Paper

Intelligent decision system based on the evidential reasoning approach and its applications

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Abstract—Intelligent decision system (IDS) is a window-based software package that has been developed on the basis of the evidential reasoning (ER) approach, a recent development in handling hybrid multiple criteria decision analysis (MCDA) problems with uncertainties. In this paper, the evidential reasoning approach will be briefly described first, and its major differences from and the relationships with conventional MCDA methods will also be discussed. Then the main features, advantages and benefits of IDS will be demonstrated and explained using two application examples: supplier pre-qualification assessment and customer satisfaction survey analysis, which have been investigated as part of the research projects led by the authors and funded by the UK government and the EC. It is concluded in the paper that the ER approach can be used not only to deal with problems that traditional methods can solve, but also to model and analyse more complicated decision problems that traditional methods are incapable of handling.

Keywords— multicriteria decision support systems, knowledge management, intelligent decision system, the evidential reasoning approach.

1. Introduction

In increasingly competitive, demanding and hostile business environments, many organisations are under pressure to cut costs and improve quality of their services and products. During the past several years, we have been in close collaboration with a number of companies in applying multicriteria decision analysis methods to help them achieve those goals. Assessing suppliers systematically in e-procurement processes and conducting quality and service surveys among customers are two of the areas where many companies have asked us to provide support.

Such assessments and surveys are normally based on specially designed models and can be regarded as a typical type of multiple criteria decision analysis (MCDA) problems [1, 13], which normally include a large number of criteria having both a quantitative and qualitative nature. Traditional ways of conducting such assessments and surveys include the use of average scores as performance indicators. The advantage of such methods is their simplicity and practicality. However, an average score does not provide sufficient information on the diversity of the performances of a business, nor can it indicate where the business is doing well and where it needs to improve if its average performance is acceptable. Therefore strengths and weaknesses need to be identified separately to supplement average scores. However, questions have been raised as to the accuracy of average scores generated and the consistency between average scores and strengths and weaknesses identified [6, 8].

Recently, significant effort has been made by the authors and their colleagues to introduce a new MCDA method, the evidential reasoning (ER) approach into such assessment exercises [6, 12, 13]. Several projects have been funded by the UK Engineering and Physical Science Research Council (EPSRC) and the European Commission (EC) to conduct research in applying the ER approach to support such assessments. A number of papers and research reports have been generated and published as the results of the research projects. These results show that the ER approach can help to reduce subjectivity in the assessment processes and generate a range of useful information for an organisation in question. This paper will describe how the ER approach and its software realisation intelligent decision system (IDS) [9] can be applied to support supplier assessment and customer quality survey analysis.

In the following section, the ER approach and its development history will be described first and the IDS software will be introduced as well. A supplier pre-qualification assessment model and its implementation will then be discussed, followed by the description of a customer quality survey analysis using the IDS software. The paper will conclude in Section 5.

2. The evidential reasoning approach and its software realisation – IDS

The evidential reasoning approach uses an evidence-based reasoning process to reach a conclusion, which differs from traditional MCDA methods. The motivation of developing the ER approach originates from the authors' experiences of working with industry in developing decision support systems [16], in particular to deal with MCDA problems having both quantitative and qualitative information with uncertainties and subjectivity. The ER approach has been developed using the concepts from several disciplines, including decision sciences (in particular utility theory), artificial intelligence, statistical analysis, fuzzy set theory, and computer technology [10–12, 14–16].

The development of the ER approach has experienced five major stages. The first stage was the introduction of a belief structure into a decision matrix [16]. This provides a novel way to model MCDA problems, in particular those having both quantitative and qualitative criteria with uncertainties. In conventional methods, a MCDA problem is modelled using a decision matrix, with each criterion assessed at each alternative decision by a single value. In the ER approach, a MCDA problem is described using a belief decision matrix, with each criterion assessed at each alternative by a two-dimensional variable: possible criterion referential values (assessment grades) and their associated degrees of belief.

Mathematically, in the ER approach a MCDA problem with L criteria A_i $(i=1,\ldots,L)$, K alternatives O_j $(j=1,\ldots,K)$ and N evaluation grades H_n $(n=1,\ldots,N)$ for each criterion is represented using a belief decision matrix with $S\big(A_i(O_j)\big)$ as its element at the ith row and jth column, where $S\big(A_i(O_j)\big)$ is given as follows:

$$S\big(A_i(O_j)\big)=\Big\{\big(H_n,\beta_{n,i}(O_j)\big),\ n=1,\ldots,N\Big\}\quad i=1,\ldots,L,\ j=1,\ldots,K,$$

where $\beta_{n,i}(O_j)$ is the degree of belief to which the alternative O_j is assessed to the nth grade of the ith criterion. It should be noted that a criterion could have its own set of evaluation grades that may be different from those of other criteria and also criteria could consist of a hierarchy [12].

The above ER framework allows more information to be contained in the model where the decision maker is no longer forced to pre-aggregate decision information into a single value when the original information is truly two-dimensional. In this context, the ER framework not only provides flexibility in describing a MCDA problem, it also prevents any loss of information due to the conversion from two-dimensional to one-dimensional values in the modeling process.

The second stage was the introduction of the Dempster-Shafer theory [2, 5] into the ER approach so that the two-dimensional information contained in the belief decision matrix could be aggregated to produce rational and consistent assessment results. For years, the authors have been searching for appropriate theoretical frameworks to fulfil such a task and the Dempster-Shafer theory has been chosen because of its unique capacity of dealing with ignorance which is inherent in subjective assessments, its powerful evidence combination rules and the reasonable requirements to apply the rules [2, 3, 10, 11].

Instead of aggregating average scores, the ER approach employs an evidential reasoning algorithm to aggregate belief degrees, which has been developed on the basis of the belief decision matrix, decision theory and the evidence combination rule of the Dempster-Shafer theory [10–12, 14]. Thus, scaling grades is not necessary for aggregating criteria in the ER approach and it is in this way that the ER approach is different from other MCDA approaches, most of which aggregate average scores or utilities.

The ER aggregation process is briefly described as follows. The following descriptions are of a mathematical nature and may be skipped until the end of the last set of equations. First, the degrees of belief $\beta_{n,i}(O_j)$ (or $\beta_{n,i}$ for short) for all $n=1,\ldots,N$, $i=1,\ldots,L$ are transformed into basic probability masses [12, 14]. Let ω_i be the weight of the ith criterion, $m_{n,i}$ a basic probability mass representing the degree to which the ith criterion is assessed to the nth evaluation grade H_n. Let $m_{H,i}$ be a remaining probability mass unassigned to any individual grade after the ith criterion has been assessed; $m_{n,i}$ and $m_{H,i}$ are calculated as follows:

$$m_{n,i}=\omega_i\beta_{n,i}\quad n=1,\ldots,N,$$

$$m_{H,i}=1-\sum_{n-1}^{N}m_{n,i}=1-\omega_i\sum_{n=1}^{N}\beta_{n,i},\quad i=1,\ldots,L,$$

$$\overline{m}_{H,i}=1-\omega_i\quad\text{and}\quad\widetilde{m}_{H,i}=\omega_i\Big(1-\sum_{n=1}^{N}\beta_{n,i}\Big)$$

with $m_{H,i}=\overline{m}_{H,i}+\widetilde{m}_{H,i}$ for all $i=1,\ldots,L$ and $\sum_{i=1}^{L}\omega_i=1$. The probability mass assigned to the whole set of grades $H=[H_1,H_2,\ldots,H_N]$, which is unassigned to any individual grade H_n, is split into two parts, one caused by the relative importance of the ith criterion or $\overline{m}_{H,i}$ and the other by the incompleteness of the ith criterion or $\widetilde{m}_{H,i}$.

Then, all L criteria are aggregated to generate the combined degree of belief for each possible grade H_n. Let $m_{n,I(1)}=m_{n,1}$ $(n=1,\ldots,N)$, $\overline{m}_{H,I(1)}=\overline{m}_{H,1}$, $\widetilde{m}_{H,I(1)}=\widetilde{m}_{H,1}$ and $m_{H,I(1)}=m_{H,1}$. The combined probability assignments $m_{n,I(L)}$ $(n=1,\ldots,N)$, $\overline{m}_{H,I(L)}$, $\widetilde{m}_{H,I(L)}$, and $m_{H,I(L)}$ can be generated by aggregating all the basic probability masses using the recursive evidential reasoning algorithm [14]:

$$\{H_n\}:\quad m_{n,I(i+1)}=K_{I(i+1)}\big[m_{n,I(i)}m_{n,i+1}+m_{H,I(i)}m_{n,i+1}+m_{n,I(i)}m_{H,i+1}\big]\quad n=1,2,\ldots,N$$

$$\{H\}:\quad m_{H,I(i)}=\widetilde{m}_{H,I(i)}+\overline{m}_{H,I(i)}$$

$$\widetilde{m}_{H,I(i+1)}=K_{I(i+1)}\big[\widetilde{m}_{H,I(i)}\widetilde{m}_{H,i+1}+\overline{m}_{H,I(i)}\widetilde{m}_{H,i+1}+\widetilde{m}_{H,I(i)}\overline{m}_{H,i+1}\big]$$

$$\overline{m}_{H,I(i+1)}=K_{I(i+1)}\big[\overline{m}_{H,I(i)}\overline{m}_{H,i+1}\big]$$

$$K_{I(i+1)}=\Bigg[1-\sum_{t=1}^{N}\sum_{\substack{i=1\\ j\neq t}}^{N}m_{t,I(i)}m_{j,i+1}\Bigg]^{-1}\quad i=\{1,2,\ldots,L-1\}$$

$$\{H\}:\quad\beta_H=\frac{\widetilde{m}_{H,I(L)}}{1-\overline{m}_{H,I(L)}}$$

$$\{H_n\}:\quad\beta_n=\frac{m_{n,I(L)}}{1-\overline{m}_{H,I(L)}}\quad n=1,2,\ldots,N$$

Parameter β_n denotes the degree of belief to which the L criteria are assessed to the grade H_n and β_H represents the remaining belief degrees unassigned to any H_n. It has been proved that $\sum_{n=1}^{N}\beta_n+\beta_H=1$ [14]. The final distribution assessment for O_j generated by aggregating the L criteria can be represented as follows:

$$S(O_j)=\left\{\left(H_n,\beta_n(O_j)\right),\quad n-1,\ldots,N\right\}.$$

Suppose the utility (or score) of an individual output term H_n is denoted by $u(H_n)$. The average utility of $S(O_j)$ can be given as follows [12]:

$$u(O_j)=\sum_{n=1}^{N}\beta_n(O_j)u(H_n).$$

Note that β_n denotes the lower bound of the likelihood that the alternative O_j is assessed to H_n. The upper bound of the likelihood is given by $(\beta_n+\beta_H)$. Complementary to the above distribution assessment, a utility interval can also be established [12] if the assessment is incomplete or imprecise, characterized by the maximum, minimum and average utilities of $S(A^*)$ defined as follows given $u(H_{n+1})\geq u(H_n)$:

$$u_{\max}(O_j)=\sum_{n=1}^{N-1}\beta_n(O_j)u(H_n)+\left(\beta_N(O_j)+\beta_H(O_j)\right)u(H_N),$$

$$u_{\min}(O_j)=\left(\beta_1(O_j)+\beta_H(O_j)\right)u(H_1)+\sum_{n=2}^{N}\beta_n(O_j)u(H_n),$$

$$u_{avg}(O_j)=\frac{u_{\max}(O_j)+u_{\min}(O_j)}{2}.$$

Note that if all original assessments $S\left(A_i(O_j)\right)$ in the belief decision matrix are complete, then $\beta_H(O_j)=0$ and $u\left(S(O_j)\right)=u_{\max}(O_j)=u_{\min}(O_j)=u_{avg}(O_j)$. It should also be noted that the above utilities are only used for characterizing an assessment but not for criterion aggregation.

The computational complexity using the combination rule of the Dempster-Shafer theory could be one of the major points of criticism if the combination rule is not used properly. In fact, Orponen [4] showed that the combination of mass functions or basic probability assignments (BPAs) using Dempster's rule is #P-complete (the class #P is a functional analogue of the class NP of decision problems). But the computational complexity of reasoning using Dempster's rule based on the above specific ER framework becomes linear rather than #P-complete [10–12]. It should also be noted that conflicting information can be explicitly modelled using the ER framework with the normalized ω_k and logically processed using the ER algorithm, thereby overcoming another drawback of the original combination rule of the Dempster-Shafer theory in dealing with conflicting evidence.

The third stage was the development of the rule and utility-based information transformation techniques to transform various types of evaluation information to a unified framework so that all criteria of both a quantitative and qualitative nature can be assessed in a consistent and compatible manner in the ER framework [12]. This to certain extent mirrors the traditional normalisation techniques used to handle quantitative criteria with different units in MCDA problems. The key difference is that in the ER framework the new techniques can in a sense preserve the two-dimensional information represented in the belief structure. It has been proved that by using the developed information transformation techniques not only the expected utilities of the original and the transformed assessments are equivalent but the degrees of incompleteness or completeness in the original assessments are also preserved.

The fourth stage is the enhancement of the approximate reasoning process of the original ER approach. Although the Dempster-Shafer theory has been used as the theoretical framework for information aggregation in the ER approach, its original evidence combination rule would generate irrational synthesis results if there is conflicting evidence. Significant modifications have been made since the theory was first introduced into the ER approach to deal with MCDA problems. It is proved that the new reasoning process of the ER approach satisfies the following common sense synthesis rules (CSSR) [14]:

CSSR 1: *If no sub-criterion is assessed to an evaluation grade at all then the upper-level criterion should not be assessed to the same grade either.*

CSSR 2: *If all sub-criteria are precisely assessed to an individual grade, then the upper-level criterion should also be precisely assessed to the same grade.*

CSSR 3: *If all sub-criteria are completely assessed to a subset of grades, then the upper-level criterion should be completely assessed to the same subset as well.*

CSSR 4: *If sub-criterion assessments are incomplete, then an upper-level assessment obtained by aggregating the incomplete basic assessments should also be incomplete with the degree of incompleteness properly expressed.*

The fifth stage is the implementation of the ER approach by developing a Windows based software package, the intelligent decision system [9, 12, 14, 15]. As mentioned earlier, the ER approach models a MCDA problem using a belief decision matrix with two-dimensional values, so inevitably the calculations involved in the aggregation processes could be more complicated than some traditional methods such as the additive utility function approach. Without a user-friendly computer interface to facilitate information collection, processing and display, the task could be rather difficult to accomplish by hands, even for a relatively small scale MCDA problem.

Although the ER approach involves relatively complicated calculations, its computational requirements are linearly proportional to the scale of a MCDA problem, namely the numbers of criteria and alternatives in a problem. IDS has been used in a variety of applications, such as motorcycle assessment [10], general cargo ship design selection (or assessment), marine system safety analysis and synthesis, executive car assessment, project management and organizational self-assessment [6, 13]. The experiences gained from these applications indicate that for MCDA problems with up to a few thousands of criteria and many alternatives, the calculation time using a PC is unnoticeable. It has also been proved in these applications that the ER approach not only produces consistent and reliable results for problems that can be solved using conventional MCDA methods, but also is capable of dealing with MCDA problems of the following features, which are difficult to handle using conventional methods without making further assumptions:

– mixture of quantitative and qualitative information,

– mixture of deterministic and random information,

– incomplete (missing) information,

– vague (fuzzy) information,

– large number (hundreds) of criteria in a hierarchy,

– large number of alternatives.

In addition to its mathematical functions, IDS is also a knowledge management tool. It records assessment information including evidence and comments in organised structures, provides systematic help at every stage of the assessment process including guidelines for grading criteria, and at the end of an assessment generates a tailored report with strengths and weaknesses highlighted at a click of a button. In the following sections, two application examples are to be examined to demonstrate some of the features of the IDS software package.

3. Supplier pre-qualification assessment

World markets have become increasingly competitive and integrated. In a global marketplace, a good supplier appears to be an invaluable resource for a buying organisation. The selection and management of right suppliers is the key element for a company to achieve its own performance targets.
Supplier pre-qualification assessment is considered as the critical step of a supplier selection process. Its objective is to screen out supply applicants who do not meet the basic requirements to such a degree that any further detailed assessment of their applications would be unnecessary. It also aims to provide feedback information to an applicant about where it should improve in order to be qualified as a supplier. It thus consists of both establishing minimal capacities below which a vendor will not be considered and determining whether an applicant can fulfil these basic requirements.
In recent years, the authors have established and supervised a number of summer consultancy projects for supplier assessment together with the Purchase Department of the Shared Service Ltd of Siemens UK, a global leading company in communications, electronics and electrical engineering. The objectives of such projects are to help investigate existing supplier assessment models, develop new models and realise them using the IDS software package both online and offline. One of such projects was dedicated to developing a supplier pre-qualification assessment model for the company [7]. The model has a hierarchy of criteria as shown in Fig. 1, which is the IDS main window for displaying an assessment model.

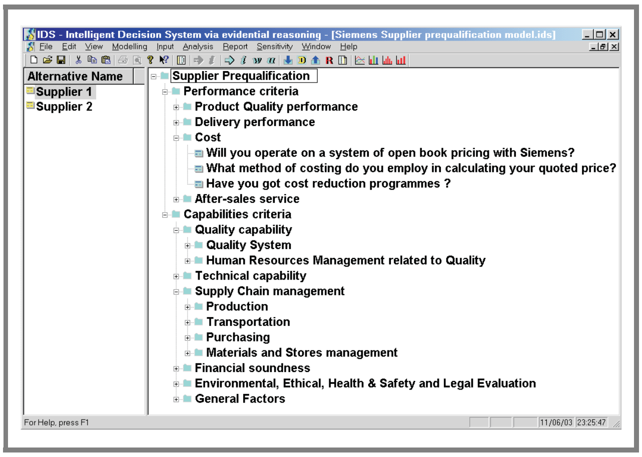

Fig. 1. IDS main window for Siemens UK supplier pre-qualification model.

The IDS main window consists of a tree view on the right side to display the names of a hierarchy of criteria; a list view on the left side to show the names of alternative suppliers to be assessed; a menu bar where all IDS functions can be assessed for model building, data input, result analysis, reporting and sensitivity analysis; and a short cut bar for easy access to frequently used IDS functions.

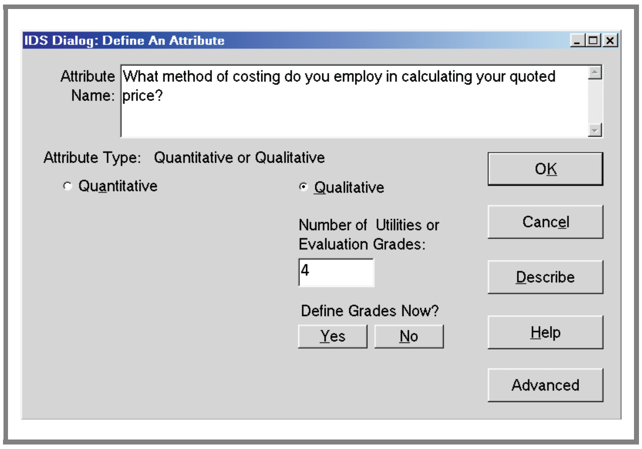

Fig. 2. Define a qualitative criterion using IDS dialog.

The criteria hierarchy can be fully expanded in the same way as in Window Explorer. A criterion can be defined as a quantitative, qualitative or uncertain criterion using the IDS dialog windows [9]. For example, Fig. 2 shows the IDS dialog window for defining a qualitative criterion where the user can enter the name of the criterion, choose the number of assessment grades and provide a description about the criterion. Many of the criteria in the Siemens pre-qualification model are of a similar qualitative nature.

Not only can the user define the number of assessment grades, but they can describe and define each grade as well. Figure 3 shows the IDS dialog window for this purpose. Guidelines about how each grade could be chosen can be described by clicking the Define button. The utilities of grades are determined by both the utilities of the grades of high-level criteria and the propagation rules from lower level criteria to high level criteria.

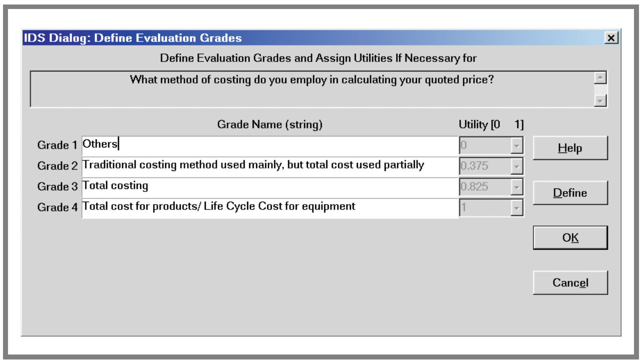

Fig. 3. Define assessment grades using IDS dialog.

A qualitative criterion can be assessed using the grades and a degree of belief to which each grade is assessed. Figure 4 shows an IDS input data dialog window where the user can choose one or more answers with different degrees of belief. The grade definition provides guidelines and/good practices about what a grade actually means, in what circumstances a grade (or answer) should be selected and to what degree a grade could be assessed to. Furthermore, the user can collect evidence to support an assessment and also provide comments on why the assessment is given this way. Such an assessment process is referred to as an evidence-based mapping process, which is designed to improve the objectivity and accuracy of the inherent subjective process. This also provides a structured knowledge base which is easy to access and could be used to support the assessment in subsequent discusses.

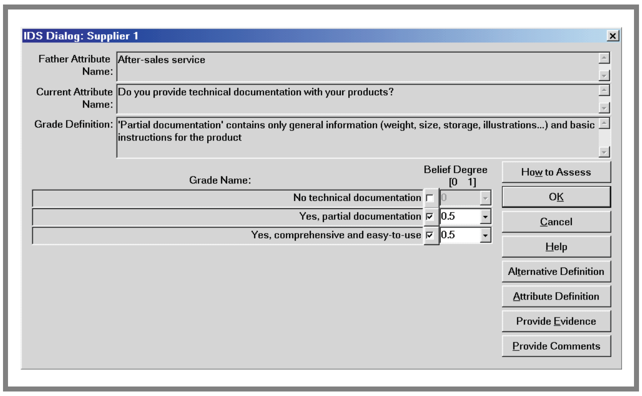

Fig. 4. Enter subjective assessment using IDS dialog.

Quantitative criteria can also be defined and used together with qualitative criteria for assessment. Figure 5 shows the numerical data input window. The best value and the worst value define the range of data that can be entered, which is

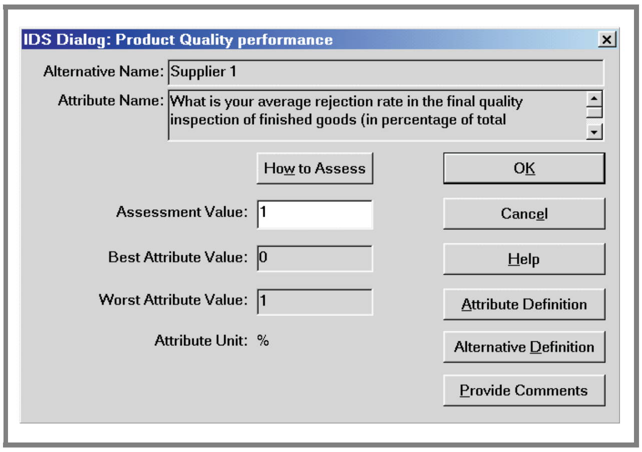

Fig. 5. Enter numerical data using IDS dialog.

defined by the user and between which an assessment figure can be assigned. Random numbers with various probabilities can also be defined and both the possible values and the likelihood can be entered as well, though this model does not contain such criteria.

Apart from screening out poor supply applicants, the main purpose of such assessment includes the identification of strengths and weaknesses of an applicant, which could form a basis for subsequent detailed assessments and for creating action plans to address the weaknesses identified. As such, the concept of the distribution assessment developed in the ER approach would be helpful in identifying strengths and weaknesses. For example, Fig. 6 shows the final distribution assessment for a Siemens supplier "Supplier 1", which provides a panoramic view about the overall

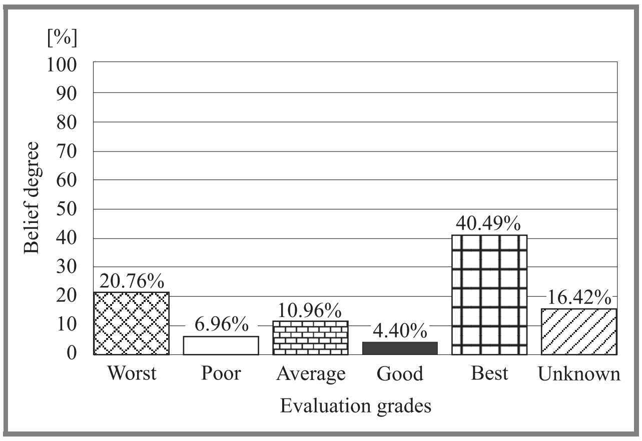

Fig. 6. Distribution assessment generated by IDS.

performance of the supplier in all areas. Clearly, the company has achieved the best performance in many areas, as over 40% of the areas are assessed to be "Best". However, the company does need to improve in nearly 21% of all assessed areas. Also, the company was unable to answer some of the questions put forward by Siemens. In other words, over 16% of the areas need to be further investigated. On the whole, the average percentage score that the company has achieved is just below 60% with a variation between 51% and 57% (Fig. 7). The variation is caused due to the unanswered questions.

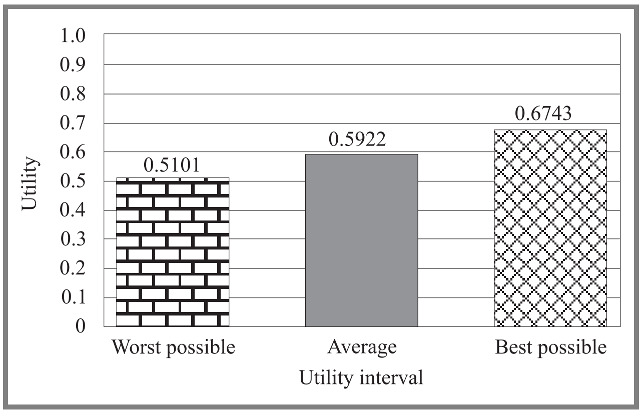

Fig. 7. Average assessment generated by IDS.

Using IDS, the performance distributions of the company on any criterion can be examined in a similar way. This enables Siemens to investigate the areas where the supplier has done well as well as the areas where the supplier has to improve. For example, the company received a zero score or the 100% "Worst" grading on the *product quality performance* criterion because of two problems. The first problem is that "*its average rejection rate in the final quality inspection of finished goods in percentage of total production*" is 3% whilst the lowest acceptable rate by Siemens is only 1%. The second problem is that "*its average return rate from customers in percentage of products or services delivered*" is 7% whilst the lowest acceptable rate by Siemens is only 1% as well. Such investigations provide both sides, Siemens on the customer side and Supplier 1 on the supplier side, with a clear objective view about what Supplier 1 needs to improve to achieve the standards required by Siemens.

The managers of Siemens UK and Supplier 1 both took part in the modeling process, the data collection and the result analysis. They are satisfied with the accuracy and objectivity of the investigation conducted using the ER approach supported by the IDS software.

4. Customer quality and service survey analysis

Customer quality and service survey can provide useful information for a company to improve the quality of its services and products. Silcoms is a medium manufacturing company, located in North West England and specialised in supplying components to aerospace industry among other businesses. The company faces tough competition from overseas in particular Asian companies which can supply cheap products. The management of Silcoms are aware of the competition and are totally committed to improving quality not only for the products they manufacture but also for the services they provide. The company has been given quality awards by the Excellence North West of England. The authors have collaborated closely with the company management and have been very much impressed by their desire to improve their products and services, which have already achieved high standards.

The company, together with the help of external consultants and academics including the authors, has developed a model for conducting quality and service survey among its customers. Figure 8 shows the model structure having four major areas each of which is addressed using a number of questions. To facilitate data collection, the answers to the questions adopt a five-grade scale.

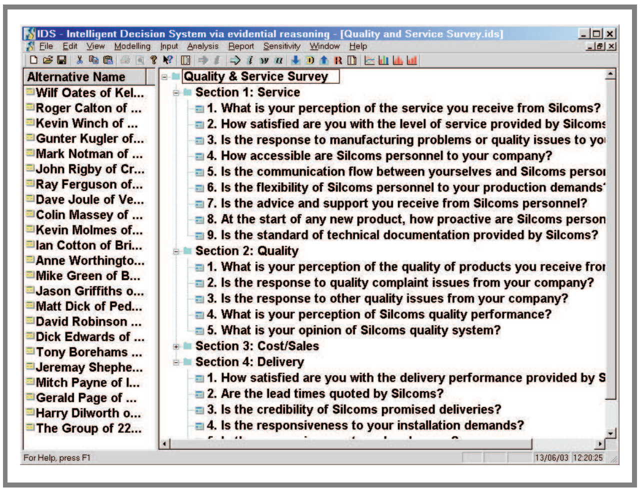

Fig. 8. Questions numbered in four major sections.

Data were collected using a paper version of the model which was nicely bound together and individually sent to each customer. Figure 9 shows a typical answer window and no definition for the grades is provided as the question (criterion) and the answers (grades) are regarded to be straightforward. The customers often chose one answer and occasionally opted to not answer some questions either because the questions are irrelevant to their companies or there may be a lack of information.

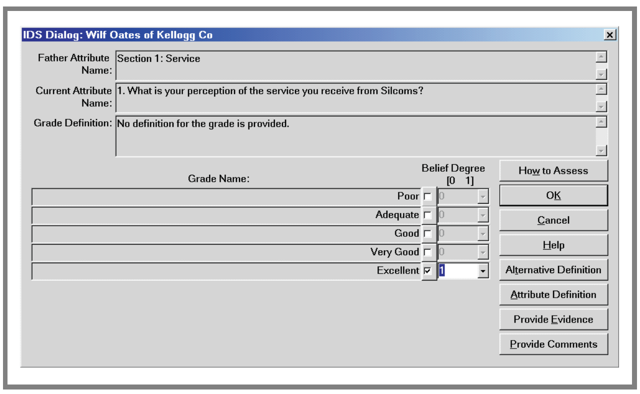

Fig. 9. Original answer provided by a customer.

In Fig. 8, the last alternative *The group of 22 customers* was generated by averaging the answers given by the 22 customers. In Fig. 10, the belief degree assigned to an answer was therefore the percentage of the 22 customers who had chosen this answer. IDS provides a function to combine the original answers provided by individual customers for group analysis. In Fig. 10 it is clear that nearly 80% of the customers have graded their perception of Silcoms service to be *Very good* or *Excellent*, which is an impressive result, considering that most customers were randomly selected with two known "critical" customers chosen deliberately.

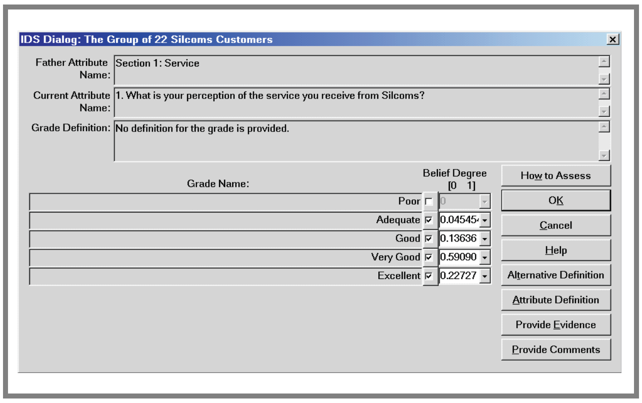

Fig. 10. Degrees of belief assigned by a group of customers.

The IDS provides a range of functions to support the analysis of such surveys, including the analyses of the individual customers' responses on any criteria and the comparison of results provided by the customers. Different groups of the customers can also be combined to show the collective opinions of these groups on any criteria. For example, Fig. 11 shows the collective assessment of the 22 customers on the quality and services provided by Silcoms. The distribution assessment shown in Fig. 11 provides a holistic

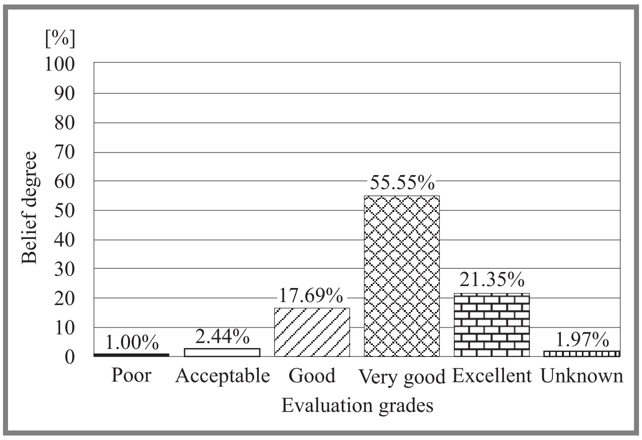

Fig. 11. Collective assessment of Silcoms quality and services.

view of the overall performances of Silcoms. The majority of the customers graded Silcoms at the *Very good* and *Excellent* grades in most areas with the combined belief degree of over 76%. This is a very good result for Silcoms, supporting the company's policy of placing services and quality in the first priority of their policies and strategies. However, there are a couple of customers who did provide critical assessment in some areas, which is clearly displayed. Unlike an average score, this panoramic view will not hide any unsatisfied areas for the good average assessment, thereby preventing the company from missing the opportunity of further improvement.

5. Conclusions

In this paper, the evidential reasoning approach and the intelligent decision system were briefly introduced. Their applications to supplier assessments and the customer surveys of quality and service for two companies in the North West England were reported in some detail. The main feature of this kind of decision problems is that both quantitative and qualitative assessments are included and need to be treated both simultaneously and rationally. Using conventional decision methods, one may need to provide precise number for each assessment, which could be difficult from time to time. Also, assumptions may need to be made in cases where there are missing data or other uncertainties. Traditional methods may only be able to generate average numbers, where bad performances may be averaged out by good performance thereby missing opportunities to identify areas for improvement, which is indeed the very purpose of conducting such assessments in most cases. The IDS software provides easy to use functions to build assessment models, organise and manage knowledge, conduct analysis and generate results.

Acknowledgement

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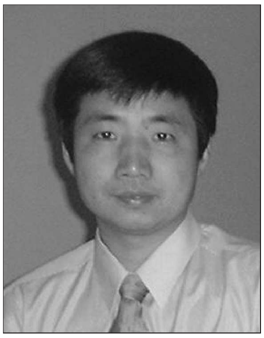

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