Decision support systems for environmental problems: 
Scientific approach, requirements of 
structure and data on specific purpose types

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Abstract

Decision support systems (dss) are used for the solution of a wide range of environmental related problems. In order to use dss more efficient it is necessary to divide them according to specific purpose types. Classic dss can be applied to situations in order to investigate the change of a system under certain one-time actions. Because of usual complex initial situations and huge demand of data it is necessary to integrate strategies of complexity-reduction into the decision making process. Normally this can be done by integrating human expert knowledge about the system into the decision making process. For repeating situations with similar initial conditions dynamic dss can be used. For these problems (e. g. environmental engineering processes) it is most often necessary to optimize the solutions under strict conditions. Dynamic dss shall therefore learn from previous decision makings in order to improve the decision making process. As a last type, operational dss are used to operate all kinds of technical equipment and systems. They must be designed to operate on high levels of reliability; sometimes their decisions have to meet legal requirements.

1. Introduction

Decision support systems (dss) are applied to a wide range of environmental problems: land use policy (Soltanmohammadi et al. 2010), mine closure procedures (Laurence 2006), regulatory decisions for environmental protection (Rodrigues et al. 2009) and brownfield development (Chen et al. 2009). Specific dss are used by engineers to optimize processes (Coleman et al. 2003, Pollmann 2006) and by natural scientists to find solutions to environmental problems (Mickovski & van Beek 2006) or even to manage disasters (Ahmad & Simonovic 2006). All application types provide the user with a recommended course of actions. The structure, required data input and calculation of the suggested solution differ between each application type. A common problem encountered during the development and use of environmental related dss is the large amount of data required to construct the model (Carlon et al. 2008). The systems must handle quantitative as well as qualitative data (Nolan 1997). One successful option is to mimic the human brain in the decision making process. Several soft computing techniques exist for an adequate decision making process (Zeleznikow & Nolan 2001). According to Zadeh (in Zeleznikow & Nolan 2001, p.2)
fuzzy logic is primarily concerned with imprecision, neural networks with learning and probabilistic reasoning with uncertainty. Even so the areas of these techniques can overlap. This paper will show a new strategic approach to combine several ideas in order to receive a fast and robust decision making process for different types of environmental problems. In opposite to decision making in measurement and control technology, environmental problems are affected by a greater variety of parameters. Most often these parameters are hard to measure. Furthermore the interactions between the elements are difficult to describe in a mathematical way. Bellmann (1961) described the multi-dimensional problem as “curse of dimensionality”, referring to the increasing time for problem-solving for every additional dimension of a problem. Therefore, strategies were developed to reduce the complexity of the problem and to integrate human intelligence into the dss. Expert knowledge about the environmental interactions is vital for the development of a decision support system. Field experiments are conducted to verify the assumptions and to optimize future decision support. This two-way-approach proved, in a number of different examples, to be successful.

According to Haettenschwiler (1999) dss can be classified by their user-relationship. Referring to Power (2002) dss can be divided by their mode of assistance. Institutional and ad hoc dss are classification classes by Donovan & Madnick (1977). This paper will concentrate on active dss (Haettenschwiler 1999) that support users with recommended decisions. Therefore the users need not to be a perfect expert in the specific application area. According to specific purpose types, active dss are presented that are knowledge-driven or model-driven and ad hoc or institutional. On the opposite passive dss need well-educated users and therefore the distribution and application of the specific dss is strictly limited.

This paper proposes that, in general, active dss can be sorted into three categories of application types, each with specific requirements regarding data structure and input. However, the borders between the three categories are not exactly defined and even dss of hybrid-types may be possible.

2. Types of decision support systems

2.1 Classic decision support systems

Classic decision support systems are usually applied to well-known systems and initial situations. The change of such systems under certain conditions and actions is predicted using classic dss. Usually there is only a one-time event that needs to be evaluated in terms of its effects on the initial situation. According to Donovan & Madnick (1977) this is typically for ad hoc dss. Furthermore the dss is knowledge-driven (Power 2002) due to the necessary integration of human intelligence.

The initial complex environmental situation has to be thoroughly investigated and described, a process requiring both a lot of time and financial input. The dss needs to be constructed in such a manner that it can take into account the possible interactions and feedbacks between the relevant elements of the system.

An example for such a classic dss is the re-vegetation of different vegetation free extreme sites. Such extreme sites include artificial tailings storage facilities, resulting from mining activities, or natural sites like shifting sand dunes. These sites are a potential source of negative impact on surrounding areas by fluvial and / or aeolian transport of matter. A common international practice is re-vegetation aided by means of soil amelioration products (Meyer et al. 2009, van Rensburg & Morgenthal 2004). The initial situation at a site, often with extreme substratum parameters such as low pH-values, nutrients content, soil organic matter and high amounts of harmful substances, needs to be investigated. Further information about climatic conditions and proposed future use of the site must be gathered as well.

The development of the dss for re-vegetation of extreme sites took place on a two-way-approach: (1) Retrieving expertise from field experiments and (2) integration of interdisciplinary expert knowledge. Field experiments had to be conducted in order to generate knowledge about the impact of different soil ameli-
oration products on the rehabilitation success. This cannot be done in laboratory and greenhouse trials because of missing influence from e.g. climatic conditions. The results of field experiments are discussed by e.g. Meyer et al. (2009). Only with knowledge received from field experiments it is possible to integrate the relevant facts into the dss. The field experiments proved that only one remediation measure needs to take place in order to achieve a sustainable vegetation cover. Own results of up to three growing seasons show that the established vegetation seems to be persisting and self-sustainable.

The dss must represent the interactions between the input data and possible re-vegetation measures. In order to predict the interactions a modified neural network is applied to the problem. Meyer et al. (2010) describes why a neural network can be successful for this problem. The neural network consists of three layers (fig. 1):

1. the input layer with identified relevant site parameters,
2. the hidden layer with the relevant interactions between the input parameters and
3. the output-layer with a recommended mixture ratio of different soil amelioration products.

Developing the neural network is a first step towards solving the problem. As a second aspect of the two way approach expert knowledge about important elements of the input layer can be integrated into the development process: Knowing the parameters that can influence the plant growth are well known facts in geo and agro science. In order to mimic the human decision process the hidden layer is introduced as “pool-layer”. Taking the construct “pool” from system theory (Blumenstein et al. 2000) allows a more structured decision making. Plant growths mainly depend on the following three soil parameters:

1. plant available water,
2. plant available nutrients and
3. plant available harmful substances (such as heavy metals).

Figure 1: Structure of 3-layer adapted neural network

Interactions are created between the first and second layer where an objective dependency exists. E.g. the interaction between pH-value and plant available water is neglected because they are not interacting. Inte-
rations between second and third layer exist where a pool-result leads to the usage of a specific ameliorant. Also knowing that almost all elements interact, the first version of the dss incorporates only the interactions with high intensities. This is a fundamental element in a strategy of reducing the complexity of a system (Bellmann 1961).

Having a structure for the dss leads to the next problem. It is necessary to describe the interactions and nodes mathematical and / or with logical operations. In order to follow a strategy of complexity-reduction it is necessary to check whether interactions must be described continuously or discretely. A continuous description and parameterization of the interactions requires statistical reliable data. Due to the fact that these data are not available it is possible to have a look into (geo-) ecological science. There are lots of examples from botany and ecology where categorical variables are used for description of interactions. Using the vegetation cover according to Braun-Blanquet (1967) is still a standard method in field botany and using the indicator value from Ellenberg et al. (1992) it is possible to have a fast impression of some soil chemical characteristics of a specific site. Therefore as a first step we decided to describe the interactions between the elements in the modified neural network not as continuous interaction but as defined levels (Meyer et al. 2010). The advantage of this strategy is a reduced data amount for the description of the interactions.

For the decision making within the pools we tried to mimic the human brain again. As an example the pool of available heavy metals is presented. What are the main questions that come up in a decision making process?

(1) What are the concentrations of plant available heavy metals?
(2) What is the state of my system – meaning what are the values of important factors (like the pH-value) that influence the availability of heavy metals?

![Decision tree: Plant-available contaminant pool](image)

Figure 2: Example for decision tree: Plant-available contaminant pool

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Because the expert uses only a limited number of questions to make up a solution it is possible to mimic this process by using a decision tree model. As an example, Fig. 2 shows the beginning of the decision tree for the pool of plant available heavy metals. For the remediation success the heavy metals are only relevant if the amount exceed a prior defined level. If they are below these levels no further measures are necessary. Only in case they are above the levels further questions on specific availabilities have to be answered. An expert would then have a detailed look on further system parameters like pH-value, content of soil organic matter and particle size distribution. According to Scheffer & Schachtschabel (2002) the mobility of heavy metals mainly depends on the pH-value. Based on laboratory analyses an increased value of heavy metals can be still tolerable if the pH-value is around 7.0 and the particle size distribution is likely for high values of cation exchange capacity. Only if high contents of heavy metals concur with extreme low or high pH-values measures must take place to change the pH-value and hence leading to a lower mobility of heavy metals. Depending on further substratum characteristics the specific soil amelioration products are selected on a matrix base.

After the first phase of development, the DSS includes basic interactions between important parameters. Further field experiments must proof the performance of the DSS. The aim is that the results of the DSS perform at least equal and in future even better than decision by human experts. Therefore it is suggested that human experts as well as the DSS recommend each a mixture ratio of soil amelioration products. Both variants should be conducted in field plots and after a certain time the results are compared. Having this long-term feedback will lead over several years and with the support of first users to a continuous improvement of the DSS.

### 2.2 Dynamic decision support systems

Dynamic decision support systems are used for periodical applications. According to Donovan & Madnick (1977) they are classified as institutional DSS and to Power (2002) as model-driven DSS. Commonly they are applied to very specific problems and most often used to provide an optimized solution. In a similar manner to classic DSS, the initial situation has to be defined well. Dynamic DSS are applied to datasets of known input data and boundary conditions. In order to optimize a solution it is necessary to define a quality function (Lugner 2001, Pollmann 2006). For these kinds of situations the function must be clearly described mathematically in terms of how the initial conditions and possible measures affect the calculation. Another characteristic of dynamic DSS is that you see the quality of the recommended decision within hours or days. Therefore you receive a feedback on the quality of the decision support quite quickly. Furthermore it is necessary to think about adequate methods and the necessary quality of the required decision support.

An example of an environmentally related dynamic DSS is the valorization – in terms of upgrading the quality – of tailings (Pollmann et al. 2009). Mine tailings are a contaminated by-product of the mining industry, produced at a rate of millions of tons per year. Investigations have proven that ameliorated tailings are no longer contaminated waste but rather a resource. Valorized tailings can be used for rehabilitation of disturbed landscapes (Pollmann et al. 2008).

In order to upgrade tailings substrate it is necessary to be efficient in both ecological as well as economical aspects. Therefore a method was developed to integrate the costs of measures into the calculation by an additional term. The upgrading process must therefore be optimized with the aid of a quality function. The quality function describes the multi-optimization problem in an adequate way. The known information about the tailings is related to possible measures. Similar to the example in chapter 2.1 investigations on the system, the dependencies and the interactions had to be conducted. Parameters from different fields of natural science where selected to evaluate the quality of the valorization. In the next step a mathematical method was selected that is able to find the global optimum of the problem within a reasonable time and accuracy. By applying mathematical methods like evolutionary algorithms to this optimization problem it
is possible to solve it (fig. 3). Well-fitted evolutionary algorithms are time-efficient compared to usual numerical methods (Gerdes et al. 2004). Due to repetitive production cycles it is possible to integrate quick feedbacks into the dynamic dss in order to receive an improved decision support (Pollmann et al. 2009).

![Chart: Percentage of ameliorant vs. amount of population in calculation]

Figure 3: Example for valorisation of tailings: poly-optimisation by evolutionary algorithms

### 2.3 Operational decision support systems

Operational decision support systems are used to operate systems. Therefore they can be classified according to Donovan & Madnick (1977) as institutional dss. They are designed and manufactured for a specific purpose. Their objective is the real-time evaluation of input data as well as the decision making process itself, leading to an autonomous running of control units. Operational dss have a continuously input of measured parameters that are needed for calculation. These input parameters must be automatically measurable in order to generate a data input stream. The operational dss knows the interactions between the input data and the criteria for the control decisions and may anticipate developments within the input data at different times in order to take preemptive actions.

At the beginning a detailed understanding of the system is necessary. Therefore usually large field measurement campaigns are conducted to gain a correct understanding of the systems, its elements and the boundary conditions. Only then the development of the operational dss can concentrate on the important interactions and factors.

An example is the water quality management in ancient potable and irrigation water systems (Qanats). These Qanat-systems are known from ancient times in arid and semi-arid regions (Beaumont et al. 1989, English 1968). Groundwater is collected from Holocene sediments at the periphery of mountains and delivered to the irrigation areas. Due to percolation through sediments the water quality met, and sometimes still meets, high requirements what was proved by own investigations. Nowadays anthropogenic effects in the catchment areas may impact the water quality and quantity and thus these Qanat-systems require an optimal management. In order to create an operational dss it is necessary to conduct a detailed environmental field investigation on the catchment. That includes information about catchment area, geological
and pedological properties, land use as well as water quality and all possible sources of water pollution. Furthermore, it is necessary to know the climatic conditions within the catchment (fig. 4).

![Diagram of Qanat-catchment with (geo-)system elements under field investigation](image)

The operational dss must operate the water management system according to strict legal regulations on water quality standards. The legal regulations standardize parameter limits for different water quality types, e.g. drinking water, irrigation water or process water with different threshold values for pollutants which must be followed at all times. Therefore the system must operate reliably on a real-time base. Especially the operation on a real-time base and the strict requirements on the recommended decision are constraints that classic and dynamic dss are not complying with. The classic dss usually evaluates the effects of one-time events on the initial situation without any further feedback (see chapter 2.1) whereas the calculating time of dynamic dss can be too long for a real-time operational management of Qanat-systems. The operational dss integrates different kinds of information from different locations within the catchment for prediction of trends in water quality and quantity. Therefore the operational dss interacts with stationary measuring units that collect the required data directly in situ the catchment area and in the Qanat channels (fig. 5). With thus collected data the operational dss predicts water shortages, signalizes the exceedance of respective thresholds in advance or even makes suggestions to the operators for different kinds of water use (drinking water, potable water, irrigation water). For this decision and prediction...
It is aspired to operate the Qanat-system according to the decisions made by the operational dss. Among the decision and prediction process – according to clear action rules stated by the operational dss – it must operate the water flow into different distribution networks, store excess water or even make suggestions to the operators for water treatment options.

The operational dss can improve the usability of available water in the catchment areas of Qanat-systems or – on the other hand – verify agricultural management strategies in the catchment area (land use, irrigation, crop rotation etc.) according to the required water quality.

### 3. Conclusion and outlook

Sorting dss to specific application types enables the developer to use specific strategies for a more tightly focussed decision making. Classic dss deal with highly complex environmental initial situations. Expert knowledge can lead to a selection of relevant parameters and therefore to a reduction in complexity. Mimic of human decision making means applying, adapting and modifying different mathematical methods like neural networks and decision trees to the problem. The main challenge in developing such a dss is the integration of human knowledge into the decision making process. This is a time-consuming process that can be done best in an interdisciplinary working group.

Dynamic dss essentially need a mathematical quality function. Only then a process optimisation is possible. Therefore complete data sets are necessary for each application. An adequate selection of the optimisation method should take place in order to run the optimisation with a minimum expenditure of work to the required level of precision and accuracy.

Operational dss are the most complex dss. They have high requirements to almost all aspects. They presume a detailed understanding of the environmental system with its interactions and feedback that they are applied to. That can most often only be accomplished by large field investigation campaigns. The decision making process must deal with continuous data input as well as strict (legal) requirements to the recom-
mended decision. Furthermore the geo-system might not be stable and may change between different states (e. g. summer dryness – winter rain).
Nevertheless, analyzing environmental problems according to application types, data requirements and structure leads to an easier development of adequate dss. Possible strategies for the reduction of complexity include integration of expert knowledge as well as mimic of human brain proved to be successful.

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5. Literature

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