Experiences from Developing an Algorithm to Support Risk-Based Decisions for Offshore Installations

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Abstract: We present our experiences from developing a decision model to support risk-based decisions on offshore installations. The model was developed using the DEXi tool for multi-criteria decision modeling. We report on the method we employed, the efforts spent, and the evaluation of the resulting model, including feedback from domain experts representing the target group. In our view the results are promising, and we believe that the approach can be fruitful in a wider range of risk-based decision support scenarios.

Keywords: safety risk, operational risk, offshore, multi-criteria decision making

1 INTRODUCTION

During the autumn of 2016, we developed a computerized model to support decisions based on operational safety risk offshore. The model automatically provides a decision advice based on 28 input parameters, and was developed using DEXi [4], which is a tool for multi-criteria decision modeling. The choice of DEXi was made based on early experience two of the authors had from using DEXi in the domain of cyber-risk [7].

The contribution of this paper is a report on our experiences, the efforts spent on the model development, and an initial evaluation of the results. The aim is to help others who face related challenges to consider whether a similar approach may be suitable for them. We start by explaining the challenge and our success criteria.

During major maintenance projects on offshore installations, flotels are often used to accommodate the personnel. A flotel ("floating hotel") is a vessel providing sleeping quarters and other facilities. A gangway connects the flotel to the installation. The flotel needs to keep its position in a very limited area close to the installation. This can be done by means of Dynamic Positioning (DP), thruster assisted mooring or mooring systems. DP implies employing a computer-controlled system that allows the flotel to automatically keep its position by using its own thrusters. However, keeping the position is highly challenging due to the weather, waves, and other conditions offshore.

If conditions are unfavorable, the responsible offshore operatives need to decide whether to lift (disconnect) the gangway from the installation. If this is not done, there is a risk that an uncontrolled autolift (disconnection) occurs, causing harm to personnel and equipment. The decision is difficult because many different factors affect the risk. Moreover, lifting the gangway has high economic cost, as workers will be prevented from performing their tasks on the installation. Currently, the offshore operatives make use of paper-based Location Specific Operational Guidelines (LSOG), along with a number of other sources of information, e.g. the prevailing weather conditions and the weather forecast, to guide the decision.

To provide alternative decision support, ease the information handling and reduce dependency on the experience, competence and mental state of the individuals on duty at any given time, we envision a solution where advice is automatically generated based on a wider range of input parameters compared to the LSOG. This solution is illustrated in Figure 1. The Input Collector collects all the data for the input parameters, such as weather forecasts and sensor readings. The Decision Support Model aggregates these data to compute an advice. This

Figure 1: Vision for overall decision support solution.

advice is presented in the End User Interface, which should be tailored to the human offshore operatives making the decision.

The work presented in this paper concerns the Decision Support Model. We identified the following success criteria for the model:

C1: *The model should provide advice that correspond with expert expectations.*

C2: *The model should capture all aspects that are important for the assessment.*

C3: *The model should be comprehensible for domain experts.*

C4: *The expected benefit should justify the effort required to develop the model.*

The rest of this paper is structured as follows. First, in Section 2 we introduce the DEXi tool, before explaining the method used for the development in Section 3. Section 4 presents the decision support model, as well as expert feedback on the model. In Section 5 we discuss and evaluate the model with respect to criteria C1-C4. In Section 6, we present related work, before concluding in Section 7.

2 THE DEXi TOOL

DEXi [4] is a computer program for the development of multi-criteria decision models and the evaluation of options. Multi-criteria (also called multi-attribute) models are a class of models used for decision analysis that evaluate options according to several, possibly conflicting, goals or objectives. In this section, we introduce DEXi, focusing on the parts needed to understand the rest of this paper. For a detailed description, we refer to the DEXi User Manual [1].

A multi-attribute model decomposes a decision problem into a tree (or graph) structure. The overall problem is represented by the top attribute. All other attributes in the tree represent sub-problems, which are smaller and less complex than the overall problem. Each attribute is assigned a value. The set of values that an attribute can take is called the *scale* of the attribute. DEXi supports definition of discrete ordinal scales; typically, each step consists of a textual description. An example of an ordinal scale is {Unacceptable; Acceptable; Good; Excellent}.

Every attribute is either a basic attribute or an aggregate attribute. *Basic attributes* represent the inputs to the multi-attribute model. They have no child attributes. The value of a basic attribute is determined solely by the input to (or selected value for) the attribute.

Aggregate attributes are characterized by having child attributes (which may be basic or aggregate). The value of an aggregate attribute is a function of the values of its child attributes. This function is called the *utility function* of the attribute. The utility function of each aggregate attribute is defined by stating, for each possible combination of its child attribute values, what is the corresponding value of the aggregate attribute.

In summary, developing a DEXi model implies the following: (i) define the attributes and tree structure, (ii) define the scale for each attribute, and (iii) define the utility function for each aggregate attribute. For any given set of values for the basic attributes, the value assigned to the top attribute represents the overall aggregated evaluation.

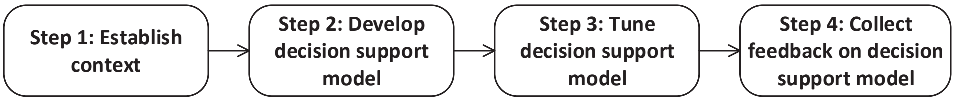


Figure 2: Overview of method.

3 METHOD FOR MODEL DEVELOPMENT

As illustrated in Figure 2, we developed the model in four steps. In the first step, we established the context by identifying the purpose and scope, as well as deciding which tool to use. In the second step, we developed the decision support model by carrying out points (i)–(iii) described in Section 2. This was primarily done during video meetings where the analysis leader shared his screen and edited the DEXi model based on input and comments from the domain experts, while the analysis secretary took notes about the reasoning and discussions. Some modifications and corrections where also done offline, through email interaction.

In the third step, we tuned the decision support model by first defining a set of six scenarios based on the following criteria: 1) All scenarios should be realistic, i.e. represent conditions that might actually occur. 2) The set should include scenarios that cover all the possible decision alternatives defined in the LSOG. After describing the scenarios textually, each of the identified scenarios was translated to an assignment of a value to each basic attribute, referred to as an *option* in the DEXi tool. This allowed us to compare the advice produced by the model for each scenario with the guidelines provided by the LSOG. In cases of mismatch, we updated the DEXi model. In the fourth step, we collected feedback on the model, with focus on model structure and outcome for the six scenarios defined in the preceding step.

As shown in Table 1, the above steps were carried out in 12 meetings held within a period of three months (from August 2016 to November 2016). All the authors took part in the model development. Of these, three are domain experts with technical experience within ship technology and marine systems in the petroleum industry, as well as software systems to support the petroleum industry with respect to risk-based decision-making. The remaining two (from SINTEF) served as analysis leader and secretary. The fourth step, i.e. feedback on the model, took place in meeting 12 (with preparations in meeting 11). The feedback was collected from three offshore operatives who represented the target group and who had not participated in developing the model or been involved in any other way before meeting 12. The feedback is explained further in Section 4. All meetings except meeting 12 were video meetings, while the 12th meeting was a combined physical and video meeting where one of the offshore operatives participated remotely from an offshore location.

Although the steps are presented chronologically, they were sometimes revisited to make updates and adjustments or to capture new factors that were brought forward by the domain experts. Roughly speaking, the first step took place in meeting 1 and meeting 2, the second step took place from meeting 3 to meeting 7, the third step took place from meeting 8 to meeting 10, and the fourth step took place in meeting 11 and meeting 12.

4 RESULTS FROM APPLYING THE METHOD

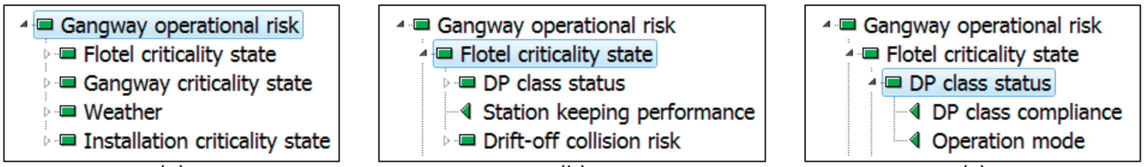
In this section, we first provide an overview of the decision support model, and then we present the feedback on the model.

The decision support model consists of 16 aggregate attributes including the top attribute and 28 basic attributes. It is beyond the scope of this paper to explain all details of the model. Instead we focus on a fragment.

Figures 3(a)–3(c) illustrate parts of the model, as shown in DEXi, starting from the top attribute and ending at three of the basic attributes. Aggregate attributes are labeled by a

Table 1: Overview of meetings. M=Meeting, D=Duration, S=Step in method.

M	Date	D	S	Activity
1	25.08.16	1.5 h	1	Establish context
2	16.09.16	2.5 h	1	Finalize context establishment, present DEXi and progress plan, and develop initial model structure
3	22.09.16	2 h	2	Continue developing model structure
4	06.10.16	2 h	2	Complete model structure, define scales for attributes and utility functions for aggregate attributes
5	13.10.16	3 h	2	Continue defining attribute scales and utility functions
6	25.10.16	3 h	2	Continue defining attribute scales and utility functions
7	27.10.16	2 h	2	Complete defining attribute scales and utility functions
8	02.11.16	2 h	3	Perform model tuning
9	11.11.16	2.5 h	3	Perform model tuning
10	24.11.16	2 h	3	Complete model tuning
11	28.11.16	1 h	4	Prepare feedback collection
12	30.11.16	6 h	4	Collect feedback from offshore operatives



(a) (b) (c)

Figure 3: A small fragment of the decision support model.

small rectangle in front of their name, while basic attributes are represented by a triangle pointing horizontally to the left as illustrated in Figures 3(b) and 3(c). As can be seen in Figure 3(a), the top attribute is *Gangway operational risk*, which represents the operational risk for the gangway between the flotel and the installation.

The top attribute has the following child attributes: *Flotel criticality state*, *Gangway criticality state*, *Weather*, and *Installation criticality state*. In Figure 3(b) we have expanded the child attribute *Flotel criticality state*, which in turn has three child attributes: two aggregate attributes and one basic attribute. In Figure 3(c) we have expanded *DP class status*, which has two basic attributes as child attributes.

The value assigned to the top attribute represents the advice to the decision makers. Depending on the combinations of values assigned to the 28 different basic attributes, the top attribute is assigned one of following values {Abandon operation; Prepare to abandon operation; Advisory state; Normal state}. *Abandon operation* indicates that there are very strong reasons for an immediate disconnection of the gangway, for example since an autolift of the gangway may occur. *Prepare to abandon operation* indicates that there are strong reasons for disconnecting the gangway. Preparations for disconnection should be considered. *Advisory state* indicates an attentive state; the responsible offshore operatives need to hold an advisory meeting to assess if one or more states may be changed in order to improve the current or future operating conditions of the flotel and the gangway. Finally, *Normal state* indicates that the gangway may safely be (or remain) connected. Notice that these four values correspond directly to four risk levels, where *Abandon operation* corresponds to the highest risk and *Normal state* corresponds to the lowest risk.

Regarding feedback on model structure, the offshore operatives were asked to consider the following three questions: Are there any important attributes that are omitted? Are there any attributes that should be removed? Are the attributes properly organized? Everyone agreed on the overall model structure. At the detailed level, we received three suggestions for additional attributes to be considered as descendants of one of the four existing attributes under *Gangway operational risk* shown in Figure 3(a). In addition, there was one suggestion for an attribute that could be removed, as it was judged to have little impact. Finally, there was one attribute for which a refinement of the scale was proposed in order allow a more fine-grained distinction between states.

With respect to feedback on outcomes for selected scenarios, the offshore operatives were asked whether they agreed with the advice produced by the model for the scenarios. They unanimously agreed for five of the six scenarios. For the sixth scenario, two expressed doubt or disagreement, even though the advice was consistent with the LSOG. The offshore operatives emphasized that the LSOG represents guidelines, rather than a set answer.

5 DISCUSSION AND EVALUATION

Based on our experience, we now discuss and evaluate the fulfillment of criteria C1-C4 defined in Section 1.

C1: In our context, expert expectations are represented by the opinions of the offshore operatives taking part in the evaluation in the final meeting, as well as the LSOG, which is based on expert knowledge. As explained in Section 3, we made sure that the advice produced by the model were consistent with the LSOG for the identified scenarios. DEXi proved to have the expressive power to achieve this without any problems. For the one scenario where the offshore operatives did not agree with the model, the disagreement was due to a discrepancy between the guidelines in the LSOG and the opinions of the offshore operatives. Hence, the contended scenario is actually an issue of resolving discrepancy between different experts. We consider our results promising, although a thorough evaluation of criterion **C1** requires a more extensive validation, preferably using more scenarios based on historical data, as well as involving more domain experts.

C2: The feedback on the model showed that the offshore operatives agreed with the overall structure and attributes. Incorporating their proposed modifications would not be a problem. Hence, we are confident that all the factors that the domain experts identified can be captured in the model. The aspects covered by the LSOG, which represent the current solution, is a proper subset of the aspects covered by the model.

However, one aspect not captured by the model is uncertainty. For example, input parameters, such as the weather forecast, are more or less uncertain. Even though the weather services provide an assessment of the uncertainty, this is ignored by the model. We considered including and aggregating uncertainty in the model, so that the advice offered as output could be accompanied by an aggregated assessment of the uncertainty. However, we saw no way to achieve this without significantly complicating the model, and the LSOG does not address the uncertainty of its guidelines. We therefore decided not to include uncertainty in the model.

While discussing **C2**, it is also interesting to touch on the issue of scalability. The most important aspect in this respect seems to be the size of the utility function for each attribute, i.e. number of possible combinations of values for its child attributes. This is determined by the number of child attributes and the granularity of their scales. The DEXi manual states that defining a utility function is quite hard for a size of 100 [1, p. 19]. In our model, the largest utility function, which belongs to the top attribute *Gangway operational risk*, has size 144. For this attribute, it was not acceptable to reduce the number of the child attributes, as the structure illustrated by Figure 3(a) was considered most appropriate. We found the size 144 to be manageable, due to functionality that DEXi offers for checking consistency of a utility function and automatically suggesting possible values for missing entries based on already inserted entries. Still, we believe that utility functions larger than ca. 150 would be highly impractical.

C3: This criterion implies that the domain experts should be able to understand the algorithm by inspecting the model. This increases trust in the outputs from the model, and means that the model can also facilitate knowledge sharing and learning. None of the domain experts had any knowledge about DEXi before the process. Even so, after a brief introduction, they quickly grasped the DEXi concepts and were able to contribute to the model development. Throughout the process, the comments, suggestions and discussions demonstrated that all participants were able to understand the details of the evolving model. Thus, we avoided the misunderstandings and problems typically encountered when an executable algorithm is implemented in a language not understood by the domain experts. Basically, the DEXi model served as a combined specification and implementation of the assessment algorithm that was fully transparent for all participants.

C4: Our estimate indicates that the model development amounts to ca. 150 person hours in total. This includes ca. 100 hours spent on meetings 2 to 11. The estimate does not include meetings 1 and 12, as no model development or updates were done in these meetings. Ca. 50 hours was spent on work between meetings. Of the latter, ca. 16 hours was spent by the domain experts on checking the model and defining scenarios, while the remaining 34 hours was spent by the analysis leader and secretary on taking notes and correcting the model. We are not aware of other works reporting on the effort required to develop this type of model. However, for the model-based risk analysis method CORAS [5], the authors state that the expected effort required to carry out a CORAS analysis is typically from 150 to 300 hours. This gives at least an indication that the amount spent on developing our decision support model is reasonable.

Of course, a thorough evaluation of criterion **C4** would require that we quantify the benefit, as well as the cost. This is very hard, and we have not attempted to do so. Still, we believe that the benefit justifies the effort. First, the model produces consistent advice which may be a valuable supplement to a largely experience based decision making process. There is also a potential for reuse of (parts of) the model to support related decisions. Second, the process of developing the model collectively in a group creates learning and raises the awareness of those taking part. Third, the resulting model codifies and documents knowledge from all those taking part in the development, thus serving as a vehicle for knowledge transfer throughout the organization. While the first point was a central part of our motivation for initiating the work, and known in advance, the added benefit of the last two points became clear to us during the process.

6 RELATED WORK

DEXi is one of many approaches within the field of multi-criteria decision making (on which there is huge literature [8]), and has been tried out in a wide range of domains such as health care, finance, construction, cropping systems, waste treatment systems, medicine, tourism, banking, manufacturing of electric motors, and energy [3, 4]. To the best of our knowledge, DEXi has not been used to assess safety risks within offshore as reported in this paper. However, it has been applied to assess safety risks within highway traffic [6] and ski resorts [2].

The aforementioned two approaches are similar to our approach in the sense that they use DEXi models as the underlying algorithm to compute an advice based on relevant input data. In particular, the approach provided by Omerčević et al. [6] use DEXi models in a framework where input data is collected via sensors in the highway. This is in line with our envisioned automated solution illustrated in Figure 1. The details of the End User Interface and the Input Collector are beyond the scope of this paper and therefore not explained further. However, we are confident that our envisioned solution is feasible as we have in fact taken part in implementing a similar approach in a framework for real-time cyber-risk assessment [7] developed by the WISER-project [9].

Unlike most of the existing publications on DEXi, we have focused on the overall approach, rather than the details of the model. In particular, we address the efforts spent to develop the model, the involvement of domain experts, and the comprehensibility of the model, as well as the quality of the final result. These aspects are important for others who consider a similar approach.

7 CONCLUSION

In this paper, we shared our experiences from using DEXi to develop support for risk-based decisions for offshore flotels. Our motivation was to make others who face related challenges aware of the possibilities, and help them to consider whether a similar approach is suitable for their needs. Space restrictions have prevented us from going deep into all the details of the process and resulting model. We have focused on the issues that we think are of general relevance. Based on our experience and overall evaluation, we consider our results quite promising, and believe that the approach can be fruitful for a wider range of risk-based decisions. In future projects, we hope to explore these possibilities further.

Acknowledgements

This work has been conducted as part of the AGRA project (236657) funded by the Research Council of Norway. The authors would like to thank Ketil Stølen for valuable feedback.

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