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Optimizing Observation Strategy in Emergency Response by Combining Bayesian Network and Multi-Criteria Decision Analysis

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Within the realm of protection of infrastructures, it is essential to quickly identify potential risks in case of safety or security incidents. When alarms are triggered, the full extent of threats or damages is sometimes not clear. For example, unknown hazardous materials may be released or the structural integrity of a building could be compromised. In such cases, reconnaissance activities are required. Here, we study how the usage of autonomous systems equipped with portable sensors may support scenario identification and thus might help to decrease risks for emergency response personnel during scenario exploration. The process of reconnaissance can be viewed as an optimisation problem with many different criteria that affect the selection process of an optimal route through a location. Besides the gain in information about the situation, other criteria such as the safety of the autonomous system should be considered. As these criteria can be conflicting, the application of multi-criteria decision analysis (MCDA) methods might proof beneficial. In this work, we present a first approach to optimise the observation strategy in emergency response. A Bayesian network is established to infer key aspects of the situation based on new information provided by the sensors of the autonomous system. A sequential multi-criteria decision analysis is performed based on predefined criteria and current information obtained from the Bayesian network. The approach is illustrated by a simplified generic case study of a small building with multiple rooms. First results show that even simplified situations may lead to complex decision-making processes.

Keywords: Emergency Response, Scenario Identification, Robotics, Critical Infrastructure Protection, Bayesian Network, Multi-Criteria Decision Analysis, PROMETHEE.

1. Introduction

Securing critical infrastructures in case of sudden disruptions is crucial to ensure the supply of goods and services that provide stability in our society (Lichte et al., 2022). When critical infrastructures face threats or disruptions, autonomous systems, such as robots or drones, may be employed not only to monitor the correct function of the infrastructure but also to intervene in case of an emergency (Milana, 2022). Dangerous conditions, such as the presence of unknown hazardous substances, can threaten emergency response personnel, affecting their work or even endanger their lives (Rosas et al., 2020). In such situations, robotic systems can be deployed to support firefighters and first responders in their emergency task (Schneider and Wildermuth, 2017). Robotic systems can perform several tasks, such as extinguish fire, search for hazardous material or improve situation awareness (Timotheou and Loukas, 2009; Rosas et al., 2020; Schneider and Wildermuth, 2017). It can be necessary to observe a variety of locations at an emergency site to gain a comprehensive picture of the situation and thus enhance situation awareness. These locations of special interest might be considered as checkpoints which need to be visited during the process of scenario identification. This process aims to identify the current situation and immediately pending events, i.e. contributes to enhance situation awareness (Mentges et al., 2023). Several criteria can be considered when deciding on the order in which a robot should approach these checkpoints. For example, the safety of the robot or the distance to the next checkpoint can be important, and in some cases, conflicting criteria.

In this work, we present a first approach to support such decisions. A simple case study composed of a building with three rooms is introduced. A Bayesian network is set up to estimate the probability of fire in predefined checkpoints that are distributed over these rooms. Based on observations of the robot at the respective checkpoint, inference in the Bayesian network is performed (see Schneider et al. (2022) for more details on risk scenario identification based on observations). In order to decide which checkpoint the robot should visit next, a multi-criteria decision analysis is applied based on the available knowledge in that moment. When another checkpoint is observed, an additional multi-criteria decision analysis is performed until all checkpoints have been visited. In the following, first, the main methods used in the approach are introduced. Second, the approach is outlined based on the aforementioned case study. Third, the results and limitations are discussed, followed by a conclusion and outline of future work.

2. Methods

In this section, Bayesian networks (BNs) and multi-criteria decision analysis (MCDA) are introduced. Special emphasis is placed on the MCDA method called PROMETHEE II which is used in this work.

2.1. *Bayesian Networks*

Bayesian networks are probabilistic graphical models based on a directed acyclic graph (DAG) (Pearl, 1985). A BN is composed of nodes that represent variables and edges which represent their probabilistic dependencies. To build a BN, three sequential tasks are performed: (1) variables are identified as well as their possible values, (2) the DAG is set up, and (3) probability values are determined to quantify the relations between the variables (Druzdzel and van der Gaag, 2000). Given an observation, BNs enable a prediction of possible causes and vice versa (Ramírez-Agudelo et al., 2021) making them a powerful tool to perform inference based on evidential findings.

2.2. *Multi-Criteria Decision Analysis*

Multi-criteria decision analysis deals with decision problems which consist of different alternatives and multiple, often conflicting, criteria. Multi-attribute decision-making (MADM) is a subfield of MCDA in which only discrete alternatives are considered (Hwang and Yoon, 1981). The set of alternatives $A = \{a_1, ..., a_i, ..., a_n\}$ and the set of criteria $G = \{g_1, ..., g_j, ..., g_k\}$ are distinguished (Brans and Smet, 2016). Thus, MADM decision problems can be expressed by a $n \times k$ matrix M (Geldermann and Schöbel, 2011). The element of the matrix $g_j(a_i)$ is the evaluation of the alternative a_i with respect to the criterion g_j (see Eq. (1)).

$$M := \begin{pmatrix} g_1(a_1) & \cdots & g_k(a_1) \\ \vdots & g_j(a_i) & \vdots \\ g_1(a_n) & \cdots & g_k(a_n) \end{pmatrix} \tag{1}$$

Various methods can be applied to perform the MCDA (see Kabir et al. (2014) for a review on MCDA methods). In this work, we focus on the outranking approach *preference ranking organization method for enrichment evaluations* (PROMETHEE) that is based on pairwise comparisons of the alternatives (Brans and Smet, 2016). In PROMETHEE, the decision maker has to assign a preference function to each criterion. Six types of preference functions can be applied. The pairwise comparison of alternative a_i and alternative a_x with respect to the preference function P_j is denoted by $P_j(a_i, a_x)$. Furthermore, the decision maker has to determine a set of suitable criteria weights $\Omega = \{\omega_1, ..., \omega_j, ..., \omega_k\}$. In addition, the sum of the criteria weights must be 1. Two outranking flows are computed for all alternatives of the decision problem. Equation (2) shows the calculation of the positive outranking flow $\phi^+(a_i)$ of the alternative a_i.

$$\phi^+(a_i) = \frac{1}{n-1} \sum_{j=1}^{k} \sum_{a_x \in A} P_j(a_i, a_x)\, \omega_j \tag{2}$$

The negative outranking flow $\phi^-(a_i)$ of the same alternative a_i is shown in Eq. (3).

$$\phi^-(a_i) = \frac{1}{n-1} \sum_{j=1}^{k} \sum_{a_x \in A} P_j(a_x, a_i)\, \omega_j \tag{3}$$

The method PROMETHEE II is used to obtain a complete ranking of alternatives by calculating the net flow of each alternative. Equation (4) shows the net flow $\phi^{net}(a_i)$ of the alternative a_i.

$$\phi^{net}(a_i) = \phi^{+}(a_i) - \phi^{-}(a_i) \quad (4)$$

The net flow of the alternative a_i lies in the interval $\phi^{net}(a_i) \in [-1; 1]$. A net flow $\phi^{net}(a_i) > 0$ means that the alternative a_i is outranking the other alternatives. In contrast, a net flow $\phi^{net}(a_i) < 0$ means that the alternative a_i is outranked by the other alternatives.

3. Approach

In the following, the approach to a sequential MCDA supporting the optimization of observation strategy is presented. The goal of this work is to support the strategy of selecting a route through a building under multiple criteria such as the safety of the robot or the expected gain of information in specific areas of the building. A Bayesian network is used to estimate the probability of specific aspects of the situation, such as the probability of fire in predefined areas. Each time the robot reaches a new checkpoint, the values of the respective probabilistic variables of the BN are updated based on the observations provided by the sensors of the robot. MCDA is applied to support the decision of which checkpoint to go to next. Thus, MCDA is applied each time the robot reaches a new checkpoint.

In order to introduce the approach, first, the case study is presented. Second, the resulting Bayesian network is described, followed by the criteria that are considered to perform the MCDA. In Section 4, the approach is applied to two different preference types (e.g. two stakeholders with different preferences regarding the weights of the decision criteria) resulting in two exemplary paths of the robot.

3.1. *Case Study*

The aim of this case study is to illustrate the approach using a simplified example. The conceptual study consists of a simplified building of a production company. The building is divided into three rooms: the production, a storage room and a hallway which connects the other rooms. The storage room has about twice the floor space of the production. The main entrance (marked with an *S*) is located at the hallway. An additional emergency exits is at the left side of the storage room. A total of five checkpoints are distributed over both main rooms, two in the production and three in the storage room. These exemplary checkpoints are selected in a way that a large area of both rooms is covered when observing all checkpoints. Figure 1 shows the floorplan of the building including the main entrance *S*, the emergency exit as well as the five checkpoints *I-V*. The distances between the checkpoints and the main entrance are shown in Eq. (5). The sensors of the robot are assumed to be capable of detecting fire (high temperatures) and smoke from a short distance. This allows fire and smoke to be detected at each checkpoint and in the near surrounding area, but not from any further distant location.

In this case study, we assume that fire is located at checkpoint *IV*, while smoke has spread over checkpoints *III* and *IV*.

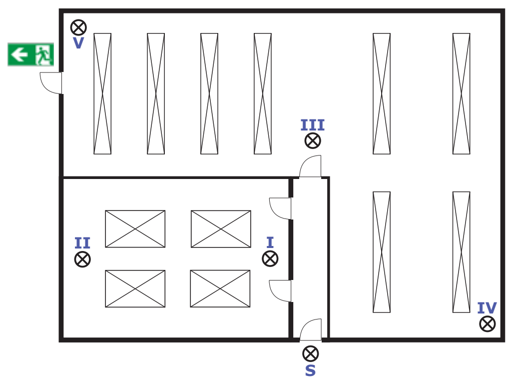

Fig. 1. **Floorplan of the case study.** The case study is composed of three rooms, the production (bottom left), a storage room and a small hallway connecting both rooms. Dots indicate the checkpoint for the robot *I-V* as well as the main entrance *S*. The emergency exit is located at the left side of the storage room.

3.2. *Bayesian Network of the Case Study*

The BN (Figure 2) is used to estimate (1) the probability of fire in each checkpoint (nodes *Fire in I-V*) and (2) the probability of burning hazardous material in each checkpoint (nodes *B.H.M in I-V*). The nodes *Burning Hazardous Material (B.H.M) in I-V* are child nodes of the respective node *Fire* at the checkpoint as well as a node *Hazardous Material (H.M.)* indicating the probability of the existence of hazardous material in the area of the checkpoint. Additionally, each *Fire* node is a parent node of the respective *Smoke* node. Smoke and fire can be detected by the robot. The *Smoke* nodes are linked by a *Smoke Alarm* node. This node has three states: *Single Alarm, Distributed Alarm* and *None*. Thus, it can be distinguished whether only a single alarm triggered the emergency response or several alarms in the same building. In case of a single alarm, it is more likely that fire is present in only one room. Subsequently, all *Fire* nodes are connected by the node *Fire in both Rooms* which indicates the probability that a fire has spread into the second room.

Given an observation on one of the *Fire* or *Smoke* nodes, the beliefs on all other conditional nodes in the BN are updated. Prior probabilities of the occurrence of hazardous material at the checkpoints are e.g. provided by local employees.

3.3. *Criteria*

Four criteria are considered in the case study for the MCDA. (1) The *Distance* to the next checkpoint. Assuming a constant speed of the robot, the distance is proportional to the time that is required to reach the next checkpoint. This criterion is to be minimized. The corresponding values for the distance between checkpoints are taken from Eq. (5). (2) The *Safety* of the robot itself, which is linked to the estimated probability of fire in a certain checkpoint (see nodes *Fire in I-V* in Figure 2). In order to enhance the safety of the robot, checkpoints with a lower probability of fire are to be selected according to this criterion. (3) The *Gain of information about the condition of the emergency exit*. In order to quickly gain knowledge about the accessibility of the emergency exit, the robot should visit checkpoint *V* early on its route through the building. Therefore, this criterion aims to minimise the distance to checkpoint *V* during the process of selecting the next checkpoint. The values of the distance to checkpoint *V* is taken from Eq. (6). (4) The *Gain of information about burning hazardous material*, which is linked to the nodes named *B.H.M. I-V* of the respective checkpoints being in state *True* (see Figure 2).

These criteria can be mutually conflicting. For example, preferring *Safety*-criterion would hinder going to the checkpoint where a fire is expected with the highest probability. The *Information gain about burning hazardous material* on the other hand, would support to go to the checkpoint with a high probability of fire, if preferred.

$$Distance = \begin{array}{c c} & \begin{array}{cccccc} S & I & II & III & IV & V \end{array} \\ \begin{array}{c} S \\ I \\ II \\ III \\ IV \\ V \end{array} & \begin{pmatrix} 0 & 5 & 12 & 16 & 26 & 28 \\ 5 & 0 & 10 & 6 & 20 & 22 \\ 12 & 10 & 0 & 16 & 30 & 32 \\ 16 & 6 & 16 & 0 & 14 & 16 \\ 26 & 20 & 30 & 14 & 0 & 30 \\ 28 & 22 & 32 & 16 & 30 & 0 \end{pmatrix} \end{array} \quad (5)$$

$$Distance\_to\_V = \begin{array}{c} \begin{array}{ccccc} I & II & III & IV & V \end{array} \\ \begin{pmatrix} 22 & 32 & 16 & 30 & 0 \end{pmatrix} \end{array} \quad (6)$$

4. Results

In this case study, an exemplary fire scenario with a distribution of fire and smoke is assumed. In the considered exemplary scenario, a fire occurs in the area of checkpoint *IV*, smoke has spread over the areas of checkpoint *III* and *IV*. Furthermore, the smoke detectors indicate a single smoke alarm, i.e. the node *Smoke Alarm* is in state *Single Alarm*.

In order to compute results, additional information are required. First, the MCDA method is to be selected. In this approach, PROMETHEE II is applied (see Section 2.2). In order to do so, a preference function is selected for each criterion. Preference function type III and V (see (Brans and Smet, 2016)) are selected in this example. For both, threshold values (q-value and p-value as shown in Figure 3) are determined. In case of a q-value equal to zero, preference function type III and V are equivalent. An overview of the selected values for each criterion is shown in

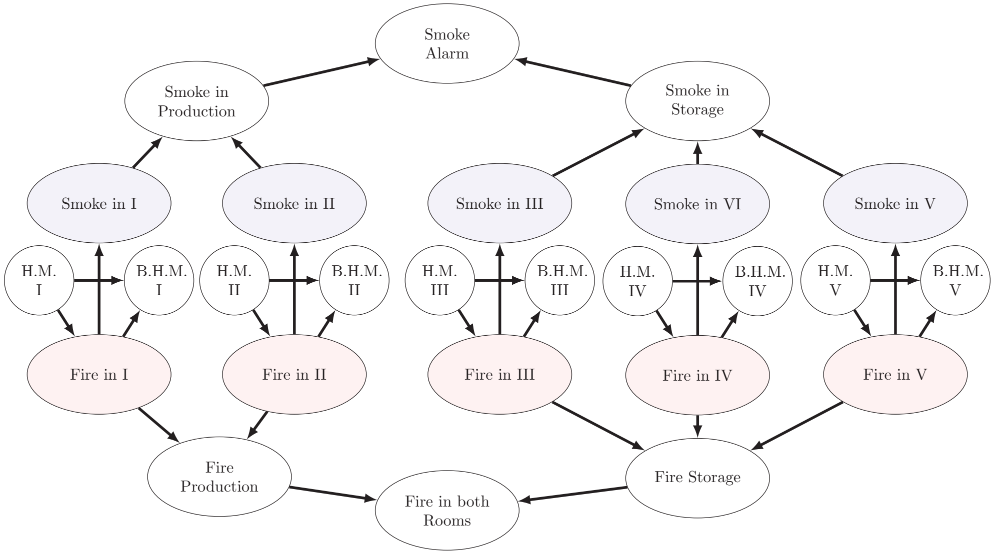

Fig. 2. **Bayesian network of the case study.** The BN shows several nodes for each checkpoint shown in Figure 1. The abbreviation *H.M.* stands for *Hazardous Material*. The abbreviation *B.H.M.* stands for *Burning Hazardous Material*. All nodes, besides node *Smoke Alarm*, are binary with states *True* and *False*. The node *Smoke Alarm* shows three potential states, namely *Single Alarm, Distributed Alarm* and *No Alarm*. The highlighted nodes *Fire in I-V* and *Smoke in I-V* can be observed by the robot.

Table 1. Additionally, a preference type is required stating the criteria weights. Table 2 shows two exemplary preference types that show different criteria weights. For the first preference type, the criterion of *Safety* is given the highest weight, for the second preference type, the *Distance* criterion is given the highest weight.

For both preference types, a MCDA is performed each time the robot visits a new checkpoint, and more than one checkpoint can be visited next. In order to enable a traceability of the results, an exemplary evaluation table is shown in Table 3. In this decision, the robot enters the building and can move to either checkpoint *I* or *III*. Thus, the set of alternatives is $A = \{I, III\}$. For preference type *I*, the ranking of alternatives, including the corresponding outranking flows, is: $\phi^{net}_{\Omega_1}(I) = -0.124$ and $\phi^{net}_{\Omega_1}(III) = 0.124$. For preference type *III*, ranking of the alternatives, including the outranking flows, is: $\phi^{net}_{\Omega_2}(I) = 0.076$ and $\phi^{net}_{\Omega_2}(III) = -0.076$.

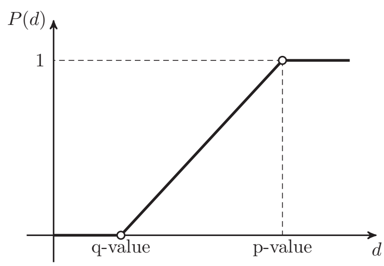

Fig. 3. **Preference function type V-shape with indifference criterion.** The q-value is the threshold of indifference, the p-value is the threshold of strict preference. In case of $q = 0$, the preference function is equal to the third type called V-shape criterion. For more information see Brans and Smet (2016).

4.1. *Paths of Preference Types*

Both complete paths, given the preference types shown in Table 2, are shown in Figure 4 and 5. Each figure shows the resulting path and highlights the decision between two to three checkpoints. For preference type *I* (see Figure 4), four decisions are made. Two decisions between

Table 1. **Values for preference function.** The values correspond to the description in Figure 3.

Criterion	q-value	p-value
Distance	0	16
Safety	0.05	0.4
Info. Exit	0	30
Info. Material	0.05	0.25

two checkpoints and two decisions between three checkpoints. For preference type *II* (see Figure 5), three decisions are made, all between two checkpoints.

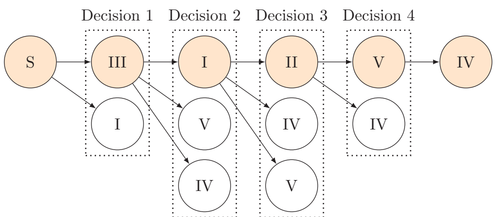

Fig. 4. **Path and decisions of preference type I (see Table 2).** Starting at *S* the chosen path based on the MCDA is highlighted in orange.

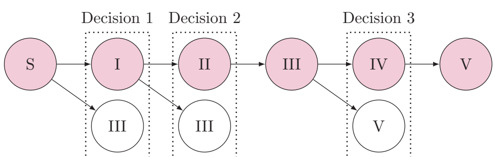

Fig. 5. **Path and decisions of preference type II (see Table 2).** Starting at *S* the chosen path based on the MCDA is highlighted in purple.

5. Discussion

The selected case study is highly simplified. Nevertheless, this example already illustrates the complexity of the resulting decision process as well as the benefits of the presented approach. Given only five checkpoints in the presented floorplan (see Figure 1), a total of 20 differing routs are feasible. The resulting BN (see Figure 2) is already composed of 26 nodes. One major benefit of the approach is the potential to build up the BN based on rules that fill in the Conditional Probability Tables. In this way, the number of checkpoints, and thus the number of nodes considered in the BN, can be easily expanded. Checkpoints can individually be selected by emergency response personnel at locations of high interest. In addition to checkpoints, probability values indicating the probability of existence of hazardous materials in the area of the checkpoint are required as inputs.

Within the presented approach, only fire and smoke can be detected. In a real-world use case, more sensors could be added and the sensor information could be merged with the observations of the emergency responders. Adding new sensor types would require additional nodes in the BN. Merging of observations by emergency responders could be achieved by manually inserting evidence into the BN.

Whenever a decision is made as to which checkpoint to move to next, another MCDA is performed. The MCDA is based on the previously defined criteria. The MCDA evaluation table is updated when a checkpoint is reached and observations are made using the sensors. This is done by inference in the BN, taking into account the new observations as well as the new position of the robot in the building. A limitation of the approach is that in some cases only one step (in terms of the transition to the next control point) is considered. For the criterion *Gain of information about the emergency exit* more than one step ahead is considered due the absolute distance to checkpoint *V*. This limitation occurs, for example, when the distance criterion is strongly preferred. Always targeting the checkpoints with the smallest distance does not necessarily lead to the shortest total distance of the overall path.

The results represented by the paths shown in Figure 4 and 5 illustrate how strongly the resulting path is depended on the criteria weights as well as the setup of the floorplan of the building. The resulting path of preference type *I* (see Figure 4) shows four decisions with two to three alterna-

Table 2. **Criteria weights of two preference types.** The criteria weights of one preference type sum up to one. Both types show different criteria weights in order to illustrate the impact of these weights on the resulting route of the robot.

Preference Type	Criteria			
	Distance	Safety	Info. Gain Exit Availability	Info. Gain Burning H. Material
Ω_I	20%	35%	30%	15%
Ω_{II}	35%	15%	20%	30%

Table 3. **Exemplary evaluation table of the MCDA.** The table shows the evaluation table of the MCDA at checkpoint *S*. The alternatives are moving to checkpoint *I* or *III* as shown in Figure 1. The values of the *Safety*-criterion correspond to the probability of a fire in the respective checkpoints. The values of the *Info. Gain Burning H. Material*-criterion correspond to the probability of the respective node in the BN of the checkpoints. The *Distance* is taken from Eq. (5). The value for the remaining criterion *Info. Gain Exit Availability* is taken from Eq. (6).

Alternatives	Criteria			
	Distance [m]	Safety [%]	Info. Gain Exit Availability [m]	Info. Gain Burning H. Material [%]
I	5	15	22	4
III	16	18	16	2

tives. Given the criteria weights of preference type *II*, three decisions are made, each time between only two alternative checkpoints.

Additionally, the results are shaped by the input data used to set up the BN and to perform the MCDA. The MCDA method used, PROMETHEE II, shows a great benefit by using preference functions that allow for the inclusion of thresholds for indifference as well as for strict preference (see q-value and p-value in Figure 3) between two alternatives. In this way, the influence of a small difference in one criterion can be limited and full preference can be introduced. These thresholds can be adjusted to the potential values obtained by the BN and the floorplan.

6. Conclusion and Outlook

When searching for the optimal observation strategy in emergency response by a robotic system, multiple - often conflicting - criteria can be considered such as the safety of the robot itself or the expected information gain at different areas of the building. This paper presents a first approach to consider different criteria in optimizing observation strategy. The approach combines a Bayesian network to estimate the states of key aspects of the emergency scenario and a Multi-Criteria Decision Analysis to formalize the decision process. To perform the MCDA, PROMETHEE II is applied.

First, areas of interest, i.e., checkpoints, are identified on a floorplan of the building at risk. Starting at the entrance, a decision is made on which checkpoint to visit first. The number of alternative checkpoints to visit next depends on the location of the robot as well as the floorplan. Each time a checkpoint is visited, observations by the sensors based on the robot are made and considered in the BN to perform belief update on the variables in the network. Based on the new location of the robot and the updated beliefs in the BN, the next MCDA is performed to select the next checkpoint. This process is performed until each checkpoint is observed.

The case study presented in this paper is simplified, but illustrates the main principles of the approach and illustrates the complexity of the decision process. The results show that changes in the weighting of the criteria have a large impact on the resulting path. The approach can be adopted to allow consideration of more checkpoints in different floorplan layouts as well as consideration of more criteria in the MCDA.

In future work, the approach should be extended so that more than one step ahead is planned. In addition, the approach should be evaluated with domain experts based on a real-life use case considering more criteria as well as checkpoints.

References

Brans, J.-P. and Y. D. Smet (2016). PROMETHEE methods. *International Series in Operations Research and Management Science 233*, 163–186.

Druzdzel, M. and L. van der Gaag (2000, July). Building probabilistic networks: "Where do the numbers come from?" guest editors' introduction. *IEEE Transactions on Knowledge and Data Engineering 12*(4), 481–486.

Geldermann, J. and A. Schöbel (2011). On the similarities of some multi-criteria decision analysis methods. *Journal of Multi-Criteria Decision Analysis 18*, 219–230.

Hwang, C.-L. and K. Yoon (1981). *Multiple Attribute Decision Making*. Springer Berlin, Heidelberg.

Kabir, G., R. Sadiq, and S. Tesfamariam (2014). A review of multi-criteria decision-making methods for infrastructure management. *Structure and Infrastructure Engineering 10*(9), 1176–1210.

Lichte, D., F. S. Torres, and E. Engler (2022, May). Framework for Operational Resilience Management of Critical Infrastructures and Organizations. *Infrastructures 7*(5), 70.

Mentges, A., L. Halekotte, M. Schneider, T. Demmer, and D. Lichte (2023). A resilience glossary shaped by context: Reviewing resilience-related terms for critical infrastructures.

Milana, E. (2022). Soft robotics for infrastructure protection. *Frontiers in Robotics and AI 9*.

Pearl, J. (1985). Bayesian networks: a model of self-activated memory for evidential reasoning. In *UCLA Computer Science Department Technical Report 850021 (R-43)*, pp. 329–334.

Ramírez-Agudelo, O. H., C. Köpke, Y. Guillouet, J. Schäfer-Frey, E. Engler, J. Mielniczek, and F. Sill Torres (2021, September). An Expert-Driven Probabilistic Assessment of the Safety and Security of Offshore Wind Farms. *Energies*.

Rosas, F. G., F. Hoeller, and F. E. Schneider (2020, August). Autonomous Robot Exploration and Measuring in Disaster Scenarios using Behavior Trees. In *2020 IEEE 10th International Conference on Intelligent Systems (IS)*, pp. 469–474. ISSN: 1541-1672.

Schneider, F. E. and D. Wildermuth (2017, May). Using robots for firefighters and first responders: Scenario specification and exemplary system description. In *2017 18th International Carpathian Control Conference (ICCC)*, pp. 216–221.

Schneider, M., O. H. Ramírez-Agudelo, L. Halekotte, and D. Lichte (2022). A probabilistic approach to dynamic risk scenario identification. In L. P. Maria Chiara Leva, Edoardo Patelli and S. Wilson (Eds.), *Proceedings of the 32nd European Safety and Reliability Conference (ESREL 2022)*, pp. 196–203. Research Publishing, Singapore.

Timotheou, S. and G. Loukas (2009). Autonomous networked robots for the establishment of wireless communication in uncertain emergency response scenarios. In *Proceedings of the 2009 ACM Symposium on Applied Computing*, SAC '09, New York, NY, USA, pp. 1171–1175. Association for Computing Machinery.