$, if $q_{r_k} \geqslant Q_0 - \sum_{i=1}^{k-1} q_{r_i}$, we have $q_k^* = Q_0 - \sum_{i=1}^{k-1} q_{r_i}$, and $q_{k+1}^* = q_{k+2}^* = \ldots = q_l^* = 0$, which means that the allocation is complete, and the suppliers whose grey correlation degree in the top k ranks are selected. If $q_{r_k} < Q_0 - \sum_{i=1}^{k-1} q_{r_i}$, then $q_k^* = q_{r_k}$, and the residual amount $Q_0 - \sum_{i=1}^{k} q_{r_i}$ will be allocated to the rest of the suppliers sequentially.

When $k = h$, $3 \leqslant h \leqslant l$, amount Q_0 is fully allocated. Then the suppliers whose grey correlation degree is in the top h ranks are selected. Suppose the buyer procures the goods based on some discriminatory price, then the transaction price is the unit price in each winner's bid, i.e., $p_i^* = p_i$. For these h suppliers, the paid rules are given as follows. The winner i will obtain the allowable supply quantity q_i^* and is paid the total payment $p_i q_i^*$ by the buyer. All winners must supply their promised goods to the buyer within the delivery time given in their bids.

3.3. Implementation of two-stage compound mechanism

Combining the analysis and discussion in Sections 3.1 and 3.2, we now summarize the implementation steps of our two-stage compound mechanism for the procurement of divisible goods.

Step 1: At the start of the procurement auction, a buyer announces some standards and rules to the suppliers such as the score rule $S_i = \sum_{k=1}^{s} u_{ik}(a_{ik}) + u_i(t_i) - p_i$, the reserve price $\bar{p}$, the reserve values of quantity $\underline{a}$, the longest delivery time $\bar{t}$, and the maximum supply quantity $\bar{q}$ for all suppliers.

Step 2: Every supplier submits a sealed bid with the form $(a_{i1}, a_{i2}, \ldots, a_{is}, p_i, q_i, t_i)$ based on the standards and rules set by the buyer. Every supplier has only one chance to submit the bid.

Step 3: After all suppliers submit their bids, the buyer computes the scores according to the score rule $S_i = \sum_{k=1}^{s} u_{ik}(a_{ik}) + u_i(t_i) - p_i$, and ranks the scores from high to low. The buyer selects l suppliers whose scores are in the top l as the shortlist according to his actual total procurement amount and all of the suppliers' maximum supply quantity in the bids.

Step 4: For the l finalists determined in the first stage, we further consider 7 risk attributes in addition to the 4 attributes under a commercial criterion, and construct a decision matrix $X = (x_{ij})_{m \times 11}$, $i = 1, 2, \ldots, l$.

Step 5: Using the transformation method in Definition 1, the linguistic fuzzy variables in $X = (x_{ij})_{m \times 11}$ are transformed as interval numbers, and a new decision matrix $Y = (y_{ij})_{l \times 11}$ is found.

Step 6: Use Eqs. (1)–(4) to process the data in matrix $Y = (y_{ij})_{l \times 11}$, the normalized decision making matrix $Z = (z_{ij})_{l \times 11}$ is obtained.

Step 7: Use Eqs. (5) and (6) to determine the positive ideal (reference sequence) z_0 and compared sequences $z_1, z_2, \ldots, z_l$ from $Z = (z_{ij})_{l \times 11}$.

Step 8: Use Eqs. (7) and (8) to calculate the grey correlation degree $r(z_0, z_i)$ $(i = 1, 2, \ldots, l)$ between the compared sequence z_i and the reference sequence z_0.

Step 9: Rank all the finalists in accordance to the value $r(z_0, z_i)$, $i = 1, 2, \ldots, l$.

Step 10: Use the winner selection method of Section 3.2.3 to determine the final winners. The winner (supplier i) will get the total payment $p_i q_i^*$ to supply quantity q_i^* to the buyer.

4. Multi-source procurement of electricity coal

We now give an example for the multi-source procurement of electricity coal to show how to implement our two-stage compound mechanism, and to demonstrate the effectiveness of this compound mechanism.

Suppose a buyer of a power-generation firm wants to procure 800 tons of electricity coal. Ten risk neutral suppliers participate in the supply competition i.e. $M = \{1, 2, \ldots, 10\}$. Here we use the above 11 attributes to select the optimal supplier(s), i.e., A_1 quality, A_2 price (price per ton electricity coal, in yuan/ton), A_3 quantity (maximum supply quantity, in tons), A_4 delivery time (in days), A_5 technology risk, A_6 information risk, A_7 management risk, A_8 economic risk, A_9 environmental risk, A_{10} societal risk, and A_{11} ethical risk, where A_1 quality includes the following two sub-attributes.

B_1 (tvdaf, in percentage). Tvdaf is the core index to distinguish the combustion characteristic for electricity coal. The higher the value of Tvdaf, the easier it is to burn coal.

B_2 (calorific value, in kcal/g). Calorific value is an important basis for boiler design.

For supplier i, $i = 1, 2, \ldots, 10$, the values of the above 12 attributes and sub-attributes are now denoted as $a_{i1}, a_{i2}, p_i, q_i, t_i, b_{i1}, b_{i2}, b_{i3}, b_{i4}, b_{i5}, b_{i6}, b_{i7}$ respectively. Let the weight set of the 12 attributes be $W = (w_1, w_2, \ldots, w_{12}) = (0.1, 0.1, 0.15, 0.05, 0.1, 0.1, 0.1, 0.1, 0.1, 0.025, 0.025, 0.05)$. We now show how to implement the two-stage compound mechanism.

4.1. Decision making process

(1) Stage 1: determine the shortlist by a multi-auction mechanism

The buyer announces the relative auction rules: the calorific value a_{i1} in each supplier's bid must be at least 5 kcal/g, the tvdaf value a_{i2} in each supplier's bid must be at least 24%. The bid price per ton of electricity coal is no greater than 190 yuan/ton. The delivery time must be less than or equal to 20 days. The maximum supply quantity in each supplier's bid must be less than or equal to 400 tons. All bids must satisfy these rules.

Set supplier i's cost function on quality attribute A_j as $C_i(a_{i1}, a_{i2}, t_i) = k_1 a_{i1} + k_2 a_{i2} + \frac{h_1}{t_i}$, $i = 1, 2, \ldots, 10$ where k_1 and k_2 are the quality attribute coefficients of attributes B_1 and B_2 respectively for the suppliers, h_1 is the delivery time coefficient for the suppliers. k_1, k_2 and h_1 are the same for all suppliers. Then supplier i's utility generated by a unit quantity of goods can be expressed as

$$U_{si}(a_{i1}, a_{i2}, p_i, t_i) = p_i - C_i(a_{i1}, a_{i2}, t_i) = p_i - \left(k_1 a_{i1} + k_2 a_{i2} + \frac{h_1}{t_i}\right).$$

In this example, we set $k_1 = 150$, $k_2 = 100$, $h_1 = 200$.

When supplier i submits a bid $(a_{i1}, a_{i2}, p_i, q_i, t_i)$, the buyer's total utility from supplier i is $U_{bi}(a_{i1}, a_{i2}, p_i, q_i, t_i) = q_i\left[\sum_{k=1}^{2} u_{ik}(a_{ik}) + u_i(t_i) - p_i\right] = q_i\left[l_1\sqrt{a_{i1}} + l_2\sqrt{a_{i2}} + \frac{h_2}{t_i}\right]$, $i = 1, 2, \ldots, 10$. So the score function is $S_i = \sum_{k=1}^{2} u_{ik}(a_{ik}) + u_i(t_i) - p_i = l_1\sqrt{a_{i1}} + l_2\sqrt{a_{i2}} + \frac{h_2}{t_i} - p_i$, $i = 1, 2, \ldots, 10$ where l_1 and l_2 are the quality attribute coefficients of attributes B_1 and B_2 respectively for the buyer. h_2 is the delivery time coefficient for the suppliers. We set $l_1 = 50$, $l_2 = 60$, $h_2 = 30$.

Suppose the suppliers submit their bids based on their actual cost and the bidding rules.

Supplier 1: $(a_{11}, a_{12}, p_1, q_1, t_1)$ = (7.5, 26.3, 170, 300, 16).
Supplier 2: $(a_{21}, a_{22}, p_2, q_2, t_2)$ = (7.2, 23.5, 160, 280, 14).
Supplier 3: $(a_{31}, a_{32}, p_3, q_3, t_3)$ = (6.8, 28.9, 165, 320, 17).
Supplier 4: $(a_{41}, a_{42}, p_4, q_4, t_4)$ = (6.5, 25.7, 190, 255, 18).
Supplier 5: $(a_{51}, a_{52}, p_5, q_5, t_5)$ = (7.9, 24.6, 175, 380, 19).
Supplier 6: $(a_{61}, a_{62}, p_6, q_6, t_6)$ = (8.5, 20.9, 185, 350, 15).
Supplier 7: $(a_{71}, a_{72}, p_7, q_7, t_7)$ = (8.1, 25.8, 180, 360, 17).
Supplier 8: $(a_{81}, a_{82}, p_8, q_8, t_8)$ = (6.9, 27.7, 170, 340, 18).
Supplier 9: $(a_{91}, a_{92}, p_9, q_9, t_9)$ = (7.7, 24.2, 175, 310, 17).
Supplier 10: $(a_{101}, a_{102}, p_{10}, q_{10}, t_{10})$ = (7.1, 24.6, 180, 300, 19).

where each supplier's quantity q_i is determined according to his production ability within the contracted time and maximum bid quantity of $q_{\max} = 400$ tons set by the buyer.

From the score function $S_i = l_1\sqrt{a_{i1}} + l_2\sqrt{a_{i2}} + \frac{h_2}{t_i} - p_i$, we obtain the suppliers' scores: S_1 = 276.5, S_2 = 267.2, S_3 = 289.7, S_4 = 243.3, S_5 = 264.7, S_6 = 237.1, S_7 = 268.8, S_8 = 278.8, S_9 = 260.7, and S_{10} = 252.4.

Thus, $S_3 > S_8 > S_1 > S_7 > S_2 > S_5 > S_9 > S_{10} > S_4 > S_6$. According to this ranking result, we shortlist suppliers 3, 8, 1, 7, 2 and 5. These six finalists are allowed to enter the second stage.

(2) Stage 2: determine the winners by multi-attribute decision making

We now consider the risk factors of the finalists. We synthesize the five attributes under a commercial criterion and the seven risk attributes, and construct the original decision matrix $X = (x_{ij})_{6\times12}$, $i = 1, 2, \ldots, 6$, where the values $a_{i1}, a_{i2}, p_i, q_i, t_i$ of the five attributes B_1, B_2, A_2, A_3, A_4 are obtained in the finalists' bids, and the other values $b_{i1}, b_{i2}, b_{i3}, b_{i4}, b_{i5}, b_{i6}, b_{i7}$ of the seven risk attributes A_5, A_6, A_7, A_8, A_9, A_{10}, A_{11} are set by the buyer. All data are listed in Table 9.

The decision process is as follows.

(1) Using the transformation method in Definition 1, i.e., f_1 = [0.9, 1], f_2 = [0.7, 0.9], f_3 = [0.5, 0.7], f_4 = [0.2, 0.5], the linguistic fuzzy variables in Table 9 are transformed as interval numbers, and the new decision matrix $Y = (y_{ij})_{6\times12}$ is obtained as follows.

$$Y = \begin{pmatrix} 7.5 & 26.3 & 170 & 300 & 16 & [0.7,0.9] & [0.9,1] & [0.5,0.7] & [0.9,1] & [0.7,0.9] & [0.5,0.7] & [0.9,1] \\ 7.2 & 23.5 & 160 & 280 & 14 & [0.5,0.7] & [0.5,0.7] & [0.9,1] & [0.2,0.5] & [0.7,0.9] & [0.9,1] & [0.9,1] \\ 6.8 & 28.9 & 165 & 320 & 17 & [0.9,1] & [0.7,0.9] & [0.7,0.9] & [0.5,0.7] & [0.9,1] & [0.7,0.9] & [0.7,0.9] \\ 7.9 & 24.6 & 175 & 380 & 19 & [0.7,0.9] & [0.5,0.7] & [0.7,0.9] & [0.7,0.9] & [0.5,0.7] & [0.2,0.5] & [0.5,0.7] \\ 8.1 & 25.8 & 180 & 360 & 17 & [0.5,0.7] & [0.7,0.9] & [0.9,1] & [0.5,0.7] & [0.5,0.7] & [0.7,0.9] & [0.7,0.9] \\ 6.9 & 27.7 & 170 & 340 & 18 & [0.9,1] & [0.5,0.7] & [0.7,0.9] & [0.9,1] & [0.7,0.9] & [0.5,0.7] & [0.9,1] \end{pmatrix}$$

(2) Using Eqs. (1)–(4) to process the data in matrix Y, the normalized decision matrix is obtained as

$$Z = \begin{pmatrix} 0.54 & 0.52 & 0.5 & 0.2 & 0.6 & [0.33,0.51] & [0.45,0.63] & [0.23,0.38] & [0.45,0.61] & [0.33,0.54] & [0.25,0.46] & [0.40,0.52] \\ 0.31 & 0 & 1 & 0 & 1 & [0.23,0.40] & [0.25,0.44] & [0.41,0.55] & [0.10,0.31] & [0.33,0.54] & [0.46,0.66] & [0.40,0.52] \\ 0 & 1 & 0.75 & 0.4 & 0.4 & [0.42,0.57] & [0.35,0.56] & [0.32,0.49] & [0.25,0.43] & [0.43,0.60] & [0.36,0.59] & [0.31,0.47] \\ 0.85 & 0.20 & 0.25 & 1 & 0 & [0.33,0.51] & [0.25,0.44] & [0.32,0.49] & [0.35,0.55] & [0.24,0.42] & [0.10,0.33] & [0.22,0.37] \\ 1 & 0.43 & 0 & 0.8 & 0.4 & [0.23,0.40] & [0.35,0.56] & [0.41,0.55] & [0.25,0.43] & [0.24,0.42] & [0.36,0.59] & [0.31,0.47] \\ 0.08 & 0.78 & 0.5 & 0.6 & 0.2 & [0.42,0.57] & [0.25,0.44] & [0.32,0.49] & [0.45,0.61] & [0.33,0.54] & [0.25,0.46] & [0.40,0.52] \end{pmatrix}$$

(3) Use Eqs. (5) and (6) to determine the positive ideal (reference sequence) z_0 and compared sequences $z_1, z_2, \ldots, z_l$.

$$z_0 = (1, 1, 1, 1, 1, [0.42, 0.57], [0.45, 0.63], [0.41, 0.55], [0.45, 0.61], [0.43, 0.60], [0.46, 0.66], [0.40, 0.52]),$$

$$z_1 = (0.54, 0.52, 0.5, 0.2, 0.6, [0.33, 0.51], [0.45, 0.63], [0.23, 0.38], [0.45, 0.61], [0.33, 0.54], [0.25, 0.46], [0.40, 0.52]),$$

$$z_2 = (0.31, 0, 1, 0, 1, [0.23, 0.40], [0.25, 0.44], [0.41, 0.55], [0.10, 0.31], [0.33, 0.54], [0.46, 0.66], [0.40, 0.52]),$$

$$z_3 = (0, 1, 0.75, 0.4, 0.4, [0.42, 0.57], [0.35, 0.56], [0.32, 0.49], [0.25, 0.43], [0.43, 0.60], [0.36, 0.59], [0.31, 0.47]),$$

$$z_4 = (0.85, 0.20, 0.25, 1, 0, [0.33, 0.51], [0.25, 0.44], [0.32, 0.49], [0.35, 0.55], [0.24, 0.42], [0.10, 0.33], [0.22, 0.37]),$$

$$z_5 = (1, 0.43, 0, 0.8, 0.4, [0.23, 0.40], [0.35, 0.56], [0.41, 0.55], [0.25, 0.43], [0.24, 0.42], [0.36, 0.59], [0.31, 0.47]),$$

$$z_6 = (0.08, 0.78, 0.5, 0.6, 0.2, [0.42, 0.57], [0.25, 0.44], [0.32, 0.49], [0.45, 0.61], [0.33, 0.54], [0.25, 0.46], [0.40, 0.52]).$$

(4) Use Eqs. (7) and (8) to calculate the grey correlation degree $r(z_0, z_i)$ between the compared sequence z_i and the reference sequence z_0; the results are as follows. $r(z_0, z_1) = 0.700$, $r(z_0, z_2) = 0.745$, $r(z_0, z_3) = 0.728$, $r(z_0, z_4) = 0.659$, $r(z_0, z_5) = 0.673$, $r(z_0, z_6) = 0.686$.

(5) Rank the shortlist in accordance with $r(z_0, z_i)$, $i = 1, 2, \ldots, 6$. Since $r(z_0, z_2) > r(z_0, z_3) > r(z_0, z_1) > r(z_0, z_6) > r(z_0, z_5) > r(z_0, z_4)$, the finalists are ranked as supplier 2 $\succ$ supplier 3 $\succ$ supplier 1 $\succ$ supplier 8 $\succ$ supplier 7 $\succ$ supplier 5.

(6) Use the supplier selection method given in Section 3.2.3 to determine the final suppliers.

The buyer allocates Q_0 = 800 tons to the supplier with the greatest grey correlation degree. First, the buyer will allocate the total amount Q_0 = 800 tons to supplier 2 who has the greatest grey correlation degree. Since the maximum supplied quantity in supplier 2's bid is $q_2 = 280$ tons, supplier 2 can supply quantity $q_2^* = q_2 = 280$ tons. Thus the remaining supply quantity is $Q_0 - q_2^* = 800 - 280 = 520$ tons. The buyer then allocates the remaining amount 520 tons to supplier 3. As the maximum supply quantity in supplier 3's bid is $q_3 = 320$ tons, so supplier 3 can supply quantity $q_3^* = q_3 = 320$ tons, and the remaining supply quantity is $Q_0 - q_2^* - q_3^* = 800 - 280 - 320 = 200$ tons. The buyer then allocates the remaining 200 tons to supplier 1. Since $q_1 = 300 > 200$, supplier 1 can supply quantity $q_1^* = Q_0 - q_2^* - q_3^* = 200$ tons. The allocation is now complete.

Supplier 2 will supply 280 tons of electricity coal to the buyer at a transaction price of 160 yuan/ton. Supplier 3 will supply 320 tons of electricity coal at 165 yuan/ton. Supplier 1 will supply 200 tons of electricity coal at 170 yuan/ton.

4.2. Sensitivity analysis

Now a sensitivity analysis is provided to determine the influence of modeling criteria weights.

For the same example above, we suppose that the weight set of the 12 attributes ($B_1, B_2, A_2, A_3, A_4, A_5, A_6, A_7, A_8, A_9, A_{10}, A_{11}$) is $W = (w_1, w_2, \ldots, w_{12})$. By using the same decision-making steps from (1) to (4) above, we can obtain the grey correlation degree $r(z_0, z_i)$ $(i = 1, 2, \ldots, 6)$ for six shortlist as follows.

$$r(z_0, z_1) = 0.5208w_1 + 0.8613w_{10} + 0.7109w_{11} + 0.9954w_{12} + 0.5102w_2 + 0.5w_3 + 0.3846w_4 + 0.5556w_5 + 0.8648w_6 + 0.9922w_7 + 0.7396w_8 + 0.9932w_9$$

$$r(z_0, z_2) = 0.4202w_1 + 0.8613w_{10} + 0.9929w_{11} + 0.9954w_{12} + 0.3333w_2 + w3 + 0.3333w_4 + w_5 + 0.7355w_6 + 0.7175w_7 + 0.9928w_8 + 0.6042w_9;$$

$$r(z_0, z_3) = 0.3333w_1 + 0.9980w_{10} + 0.8498w_{11} + 0.8728w_{12} + w2 + 0.6667w_3 + 0.4545w_4 + 0.4545w_5 + 0.9971w_6 + 0.8521w_7 + 0.8648w_8 + 0.7237w_9;$$

$$r(z_0, z_4) = 0.7692w_1 + 0.7287w_{10} + 0.5914w_{11} + 0.7497w_{12} + 0.3846w_2 + 0.4w_3 + w_4 + 0.3333w_5 + 0.8648w_6 + 0.7175w_7 + 0.8648w_8 + 0.8584w_9;$$

$$r(z_0, z_5) = w_1 + 0.7287w_{10} + 0.8498w_{11} + 0.8728w_{12} + 0.4673w_2 + 0.3333w_3 + 0.7143w_4 + 0.4545w_5 + 0.7355w_6 + 0.8521w_7 + 0.9928w_8 + 0.7237w_9;$$

$$r(z_0, z_6) = 0.3521w_1 + 0.8613w_{10} + 0.7109w_{11} + 0.9954w_{12} + 0.6944w_2 + 0.5w_3 + 0.5556w_4 + 0.3846w_5 + 0.9971w_6 + 0.7175w_7 + 0.8648w_8 + 0.9932w_9.$$

From Section 4.1, the ranking order of $r(z_0, z_i)$ $(i = 1, 2, \ldots, 6)$ is

Table 9
Original decision making matrix.

Shortlist	B_1	B_2	A_2	A_3	A_4	A_5	A_6	A_7	A_8	A_9	A_{10}	A_{11}
Supplier 1	7.5	26.3	170	300	16	f_2	f_1	f_3	f_1	f_2	f_3	f_1
Supplier 2	7.2	23.5	160	280	14	f_3	f_3	f_1	f_4	f_2	f_1	f_1
Supplier 3	6.8	28.9	165	320	17	f_1	f_2	f_2	f_3	f_1	f_2	f_2
Supplier 5	7.9	24.6	175	380	19	f_2	f_3	f_2	f_2	f_3	f_4	f_3
Supplier 7	8.1	25.8	180	360	17	f_3	f_2	f_1	f_3	f_3	f_2	f_2
Supplier 8	6.9	27.7	170	340	18	f_1	f_3	f_2	f_1	f_2	f_3	f_1

$$r(z_0, z_2) > r(z_0, z_3) > r(z_0, z_1) > r(z_0, z_6) > r(z_0, z_5) > r(z_0, z_4), \quad (9)$$

Let the change interval of the weight for the attribute j be $\bar{w}_j = [w_{js}, w_{jr}]$, which keeps the ranking order (9) unchanged, then the following optimization problems must be satisfied

$$\begin{cases} \text{Min } w_j = w_{js}, \quad j = 1, 2, \ldots, 12 \\ \text{s.t. } r(z_0, z_2) > r(z_0, z_3) > r(z_0, z_1) > r(z_0, z_6) > r(z_0, z_5) > r(z_0, z_4) \\ 0 \leqslant w_j \leqslant 1, \quad j = 1, 2, \ldots, 12 \\ \sum_{j=1}^{12} w_j = 1 \end{cases} \quad (10)$$

and

$$\begin{cases} \text{Max } w_j = w_{jr}, \quad j = 1, 2, \ldots, 12 \\ \text{s.t. } r(z_0, z_2) > r(z_0, z_3) > r(z_0, z_1) > r(z_0, z_6) > r(z_0, z_5) > r(z_0, z_4) \\ 0 \leqslant w_j \leqslant 1, \quad j = 1, 2, \ldots, 12 \\ \sum_{j=1}^{12} w_j = 1 \end{cases} \quad (11)$$

By using the software of Lingo 9.0 to solve above optimization problems (10) and (11), we obtain all change intervals of the weights for 12 attributes as follows.

$$\bar{w}_1 = [w_{1s}, w_{1r}] = [0, 0.2549], \ \bar{w}_2 = [w_{2s}, w_{2r}] = [0, 0.4500], \ \bar{w}_3 = [w_{3s}, w_{3r}] = [0, 0.7900],$$

$$\bar{w}_4 = [w_{4s}, w_{4r}] = [0, 0.2648], \ \bar{w}_5 = [w_{5s}, w_{5r}] = [0, 0.7750], \ \bar{w}_6 = [w_{6s}, w_{6r}] = [0, 0.5649],$$

$$\bar{w}_7 = [w_{7s}, w_{7r}] = [0, 0.5755], \ \bar{w}_8 = [w_{8s}, w_{8r}] = [0, 0.4339], \ \bar{w}_9 = [w_{9s}, w_{9r}] = [0, 0.3924],$$

$$\bar{w}_{10} = [w_{10s}, w_{10r}] = [0, 0.7996], \ \bar{w}_{11} = [w_{11s}, w_{11r}] = [0, 0.6599], \ \bar{w}_{12} = [w_{12s}, w_{12r}] = [0, 0.6377].$$

The length of the change interval $\bar{w}_j = [w_{js}, w_{jr}]$ is denoted as

$$L_j = w_{jr} - w_{js}, \quad j = 1, 2, \ldots, 12.$$

Thus, we have

$$L_1 = 0.2549, \ L_2 = 0.4500, \ L_3 = 0.7900,$$

$$L_4 = 0.2648, \ L_5 = 0.7750, \ L_6 = 0.5649,$$

$$L_7 = 0.5755, \ L_8 = 0.4339, \ L_{=}0.3924,$$

$$L_{10} = 0.7996, \ L_{11} = 0.6599, \ L_{12} = 0.6377.$$

From this result, if the ranking order of all shortlist keeps unchanged, i.e., the finalists are ranked as supplier 2 $\succ$ supplier 3 $\succ$ supplier 1 $\succ$ supplier 8 $\succ$ supplier 7 $\succ$ supplier 5, then the length of the change interval L_j $(j = 1, 2, \ldots, 12)$ must satisfy the following condition

$$L_{10} > L_3 > L_5 > L_{11} > L_{12} > L_7 > L_6 > L_2 > L_8 > L_9 > L_4 > L_1.$$

The ranking order means that the change range of the first attribute's (B_1) weight is the smallest, so its sensitivity is the greatest, i.e., the first attribute (B_1) is the greatest impact on the ranking result of all shortlist. The next few are the forth attribute (A_3), the ninth attribute (A_8), and so on. On the contrary, the change range of the tenth attribute's (A_9) weight is the greatest, so its sensitivity is minimal.

4.3. Discussion

Compared with the existing supplier selection methods such as fuzzy AHP (Shawa et al., 2012), D-AHP (Deng et al., 2014), integrated fuzzy TOPSIS and MCGP (Liao & Kao, 2011), integrated approach including fuzzy TOPSIS and a mixed integer linear programming model (Kilic, 2013), and so on, the contribution of two-stage compound mechanism proposed in this paper is as follows.

(i) In the most existing procurement mechanisms of multi-item, the buyer selects the winners according to the suppliers' declared information. However, every supplier's declared information is his private information, and it is complicated and unsymmetrical. So the facticity of the information cannot be guaranteed. And it may lead to an inefficient allocation result and is difficult to achieve optimal procurement. Thus, in order to reduce the procurement cost, optimize the procurement channels and improve the quality of procurement goods, the buyer must design incentive multi-attribute and multi-source procurement mechanisms, which can induce the suppliers to announce their actual costs truthfully. Based on this research background, this paper designs an incentive two-stage compound mechanism for supplier selection.

(ii) The existing procurement mechanisms and methods are proposed mostly by considering the multi-attribute procurement for a unique good or multiple indivisible goods. The research on the procurement mechanism design for divisible goods with the characteristic of homogeneousness and continuity is few. This paper investigates the problem of procurement mechanism design for a kind of divisible goods. Considering the supply level of a single supplier on quantity and variety is limited, and it is often difficult to meet the needs of buyers within the specified time. If the buyer selection unique supplier, then once the supply of raw materials occurs the unexpected events such as out of stock or delay, which will cause interference for normal production of production enterprises inevitably, and increase corresponding risk for the production enterprise. Thus, the compound mechanism in this paper regards divisible goods procurement as a kind of multi-attribute and multi-source procurement, which means the buyer can select multiple winners to supply the goods at the same time. This paper effectively improves the method with the winner (the winning bidder) is unique in the existing literatures.

(iii) In supply chain management, the structure of the supply chain is becoming more complex, which will lead to more and more supply chain risks. Supplier evaluation is the foundation of supply chain management, and when selecting the winners the buyer must take into account the affecting factors under commercial criterions as well as risk factors. However, the traditional literature in the evaluation of suppliers, most of them only consider the affecting factors under commercial criterions (such as quality, price and delivery time), there is few study to discuss and analyze the suppliers' risk issues based on supply chain risk management. In order to comprehensively measure the overall level of suppliers, especially the risk management level, this paper considers the seven risk attributes in addition to four attributes under the commercial criterion, and proposes a new index system for supplier selection, and then designs a two-stage compound mechanism based on multi-attribute auction and risk management of supply chain. The multi-attribute auction in the first stage can effectively motivate suppliers to report their true declare information and to help the buyer some outstanding finalists suppliers. In the second stage, the risk level of all finalists is further considered, and a new ranking method based on grey correlation degree of mixed sequence is proposed to rank the finalists and to select the final winners. This compound mechanism may well improve the procurement efficiency of divisible goods and greatly reduce the procurement risk.

5. Conclusion

Focusing on the problem of selecting suppliers in multi-source procurement of divisible goods, this paper designs a two-stage compound mechanism of selecting suppliers based on multi-attribute auctioning and supply chain risk management. This paper effectively improves the method with the winning bidder as it considers factors beyond commercial criteria (such as quality, price, delivery time), to include seven risk attributes. The multi-attribute auction in the first stage can effectively motivate suppliers to report true information and to help the buyer effectively shortlist good suppliers. In the second stage, the risk level of all shortlisted suppliers is further considered, and a new ranking method based on grey correlation degree of mixed sequence is proposed to rank and select the best supplier(s). This compound mechanism may well improve the procurement efficiency of divisible goods and greatly reduce the procurement risk. In future work we intend to design an interactive multi-attribute and multi-source e-procurement system of divisible goods based on the two-stage compound mechanism proposed in this paper.

Acknowledgements

This work is supported by the National Natural Science Foundation of China (Nos. 71671135, 71540027, 71371147, 61403288), and the Fundamental Research Funds for the Central Universities (No. 2017 IVA 067).

References

Adida, E., & DeMiguel, V. (2011). Supply chain competition with multiple manufacturers and retailers. *Operations Research, 59*, 156–172.
Aliabadi, D. E., Kaazemi, A., & Pourghannad, B. (2013). A two-level GA to solve an integrated multi-item supplier selection model. *Applied Mathematics and Computation, 219*, 7600–7615.
Amid, A., Ghodsypour, S. H., & O'Brien, C. (2011). A weighted max–min model for fuzzy multi-objective supplier selection in a supply chain. *International Journal of Production Economics, 131*, 139–145.
Amindousta, A., Ahmeda, S., Saghafiniab, A., & Bahreininejada, A. (2012). Sustainable supplier selection: A ranking model based on fuzzy inference system. *Applied Soft Computing, 12*, 1668–1677.
Amorim, P., Curcio, E., Almada-Lobo, B., Barbosa-Póvoa, A. P. F. D., & Grossmann, I. E. (2016). Supplier selection in the processed food industry under uncertainty. *European Journal of Operational Research, 252*, 801–814.
Aqlan, F., & Lam, S. S. (2015). Supply chain risk modelling and mitigation. *International Journal of Production Research, 53*(18), 5640–5656.
Arikan, F. (2013). A fuzzy solution approach for multi objective supplier selection. *Expert Systems with Applications, 40*, 947–952.
Ayhan, M. B., & Kilic, H. S. (2015). A two stage approach for supplier selection problem in multi-item/multi-supplier environment with quantity discounts. *Computers & Industrial Engineering, 85*, 1–12.
Azadi, M., Jafarian, M., Saen, R. F., & Mirhedayatian, S. M. (2015). A new fuzzy DEA model for evaluation of efficiency and effectiveness of suppliers in sustainable supply chain management context. *Computers & Operations Research, 54*, 274–285.
Cao, J. J. (2012). *Research on supplier evaluation and selection from the perspective of supply chain risk management*. Master degree paper of Chongqing Normal University.
Cárdenas-Barrón, L. E., González-Velarde, J. L., & Treviño-Garza, G. (2015). A new approach to solve the multi-product multi-period inventory lot sizing with supplier selection problem. *Computers & Operations Research, 64*, 225–232.
Chai, J. Y., & Liu, J. N. K. (2014). A novel believable rough set approach for supplier selection. *Expert Systems with Applications, 41*, 92–104.
Chen, P. S., & Wu, M. T. (2013). A modified failure mode and effects analysis method for supplier selection problems in the supply chain risk environment: A case study. *Computers & Industrial Engineering, 66*, 634–642.
Choudhary, D., & Shankar, R. (2014). A goal programming model for joint decision making of inventory lot-size, supplier selection and carrier selection. *Computers & Industrial Engineering, 71*, 1–9.
Choy, K. L., & Lee, W. B. (2003). A generic supplier management tool for outsourcing manufacturing. *Journal of Supply Chain Management, 8*, 140–154.
David, E., Azoulay-Schwartz, R., & Kraus, R. S. (2006). Bidding in sealed-bid and English multi-attribute auctions. *Decision Support Systems, 42*, 527–556.
Deng, X. Y., Hu, Y., Deng, Y., & Mahadevan, S. (2014). Supplier selection using AHP methodology extended by D numbers. *Expert Systems with Applications, 41*, 156–167.
Dickson, G. (1966). An analysis of vender selection systems and decisions. *Journal of Purchasing, 2*, 5–17.
Federgruen, A., & Yang, N. (2008). Selecting a portfolio of suppliers under demand and supply risks. *Operations Research, 56*, 916–936.
Federgruen, A., & Yang, N. (2011). Procurement strategies with unreliable suppliers. *Operations Research, l59*, 1033–1039.
Ghorabaee, M. K., Zavadskas, E. K., Amiri, M., & Esmaeili, A. (2016). Multi-criteria evaluation of green suppliers using an extended WASPAS method with interval type-2 fuzzy sets. *Journal of Cleaner Production, 137*, 213–229.
Güneri, A. F., Ertay, T., & Yücel, A. (2011). An approach based on ANFIS input selection and modeling for supplier selection problem. *Expert Systems with Applications, 38*, 14907–14917.
Hammami, R., Temponi, C., & Frein, Y. (2014). A scenario-based stochastic model for supplier selection in global context with multiple buyers, currency fluctuation uncertainties, and price discounts. *European Journal of Operational Research, 233*, 159–170.
Hashemi, S. H., Karimi, A., & Tavana, M. (2015). An integrated green supplier selection approach with analytic network process and improved grey relational analysis. *International Journal of Production Economics, 159*, 178–191.
Heidarzadea, A., Mahdavi, I., & Mahdavi-Amiri, N. (2016). Supplier selection using a clustering method based on a new distance for interval type-2 fuzzy sets: A case study. *Applied Soft Computing, 38*, 213–231.
Ho, W., Xu, X., & Dey, P. K. (2010). Multi-criteria decision making approaches for supplier evaluation and selection: A literature review. *European Journal of Operational Research, 202*(1), 16–24.
Ho, W., Zheng, T., Yildiz, H., & Talluri, S. (2015). Supply chain risk management: A literature review. *International Journal of Production Research, 53*(16), 5031–5069.
Hosseini, S., & Barker, K. (2016). A Bayesian network model for resilience-based supplier selection. *International Journal of Production Economics, 180*, 68–87.
Jadidi, O., Cavalieri, S., & Zolfaghari, S. (2015). An improved multi-choice goal programming approach for supplier selection problems. *Applied Mathematical Modelling, 39*, 4213–4222.
Jadidi, O., Zolfaghari, S., & Cavalieri, S. (2014). A new normalized goal programming model for multi-objective problems: A case of supplier selection and order allocation. *International Journal of Production Economics, 148*, 158–165.
Ji, Y., & Goh, M. (2016). Proximal point algorithms for multi-criteria DC programming with applications to Portfolio optimization. *Journal of Optimization Theory and Applications, 169*(1), 280–289.
Karsak, E. E., & Dursun, M. (2015). An integrated fuzzy MCDM approach for supplier evaluation and selection. *Computers & Industrial Engineering, 8*, 282–293.
Kilic, H. S. (2013). An integrated approach for supplier selection in multi-item multi-supplier environment. *Applied Mathematical Modelling, 37*, 7752–7763.
Kumar, A., Jain, V., & Kumar, S. (2014). A comprehensive environment friendly approach for supplier selection. *Omega, 42*, 109–123.
Li, C. H. (2013). Sourcing for supplier effort and competition: Design of the supply base and pricing mechanism. *Management Science, 59*(6), 1389–1406.
Li, D. F. (2014). Notes on "Possibilistic programming approach for fuzzy multidimensional analysis of preference in group decision making". *Computers & Industrial Engineering, 73*, 1–4.
Li, D. F., & Liu, J. C. (2015). A parameterized non-linear programming approach to solve matrix games with payoffs of I-fuzzy numbers. *IEEE Transactions on Fuzzy Systems, 23*(4), 885–896.
Li, D. F., & Ren, H. P. (2015). Multi-attribute decision making method considering the amount and reliability of intuitionistic fuzzy information. *Journal of Intelligent & Fuzzy Systems, 28*, 1877–1883.
Liao, C. N., & Kao, H. P. (2011). An integrated fuzzy TOPSIS and MCGP approach to supplier selection in supply chain management. *Expert Systems with Applications, 38*, 10803–10811.
Liao, H. C., Xu, Z. S., & Zeng, X. J. (2015). Hesitant fuzzy linguistic VIKOR method and its application in qualitative multiple criteria decision making. *IEEE Transactions on Fuzzy Systems, 23*(5), 1343–1355.
Liao, H. C., Xu, Z. S., Zeng, X. J., & Xu, D. L. (2016). An enhanced consensus reaching process in group decision making with intuitionistic fuzzy preference relations. *Information Sciences, 329*, 274–286.
Liou, J. J. H., Chuang, Y. C., & Tzeng, G. H. (2014). A fuzzy integral-based model for supplier evaluation and improvement. *Information Sciences, 266*, 199–217.
Ma, S. H., Lin, Y., & Chen, Z. Q. (2000). *Supply chain management*. Beijing: China Machine Press.
Memon, M. S., Lee, Y. H., & Mari, S. I. (2015). Group multi-criteria supplier selection using combined grey systems theory and uncertainty theory. *Expert Systems with Applications, 42*, 7951–7959.
Menon, M. K., McGinnis, M. A., & Ackerman, K. B. (2008). Selection criteria for providers of third party logistics services: An exploratory study. *Journal of Business Logistics, 19*, 121–137.

Orji, I. J., & Wei, S. (2015). An innovative integration of fuzzy-logic and systems dynamics in sustainable supplier selection: A case on manufacturing industry. *Computers & Industrial Engineering, 88*, 1–12.

Patton, W. E. (2008). Use of human judgment models in industrial buyers, vendor selection decisions. *Industrial Marketing Management, 25*, 135–149.

Petroni, A., & Braglia, M. (2010). Vendor selection using principal component analysis. *Journal of Supply Chain Management, 36*, 63–69.

Qu, S. J., Goh, M., Ji, Y., & Robert, D. S. (2015). A new algorithm for linearly constrained C-convex vector optimization with a supply chain network risk application. *European Journal of Operational Research, 247*, 359–365.

Rao, C. J., Goh, M., Zhao, Y., & Zheng, J. J. (2015). Location selection of sustainability city logistics centers. *Transportation Research Part D: Transport and Environment, 36*, 29–44.

Rao, C. J., & Peng, J. (2009). Fuzzy group decision making model based on credibility theory and gray relative degree. *International Journal of Information Technology & Decision Making, 8*, 515–527.

Rao, C. J., & Zhao, Y. (2011). Optimal multi-attribute auctions for divisible goods. *International Journal of Information Technology & Decision Making, 10*, 891–911.

Rao, C. J., Zhao, Y., & Ma, S. H. (2012). Procurement decision making mechanism of divisible goods based on multi-attribute auction. *Electronic Commerce Research and Applications, 11*(4), 397–406.

Rao, C. J., Zhao, Y., Zheng, J. J., Wang, C., & Chen, Z. W. (2016b). An extended uniform price auction mechanism of homogeneous divisible goods: Supply optimization and non-strategic bidding. *International Journal of Production Research, 54*(13), 4028–4042.

Rao, C. J., Zheng, J. J., Wang, C., & Xiao, X. P. (2016a). A hybrid multi-attribute group decision making method based on grey linguistic 2-tuple. *Iranian Journal of Fuzzy Systems, 13*(2), 37–59.

Rezaei, J., & Davoodi, M. (2011). Multi-objective models for lot-sizing with supplier selection. *International Journal of Production Economics, 130*, 77–86.

Rezaei, J., Nispeling, T., Sarkis, J., & Tavasszy, L. (2016). A supplier selection life cycle approach integrating traditional and environmental criteria using the best worst method. *Journal of Cleaner Production, 135*, 577–588.

Sawik, T. (2014). Joint supplier selection and scheduling of customer orders under disruption risks: Single vs. dual sourcing. *Omega, 43*, 83–95.

Shawa, K., Shankar, R., Yadav, S. S., & Thakur, L. S. (2012). Supplier selection using fuzzy AHP and fuzzy multi-objective linear programming for developing low carbon supply chain. *Expert Systems with Applications, 39*, 8182–8192.

Shemshadi, A., Shirazi, H., Toreihi, M., & Tarokh, M. J. (2011). A fuzzy VIKOR method for supplier selection based on entropy measure for objective weighting. *Expert Systems with Applications, 38*, 12160–12167.

Sodenkamp, M. A., Tavana, M., & Caprio, D. D. (2016). Modeling synergies in multi-criteria supplier selection and order allocation: An application to commodity trading. *European Journal of Operational Research, 254*, 859–874.

Toloo, M., & Nalchigar, S. (2011). A new DEA method for supplier selection in presence of both cardinal and ordinal data. *Expert Systems with Applications, 38*, 14726–14731.

Torabi, S. A., Baghersad, M., & Mansouri, S. A. (2015). Resilient supplier selection and order allocation under operational and disruption risks. *Transportation Research Part E, 79*, 22–48.

Vahdani, B., Iranmanesh, S. H., Mousavi, S., & Abdollahzade, M. (2012). A locally linear neuro-fuzzy model for supplier selection in cosmetics industry. *Applied Mathematical Modelling, 36*, 4714–4727.

Ventura, J. A., Valdebenito, V. A., & Golany, B. (2013). A dynamic inventory model with supplier selection in a serial supply chain structure. *European Journal of Operational Research, 230*, 258–271.

Weber, C. A., Current, J. R., & Benton, W. C. (1991). Vendor selection criteria and method. *European Journal of Operational Research, 50*, 2–18.

Willis, T. H., Huston, R., & Pohlkamp, P. F. (2005). Evaluation measures of just-in-time supplier performance. *Production and Inventory Management Journal, 34*, l–5.

Wilson, E. L. (2006). The relative importance of supplier selection criteria: A review and update. *International Journal of Purchasing and Materials Management, 25*, 35–41.

Xiao, X. P., Song, Z. M., & Li, F. (2005). *Grey technology and its application*. Beijing: Science Press.

Xu, Z. (1999). *Uncertain multiple attribute decision making: Methods and applications*. New York: Springer-Verlag.

Xu, Z. S., & Zhang, X. L. (2013). Hesitant fuzzy multi-attribute decision making based on TOPSIS with incomplete weight information. *Knowledge-Based Systems, 52*, 53–64.

Yahya, S., & Kingsman, B. (2009). Vender rating for an entrepreneur development programme: A case study using the analytic hierarchy process method. *Journal of Operational Research Society, 50*, 916–930.

Yu, F., Kaihara, T., Fujii, N., Sun, C. Y., & Yang, W. K. (2015). A multi-attribute multi-item negotiation mechanism of supply chain networks between buyers and sellers. *International Journal of Production Research, 53*(20), 6143–6160.

Yu, F., Xue, L., Sun, C. Y., & Zhang, C. (2016). Product transportation distance based supplier selection in sustainable supply chain network. *Journal of Cleaner Production, 137*, 29–39.

Zhang, J. L., & Chen, J. (2013). Supplier selection and procurement decisions with uncertain demand, fixed selection costs and quantity discounts. *Computers & Operations Research, 40*, 2703–2710.