Multi Criteria Decision Analysis: Uncertainties and Combining Decision Making Methods

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Introduction

Support of decision making is a form of data transformation by analysing complex circumstances and processing large amounts of data with the goal to present helpful information to decision makers in a simplified and better understandable way. Within the terms of this broad definition, many methods, algorithms, and visualisation means qualify as decision support. However, there is no best method in a general sense, as all these methods have their pros and cons in respect to the specific situation they are applied to. In addition, different methods can be combined to improve the overall performance of decision support.

Originally, decision support methods used deterministic data and thus their output was deterministic as well. Consequently, such information leads to binary thinking and hard decision making, e.g. if a countermeasure strategy is to be chosen, deterministic decision support forces the view that one specific strategy is unconditionally the best and superior to all other available strategies. However, depending on the method used for decision support, minor changes in the input data can have a huge impact and can cause a different outcome. As input data is in general not deterministic but affected by uncertainties, this may result in recommendations of suboptimal strategies in emergency management. Therefore, it is necessary to consider uncertainties in decision making methods to improve the overall decision support.

Uncertainty influencing decision making

Many forms of uncertainty can be identified that have an influence on the assessment of an emergency and its development over time. The following list is certainly incomplete but gives an impression of uncertainty types: stochastic uncertainties in form of physical randomness, epistemological uncertainties by lack of scientific knowledge, endpoint uncertainties when the desired goal endpoint is ill-defined, judgemental uncertainties by defining personal preferences as facts, and computational uncertainties by e.g. inaccuracy through numerical instability or modelling errors as models are always a simplification of the real world and therefore limited in one way or the other [1]. Sometimes the errors introduced by these uncertainties may be small, but as they add up they could lead to choosing inferior strategies in the end.

The CONFIDENCE project

The European project CONFIDENCE (2017-2019) aimed to analyse uncertainties and to improve the support for emergency management, especially focussing on nuclear accidents [2]. CONFIDENCE investigated the influence of uncertainties on the different phases of the full chain of managing a nuclear accident beginning with the assessment of data (weather, source term), continuing with simulation of the situation development (dispersion, food chain), over analysis of possible countermeasure strategies (decision support) up to the communication of situation development and strategies to the public (social science). Within this project the Accident Management

Systems (AMS) group of ITES had a leading role as coordinator of the project and as leader of work package 6, which investigated the influence of and coping with uncertainties in decision making. The work package especially focussed on enhancing the existing Multi Criteria Decision Support (MCDA) tool to handle uncertainties as well as Agent Based Modelling (ABM) to analyse and better understand the effects of uncertainties on the decision making process. A special issue of the Radioprotection Journal is dedicated to the CONFIDENCE project and will be available in the second half of 2020.

Multi Criteria Decision Analysis as decision support

Multi Criteria Decision Analysis (MCDA) covers various decision support methods, that in general provide a ranking on a set of alternatives by integrating (contradictory) decision criteria of different scale according to given (personal) preferences [3]. The ranking helps decision makers to choose the best suited alternative, which is frequently, but not necessarily, the highest ranked alternative. Considering emergency management, MCDA syste-matically combines the pros and cons of feasible actions to be aggregated into a single numeric value, which makes them easily comparable between each other. The higher the value, the better the according action is rated. In managing nuclear emergencies, the actions are in general a set of countermeasure strategies like “Evacuate people and clean surfaces before they return”.

Each action is assigned a ranking value $A_1,\cdots, A_n$. The criteria are either quantitative values like “Estimated dose” or qualitative values like “Public acceptance”. The criteria values $C_1,\cdots, C_m$ are either simply measured or determined. For numerical evaluation, qualitative value ranges like {“low”,”high”} have to be mapped to quantitative value ranges like {1,2}. Since the criteria are typically of different units and scales, the criteria values have to be normalised onto a unified scale before combining them. For this purpose, normalisation functions $N_1,\cdots, N_m$, such as e.g. min-max normalisation, have to be defined for every single criterion. The personal preferences of each criterion are represented through weights. The relative importance of a criterion is reflected in a specific normalised weight $w_1,\cdots,w_m$. The normalised values of criteria are aggregated in a ranking value by using an aggregation method according to their weight. One of the most popular aggregation methods is the computation of the weighted sum, which for each alternative requires the following computation:

$$A_i = \sum_{k=1}^{m} w_k \cdot N_k\left(C_{k,i}\right) \quad \forall\, i \in n$$

The actions are sorted according to their ranking values, indicating their order of recommendation. Ranking and results can be presented in multiple ways like e.g. charts, graphs, textual report, and others depending on the specific requirements of the decision makers (e.g. Figure 2, Figure 3).

Though from the mathematical point of view the method is plain and straightforward, there are several catches to consider when applying it. Firstly, the actions to rank are not generated but determined externally, either by another tool or by the decision makers themselves. Secondly, the determination of feasible criteria is also up to the decision makers. As emergency management is in general subject to a group of decision makers respectively advisories they have to agree on such a set of criteria as a group, finding a common consensus. The same holds for determination of qualitative criteria values, which may be based on personal assessment. Finally, the weights are dependent on personal preference and therefore need to be agreed upon within the group. This leads to a time consuming setup and intense discussions among the group members, making the MCDA method preferable in situations where time is available, e.g. in preparation, training or long term recovery decision making. On the other hand, as a benefit, the intense discussions result in transparency and documentation how the ranking and therefore the decision was justified.

Considering uncertainties in MCDA

The MCDA as described above will process deterministic parameters, yet most, if not all, scenarios of decision making are affected by uncertainties, which requires processing of probabilistic parameters. The following section describes how this limitation can be overcome.

Two obvious parts of MCDA can be affected by uncertainty: the criteria values and the criteria weight values. Such uncertain values can be described probabilistically: either as functions or histograms. Histograms can be easily achieved by binning and counting according values, e.g. for a histogram of a criterion weight let all decision makers provide an integer weight value between 1 and 10 according to their preference and accumulate the values. On the other hand, determining distribution functions for criteria values like the “Estimated dose” is rather difficult. Yet the important part is not to achieve higher accuracy, but to introduce the potential variety of values into the ranking, thus sensitising decision makers to rather look for the most robust solution in all circumstances instead of the best solution for one specific case.

MCDA cannot process distribution functions or histograms as input values. For this reason, ensemble evaluation is applied to overcome this limitation. Simply put, from the probabilistic MCDA a number of deterministic MCDA are generated and evaluated one by one. The deterministic results are combined back into one probabilistic result. Because of its simplicity several thousand MCDA can be generated and evaluated within a second, allowing for large sample sets.

The MCDA tool has been enhanced in that way to define probabilistic input, to perform ensemble evaluation, and to present probabilistic results [4]. Figure 1, Figure 2, and Figure 3 give an impression on the implemented enhancements.

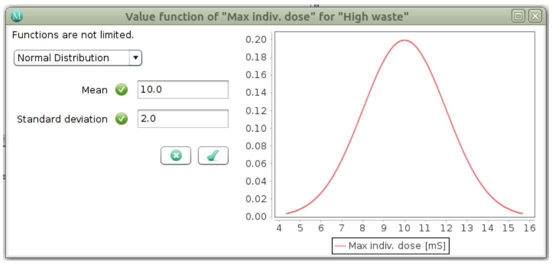

Figure 1: Definition of a criterion value as normally distributed.

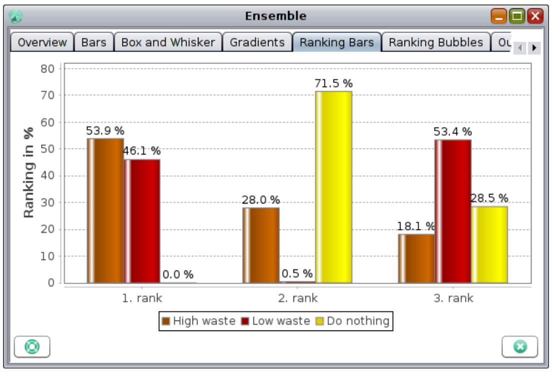

Figure 2: Overview on probabilistic ranking of 3 alternatives. In this example "High waste" was ranked first place in 53.9 percent of all evaluations of the ensemble set.

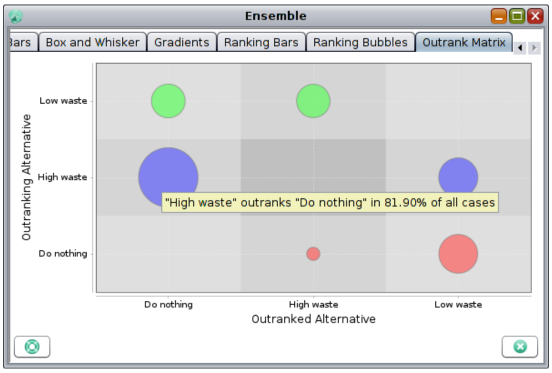

Figure 3: An outranking matrix indicating how often an alternative was ranked better than another one.

Agent Based Modelling of the decision making process

The decision making process of stakeholders is much more complicated than one would expect at first glance, as not only plain numbers are considered but also personal preferences, experience, prognosis of situation development and behaviour of affected people, etc. The decision makers involved in emergency management may have different backgrounds and may belong to different organisations, which is reflected in their individual personality and their assessment of the emergency situation, thus introducing uncertainties in the decision making process.

To consolidate their different personal decisions into a single one they have to work together, share thoughts, negotiate, and finally find a compromise that is acceptable for everyone. The best way to understand this process would be to interview and observe the decision makers while they are confronted with a large number of different scenarios. However, this would take a considerable amount of time, especially of the stakeholder's time, and therefore is not feasible in praxis. A practicable approach to address this is to model the behaviour of decision makers and the process of decision making. Such a model allows for simulation and analysis of a large number of different scenarios, leading to a better understanding of the underlying uncertainties.

Agent Based Modelling (ABM) is a programming paradigm that allows for simulation of (intelligent) individuals, so called agents, and the complex interactions between them. More specific, a software agent is defined as a computer system (program) that is situated in some environment, and that is capable of autonomous actions in this environment in order to achieve its delegated objectives [5]. ABM is therefore inherently predestined to model and analyse decision makers as individuals and their interaction and hence was chosen for this task in CONFIDENCE.

Figure 4 displays the concept of a software agent in more detail. The agent to the right interacts with the environment and also other agents on the left. It perceives observations on the environment by its sensors. The same way it is capable to perform actions on the environment with its actuators. Agents are capable of evaluating their environment and of decision making by means of simple rules up to artificial intelligence.

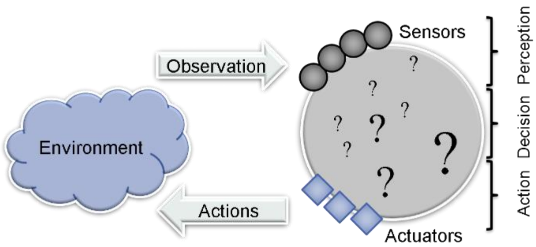

Figure 4: Structure of an autonomous (software) agent interacting with its environment.

It is obviously the decision making, that defines an agent in the end. In the context of modelling nuclear emergency management, an agent has to select the best countermeasure strategy from a set of strategies on the basis of parameters. In CONFIDENCE we interviewed emergency managers from different countries by questionnaires, on how they make their decision, what rules they follow, etc. From this information a set of agent types was modelled and implemented as well as methods for negotiation between agents to find to a common consensus. An intelligent strategy evaluation system based on the agent-based negotiation simulation has been introduced in order to simulate the decision making process of stakeholders on computationally tractable assumptions. In the framework of the system, agents can score the recommended strategies before negotiation and negotiate them by using different negotiation skills [6,7]. Moreover, one indicator was introduced to describe how much the agents can compromise in each negotiation [7]. This parameter may also reflect the degree of selfishness behaviour of agents. Figure 5 displays a chart of the demonstrator, where agents negotiate on the ranking value of a strategy.

Figure 5: A group of 12 agents agreeing on a ranking value for a one strategy within 14 iterations.

Combining methods

Decision making methods have their own specific upsides and downsides, e.g. an upside of MCDA is that it is simple and increases transparency, while as downside the alternatives to rank have to be known beforehand. Carefully combining decision making methods can greatly improve the overall usability as well as the quality of results. In the following two combinations of methods are presented that can benefit from each other.

Evolutionary Algorithms, ABM, and MCDA

Evolutionary Algorithms (EA) are constructive optimisation methods, i.e. they search for an optimal, or in praxis close to optimal, solution within given parameter ranges, especially if no knowledge is available how to construct the optimal solution [8]. Regarding emergency management this means existing countermeasure strategies are modified in a way that they fit to the current emergency situation.

The basic idea of EA is to encode a solution respectively countermeasure strategy as a genome of an individual and to have a large population of individuals evolve in the desired way. For this, each individual is evaluated in respect to its survivability, called fitness. The least fit individuals are removed and the population is filled up with new child individuals derived from the ones that survived by combining and modifying the genes of some parents in a process called crossover and mutation. The process is repeated until some criterion to stop is reached. While the method is straightforward the challenge is obviously the encoding of a strategy as genome and the evaluation of the fitness of the individuals.

In a complex decision support system based on ABM, e.g. for simulation of power supply management of a city, the EA can be introduced as a “super-agent” that constructs strategies and interacts with the agents for fitness evaluation. In addition to the negotiations with other agents, the agents as autonomous individuals have their personal preferences on the suggested strategies. Therefore, it seems evident to model such individual behaviour by MCDA. That way the advantages of the three methods can be combined into a more efficient decision support system. Currently we follow this approach in the framework of the HGF portfolio security for evaluating power distribution management in future cities.

Case Based Reasoning and MCDA

As mentioned above, one integral and challenging part of MCDA is to define alternative actions to be evaluated. An EA is one opportunity to construct strategies to be further analysed according to different criteria. Another approach is prepare a database with different scenarios and strategies beforehand to be used in a decision situation. This approach was particularly pursued in CONFIDENCE where Case Based Reasoning [9], a problem-solving paradigm, was applied to select strategies to be negotiated in the framework of ABM of the decision making process [6].

Hence, for defining decision alternatives, CBR can be applied to limit the set of possible options. Originating from cognitive science, CBR utilizes specific knowledge of previously experienced problem situations to solve a new problem. The main assumption is that similar problems have similar solutions. Hence, a possible set of decision alternatives is based on experiences of similar and solved problems, which in our context, correspond to simulation results. This approach and especially the determination of suitable criteria have been further elaborated in the framework of nuclear emergencies, where MCDA is applied to assess several possible disaster management strategies [10]. The objectives have been to rank different strategies in a transparent manner, to provide a broad discussion basis, and to preserve flexibility to account for the variability of disasters and users' preferences. In particular, the contributions of the different criteria to the overall assessment are revealed.

The basic idea for assessing strategies is to integrate commonly discussed approaches that refer to performance measures and investigating robustness. Furthermore, CBR related values that reflect the trustworthiness of the solutions proposed are respected as well. The multi-criteria assessment considers current conditions, possible future developments, utilizes simulations of strategies to account for current constraints and uncertainties with regard to time, for example, and facilitates users' trust and understanding in the mechanism of the decision support method by integrating confidence values. These different perspectives are summarized (Figure 6) where the overall objective is to protect public and environment being decomposed into the criteria 'effectiveness', 'resources', 'robustness' and 'confidence'. Specifically oriented towards nuclear emergencies, the effectiveness is measured according to (i) the factor of dose reduction (ii) the amount of waste, and (iii) public acceptance, taking into account non-radiological quantities as well. The criterion 'resources' states through which means the objectives are achieved and hence which resources and to what extent they are utilised. These results are gained by simulating the strategies considered and analysing them according to duration and uncertainties in respect of potential delays during the implementation possibly causing a reduced resource utilization. Here, a strategy mo-del that is based on Petri nets is used allowing to capture combinations of measures, their order of implementation, the objects

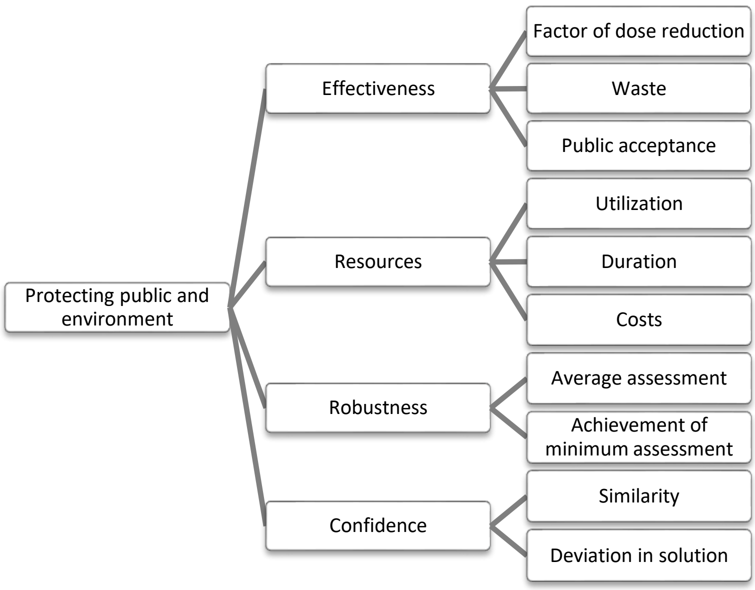

Figure 6: Hierarchy of criteria for strategy assessment [10, Figure 6.6]

measures are targeted at, and resources [11]. Simulation results of JRodos [12] particularly provide costs of strategies. The criterion 'robustness' considers uncertainties with regard to the extent of a disaster, changing environmental conditions, or insufficient information. For judging how robust a strategy is, a scenario-based approach [13] is pursued, investigating different scenarios and determining corresponding effectiveness values under these varying conditions. The criterion 'confidence' is related to CBR and can be made measurable by similarity values and deviations in the different solutions.

The multi-criteria assessment helps to structure the decision problem, reduces its complexity, and promotes discussions of the stakeholders involved by, for instance, visual support (Figure 7). In particular, different views on strategy assessment are integrated addressing various preferences that need to be respected in the final decision. Furthermore, different strategies can be discussed and analysed according to their sensitivity in respect of weights (Figure 8) or criteria values. The strategy assessment particularly respects different temporal dimensions and hence current conditions as well as future uncertainties taking into account characteristics of the underlying decision support method.

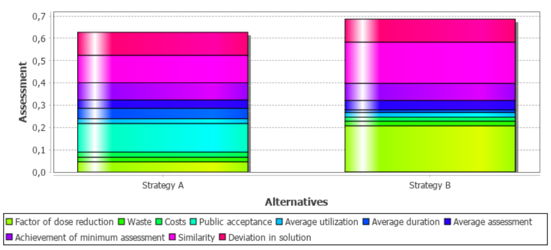

Figure 7: Assessment of strategies illustrated as stacked-bar chart depicting the contributions of criteria values to the overall assessment [10, Figure 6.8]

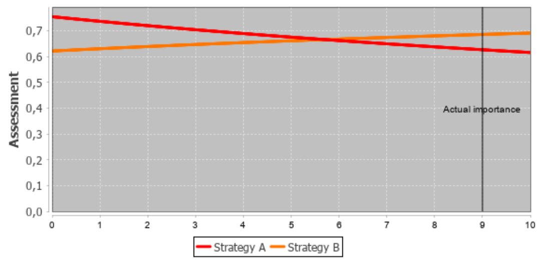

Figure 8: Stability of result according to changes in the weight of 'factor of dose reduction' [10, Figure 6.10]

Summary and Future Work

Multi Criteria Decision Analysis has proven to be a valuable tool for decision making in various interactive workshops. MCDA is relatively easy to apply once the criteria and preferences are agreed upon. It is fast in computation and therefore very interactive in its handling. The setup forces discussions among decision makers and leads to clarity as well as transparency in the decision process. Considering uncertainties in the input improves the interpretation of the results and allows to determine more robust solutions compared to the hitherto existing approach. As a drawback applying MCDA requires knowledge on the method and the consequences of choosing specific criteria or normalisation methods. The setup takes some time as discussions are required among the decision makers to reach a consensus. Therefore, it is best suited for preparation or late phase emergency management where time is less pressing.

Combining MCDA with other decision supporting methods like Agent Based Modelling, Evolutionary Algorithms, or Case Base Reasoning can improve the performance of a decision support system, especially for complex problems like the management of power distribution in urban areas. The growing complexity of dependencies between critical infrastructures and the ongoing urban transformation towards smart cities, challenge crisis management. In particular, there is a lack of knowledge on possible disruption scenarios, the range and severity of cascading effects as well as appropriate management strategies. In the framework of the HGF portfolio security, we are working on robust and comprehensible solutions for crisis management, specifically for maintaining security of supply and protecting critical infrastructures in complex crisis situations. This especially requires an understanding of emergences resulting from numerous interacting system components in an urban area. We have developed an agent based optimisation framework that will be further enhanced by, for example, multi criteria analysis capabilities for agents. Besides global strategies and objectives, individual agents aim at self-preservation and demand-driven supply of services, challenging the assessment of potential strategies and opening up various research possibilities in the context of MCDA.

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