Decision support system and Information Technology

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Using a decision support system (DSS) delays the decision-making process and commits the user to the cost of invoking the system. The existing configurations of decision support systems do not guarantee the profitability of the DSS. If the DSS generates messages that the decision maker can anticipate, then the cost and waiting time as a result of invoking the DSS will not be justified. Proposes a decision support system equipped with a knowledge-based model that tells the decision maker, prior to invoking the DSS, whether or not it is profitable to invoke the DSS; if invoking the DSS is not profitable, then the decision maker will have to base the decision on pure managerial subjective judgement. Uses a numerical example to illustrate the work of the proposed DSS.

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Introduction

Despite the evolution of definitional aspects, and the functionality of decision support systems (DSS), in addition to technological advances in computer hardware and software, current configurations of these systems fail to support their profitable use. Following Gorry and Scott-Morton's (1971) original view of a DSS, technological aspects of DSS have been continuously improved. The main directions of this improvement linked DSS to the computational approach in electronic data-processing (EDP) applications (Alter, 1980), the knowledge-base approach or symbolic processing in expert systems (Bonczek *et al.*, 1980), and the system architecture and development process (Keen, 1980; O'Keefe, 1986).

Bonczek *et al.* (1980) related DSS to expert system (ES) technology to support the knowledge-base approach, as well as the computational approach, by proposing the integration of the two technologies. Keen (1980) viewed DSS in connection with system evolution through the development process and system usability. Turban (1988) investigated the variation in definitional and technological aspects of DSS over the last two decades. However, variations in the definition, design or development of DSS still do not ensure the profitability of the system and do not solve major deficiencies in system usability studied in this paper.

Prior to making a decision, the manager may follow Simon's decision process, which is characterized by its sequential nature (1960). The manager must evaluate potential benefits as well as potential costs to be incurred throughout intelligence, design, choice and review phases. If a DSS is used to support the decision process, effective DSS messages are only obtained at the end of the decision process. The execution of the DSS-based decision is necessarily deferred (a period of time equal to the duration of invoking the system), and the high cost of the DSS must be considered. Unfortunately, the current configurations of DSS cannot predict the effect the DSS will have on the value of the manager's decision.

Raggad (1988) improved Sprague and Carlson's original's configuration (1980) of a DSS by adding the consequential model (CM). In this new configuration of the DSS (depicted in Figure 1), the consequential model is the first model to be activated by the dialog generation management system (DGMS). The model will give permission to invoke the DSS if the Bayesian value of the DSS, defined in the next section, is non-negative. If the consequential model predicts that the DSS is not profitable, given prior evidence, it transfers control to the DGMS which in turn informs the manager that managerial judgement is recommended. The article is therefore founded on two assumptions:

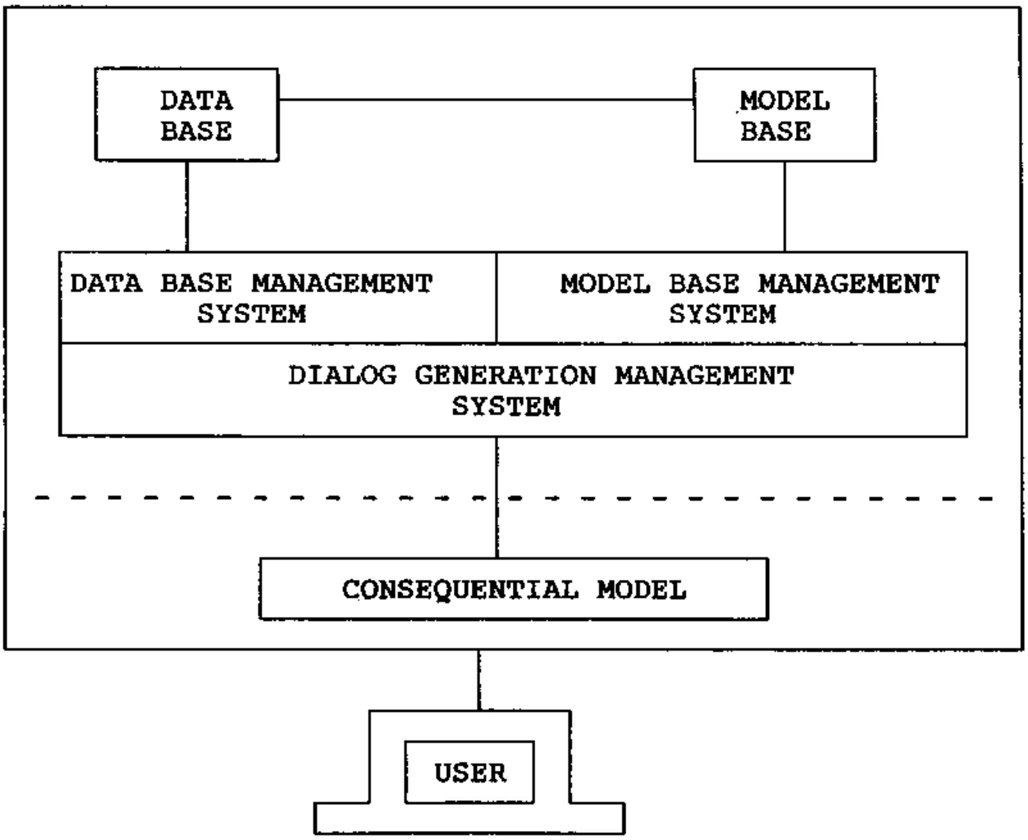
1. The cost of invoking the DSS is high, and it is substantially higher than the cost of using the consequential model.
2. The decision maker is incapable of deciding whether or not it is worthwhile to use the DSS, or at least he or she cannot effectively judge the value of using the DSS.

The first assumption follows from Dewan's work (1992) in which he studied the usefulness of DSS from an economic perspective. Dewan (1992) viewed the cost of DSS as having two components: operation cost and Bayesian update cost (message assimilation). The Bayesian update cost reflects the difficulty of making a decision in a semi-structured or structured environment.

In the consequential model (CM), the information acquisition task is not developed in an evolutionary manner. A costly planning phase is completed *ex-ante*, followed by the implementation of CM specifications. Because of its control structure, the CM operating cost is considerably less than that of the DSS. This is in contrast with the DSS in which this cost (planning and information acquisition and revision) is incurred every time the DSS is activated. This makes operating a DSS more costly than running a program like the CM. While planning the CM is costly, its realization cost and that of the DSS are sunk costs that are not considered here, given that both systems are assumed to be available in our decision support environment.

The Bayesian DSS provides a decision support environment where the end user incurs a first cost of activating the CM before a

Figure 1
Design of the consequential knowledge system for a DSS



decision is made by the CM of whether or not the end users commit themselves to the cost of invoking the DSS.

The CM cost of message assimilation or Bayesian update cost is nil since the only output messages that the CM generates are either to invoke the DSS or to use pure managerial judgement. The CM does not have, therefore, a Bayesian updating cost. The only CM cost component that remains is its operating cost which is less than that of the DSS as shown above. In fact, the DSS has a high Bayesian update cost (Dewan, 1992) that is added to its operating cost. Furthermore, the DSS Bayesian update cost is not amortized for recurrent decisions.

Several environmental factors studied by Keen (1981), Robey and Taggart (1982) and others can be used in reviewing DSS usefulness. Time is one important factor (Wright, 1974) influencing the CM decision of whether or not to invoke the DSS. Delays can reduce the expected value of the decision. Another difference between the CM and the DSS is that the CM follows a programme approach (all planning is done *ex-ante*) whereas the DSS is used in an evolutionary fashion. The DSS approach may cause prolonged delays that can add to the cost of invoking the DSS. Dewan (1992) also suggested that the DSS is sequential by nature and that the end user is responsible not only for making a business decision but also for planning and executing processes for acquiring the information needed to make the decision (Simon's intelligence phase).

Another important factor influencing the operating cost of a DSS is its partial employment for decision support. Despite the fact that end users follow, at least implicitly, all Simon's phases, DSS is often only used to support the design and choice phases. The effectiveness of the DSS will be enhanced if end users use the DSS throughout all of Simon's phases. This will certainly increase DSS operating cost as well as its effectiveness.

An additional operation cost for a DSS is DSS message processing. After incurring the Bayesian update cost for interpreting DSS messages, using DSS messages to support Simon's phases will require human processing to combine those messages with outputs obtained at each phase. The production of a final DSS-based decision will be expensive.

The cost of invoking the DSS is substantially higher than the cost of invoking the CM because:

1 the Bayesian update cost is higher for DSS;
2 this cost is not amortized for recurrent decisions;
3 the cost of the message process throughout Simon's phases is higher; and
4 the DSS operating cost is higher because of its sequential nature.

In fact, the input to the CM is the same as the initial input to the DSS without counting sequential input carried at interactive sessions during DSS operations. Using the CM raises the cost of using the DSS and the expected cost of using the CM and the DSS over a series of decisions. The effect of recurrent decisions on the usefulness of a decision support environment equipped with a CM capability deserves to be investigated (beyond this article).

The second assumption is a reasonable one because of the sequential nature of the DSS and the Bayesian update task of DSS messages. It is also easily agreed that the decision maker cannot effectively judge the value of using the DSS given the noisiness and lack of structure characterizing DSS information.

The consequential model

The framework of the consequential model provides information about the functionality of the system (S), the end user or manager (M), the decision problem (P), and the environment (E). It is presented as follows :

CM = $\{S,M,P,E\}$
S = $\{M,E,Q,c,d\}$
where:
M: set of messages generated by the DSS
E: predictability matrix
Q: reliability matrix
c: cost of invoking the DSS
d: duration

$M = \{\pi^t,U\}$
where:
π^t: prior evidence
U: utility scheme of the decision maker

$P = \{A,b\}$
where:
A: set of actions
b: Bayesian decision rule

$E = \{S,f,p^t\}$
where:
S: set of states of the world
f: discount factor
p^t: current evidence

This framework looks at the DSS as a forecasting program that transforms initial managerial judgement (prior evidence) π^t to better information (current evidence) p^t. Invoking this program lasts n time units and incurs a cost of c dollars. The consequential model studies the profitability of invoking the system, based on managerial utility U, the discount factor f and DSS predictability.

The information structure of the system is characterized by the predictability and reliability matrices. The predictability matrix E gives, for every state-message pair (s_i,m_j) in SxM, the probability c_{ij} that the DSS generates m_j given that the true state of the world is s_i. The reliability matrix Q gives, for every pair (m_i,s_j) in MxS, the probability q_{ij} that the true state of the world is s_j given that the DSS has generated a message m_i. That is:

$$c_{ij} = Pr[m_j,s_i]$$
$$q_{ij} = Pr[s_j,m_i].$$

This framework assumes that the manager holds prior knowledge about the states of the world s_j, $j = 1,2,\ldots N$. The matrix E depends considerably on the DSS information structure and will therefore be easily estimated by DSS designers. In addition to prior knowledge and predictability and reliability matrices, the Bayesian framework requires a decision rule b and an action-state utility scheme captured by a matrix U. The general term u_{ij} of U gives the manager's utility from undertaking the action a_j when the state of the world is s_i. The decision rule b is a mapping from the space of possible messages into the set of possible actions.

The Bayesian value of the DSS formulates the expected profitability from invoking the DSS given managerial recommendations based on prior evidence. It is computed as follows:

$$B(DSS) = \sum_j Pr[j] \sum_k Pr[k \mid j] u (b^*(j),k) - \sum_k \pi_k u(a^*(k)) - c \quad (1)$$

where j and k indicate respectively DSS messages and states of the world, b^* is the Bayesian decision rule (optimal b), and $a^*(k)$ is the optimal action given the state of the world k.

If the manager is risk-neutral then net present Bayesian value (NPBV) of the DSS (the net present value of the DSS Bayesian value) is computed as follows:

$$NPBV(DSS) = f^n [B(DSS) + \sum_k \pi_k u(a^*(k)) + c] - \sum_k \pi_k u(a^*(k)) - c \quad (2)$$

The consequential knowledge system

The objective of the study reported here was to improve the efficiency and effectiveness in making the decision to invoke a decision support system (DSS) equipped with a consequential model. One of the main advantages of the consequential model is its ability to prevent an unprofitable invocation of the DSS.

The manager (end user) is engaged in a process assessing the current situation in a decision problem. Situation assessment is based on external expert opinion and/or facts in a knowledge-based management system (KBMS) storing past problem situations and their solutions. The assessed situation includes the managerial belief vectors about various states of nature, the selected set of actions involved in the decision process, the properties of the DSS, etc. It is used to form the input vector of the consequential model. Invoking the DSS is usually costly and lengthy. The value of the decision is seriously affected if the DSS recommendations are not provided on time. Such a delay may also cause some frustration to the manager and may make system utilization inefficient. If the consequential model's decision is not in favour of invoking the DSS, then managers have to form their choice based on subjective judgement.

The consequential knowledge system enhances the task of the consequential model by integrating two expert systems and a knowledge-based management system with the consequential model. The first expert system is called a situation expert system (SES) and its purpose is to assist the user in producing an input vector to the consequential model. The second is called the choice expert system (CES) and is designed to validate managerial choice if the consequential model's decision is not in favour of invoking the DSS. The purpose of the knowledge-based management system (KBMS) is to store knowledge-based records composed of past situations generated by the SES and their solutions generated by the CES or the DSS (if the DSS is to be invoked).

The consequential knowledge system (CKS), used in the Bayesian DSS, is composed of the following subsystems:

1 situation expert system;
2 choice expert system;
3 knowledge-based management system (KBMS);
4 consequential model (CM).

These subsystems are studied below. The interface between these subsystems and the end user is illustrated in Figure 2.

The integration of expert systems with the consequential model, described in the next section, attempts to improve the efficiency of studying the profitability of invoking the DSS. Expert systems are also designed to make recommendations to modify input vectors when they have erroneous components. Managerial beliefs about the current states of the world and the managerial view of the current decision situation are validated by the situation expert system, before they are inserted into the CM.

After activating the CM, and in case the decision is not in favour of invoking the DSS, managerial choice of actions is also validated by the choice expert system.

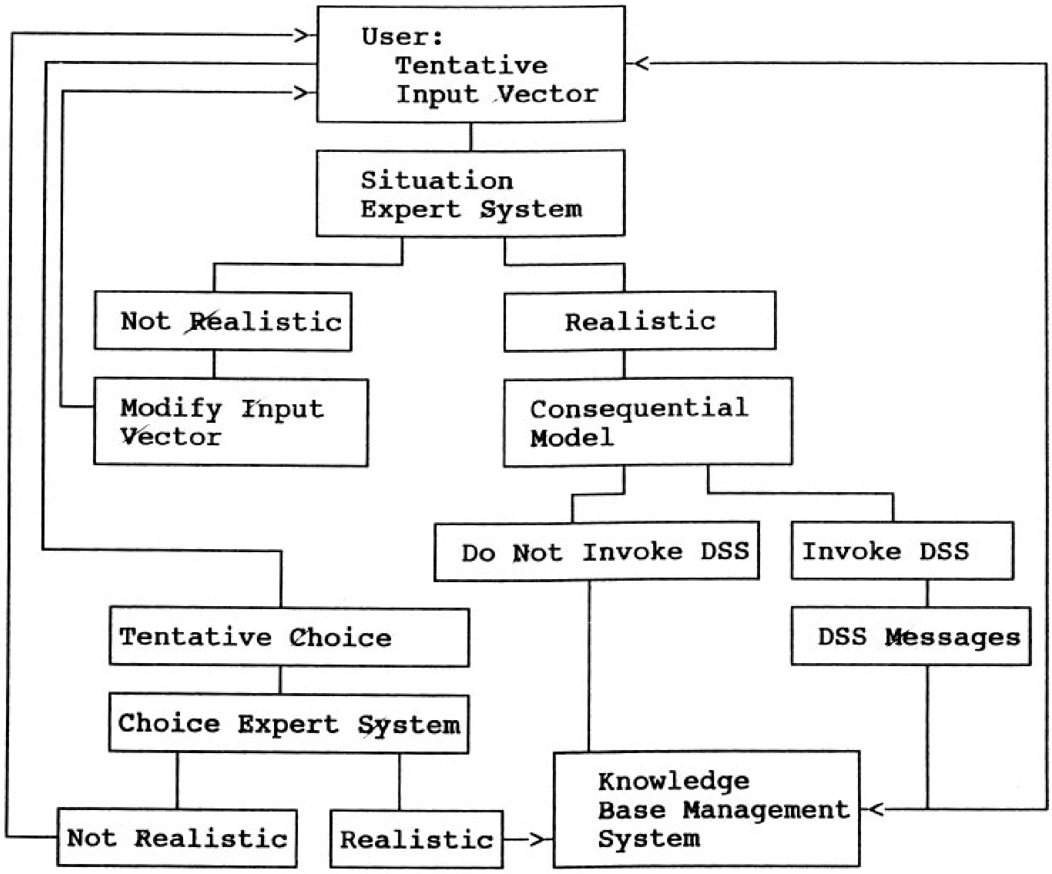
A choice expert system is designed to help the end user make a choice based on managerial belief concerning the current state of nature and consistent with past experience stored in a knowledge-based management system. This knowledge-based management system is designed to improve the decision-making process of the consequential model based on current managerial belief (prior evidence), managerial choice given prior evidence, and relevant characteristics of the DSS. The KBMS is interfaced with the user, the situation expert system, the choice expert system, and the consequential model.

The integration of expert systems in various types of models and information systems became popular in recent years because most of these models and systems can only provide support to decision problems based on numerical processing. The computational approach alone is no longer capable of coping with semistructured and non-structured decision problems or symbolic reasoning (a knowledge-based approach becomes necessary). Bonczek *et al*.(1980) integrated DSS decision models and an integration of a simulation model with two expert systems was developed by Levary and Lin (1988). O'Keefe (1986) also combined simulation and expert systems.

The situation expert system

It is important that the manager gets support from the DSS in all Simon's phases of a decision process (1960). He or she needs DSS-based information of four types: related to intelligence, design, choice, and review of the DSS-based decision. This article intentionally ignores the review phase because of the amount of noisiness associated with the evaluation of DSS-based decisions. The article

Figure 2
Interface between user and various subsystems of CKS



also does not consider recurrent decisions which one should assume if the review feature were to be included. The situation expert system (SES) is only concerned with the intelligence phase.

Information about DSS functionality is stored in the CM. The input vector should include intelligence information in the form of an objective, input, process and output. The end user produces a tentative input vector according to the above description and then submits it to the SES.

The task of the situation expert system is to enforce the validity and compatibility of various components of the input vector of the consequential model. This input vector is created by the user (manager), and is then submitted to the SES for validation before it is inserted into the consequential model. The SES alerts the user about any erroneous components in the input vector and also makes recommendations as to how and which components are to be modified.

Knowledge concerning the composition of the input vector, integrity constraints and validation conditions is elicited from experts in the domain and used in designing the set of rules characterizing the expert system. This knowledge includes the domains of all components of the input vector that characterize a meaningful and valid input vector.

The SES also results in eliminating unnecessary runs of the CM with erroneous input vectors. Since the CM makes the decision about whether to invoke the DSS or maintain managerial choice based on prior evidence, the elimination of invalid input vectors is highly desirable.

The choice expert system

The CES needs managerial information related to the design and choice phases of the decision. The constitution of a choice vector takes into account the output of the design phase, and current managerial interpretation of the situation already formulated in an input vector to the CM. The choice vector includes the input vector, and tentative managerial choice.

The choice expert system is designed to verify the validity and compatibility of managerial choice based on prior evidence when the CM's recommendation is not in favour of invoking the DSS. Managerial choice is based on the input vector previously created by the manager and validated by the SES.

The CES also suggests how to modify managerial choice to make it more realistic. The outputs from the SES and CES are considered knowledge sources which provide part of the knowledge stored in the knowledge-based management system. The interface between the user, CM, SES and CES is illustrated in Figure 2.

The knowledge-based management system

The knowledge-based management system (KBMS) contains knowledge-based records, each of which is composed of managerial belief forming the CM's input vector; managerial choice, given prior evidence; the CM's decision; and , if applicable, DSS recommendations. After each run of the CM, the user forms the current knowledge-based record and adds it to the KBMS.

The advantages of incorporating a KBMS with the consequential model are to:

1 prevent reproducing a CM run with the same input vector;
2 ease future reference to experiential data of the DSS;
3 assist the user in producing a realistic choice of actions based on prior evidence; and
5 prevent a non-profitable and unnecessary invocation of the DSS.

The KBMS is very valuable in improving the efficiency of the consequential model because the time needed to retrieve a knowledge-based record in the KBMS is very short compared with the time that managers usually take in supporting their managerial judgements. Moreover, the use of the KBMS is highly recommended because the validity of the CM's input vector and managerial choice is crucial for the CM to decide whether to invoke the DSS or maintain managerial judgement. The benefits from incorporating a KBMS in the consequential knowledge system are even larger if the utilization of the CKS increases.

Numerical example

For demonstration purposes we consider an innovation manager about to decide whether to adopt or reject a new technology. Experimenting with the new technology costs the firm $0.5m.

The innovation decision depends on market attractiveness which is low, moderate or high. The states of the world consists of the values of market attractiveness which are low (L), moderate (M), and high (H). Only two actions are available to the decision maker – adoption (A) or rejection (R) of the new technology.

The utility scheme of the decision maker is expressed using the following matrix. The pay-off from adopting the new technology is $–1m, $0m or $1m when market attractiveness is respectively L, M or H.

$$U = \begin{matrix} -1 & -0.5 \\ 0 & -0.5 \\ 1 & -0.5 \end{matrix}$$

The predictability matrix is given as follows:

$$E = \begin{matrix} 0.7 & 0.2 & 0.1 \\ 0.2 & 0.6 & 0.2 \\ 0.1 & 0.2 & 0.7 \end{matrix}$$

The prior evidence is given by:

$$\pi^t = (1/3, 1/3, 1/3)$$

The reliability matrix is obtained from above:

$$Q = \begin{matrix} 0.7 & 0.2 & 0.1 \\ 0.2 & 0.6 & 0.2 \\ 0.7 & 0.2 & 0.1 \end{matrix}$$

If the cost of invoking the DSS is $0.05m, then the Bayesian value of the DSS will be computed using equation (1) as follows:

$$B(\mathrm{DSS}) = 0.167 - c \text{ or } \$0.105\mathrm{m}$$

Given a discount factor of 0.9 and a DSS duration of two time periods, the net present Bayesian value of the DSS is computed using equation (2) as follows:

$$\mathrm{NPBV(DSS)} = \$0.035\mathrm{m}$$

The net present Bayesian value is non-negative. Invoking the DSS is the appropriate decision.

In a second case, suppose that the innovator is very confident that the market is very attractive. Prior evidence is therefore π^t=(0.0, 0.0,1). Given the above predictability matrix, the reliability matrix may be obtained as follows:

$$\mathrm{Q} = \begin{matrix} 0.0 & 0.0 & 1 \\ 0.0 & 0.0 & 1 \\ 0.0 & 0.0 & 1 \end{matrix}$$

The Bayesian value and net present Bayesian values are computed as follows:

$$\mathrm{B(DSS)} = \$ -0.450\mathrm{m}$$
$$\mathrm{NPBV(DSS)} = \$ -0.564\mathrm{m}$$

The appropriate decision is therefore to rely on managerial judgement. The end user produces a tentative input vector that is submitted to the SES for validation.

*i*0 = < enduser ID, technology type, prior evidence: (high:1/3 of the time, low: sometimes), risk attitude: averse>

After a dialog session between the SES and the end user, the end user is convinced that he wanted to express that it is equally likely that market attractiveness is low, moderate or high. The end user is also informed that the CM of the DSS cannot treat the case of risk-averse decision makers. The SES confirmed that the end user is actually risk-neutral or that his attitude can be approximated. A realistic input vector can be as follows:

i = <end-user ID, technology type, evidence: (low:1/3, medium:1/3, high:1/3), risk-neutral>

This input vector is injected into the CM which will use its computational power to produce the NPBV of the DSS. Two cases are possible:

Case 1: NPBV(DSS) ≥ 0

In this case, the appropriate decision is to invoke the DSS to generate a list of messages during two time periods. These messages are then interpreted by the end user. A final decision is made according to DSS messages.

A new knowledge record is then added to the KBMS. An example of such a knowledge record is designed as follows:

Current knowledge record:
<input vector, NPBV(DSS), duration, discount factor, cost, date and time of DSS invocation, DSS messages, final decision, date and time of final decision>

Case 2: NPBV(DSS) < 0

In this case the DSS is not invoked. The appropriate decision is to produce a final decision based on pure managerial judgement.

In a decision support environment where the DSS is not equipped with a CM, the DSS will be invoked despite the fact that this action is not optimal. The user then submits a tentative choice vector to the CES for validation. An example of such a choice vector is as follows:

Choice vector:
<input vector, final decision, date and time of CM decision, CM decision, date and time of final decision, NPBV(DSS)>

A new knowledge record is then added to the KBMS. An example of such a knowledge record is designed as follows:

Current knowledge record:
<choice vector, duration, discount factor, cost>

Limitations and future research

Even though DSS usually concerns non-routine decisions, the effect of recurrent decisions on a decision support environment equipped with a CM is worth studying. Dewan (1992) showed that DSS is very expensive to operate in the case of recurrent decisions. It is so because the Bayesian update cost is not amortized over time. Operating the CM is expected to be more profitable in the long run for recurrent decisions.

The KBMS stores records of past solutions without explaining the reasoning process. Explanations are not elicited from the DSS simply because it does not possess them. Doing so is usually the role of an expert system (ES). The solutions may have been bad. The consequential system we are proposing does not have the capability of reviewing DSS-based decisions. The management of information noisiness will be an important feature that could be added to the new decision support environment. The cost incurred by the new feature may considerably affect the profitability of the CM.

Even though we did not include information noisiness in this study, the extent to which noisiness affects the usefulness of the CM deserves to be investigated.

To what extent can the CM replace the DSS? Can the CM reach Mockler's knowledge (1989) balance with the DSS? In this case, it is expected that the symbolic power of the decision support environment strengthens while the analytical power of the CM diminishes.

DSS may play the role of the expert system when the Bayesian update task becomes negligible. It is important, then, to investigate the possibility that the CM, in the long run, will replace the DSS and the decision support environment will be that of a knowledge-based system.

Conclusion

The consequential model, incorporated in Bayesian decision support systems, adds the capability of preventing unprofitable DSS invocation to Sprague and Carlson's original configuration of DSS. The model computes the Bayesian value of the DSS and suggests whether:

1 to maintain managerial recommendations given prior evidence; or
2 to invoke the DSS.

Invoking the DSS will commit the manager possibly to a prolonged delay and to an additional cost. An unprofitable invocation of the DSS will be prevented.

The integration of a situation expert system, a choice expert system and a knowledge-based management system with the consequential model is designed to improve the efficiency and effectiveness of the consequential model in studying the profitability of invoking the DSS. The KBMS stores knowledge-based records containing historical invocation instances of the DSS.

The consequential knowledge system uses a situation expert system to assist the user in assessing subjective managerial judgement, by validating the situation input vector before it is inserted into the consequential model. The CKS is also equipped with a choice expert system designed to verify the consistency of managerial choice if the CM's decision was not in favour of invoking the DSS.

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