Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture
000(00):1–13
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DOI:doi number
http://mms.sagepub.com

Supplier Selection Based on Evidence Theory and Analytic Network Process

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Abstract

Supplier selection is a key component of the supply chain management. The methods based on analytic network process (ANP) for solving supplier selection problem have been proposed because ANP can handle the interdependent relationships of the decision attributes. However, they are not always offering an optimal solution when the supplier selection problem is presented in a vague or incomplete form. To handle the uncertainties we propose a method which combines the analytic network process (ANP) method with Dempster-Shafer (DS) evidence theory. We demonstrate the efficiency and accuracy of our method on a numerical example. By comparing our results with DS/AHP approach, we demonstrate that the proposed method is flexible and effective in dealing with the supplier selection problem.

Keywords

Supplier selection, Analytical network process, Dempster-Shafer evidence theory, DS/ANP

1. Introduction

Supplier selection plays an important role in the manufacturing process. The companies have to work with different suppliers to carry out their activities so that the components and parts can be delivered on time. It is a very important problem to work with the right supplier in the supply chain systems. Therefore, strategic partnership with better suppliers needs to be formulated to improve profitability, quality, flexibility and robust performance as well as to reduce the cost.

Supplier selection is a multi-criteria decision making (MCDM) problem. A number of MCDM methods have been proposed (1; 2), including including analytic hierarchy process (AHP) (3; 4), analytic network process (ANP) (5), TOPSIS (6; 7) and others (8). The AHP is a structured technique for organizing and analyzing complex decisions, developed by Thomas L. Saaty in the 1970s (9; 10). It focuses on comparing and evaluating different criteria towards the objective through constructing the hierarchical levels. The AHP does not perform well in situations when there interactions and dependencies

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across the criteria at different levels (11). The ANP (12) can can overcome the limitations of AHP: it can deal with the dependencies and interactions across the elements at various levels quantitatively. To date, the ANP is the most common tool for tackling the selection problems (13; 14).

In the process of determining the optimal supplier, experts' knowledge plays an important role. For example, in AHP, the comparison matrices are provided by many experts according to their knowledge. Based on experts' evaluation, we are able to allocate the appropriate weight for the corresponding criteria. However, in many cases, uncertainties appear in experts' subjective and quantitative assessment. Moreover, in many situations, it is difficult for us to use a precise way to measure the performance of each decision alternative, especially in many large systems. From this point of view, it is inevitable for us to handle the incomplete or vague information involved in many systems.

So far, many researchers have focused on the supplier selection problem under uncertain environment (15; 16; 17; 18). Several techniques have been employed to deal with this issue, such as fuzzy set, probability-based approaches etc. Among them, Dempster-Shafer theory is an efficient tool with the ability to handle vague information (19; 20). It is more general than probability and possibility theories and can be applied under uncertain situations even if limited or conflicting information is provided by experts. In addition, the basic operations of Dempster-Shafer theory allows the users to combine the random and epistemic uncertainty in a more straightforward way without any assumptions. With the ability of coping with the uncertainty or imprecision embedded in evidence, Dempster-Shafer theory is widely used in many applications, such as information fusion (21; 22; 23), target recognition (24; 25) and decision making (26; 27; 28; 29; 30).

Here, we are motivated to combine ANP and Dempster-Shafer theory theory to present a novel method named DS-ANP. By combing them together, we are capable of employing the flexibility offered by Dempster-Shafer theory theory for the incomplete and vague information and the modeling power of ANP for the supplier selection problem. To the best of the authors' knowledge, this is the first attempt to incorporate the ANP method with Dempster-Shafer theory theory of evidence to solve the supplier selection problems.

The remainder of the paper is organized as follows. Section 2 gives the literature review. Section 3 details the proposed method. A real-world case is used to illustrate the method and the results of the application are discussed in Section 4. Main findings and contributions are drawn and future work are suggested in Section 5.

2. Literature review

According to the current literatures, suppler selection is typically a multi-criteria decision making (MCDM) problem. To date, various techniques, such as the analytic hierarchy process (AHP), analytic network process (ANP), fuzzy set theory, genetic algorithm (GA), mathematical programming, simple multi-attribute rating technique (SMART), have been employed to deal with this problem. The literature on supplier selection can be summarized from two aspects. The first one is mainly focused on the introduction of mathematical or quantitative decision-making approaches, and the second deals with the uncertain information contained in the supplier selection problem. In this section, we will review the literature from these two perspectives.

Due to the flexibility and simplicity of AHP, it has been very popular in the past decades (31; 11; 32; 33). For example, Chan (34) combined an Interactive Selection Model (ISM) with AHP to handle the supplier selection process systematically and quantitatively. Yang and Chen (35) incorporated gray relational analysis to the AHP methodology to select the best suppliers for cooperation. Bei, Wang, and Hu (36) presented an AHP-based model to identify the most preferred supplier in manufacturing supply chain. Chan and Kumar (3) combined fuzzy set theory with AHP and presented the a fuzzy extended AHP (FEAHP) approach using triangular fuzzy numbers to improve the AHP method and to facilitate global supplier selection process. Chan et al. (37) and Lee (38) gave a brief review on the applications of fuzzy AHP. Shaw et al. (39) integrated fuzzy-AHP with fuzzy multi-objective linear programming for selecting the appropriate supplier in the supply chain, addressing the carbon emission issue. Recently, Deng et al. (40) presented a new effective and feasible representation of uncertain information–D numbers. Based on AHP, they have investigated its applications in supplier selection and environmental impact assessment (41).

Although AHP has been widely in many manufacturing systems, however, in contemporary society, each factor is influenced by each other. In many cases, these criteria interact with each other. For example, the cost of a car is in association with its quality. The better the quality, the higher the price. From this point of view, it is meaningful for us to take into consideration the interrelationships existing in these criteria. Although AHP is very popular method to deal with MCDM problems, it can only handle solve problems with the top-to-bottom hierarchies and cannot accommodate the variety of interactions, dependencies and feedbacks between elements (42). Therefore, ANP has been proposed to handle the interrelationships among elements in a problem setting. That's why many researchers have drawn their attention from AHP to ANP.

In recent years, the applications of the ANP in supplier selection has increased substantially when compared with AHP. Sarkis and Talluri (43) built an ANP-based supplier selection model by considering a series of factors including operational, tangible and intangible measures. Gencer and Gürpinar investigated ANP's application in the supplier selection problem and carried out in an electronic firm. Wu (44) et al. proposed an integrated multi-objective decision-making process by using analytic network process (ANP) and mixed integer programming (MIP) to determine the selection of supplier. However, they did not take into consideration the imprecise or vague information involved in the supply chain systems. Vinodh, Anesh and Gautham presented a fuzzy analytic network process (fuzzy ANP) approach (45) and used it to select the supplier for an Indian electronics switches manufacturing company. Actually, fuzzy ANP is faced with many problems, including ranking fuzzy numbers, the consistency in the fuzzy comparison matrices. The aforementioned problems need to be addressed before it can be implemented directly into real-world applications. Kuo and Lin (46) combined ANP with data envelopment analysis (DEA) technique to overcome the constraint of DEA that the users cannot set up criteria weight preferences. DEA technique is not capable of processing imprecise data or information in the process of determining the optimal decision alternative. Recently, Dou, Zhu and Sarkis introduced (47) a grey analytical network process-based (grey ANP-based) model to identify green supplier development programs that will effectively improve suppliers' performance. But grey ANP-based model is mainly used to predict the performance for an enterprise in the long run and its ability to handle the epistemic uncertainty is weak in many situations.

In addition to the above, there are also many other approaches and the hybrid methods dealing with this open issues, e.g. the mixture of FANP and fuzzy TOPSIS (48), the integration of semi-fuzzy SVDD and CC-Rule method (49), Linear Programming (50). Except for the introduction of mathematical or quantitative decision-making approaches, a lot of researchers have focused on handling the vague information in this problem.

Since uncertainty is one of the features of real-world applications, especially in the supplier selection problem, many methods have been proposed to deal with this problem (51; 52; 53; 54; 55; 56; 57; 58; 59), such as fuzzy set theory (60; 61; 62), interval theory (63; 64; 65). For example, Amin, Razmi and Zhang (66) integrated the fuzzy logic and triangular fuzzy numbers with SWOT in the context of supplier selection. Tao et al. (67) integrated DEA, AHP and TOPSIS with AFS theory (axiomatic fuzzy set theory) integrating the advantages of each method and overcome their own deficiencies to solve the supplier selection problem.

However, for fuzzy set theory and interval theory, it is required to construct the membership function under uncertain environment in advance. It is difficult to determine these values before making the decision. In real-world supply chains, it costs lots of time and money to conduct many experiments for the purpose of building such membership functions. Similarly, for the interval theory and AFS theory, the same problem exists, too. As a result, the above theories is not practical in many real-world applications due to their disadvantages and drawbacks.

Dempster-Shafer evidence theory is a novel tool capable of handling vague information and it has been applied in many fields to describe uncertainty, such as decision analysis, pattern recognition, risk assessment, supplier selection and others (19; 53; 68). For example, Beynon, Curry, and Morgan combined AHP with evidence theory and applied it into multicriteria decision modelling (69). Since then, DS/AHP has received great attention (11; 70).

Although there are abundant literatures about the selection of suitable supplier in the literature, however, to the authors' knowledge, there were relatively few works which combined Dempster-Shafer evidence theory and ANP to deal with this problem. In this paper, by combining them, we are capable of taking of advantages of both Dempster-Shafer evidence theory and ANP. As a result, we are motivated to to combine ANP and Dempster-Shafer theory theory to present a novel method named DS-ANP. By combing them together, we are capable of employing the flexibility offered by Dempster-Shafer theory theory for the incomplete and vague information and the modeling power of ANP for the supplier selection problem.

3. Proposed method

First of all, we identify criteria and sub-criteria for conducting the DS/ANP method. AHP is employed to build the initial weights associated with each criteria and sub-criteria. DS/AHP is used to construct the attribute's basic probability assignment (BPA). By considering the dependencies and interactions across the criteria, we construct the super matrix formulated by the initial weights. Based on ANP, the weight associated with each attribute can be calculated. By using Dempster's rule of combination, the performance of each supplier can be determined. The flowchart of the proposed method is shown in Fig. 1.

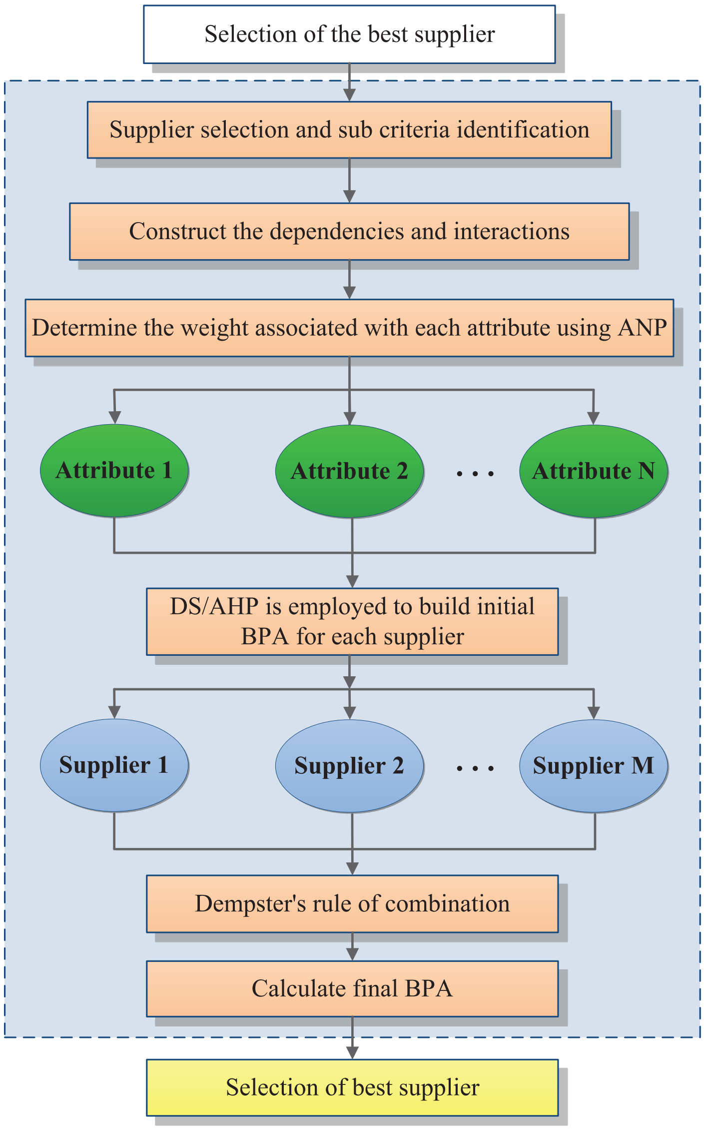

Fig. 1. Flowchart of the proposed method

3.1. Supplier selection and sub-criteria identification

To evaluate the performance of each supplier, first it is required to carefully identify all possible elements and factors that need to be inspected and assessed. In this paper, the hierarchical structure for supplier selection, as shown in Fig. 2, is originated from Ref. (45). As can be seen from Fig. 2, we have identified five criteria as the dimensions in the ANP model. These are business improvement (BI), extent of fitness (EOF), quality (Q), service (S), risks (R). The second level consists of various attributes under different criteria. BI has four attributes: reputation of industry (ROI), financial strength (FS), managing ability (MA), organization customers (OS). EOF has three attributes: sharing of expertise (SOE), flexible practices (FP), diversified customers (DC). Q has three attributes: low defect rate (LDR), commitment to quality (CTQ), and improved process capacity (IPC). S also has three attributes: on time delivery (OTD), quick responsiveness (QR), supplier capacity (SC1). R has three attributes: supply constraint (SC2), buyer supplier constraint (BSC), supplier profile (SP). All the attributes and hierarchical structures are adopted from Ref. (45).

Different from Ref. (45), we consider the interactions in the secondly level. As shown in Fig. 2, a looped arc is used in the ANP model to show such interdependencies. The alternatives that the decision-maker wishes to evaluate are shown at the bottom of the model. In this paper, we take into consideration four decision alternatives: Supplier A, Supplier B, Supplier C, Supplier D.

3.2. Constructing the weight associated with each criteria and sub-criteria

In this step, both AHP and ANP are used to construct the weights across the criteria. For the attributes in Layer 1, AHP (10) is employed to construct such weights. We build a series of pairwise comparisons to establish the relative importance of determinants in achieving the objectives. A ratio of scale 1–9 is used to compare any two criteria. Table 1 displays the pair-wise comparison scale for AHP preferences. A score of 1 means that these two elements are important equally while a score of 9 denotes that overwhelming dominance of the element over the comparison element. If an attribute has weaker impact when compared with its comparison element, the range of the scores will be reversed from 1 to 1/9. In addition to this, an index called consistency ratio (CR) is built to check the consistency of the weights across all the criteria. These criteria will be used to calculate the final supplier selection weighted index (SSWI).

Table 1. Pair-wise comparison scale for AHP preferences

Numerical Rating	Verbal judgement of preferences
1	Equally preferred
3	Moderately preferred
5	Strongly preferred
7	Very strongly preferred
9	Extremely preferred
2, 4, 6, 8	Intermediate values between the two adjacent judgments
Reciprocals	When activity i compared to j is assigned one of the above numbers, then activity j compared to i is assigned its reciprocal

For the criteria in Layer 2, as there are interdependencies among these criteria. Here, ANP will be employed to calculate the weight of each sub-criteria. The pairwise comparisons are made to capture interdependencies among the sub-criteria. One such comparison is presented in Table 2. It presents the result of BI with ROI as the controlling attribute over other sub-criteria. Specially speaking, as shown in Table 2, under the rule of reputation of industry (ROI), which one is more important among the criteria financial strength (FS), managing ability (MA), and organization customers (OS).

As can be seen from Table 2, it can be noted that FS has the maximum impact (0.6694) on the criteria BI over other attributes when ROI is treated as the controlling attribute. In a similar way, the other pairwise comparison matrices can be built. In ANP, the super matrix is formulated by such kind of pairwise comparison matrices, which allows us for resolution of interdependencies across all the attributes. After the super matrix converges to a stable state, the the relative importance measures for each attribute can be obtained. Different from traditional DS/AHP, we take into consideration the interactions and interdependencies existing in the supplier selection problem. DS/ANP is a generalization of DS/AHP and it makes DS/AHP more flexible and more reasonable when dealing with the complex systems.

Table 2. Pairwise comparison matrix for the sub-criteria in Layer 2 under the ROI criteria

ROI	FS	MA	OS	Weight
FS	1	3	7	0.6694
MA	1/3	1	3	0.2426
OS	1/7	1/3	1	0.0879

3.3. Building BPA associated with each criteria

In this step, DS/AHP is used to construct the BPA associated with each decision alternative. DS/AHP is proposed by Beynon et al. (69), which enables a measure of uncertainty and ignorance to be constructed. In DS/AHP, the decision maker expresses their preference by comparing a group of decision alternatives to θ while in AHP, it makes pairwise comparisons between individual decision alternatives. For DS/AHP, the following 5–unit scale is adopted as a basis for discriminating levels of knowledge (71). Normally, p in this scale has the value of 0.2159.

Here, we give a brief introduction to the DS/AHP approach. For the ROI attribute, we build the following knowledge matrix as shown in Table 3. The values in the final column are the measures of favourability of certain groups of decision alternatives in each row with respect to θ. It can be noted that A, D viewed as extremely favourable when compared to θ.

Table 3. Initial knowledge matrix for ROI criterion

ROI	{A,D}	{C}	θ
{A,D}	1	0	6p
{C}	0	1	4p
θ	1/(6p)	1/(4p)	1

Table 4. Priority values for groups of decision alternatives and θ

	Priority
ROI	
A,D	0.7153
C	0.1870
θ	0.0977

Following the method in Ref. (72), we can construct the weights derived as the eigenvectors of the Knowledge Matrix, which are shown in Table 4. We treat these priority allocations as BPA. As a consequence, we have:

$$m_1(\{A, D\}) = 0.3625, m(\{D\}) = 0.2417, m(\{\theta\}) = 0.3958$$

Following the same way, we can construct the BPA for the other criteria. By this way, all the BPAs can be built.

3.4. Ranking all the suppliers

In the second step, by using ANP, we have calculated the weight for each attribute in Layer 2. In addition, the BPA associated with every criterion has been built. However, we do not combine them together. In this step, we will combine the weight and the BPA of every attribute.

Definition 3.1. Let U be the frame of discernment, m_j^d be the new BPA after discounting. The discounting operation is accomplished as follows.

$$m_j^d(A_j) = \begin{cases} \alpha_j m_j(A_j), & A_j \neq U, \\ 1 - \alpha_j + \alpha_j m_j(U), & A_j = U. \end{cases} \tag{1}$$

where m_j is the BPA of focal element A_j.

By making full use the discount technique shown in Definition 1, we will apply the weight of each criterion into the corresponding BPA. According to the Dempster's rule of combination, the BPA associated with every attribute can be aggregated. In this way, the performance of each decision alternative can be calculated.

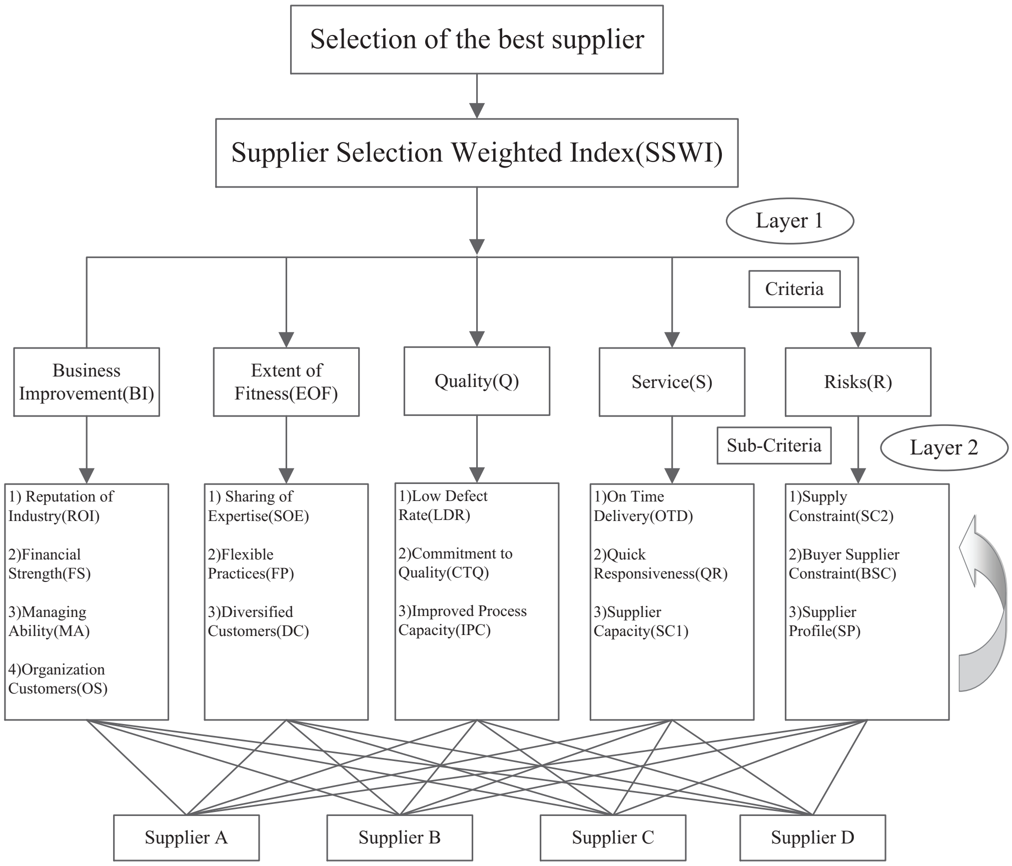

Fig. 2. The hierarchical structure for the supplier selection. Adopted from Ref. (45).

4. Case Study

The case study has been implemented at Salzer Eletronics Limited (hereafter referred to Salzer) (45). Salzer is a manufacturing company producing Cam operated rotary switches and a series of other products, which was founded in 1984. As shown in Fig. 2, the best supplier can be determined based on the calculation of SSWI. SSWI is associated with 5 factors: business improvement (BI), extent of fitness (EOF), quality (Q), services (S), and Risks (R), respectively.

First of all, we will construct the knowledge matrix for each criterion. As shown in Fig. 3, it shows us the DS/AHP decision tree for determining the supplier. For instance, for the attribute ROI, from Fig. 3, it can be noticed that two distinct groups of decision alternatives ($\{A, D\}$ and $\{C\}$) have been identified as being comparable to the frame of discernment Θ. For the other criteria, their knowledge matrices can be built in a similar way. Table 5 shows us the initial knowledge matrix for every attribute.

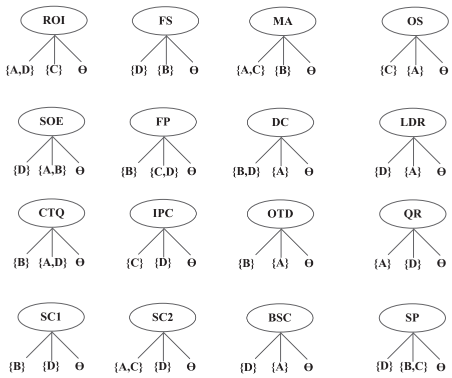

Fig. 3. Decisions when only one single criteria is considered

Table 5. Initial knowledge matrix for each attribute

ROI	{A,D}	{C}	θ	SOE	{D}	{A,B}	θ	CTQ	{B}	{A,D}	θ	SC1	{B}	{D}	θ
{A,D}	1	0	$6p$	{D}	1	0	$6p$	{B}	1	0	$6p$	{B}	1	0	$6p$
{C}	0	1	$4p$	{A,B}	0	1	$5p$	{A,D}	0	1	$2p$	{D}	0	1	$2p$
θ	$1/(6p)$	$1/(4p)$	1	θ	$1/(6p)$	$1/(5p)$	1	θ	$1/(6p)$	$1/(2p)$	1	θ	$1/(6p)$	$1/(2p)$	1
FS	{D}	{B}	θ	FP	{B}	{C,D}	θ	IPC	{C}	{D}	θ	SC2	{A,C}	{D}	θ
{D}	1	0	$4p$	{B}	1	0	$5p$	{C}	1	0	$4p$	{A,C}	1	0	$5p$
{B}	0	1	$3p$	{C,D}	0	1	$4p$	{D}	0	1	$2p$	{D}	0	1	$4p$
θ	$1/(4p)$	$1/(3p)$	1	θ	$1/(5p)$	$1/(4p)$	1	θ	$1/(4p)$	$1/(2p)$	1	θ	$1/(5p)$	$1/(4p)$	1
MA	{A,C}	{B}	θ	DC	{B,D}	{A}	θ	OTD	{B}	{A}	θ	BSC	{D}	{A}	θ
{A,C}	1	0	$6p$	{B,D}	1	0	$5p$	{B}	1	0	$5p$	{D}	1	0	$6p$
{B}	0	1	$2p$	{A}	0	1	$3p$	{A}	0	1	$3p$	{A}	0	1	$3p$
θ	$1/(6p)$	$1/(2p)$	1	θ	$1/(5p)$	$1/(3p)$	1	θ	$1/(5p)$	$1/(3p)$	1	θ	$1/(6p)$	$1/(3p)$	1
OS	{C}	{A}	θ	LDR	{D}	{A}	θ	QR	{A}	{D}	θ	SP	{D}	{B,C}	θ
{C}	1	0	$4p$	{D}	1	0	$6p$	{A}	1	0	$3p$	{D}	1	0	$5p$
{A}	0	1	$2p$	{A}	0	1	$2p$	{D}	0	1	$2p$	{B,C}	0	1	$4p$
θ	$1/(4p)$	$1/(2p)$	1	θ	$1/(6p)$	$1/(2p)$	1	θ	$1/(3p)$	$1/(2p)$	1	θ	$1/(5p)$	$1/(4p)$	1

Based on the data in Table 5, following the approach presented in Section 3.3, we can construct BPA for each attribute shown in Table 6.

Table 6. The initialized BPA associated with each attribute

Criteria	BPA
ROI	m$\{A,D\}$=0.3625,m$\{C\}$=0.2417,m$\{\Theta\}$=0.3958
FS	m$\{D\}$= 0.2952,m$\{B\}$= 0.2214,m$\{\Theta\}$= 0.4834
MA	m$\{A,C\}$= 0.4124,m$\{B\}$= 0.1375,m$\{\Theta\}$= 0.4502
OS	m$\{C\}$= 0.3187,m$\{A\}$= 0.1594,m$\{\Theta\}$= 0.5219
SOE	m$\{D\}$= 0.3419,m$\{A,B\}$= 0. 2849,m$\{\Theta\}$= 0. 3732
FP	m$\{B\}$= 0. 3215,m$\{C,D\}$= 0. 2572,m$\{\Theta\}$= 0. 4212
DC	m$\{B,D\}$= 0. 3436,m$\{A\}$= 0. 2062,m$\{\Theta\}$= 0. 4502
LDR	m$\{D\}$= 0. 4124,m$\{A\}$= 0. 1375,m$\{\Theta\}$= 0. 4502
CTQ	m$\{B\}$= 0. 4124,m$\{A,D\}$= 0. 1375,m$\{\Theta\}$= 0. 4502
IPC	m$\{C\}$= 0. 3187,m$\{D\}$= 0. 1594,m$\{\Theta\}$= 0. 5219
OTD	m$\{B\}$= 0. 3436,m$\{A\}$= 0. 2062,m$\{\Theta\}$= 0. 4502
QR	m$\{A\}$= 0. 2597,m$\{D\}$= 0. 1732,m$\{\Theta\}$= 0. 5671
SC1	m$\{B\}$= 0. 4124,m$\{D\}$= 0. 1375,m$\{\Theta\}$= 0. 4502
SC2	m$\{A,C\}$= 0. 3215,m$\{D\}$= 0. 2572,m$\{\Theta\}$= 0. 4212
BSC	m$\{D\}$= 0. 3858,m$\{A\}$= 0. 1929,m$\{\Theta\}$= 0. 4212
SP	m$\{D\}$= 0. 3215,m$\{B,C\}$= 0. 2572,m$\{\Theta\}$= 0. 4212

In what follows, the weight of every sub-criteria in layer 2 is determined using ANP. In ANP, AHP is used to evaluate each criteria's weight, which is introduced in detail in Section 3.2. Following this way, Table 7 shows the judgment matrix of each criteria in Layer 2.

Table 7. Pairwise comparison matrix for the sub-criteria in Layer 2 under different controlling criteria

ROI	FS	MA	OS	Weight	SOE	FP	DC	Weight	IPC	LDR	CTQ	Weight
FS	1	3	7	0.6694	FP	1	1/2	0.3333	LDR	1	3	0.7500
MA	1/3	1	3	0.2426	DC	2	1	0.6667	CTQ	1/3	1	0.2500
OS	1/7	1/3	1	0.0879	FP	SOE	DC	Weight	OTD	QR	SC	Weight
FS	ROI	MA	OS	Weight	SOE	1	3	0.7500	QR	1	2	0.6667
ROI	1	1/4	1/4	0.1085	DC	1/3	1	0.2500	SC	1/2	1	0.3333
MA	4	1	1/2	0.3445	DC	SOE	FP	Weight	QR	OTD	SC	Weight
OS	4	2	1	0.5469	SOE	1	1/3	0.2500	OTD	1	5	0.8333
MA	ROI	FS	OS	Weight	FP	3	1	0.7500	SC	1/5	1	0.1667
ROI	1	1/4	1/4	0.1048	LDR	CTQ	IPC	Weight	SC1	OTD	QR	Weight
FS	4	1	3	0.6046	CTQ	1	4	0.8000	OTD	1	3	0.7500
OS	4	1/3	1	0.2906	IPC	1/4	1	0.2000	QR	1/3	1	0.2500
OS	ROI	MA	FS	Weight	CTQ	LDR	IPC	Weight	SC2	BSC	SP	Weight
ROI	1	1/3	1/7	0.0879	LDR	1	1/3	0.2500	BSC	1	1/4	0.2000
MA	3	1	1/3	0.2426	IPC	3	1	0.7500	SP	4	1	0.8000
FS	7	3	1	0.6694	SP	SC	BSC	Weight				
BSC	SC	SP		Weight	SC	1	1/3	0.2500				
SC	1	1/5		0.1667	BSC	3	1	0.7500				
SP	5	1		0.8333								

Next, the relative importance of each dimension for a determinant is obtained through a pairwise comparison matrix. Four such matrices can be formulated in the present case. The matrices for the criteria BI, EOF, Q, S, R are shown in Tables 8–10. As for the criteria in the first layer, their weights are shown in Table 11.

In what follows, the weights for each attribute can be built. As shown in Table 12, the second column shows the weight associated with the criteria in the first layer while the third column displays the relative importance of the attributes in the second layer. The data in the 4th column is adopted from the converged super matrix as shown in Table 14. We give the weight associated with each attribute in the 5th column. For example, for the attribute FS, its final weight is calculated as below:

$$w_{FS} = 0.1089 * 0.1570 * 0.3187 = 0.0054$$

After normalization, the weights are shown in the final column of Table 12.

Next, according to the discounting operation shown in Eq. (1) and Dempster's combination rule, we can build the performance for each decision alternatives. In order to demonstrate the efficiency of the proposed method, we have compared it with DS/AHP method proposed in Ref. (71). Table 15 and Fig. 4 show us the performance of each supplier. It can be noticed that Supplier B has the highest priority weight both in DS/AHP and DS/ANP approaches. In addition to this, there is a 22.55% level of combined uncertainty in the DS/ANP while there is a 17.48% level of combined uncertainty in DS/AHP. Besides, from Fig. 4, we can also find that the interdependencies and interactions across the criteria play a vital role to determine the performance associated with each decision alternatives. For example, for the decision alternative D, its priority weight in DS/ANP approach is less than in DS/AHP method by a degree of 16% percent.

Table 8. Pairwise comparisons for attributes BI and EOF

(a) Pairwise comparisons for BI attribute

BI	ROI	FS	MA	OS	Weight
ROI	1	2	5	3	0.0882
FS	1/2	1	3	2	0.1570
MA	1/5	1/3	1	1/2	0.4829
OS	1/3	1/2	2	1	0.2720

(b) Pairwise comparisons for EOF criteria

EOF	SOE	FP	DC	Weight
SOE	1	3	2	0.5472
FP	1/3	1	2	0.2631
DC	1/2	1/2	1	0.1897

Table 9. Pairwise comparisons for attributes Q and S

(a) Pairwise comparisons for Q attribute

Quality	LDR	CTQ	IPC	Weight
LDR	1	1/3	1/2	0.1634
CTQ	3	1	2	0.5396
IPC	2	1/2	1	0.2970

(b) Pairwise comparisons for S criteria

Services	OTD	QR	SC	Weight
OTD	1	3	7	0.6694
QR	1/3	1	3	0.2426
SC	1/7	1/3	1	0.1897

Table 10. Pairwise comparisons for Risks (R) criteria

Risks	SC	BSC	SP	Weight
SC	1	1/2	1/3	0.1634
BSC	2	1	1/2	0.2970
SP	3	2	1	0.5396

Table 11. Weight of each criteria in Layer 1(CI=0.0895)

	BI	EOF	Q	S	R	Eigen vector
BI	1	1/2	1/4	1/5	3	0.1089
EOF	2	1	1/2	1/3	2	0.1491
Q	4	2	1	1/2	2	0.2538
S	5	3	2	1	3	0.4028
R	1/3	1/2	1/2	1/3	1	0.0854

Table 12. The final weights for each criteria

Dimensions	Attributes	1 adopted from Table 11	2 adopted from Tables 8-10	3 adopted from converged super matrix	Weights	Normalized Weights
BI	ROI	0.1089	0.0882	0.0917	0.0009	0.0024
	FS	0.1089	0.1570	0.3187	0.0054	0.0148
	MA	0.1089	0.4829	0.3155	0.0166	0.0449
	OS	0.1089	0.2720	0.2741	0.0081	0.0220
EOF	SOE	0.1491	0.5472	0.3391	0.0277	0.0749
	FP	0.1491	0.2631	0.3478	0.0136	0.0370
	DC	0.1491	0.1897	0.3131	0.0089	0.0240
Q	LDR	0.2538	0.1634	0.3299	0.0137	0.0371
	CTQ	0.2538	0.5396	0.3452	0.0473	0.1280
	IPC	0.2538	0.2970	0.3249	0.0245	0.0663
S	OTD	0.4028	0.6694	0.4452	0.1200	0.3251
	QR	0.4028	0.2426	0.3484	0.0340	0.0922
	SC1	0.4028	0.1897	0.2064	0.0158	0.0427
R	SC2	0.0854	0.1634	0.1751	0.0024	0.0066
	BSC	0.0854	0.2970	0.3735	0.0095	0.0257
	SP	0.0854	0.5396	0.4514	0.0208	0.0563

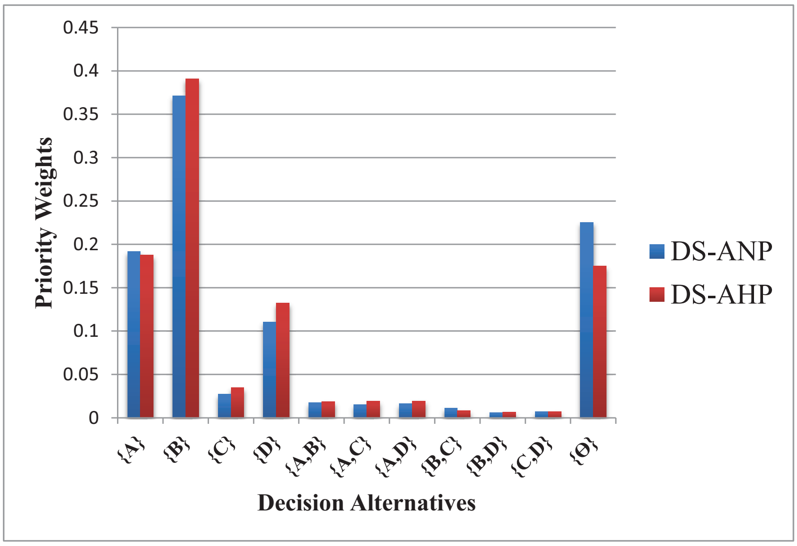

Fig. 4. The comparison results between DS/ANP and DS/AHP

Criteria	ROI	FS	MA	OS	SOE	FP	DC	LDR	CTQ	IPC	OTD	QR	SC1	SC2	BSC	SP
ROI	0	0.1085	0.1048	0.0879												
FS	0.6694	0	0.6046	0.2426												
MA	0.2426	0.3445	0	0.6694												
OS	0.0879	0.5469	0.2906	0												
SOE					0	0.7500	0.2500									
FP					0.3333	0	0.7500									
DC					6667	0.2500	0									
LDR								0	0.2500	0.7500						
CTQ								0.8000	0	0.2500						
IPC								0.2000	0.7500	0						
OTD											0	0.8333	0.7500			
QR											0.6667	0	0.2500			
SC1											0.3333	0.1667	0			
SC2														0	0.1667	0.2500
BSC														0.2000	0	0.7500
SP														0.8000	0.8333	0

Table 13. Super matrix before convergence

Weight	ROI	FS	MA	OS	SOE	FP	DC	LDR	CTQ	IPC	OTD	QR	SC1	SC2	BSC	SP
ROI	0.0917	0.0917	0.0917	0.0917												
FS	0.3187	0.3187	0.3187	0.3187												
MA	0.3155	0.3155	0.3155	0.3155												
OS	0.2741	0.2741	0.2741	0.2741												
SOE					0.3391	0.3391	0.3391									
FP					0.3478	0.3478	0.3478									
DC					0.3131	0.3131	0.3131									
LDR								0.3299	0.3299	0.3299						
CTQ								0.3452	0.3452	0.3452						
IPC								0.3249	0.3249	0.3249						
OTD											0.4452	0.4452	0.4452			
QR											0.3484	0.3484	0.3484			
SC1											0.2064	0.2064	0.2064			
SC2														0.1751	0.1751	0.1751
BSC														0.3735	0.3735	0.3735
SP														0.4514	0.4514	0.4514

Table 14. Super matrix after convergence

Table 15. The comparison results between DS/ANP and DS/AHP

Decision Alternatives	DS-ANP	DS-AHP
$\{A\}$	0.1919	0.1878
$\{B\}$	0.3715	0.3907
$\{C\}$	0.0272	0.0346
$\{D\}$	0.1108	0.1325
$\{A, C\}$	0.0155	0.0190
$\{A, D\}$	0.0162	0.0195
$\{C, D\}$	0.0071	0.0071
$\{B, D\}$	0.0060	0.0067
$\{B, C\}$	0.0112	0.0085
$\{\Theta\}$	0.2255	0.1748

5. Conclusions

Recent years we observed an explosive growth of manufacturing organisations fuelled by rapid development of e-commerce. An ideal manufacturing requires efficient suppliers. To handle the independencies and the uncertain information on potential suppliers we proposed a new method DS/ANP based on the Analytic Network Process (ANP) method and Dempster-Shafer (DS) theory of evidence. To the best of our knowledge, this is the first attempt to deal with supplier selection in a manufacturing organization using the hybrid DS/ANP approach. The advantage of the proposed method is that it overcomes the shortcomings of AHP by considering the dependencies and uncertainty across the selection criteria, and provides us with a simple and effective way for selecting the supplier. By quantitatively comparing our method with DS/AHP approach we have shown that the proposed method provides a systematic and optimal tool of the decision making.

The proposed method provides a way for simplified modelling of complex mutil-criteria decision-making problems. In addition to this, we can quantify many subjective judgements by taking advantage of the experts' experience. The decision making systems are becoming more and more complex nowadays, filled with imprecise and vague information. DS theory is good at capturing such kind of uncertain information and it provides us with a flexible and effective tool to deal with the supplier selection problem under uncertain environment. Although the model has been verified on a small example, including four distinct decision alternatives and 16 attributes, it is capable for solving more complex problems. In future studies we will demonstrate on a large-scale data sets that the method proposed in the paper could help us to reduce the risks of making poor investment decisions when dealing with complex networks of suppliers.

Declaration of conflicting interests

The authors declare that there is no conflict of interest.

Funding

The author greatly appreciate the reviews' suggestions. The work is partially supported by National Natural Science Foundation of China (Grant No. 61174022), R&D Program of China (2012BAH07B01), National High Technology Research and Development Program of China (863 Program) (Grant No. 2013AA013801), Science and Technology Planning Project of Guangdong Province, China (Grant No.2010B010600034, 2012B091100192), Business Intelligence Key Team of Guangdong University of Foreign Studies (Grant No. TD1202), the open funding project of State Key Laboratory of Virtual Reality Technology and Systems, Beihang University (Grant No.BUAA-VR-14KF-02).

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