An Expert System Approach for Criteria Weighting in Multicriteria Analysis

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Abstract
This paper presents an expert system approach to criteria weighting for solving multicriteria analysis problems involving repetitive selection of alternatives regarding multiple criteria for accomplishing a specific task. Linguistic terms modelled by fuzzy numbers are used to effectively formulate the imprecise and subjective weighting process. A fuzzy knowledge base is constructed to acquire the knowledge of experts in criteria weighting on which consistent and reliable criteria weights can be derived. An empirical study of a real dredger-dispatching problem is presented. The result shows that the expert system approach is effective and reliable for solving practical problem of this kind due to the simplicity in concept, the easiness in use, and the consistency in determining criteria weights.

1. Introduction

Criteria weighting is a complex preference elicitation process in multicriteria analysis (MA) where multiple task requirements reflecting a decision maker’s (DM) major concerns about a specific task in a given problem domain have to be addressed. Effective decision-making often requires adequately determining the criteria weights in a simple and yet consistent manner.

Many methods for criteria weighting in MA have been developed. Keeney and Raiffa [1, 5-6] first present a value tradeoff method. DMs first compare pairs of alternatives with respect to each pair of criteria, with the assumption that both alternatives have identical values on the remaining criteria. The high value of one alternative is traded off for the low value of the other through a series of adjustments until an indifference value is achieved. Criteria weights are determined after numerous value tradeoff processes.

Saaty [12] develops the analytic hierarchy process (AHP) method using pairwise comparison. A reciprocal pairwise comparison matrix is constructed. Criteria weights are obtained by synthesizing various assessments in a systematic manner. The uncertainty and imprecision of the weighting process are indirectly modeled.

Takeda et al. [14] further generalize this method to reflect the DM’s uncertainty about the estimates in the reciprocal matrix. Laarhoven and Pedrycz [7], Buckley [2] extend this method to directly handle the uncertainty and imprecision of the pairwise comparison process using fuzzy set theory. However, in certain situations this method may cause the rank reversal phenomenon, and the computation involved can be quite complex and complicated when fuzzy numbers are used in the pairwise comparison process.

Von Winterfeldt and Edwards [15] propose a direct ranking and rating method. DMs first rank all criteria in the order of their importance, and then give each criterion an estimated numerical value to indicate its relative importance. Criteria weights are obtained by normalizing these estimated values.

Mareschal [8] and Fischer [3] use a mathematical programming model with sensitivity analysis to determine the intervals of weights, within which the same ranking result is produced. This method gives DMs flexibility in judging criteria weights and helps them better understand how criteria weights affect the decision outcome, thus reducing their cognitive burden in determining precise weights. However, this process may become tedious and difficult to manage as the number of criteria increases.

In actual applications, the same DM may elicit different weights using different methods, and no single method can guarantee a more accurate result. This may be mainly due to the fact that the DM cannot always provide consistent judgements under different quantifying procedures. Different DMs using the same method may give different weights.
due to their subjective judgements. As a result, inconsistent ranking outcomes may be produced.

In addition, to solve the MA selection problem for accomplishing a specific task, existing methods virtually require the DM to consider all task requirements simultaneously in assessing criteria weights. This often places a heavy cognitive burden on the DM due to the limitations on the amount of information that humans can effectively handle [9].

The presence of imprecision, vagueness and subjectiveness in describing the task requirements further complicates the weighting process. They make it difficult for the DM to assess precisely how and to what extent these task requirements influence the criteria weights. It seems that the development of a simple and comprehensive method, which can produce consistent criteria weights, is desirable for effective decision making in practical situations.

This paper presents an expert system approach for criteria weighting in MA. Linguistic terms are used to formulate the complex weighting process. A fuzzy knowledge base is constructed to acquire the knowledge of expert DMs that can explicitly reflect the effect of individual task requirements on the importance of each criterion. As a result, consistent criteria weights for a specific decision situation can be obtained, leading to effective decisions being made in solving practical MA problems.

2. The dredger-dispatching problem

The dredger-dispatching problem is frequently confronted by a dredging company in Shanghai, China. To maintain the efficiency and effectiveness of the waterborne traffic that is the lifeline of the city’s economy, the dredging company has to regularly dispatch dredgers from its established fleet of 12 trailing suction hopper dredgers to excavate the sediments from the bottom of channels which may block normal waterborne transport.

To assign the most suitable dredger to a given dredging task, the dispatcher needs to evaluate the performance of all available dredgers based on site conditions and task requirements. The current practice in Shanghai is that experienced dispatchers use their intuition and knowledge to select a dredger by a rule of thumb. However, this ad hoc approach is not always reliable and consistent, due to the imprecise nature of human knowledge and the information available for making assessments. To make effective decisions, all the criteria to be considered should be analysed simultaneously. In this regard, MA provides a systematic framework for managing decision problems of this kind.

To formulate the dredge dispatching process as an MA problem, an investigation was conducted by consulting the expert dispatchers in Shanghai, resulting in the development the dredger-dispatching model shown as in Figure 1. The overall performance of 12 dredgers (alternatives) \(A_1, A_2, \ldots, A_{12}\) for a given dredging task can be obtained by (a) assigning weights to 5 criteria \(C_1 = \text{Efficiency}, C_2 = \text{Cost}, C_3 = \text{Quality}, C_4 = \text{Safety}, C_5 = \text{Reliability}\), (b) assessing the performance ratings of each dredger with respect to each criterion, and (c) aggregating the criteria weights and performance rating for producing an overall performance index for each dredger.

A specific dredging task is usually characterised by five requirements including the daily volume \(T_1\), the daily cost \(T_2\), the quality expectation \(T_3\), the relative danger level \(T_4\), and the site importance \(T_5\). The daily volume indicates how many cubic metres of material a dredger is expected to handle. The daily cost represents the allowable average daily operating cost, reflecting the dispatcher’s concern about the dredging cost against the dedicated funds. The quality expectation reflects the requirements of the authorities on the dredging depth, width and side slope. The site danger level is used to reflect the dispatcher’s concerns on the dredging safety. The site importance is determined by the grade of the dredging site, which reflects the overall social impact of the channel. These task requirements reflect the dispatcher’s concerns in evaluating the performance of dredgers for a given task. They are usually determined qualitatively or quantitatively by the dispatchers or the relevant authorities.

In evaluating the suitability of dredgers for a given task, the problem of how various task requirements affect criteria weights has to be addressed. For example, more concern on the daily dredging volume makes the dispatcher give a higher weight to the efficiency criterion. Less concern on the daily cost leads to a lower weight for the cost criterion. It is therefore desirable to assign criteria weights consistently under a given set of task requirements for making reliable and effective decisions. To this end, this paper proposes an expert system approach to directly link task requirements with criteria weights.

3. The expert system approach
Expert systems are computerized systems that emulate the behavior of human experts in a well-defined and narrow knowledge domain [4, 10]. They provide an effective framework for handling the uncertainty and imprecision of the human decision making process in a flexible and user-adaptive manner. They allow human-computer communications to take place in their most natural form, through the model-analytic knowledge-engineering process, thus helping DMs identify what is relevant to their decision situations.

With the characteristics of the MA problem described before, the expert system method is well suited to formulate the weighting process, as it is in essence a human solution in terms of the selection of a preferred alternative for accomplishing a specific task. The weighting process is of a fuzzy nature as the effect of the task requirements on the criteria importance is usually expressed linguistically. By incorporating fuzzy set and fuzzy logic into the process of knowledge representation, acquisition, and reasoning, reliable criteria weights can be determined consistently in a simple and less cognitively demanding manner.

The approach is developed on the concept of basic criteria weights supported by a fuzzy control scheme. It consists of six phases, including (a) the identification of the task requirements, (b) the determination of the basic criteria weights, (c) the fuzzification of the basic criteria weights using linguistic terms, (d) the determination of the linguistic terms for describing each task requirement, (e) the establishment of the fuzzy knowledge base, and (f) the test and validation of the fuzzy knowledge base, shown as in Figure 2.

![Figure 2: The expert system approach for criteria weighting](image)

Let $A_i (i = 1, 2, ..., n)$ be the alternatives to be evaluated against criteria $C_j (j = 1, 2, ..., m)$ with respect to task requirements $T_l (l = 1, 2, ..., s)$. The expert system approach starts at determining the basic criteria weights defined as the criteria weights regardless of the task requirements in a specific decision situation. This can be done through comprehensive consultation with expert DMs or by using existing methods such as AHP [12].

A fuzzification process is introduced based on the basic criteria weights to facilitate the representation of the importance of each criterion. To reduce the DM’s cognitive burden in the weighting process, linguistic terms such as {Very Unimportant (VU), Unimportant (U), Medium (M), Important (I), and Very Important (VI)} approximated by fuzzy numbers can be used. To reserve the integrity and soundness of the weighting process, the proportion of the corresponding linguistic values for various criteria is kept intact.

After determining the basic criteria weights and their corresponding linguistic representations, the task requirements involved and their corresponding linguistic representations are to be determined. The use of linguistic terms is intuitively easy for DM to represent their subjective assessments in a fuzzy environment [16, 17]. To facilitate the description of the task requirements, a unanimous agreement of the linguistic terms and their corresponding membership functions can be reached in a given decision context through comprehensive discussion and investigation.

To reduce the DM’s cognitive burden in processing large amounts of information at the same time, in particular in assessing the effect of the task requirements on criteria weights, a fuzzy expert system is used. A set of fuzzy IF-THEN rules, representing the knowledge of expert DMs by means of the production rule method [10, 17-18], are constructed. These fuzzy IF-THEN rules explicitly reflect the effect of individual task requirements on the importance of each criterion, based on the unanimous agreement on the definition of the membership function of the linguistic terms for each criterion. Each rule takes the form of:

\[
\text{IF } X \text{ is } A \text{ THEN } Y \text{ is } B
\]

Where $X$ and $Y$ are linguistic variables representing fuzzy variables in the antecedent and consequent statements respectively, and $A$ and $B$ are linguistic terms taken by $X$ and $Y$ respectively.

This set of fuzzy rules constitutes the knowledge base of the system, which expresses all of the system’s expertise on what criteria weights to take for given task requirements. The use of linguistic terms modeled by fuzzy numbers has been found to be intuitively easy in expressing the imprecision or uncertainty of human knowledge in the knowledge base, and will provide accurate and robust solutions.

The establishment of the fuzzy knowledge base allows the DM to interact with the uncertain
environment under which a decision has to be made. It greatly reduces the DM’s cognitive burden in the process of criteria weighting, as they are only required to specify the task requirement linguistically. This helps the DM better understand the decision situations and further improves the quality of the decisions. It gives the DM the flexibility required in modifying the fuzzy knowledge base when the circumstances of the problem domain have changed.

After the establishment of the fuzzy knowledge base, testing and validation of the fuzzy knowledge base should be carried out. The consistency and reliability of the knowledge base can be further improved by deleting redundant rules and adding new rules if necessary. When the decision situation is changed, the knowledge base can also be adjusted.

Using the fuzzy knowledge base, the effects of various task requirements on the relative importance of criteria can be aggregated. Consistent criteria weights can then be determined for a given set of task requirements with respect to a specific decision situation. Effective decisions can thus be made based on the consistently obtained criteria weights.

4. An empirical study

Applying the framework of the expert system approach to criteria weighting for solving the dredger-dispatching problem in Shanghai, the knowledge of expert dispatchers for assessing the influence of each task requirement on criteria weights under various situations can be represented as a set of fuzzy IF-THEN rules. Linguistic terms are used to represent the task requirements and criteria importance. For ease of data acquisition and computational efficiency, trapezoidal or triangular fuzzy numbers are used to represent linguistic terms.

The construction of the knowledge base starts with the definition of the linguistic terms for each linguistic variable used (a) to describe the states of the corresponding task requirement and (b) to represent the weights of the corresponding criterion. Figure 3 shows the membership functions of the term set {Very Low (VL), Low (L), Medium (M), High (H), Very High (VH)} used to describe the states of task requirements, obtained through extensive consultations with the expert dispatchers.

Figure 3 Membership functions of linguistic terms used for describing task requirements.

To define the membership functions of the term set {Very Unimportant (VU), Unimportant (U), Important (I), Very Important (VI)} for representing weights of the corresponding criteria, the basic weights of the five criteria are determined. In this study, the basic weights for criteria $C_1$, $C_2$, $C_3$, $C_4$ and $C_5$ are given as 0.3, 0.2, 0.2, 0.15 and 0.15 respectively through consultations with the expert dispatchers when no specific task requirements are specified. This is the ratio of criteria weights to be obtained when the same linguistic term or value is assessed for all five criteria.

Figure 4 shows the membership functions of linguistic terms used to elicit criteria weights. They are represented by triangular fuzzy numbers that are equally spread over the corresponding ranges, whose values are scaled to correspond to the ratio of the basic criteria weights. The ratio of relative criteria weights is the same for situations where all five criteria have the same linguistic value.
Figure 4 Linguistic terms and their distributions for representing criteria importance

With the linguistic terms and their membership functions defined in Figures 3 and 4, a set of 52 fuzzy rules was constructed from the knowledge of expert dispatchers through interviews. These rules specify the relationship between individual task requirements and the weights of the five criteria. One example of these rules is “If \( T_1 \) is \( H \) and \( T_2 \) is \( VL \) then \( C_1 \) is \( VP \)”. These fuzzy rules are easily understood and can be readily modified by the human dispatchers if necessary, to reflect a specific dispatching environment.

Extensive simulation tests are conducted to verify the effectiveness of the fuzzy knowledge base. After inputting the state of the five task requirements for characterising a specific task, five crisp criteria weights are generated using approximate reasoning with the centroid method for defuzzification. Figures 5, 6 and 7 show the impact of the changes of three task requirements individually on the criteria weights for the dispatching process in the simulation.

The result of the extensive simulation study demonstrates the importance of determining criteria weights in accord with task requirements in dredger dispatching. This suggests a need for a consistent approach to criteria weighting in the dredger dispatching process under uncertainty. This expert system approach to criteria weighting reduces the uncertainty of weighting process greatly, as (a) the task requirements can be specified by crisp or fuzzy data and (b) no tedious and unreliable process in a complex manner is required.

These crisp criteria weights are then used in a fuzzy MA model for generating an overall performance index for each dredger across all criteria, on which the dispatching decision is made. Due to the limitation of paper length, the fuzzy MA model and the corresponding results on the dispatching decision are not presented here. They are to be reported in another paper.
5. Conclusion

This paper presents an expert system approach for consistently determining the criteria weights for solving MA problems. The approach is based on the concept of the basic criteria weights supported by a fuzzy control scheme. A fuzzy knowledge base consisting of a set of fuzzy IF-THEN rules is built to adequately capture the expert DM’s knowledge, intuition and experience in assessing criteria weights. The inherent uncertainty, imprecision and vagueness associated with the human decision making process have been effectively modelled by means of fuzzy set theory and fuzzy logic through the use of linguistic values. As a result, effective decisions can be made on the consistently obtained criteria weights, thus providing reliable decision support to the DM in solving practical MA problems.

An empirical study of a real dispatching problem is presented. The result demonstrates the applicability of the conceptual framework of the expert system approach to criteria weighting for solving the practical MA problem. This is mainly due to the simplicity and comprehensibility in concept, the easiness in use, the consistency in deriving criteria weights, the adequacy in modelled the uncertainty and imprecision in human decision making process, and the adaptability of the approach to the changing decision situation.

References