A Feasible Approximation to Optimum Decision Support System for Multidimensional Cases through a Modular Decomposition

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Abstract

The today's decision making tasks in globalized business and manufacturing become more complex, and ill-defined, and typically multi-aspect or multi-discipline due to many influencing factors. The requirement of obtaining fast and reliable decision solutions further complicates the task. Intelligent decision support system (DSS) currently exhibit wide spread applications in business and manufacturing because of its ability to treat ill-structuredness and vagueness associated with complex decision making problems. For multi-dimensional decision problems, generally an optimum single DSS can be developed. However, with an increasing number of influencing dimensions, increasing number of their factors and relationships, complexity of such a system exponentially grows. As a result, software development and maintenance of an optimum DSS becomes cumbersome and is often practically unfeasible for real situations. This paper presents a technically feasible approximation of an optimum DSS through decreasing its complexity by a modular structure. It consists of multiple DSSs, each of which contains the homogenous knowledge's, decision making tools and possibly expertise's pertaining to a certain decision making dimension. Simple, efficient and practical integration mechanism is introduced for integrating the individual DSSs within the proposed overall DSS architecture.

Key Words*:* Decision Support System (DSS); Group Decision-Making; Multi-dimensional Decision making, Decisions Aggregation.

1. Introduction

Due to globalization, the competition in business and industries is becoming so high and a fast response is needed to cope with the huge amount of information, large number of available alternatives and options, vagueness associated with decision making tasks and transactions. In effect, in business and manufacturing, the decision making problems became more complex, more vague and ill-defined. They have become typically multi-aspect or multi-disciplinary due to many influencing factors. Examples of this situation include: detection of suspicious customs declaration transactions, new product development, environmental impact assessment and many others.

Therefore, relying on robust, reliable, comprehensible decision support system that can handle vagueness associated with inputs and relationships is needed. Intelligent decision support system (DSS) is a specific class of computerized information systems that supports business, manufacturing and organizational decision-making activities, and over and above, includes some intelligence in problem solving, understanding, and handling inputs data vagueness. Besides the mathematical models of operation research and management science techniques, the DSS employs also some artificial intelligence tools like fuzzy logic, genetic algorithms, neural networks or hybrid tools out of them. DSS can as well also include human expertise in problem solving or understanding. It can also be integrated with expert systems (ESs).

The review of literature has demonstrated that the research, development, utilization, and applications of DSS is rapidly progressing and spreading; see e.g. [5], [7], [8]. The literature provides numerous examples to show that DSS can improve decision making process and outcomes and it has been applied successfully in many areas. Quintero [7] developed DSS for improving urban infrastructure management. Considerably large number of DSS was applied in environmental decision making, e.g. [2], [3], [4], [6], particularly in the field of environmental impact assessment.

However, developing and operating single optimum DSS for multi-dimensional or multi-aspect decision problems that incorporate huge amount of variables, relationships, models, tools, multi-discipline input data, and rules is cumbersome and practically inefficient. A typical example of situations involving multi-dimension is the assessment of environmental impacts of industrial projects proposals, where there are several dimensions to evaluate impact, like: water pollution, air pollution, soil contamination, etc. Each of these disciplines contains homogenous sets of input variables and relationships. In this case constructing a single DSS that incorporates all the data and relationships of all these multiple decisions or views is

Manuscript received Oct. 16. 2009; revised Nov. 30. 2009.
Authors wish to thank the Czech Ministry of Education for support of this work by the Grant No. MSM 6046070904 "Information and knowledge support of strategic control" and Grant No. 2C06004 "Intelligent tools for content assessment of relevance of general and specialized data and knowledge resources".

not guaranteed to be practically operationally efficient. Another example includes the detection of suspicious custom declaration transactions, where importers and exporters provide declaration about their goods for customs fees. The problem typically requires several evaluation aspects to judge the correctness of such declaration for instance, automobiles spare parts requires technical expertise's, economical and international marketing expertise's, as well as some legal and historical expertise's. Therefore, a new paradigm in developing DSS is required. In fact, little researches have considered the problem of multi-dimensionality in globalized decision making. Many researches insist erroneously on developing huge DSS or ES including thousands of models, decision rules and getting finally surprised with operational inefficiency.

One adequate and sound solution to this problem is to develop multiple decision making modules or subsystems. However, finding an objective method of integrating these individual systems becomes most crucial step. Historically, the idea of integrating multiple decision making systems or knowledge sources is not new. In most cases the rationale for integration is the multi-disciplinarity or multi-dimensionality involved in the decision making problem. Several past attempts to integrate systems differ in the methods and purpose of integration.

This paper offers a new approach of integrating the multiple DSSs for multi-dimensional, large scale decision making situations, through aggregating their final decision outputs. The article first formulate the problem and then presents an adequate, simple and transparent decision making heuristic as an integration mechanism, and suitable for the given multi-aspect decision making problems.

The paper is organized as follows. Next section is dedicated for detailing pragmatic reasons behind having multiple separate decision making modules, the DSSs corresponding to each assessed decision making aspect or dimension. Section 3 presents the proposed architecture of multiple DSSs as an approximation to the optimum single DSS. In section 4, the integration of the multiple DSSs is formally stated, and the basic requirements for objective and consistent integration mechanism are explained. Section 5 introduces a simple aggregation heuristic as an integration mechanism. Finally, a conclusion is made in section 6.

2. Why multiple DSSs?

The basic components of a DSS are shown in figure 1. There is a data management subsystem, knowledge based subsystem, and model management. Some or all of these subsystems utilize AI tools. The data management subsystem manages the data directly relevant to the decision problem, including the values for the states of nature, courses of action, and measures of performance. The knowledge-based subsystem holds problem knowledge, such as guidance for selecting decision alternatives or advice in interpreting possible outcomes. The model management is a repository for the formal models of the decision problem and the algorithms and methodologies for developing outcomes from the formal models. It can include mathematical operation research models, case-based reasoning techniques, AI based models (e.g., fuzzy logic, genetic algorithm, neural network, experts' based inference rules, etc.] Decision makers communicate with the computerized DSS through the user interface. The decision-making process converts the inputs into problem-relevant outputs. Processing will involve organizing problem inputs; structuring the decision problem model; determining alternatives and identifying relevant criteria; selecting or constructing the adequate decision making models, and finally computing the best problem solution. The DSS can use knowledge drawn from the knowledge base to assist users in performing these processing tasks.

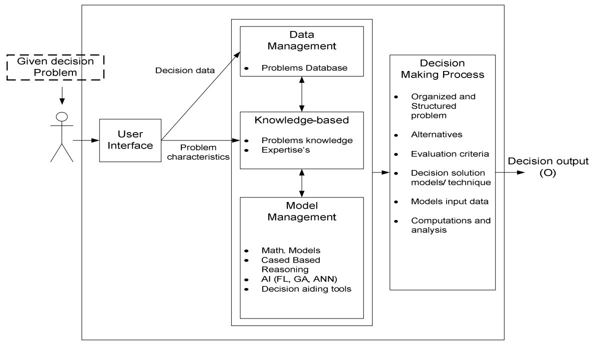

Fig. 1 The basic components of DSS.

Complexity of the DSS is proportional to a number of inputs factors, models, and relationships. As a result, software development and maintenance of an optimum DSS becomes cumbersome and it is practically unfeasible for real situations. Although, due to its intrinsic complexity, the optimum DSS cannot be used in a practical implementation, it can still serve as a theoretical upper limit of performance of the DSS. It is desirable to search for approximations of the optimum DSS, which can reduce undesirable complexity while approaching the optimum performance.

In this research, in order to facilitate the proposed integration among and with other several DSSs and for consistency, the output of each DSS should be a quantitative score of an alternative with respect to each criterion or could be an aggregated score for all criteria. Decision making explanations and outcome feedback can be included in the system.

The need for multiple DSS or, generally, multiple decision making modules can occur frequently when a complex, large scale, and multi-aspect decision problem is confronted. Besides handling complexity there are several other reasons that support constructing multiple independent DSSs for each decision making dimension or aspect as an approximation to a single optimum overall DSS. These reasons are related to the practical implementation and efficiency of operation. These reasons can be:

- Cohesion of knowledge units
- Control and final decision responsibility

- Modularity in analyzing and explaining the final decision
- Improving maintainability
- Improving performance of individual DSSs.

In a huge DSS, the increased number and amount of models, rules, and variables can quickly overload the memory and makes the application difficult to implement, whereas in a more compact and separated DSS, the performance of individual systems is improved.

In the next paragraph we shall describe such a feasible approximation of the optimum DSS, which reduces undesirable complexity while approaching the optimum performance. Authors presented some versions and parts of this solution in the International Congress on Environmental Modeling and Software, iEMSs 2008 [2].

3. The Proposed Approximation of the Optimum DSS

The previous section has explained the rationale for approximating the single optimum DSS into multiple DSSs, each of which represents the decision making process with respect to a single decision making dimension. Now, the proposed approximation of the optimum DSS consists of multiple individual decision making units, the DSSs, as shown in figure 2.

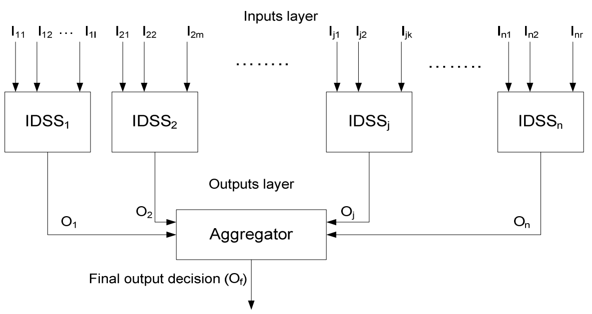

Fig. 2 The proposed architecture of Multiple DSSs.

In such proposed configuration, DSSs are connected in parallel. Each DSS has its structure as in Fig. 1 and provides its final output or decision outcome, which should be homogenous and belonging to the same unified psychometric scale. This is in order to facilitate aggregation into finally consolidated output. The output for each individual DSS represents a judgment regarding a single decision attribute like environmental impact (positive or negative), or product quality (poor, fair, or good), but the internal processing of course of each individual DSS can involve multiple criteria leading to finally judging the output attribute of each DSS. Each individual jth , DSSj, accepts different sets of relevant input factors Ijk, and produces a decision output, Oj, representing main decision attributes for which the DSS is constructed. This output can represent the score of a single evaluated alternative by each individual DSS, or could also be in form of a vector representing the score of some compared alternatives. Then, the final consolidated output of the given overall DSS is obtained through aggregation of output values of individual DSSs.

This proposed configuration constitutes a technically feasible approximation of an optimum DSS through decreasing its complexity by a modular structure (by neglecting inference rules otherwise generated by unrelated input factors). However, the decision outputs produced by each individual DSS must be crisp or quantitative values representing a decision attribute or score for each compared decision alternatives. This is in order to enable and to facilitate objective integration.

As seen from Fig. 2, our approximation leads at a group decision making. It should be noted that we have said aggregation and not combination, because actually the two words bear different meanings, and the difference between combination and aggregation of decision outputs, has been articulated and explained in [1]. In the decision making situations requiring aggregation, the existence of all knowledge sources, here the individual DSSs, are necessary to judge the overall decision making problem or decision alternatives. This is because, each DSS represents a single different decision making dimension, view, discipline or aspect, each of which is necessarily involved in order to comprehensively judge the given decision problem. For instance, in environmental impact assessment of an industrial proposal or project, we usually have different knowledge sources or aspects like air pollution, water pollution, soil contamination, etc. and we can separately construct a DSS corresponding to each different environmental dimension. Whereas, in decision making situations requiring combination, the inclusion of multiple knowledge sources aims to enhance the reliability, especially for such ill-structured and ambiguous decision problems. In both cases, as described in [1], different mathematical treat for systems integration is needed. In the aggregation case, participation of each individual DSS corresponding to one decision making aspect is compulsory for obtaining a comprehensive decision solution, and here we should accumulate (aggregate) the decision outputs of individual systems, but in case of combination, each integrated system can judge the problem comprehensively, but the inclusion of multiple system is only for the sake of reliability. In this research, the confronted decision making situation is characterized by multiple aspect or dimensions that require aggregation and not combination. Hence, the aggregation of the multiple DSSs cannot be soundly replaced by inadequate commonly used ordinary combination formulas like arithmetic mean or ordered weighted average (OWA) [9].

4. Formulating the DSSs' integration problem

The problem of aggregating the outputs of multiple parallel DSSs is defined as the process of accumulating the crisp outputs provided by these individual systems into a finally consolidated decision. In fact, the aggregation of decision outcomes belongs to the topic GDM, and is usually mixed with the concept combination, without clear differentiation. The attempt to distinguish between combination and aggregation was done in [1]. In this article, we will describe an appropriate heuristic adequate for aggregating DSSs' outputs.

It is important to agree on the format of the individual outputs provided by the DSSs, which will be the inputs to the aggregation problem. Also, it is important to specify how such unified format is to express or quantify different degrees or outcomes of the decision attribute. Therefore, it is necessary to have a unified and objective format for such decision outputs in order to be able to develop objective and appropriate aggregating methods. The next section will address this issue.

4.1 Unification of the output format of the DSSs

In order to be able to consistently aggregate the individual decision outputs of the integrated DSSs, it is necessary for these outputs to follow a standardized or unified output scale. The subjective investigation of the GDM and preference aggregation and combination literature has revealed that aggregating the outputs at the measurement level, in which the numerical score is used to determine the degree of bias or belonging to a class, permits the use of more sophisticated combination/aggregation criteria or algorithms, whereas combination at only abstract level, in which preferences are expressed by only identifying the preferred class, allows only low level or simple criteria like the majority voting to be used. Therefore, the adopted unified output scale should be objective or numerical, and should allow aggregation at the measurement level. Given this fact, every participating DSS should produce a numerical output within a unified numerical psychometric scale. There are two possible common decision making situations. The first case is when the output is binary (i.e. two possible decision outcomes or judgmental options, e.g., "Yes" or "No", "Profit" or "Loss", etc.). The second situation occurs when the final decision output of the DSS can be one of more than two outcomes; that is multi-options. In this article, we adopt two psychometric scales to express the two commonly possible decision making cases (see figures 3 and 4). Intermediate values give the degree of bias toward decision options. The corresponding values of the decision outcomes can be arbitrarily set to 100, 10, or 1…etc., without affecting the final aggregated decision solution. The basic notion behind this unified scale is to provide for consistency and homogeneity in assessing the DSSs' decision outputs.

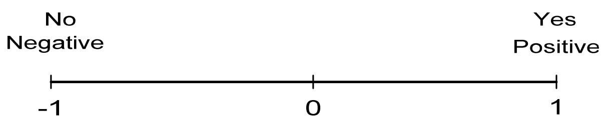

Fig.3 The psychometric numerical scale used for binary DSSs' outputs.

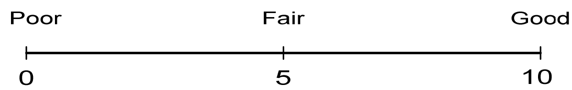

Fig.4 The psychometric numerical scale used for multi-outcome DSSs' outputs.

4.2 Problem statement

Given a whole set of DSSs, which complement each other for a finite set of decision making transactions or problem contexts. Then, based on a current transaction or context, an appropriate relevant set of DSSs, particularly suited for this current transaction or context is selected. Every DSS should provide its decision output in form of numerical output value within a maximum and minimum vales a & b, following one of the previously established unified scale. Then, the problem of aggregating the decision outputs of the DSSs can be formulated as a GDM problem, as follows:

Let $A = \{A_1, A_2 \ldots., A_n\}$ be a finite set of the possible decision outcomes.

Let $O = \{O_1, O_2, \ldots, O_j, \ldots, O_m\}$ ($m \geq 2$) be a finite set of DSSs' outputs, O_j

($a \leq O_k \leq b$) be the numerical outputs of the j[th] DSSs representing the degree of bias toward the outcomes defined by the set A, and defined correspondingly over some unified scale S (Fig. 5).

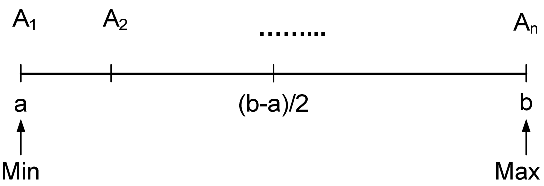

Fig.5 The generalized psychometric numerical scale used for DSSs' outputs.

Let $W = \{W_1, W_2, \ldots, W_j, \ldots, W_m\}$ be the associated weights set of the DSSs, where each j^{th} DSS gives an output O_j, and has a weight value W_j ($W_j \geq 0$, and $\sum W_j = 1$).

The problem now is to find an aggregation criterion, operator or algorithm, C, with an interpretation function, I, which accumulate the individual DSS' outputs, O, into one collective, consolidated group decision, where O_f assumes values from an aggregate or accumulated scale, $a^c \leq O_f \leq b^c$. The interpretation function, I, associated with the aggregating criterion maps the combined/aggregated output value into a decision outcome from the set A. Formally stated :

$$C: Om \rightarrow [ac, bc] \quad (1)$$

Where, O^m is the outputs vector, and

$$I: [a^c, b^c] \rightarrow \{A_1, A_2 \ldots., A_n\} \quad (2)$$

5. An aggregation heuristic for integrating the DSSs

In this section, we propose a simple heuristic for aggregating the decision outputs of the multiple collaborating DSSs. The heuristic is described for the two possible decision making situations described earlier in the problem statement; case of binary outcomes (e.g., "Yes" or "No") decision making and the case of multi-outcome decision problems. In order to apply the heuristic as an integration mechanism, every DSS provides its final outputs expressing the degree of bias toward possible decision outcomes using scales similar to that described in figures 3, 4 and 5. The heuristic makes use of the widely utilized analytical hierarchy process (AHP) (Saaty, 1980) to compute the weights of each DSS to reflect differences in importance.

The aggregation heuristic can be formally stated as follows:

Let A be a set of finite possible decision outcomes evaluated by the DSSs, A = {A1, A2, …, Ai,…, An}.

Let Oj : the output from the jth DSS, j= 1, 2, .., m.

Wj : the weight of the jth DSS.

Step 1: Compute the weights of DSSs using AHP

Step 2: Establish a total psychometric numerical scale for the final group decision from within an arbitrary range from 0 to positive value S, in case of multi-outcomes, and from –S to +S value, to represent the decisive degree decision outcomes.

Step 3: Divide the total numerical scale among the possible decision outcomes.

Step 4: Apportion the range of total numerical scale established in the previous step into smaller numerical scales allocated to the outputs of every DSS in proportion to its computed weights, as follows:

Step 4.1: In case of binary decision outcomes:

$$S_j = w_j * 2S, \qquad \forall \text{ j} \tag{3}$$

The middle value of such total scale is zero

Where,

Sj: is the total range for output scale of the jth DSS.

Then, the output of each jth DSS should be produced within the allocated numerical scale, from -Sj to +Sj.

Step 4.2: In case of multi-outcomes decision:

The middle value of such total scale is zero:

$$S_j = w_j * S, \qquad \forall \text{ j (in case of multi outcomes)} \tag{4}$$

Where,

Sj: is the total range for output scale of the jth DSS.

Then, the output of each jth DSS should be produced within the allocated numerical scale, from 0 to Sj.

Here, every DSS is allowed to influence the final group decision according to its weight. This is why, we apportion and allocate the total judgment scale over the DSSs in proportion to their weights.

Step 5: Collect the individual output values of the DSSs

Step 6: Check the individual output values against the thresholds (O_j^i):

$\forall$ j IF Oj ≤ O_j^{i*} THEN I(Of) = Ai* ; Stop, final group decision made; otherwise go to step 8.

Step 7: Given the individual output of each DSS, aggregate them by summing to give the finally aggregated group output, Of (eq. 5):

$$O_f = \sum_{i=1}^{n} Oj \tag{5}$$

Step 8: Interpret the computed final group output into a final decision outcome:

Use the established thresholds for decision outcomes to attribute the computed Of value to a certain decision outcome. Stop.

7. Conclusion

The article has presented an approximation model for an optimum DSS for the multi-dimensional decision problem assessment. The reasons for replacing the single, overall large scale DSS by multiple smaller and dimensional DSSs has been articulated. In light of a conceptual difference between aggregating different knowledge sources and combining similar knowledge sources the aggregation problem has been stated formally, and an efficient integration mechanism in form of simple aggregation heuristic adequate to the given decisions aggregation situation is introduced. The logic behind the proposed integration heuristic suits the explained decision making subject, and cannot be soundly replaced by inadequate ordinary commonly used combination formulas like arithmetic mean or ordered weighted average (OWA). Finally, the above described approximation of the optimum DSSs brings a feasible solution to a general problem of multidimensional DSS in many practical application domains.

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