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Combining Bayesian Networks and MCDA methods to maximise information gain during reconnaissance in emergency situations

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ABSTRACT

In the immediacy of an event that disrupts the operation of an infrastructure, the time between its occurrence and the arrival of qualified personnel for emergency response can be valuable. For example, it can be used for gathering information about the status of the infrastructure by using automated reconnaissance devices. In an operation that precedes the intervention of human first responders, such devices can gather information about the situation, providing knowledge about the locations of stressors (e.g. fire), the inaccessibility of parts of the infrastructure or the presence of hazardous materials. In this study, we show how a Bayesian Networks can be used for knowledge representation and how it can be combined with methods from the realm of Multi-Criteria Decision Analysis (MCDA) for situation reconnaissance and route-optimisation in emergency situations, where different criteria (current belief about the location of zones of special interest, such as emergency exits, distance to the next point of interest, etc.) can be considered. As an example, we consider the case of an outbreak of a fire in a building. A pedantic check of all rooms by an automated reconnaissance device would take too long and thus delay intervention. Due to the limited time in which the building can be explored, the route is optimised to gather the greatest possible amount of information in the available time window. Results show how it is possible to maximise the information collected in a limited time window. This is done by discovering the location of fire and any hazardous materials through causal inferences automatically calculated by the Bayesian network. Route optimisation is facilitated by sequential MCDA using a parameter selection that meets the priorities of the specific application example.

1. Introduction

Infrastructures are confronted with a variety of possible, even unexpected, disruptive events. Such a disrupting event can result in an interruption to their core processes and, in the case of working facilities, jeopardise the health of present employees. The rapid and effective deployment of forces to contain the disruption, eliminate its cause and rescue employees is therefore of great importance. However, in the event of fires breaking out or leaking hazardous gases, there is a risk that emergency services will endanger themselves. This is particularly true if information on the situation is uncertain and incomplete, for example because relevant parameters such as fire sources or the storage locations of hazardous materials are either entirely unknown or unclear. In such incidents, fast and efficient support together with a proper information gathering strategy is an important element of risk mitigation so that emergency services can be effectively deployed to minimise damage, help endangered employees and restore the operational readiness of the infrastructure as quickly as possible.

In principle, robotic systems might be used for such supportive tasks, for example to assist fire brigades or first responders in their work [1]. There are various practical examples of this, ranging from automatic fire extinguishing and the search for hazardous materials to the general improvement of situational awareness [1–3]. Ideally, autonomous robotic support systems arrive at the incident location prior to the emergency services, i.e. shortly after the alert and before the arrival of the fire brigade [4]. This period is particularly suitable to collect information on the situation, ensuring effective and safe responses. It would therefore be advantageous to use this time window to autonomously obtain information via robotic systems to provide a comprehensive picture of the situation and thus efficiently increase situational awareness [5].

The above-mentioned area of application demands various requisites on a robot system. In addition to the purely technical, physical and sensory requirements for the robot platform, special properties are essential for efficient information acquisition:

1. *Large number of locations*: It may be necessary to explore and observe a large number of different locations within the infrastructure. In order to make efficient use of the limited time

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available to gather information, it is necessary to optimise the route, considering all the available information.
2. *Causally dependent information*: Various pieces of the information necessary to build a reliable representation of the state of the system might be available. This information may be causally dependent, e.g. various sensor data that are merged into a higher-level information, as well as across locations. Hence, collecting and connecting available data is necessary to create a comprehensive picture of the situation.
3. *Sequential information*: Decisions under uncertainty are often inherently sequential, requiring to integrate changing information by sequentially updating the belief about the current state of the system.
4. *A priori expert knowledge*: Existing expert knowledge (preliminary information) should be taken into account and integrated to the comprehensive picture of the situation.
5. *Availability of knowledge*: The time between raising the alarm and the arrival of the emergency services is limited and must be utilised efficiently. The information retrieval system should therefore be available as quickly as possible and be able to analyse current information relying on limited data and very general assumptions, thus often ruling out tailored simulations like fluid-/thermo-dynamics-based ones.
6. *General applicability*: The robotic system should be able to react autonomously and ad-hoc to a variety of possible incidents or hazards. It is therefore advantageous to use a method for route finding and optimised information acquisition that can be easily adapted to different disruption and hazard scenarios.

1.1. Previous approaches for route optimisation in similar settings

The requirement of optimised route finding mentioned in 1 (*Large number of locations*) is taken up in research in two main lines, which have their origins in different disciplines. These are, on the one hand, orienteering problems from operations research and, on the other hand, informative path planning from robotics and information systems.

In the so-called orienteering problems, which extend the well-known travelling salesman problem by combining it with the knapsack problem, a subset of nodes in a network is to be selected considering a limited number of feasible steps or specific time constraints [6]. The aim of the selection is to maximise a score. For our application, approaches from the field of (a) stochastic orienteering problems, (b) generalised orienteering problems and (c) correlated orienteering problems may be adapted by maximising the information gain. Specifically, (a) considers uncertainties in the collected score, which might be interpreted as an uncertain gain in information; (b) uses sets of scores that depend on different attributes, which in our case could take the role of values to balance exploration and exploitation; (c) can be used to describe the cross-location dependency of information, since the score collected in a node is here dependent on its neighbours. However, the dynamics of the information to be collected addressed in 2 (*Causally dependent information*) and 3 (*Sequential information*) would require a sequential approach for the route exploration, based on the current (updated) information situation. Conversely, approaches for solving an orienteering problem calculate the entire route all at once at the beginning of the process. A post-disruption emergency mapping strategy based on correlated team orienteering problems for predicting hazardous materials distributions is investigated by [7]. The authors develop a heuristic by optimising the point of interest to be visited. Population density is used to prioritise points and individual points are spatially correlated. However, the routes are initially determined without sequential information updating and without causal connections for the acquired information.

In operations research, dynamic and stochastic developments of the Vehicle Routing Problem (VRP) overcome this limitation. In particular, [8] present real-time decision support solutions that link dynamic events and stochastic information. The initially optimised path is thereby adapted to newly available data at run-time. Typically, such approaches are formulated as Markov Decision Processes (MDP) and multi-stage stochastic programming. Nevertheless, such approaches are often subject to problem-specific strict assumptions, clashing with requirement 6 (*General applicability*).

The second main literature stream deals with the Informative Path Planning (IPP) problem. Here, paths are planned for robotics and information systems in order to maximise the information gain. Although the distinction is not sharp, the focus is usually on trajectories themselves rather than on specific locations. Applied methods refer, for example, to the planning of possible movement paths of robots for navigation. On this topic, [9] provide a review on path planning techniques for mobile robots, where data are collected by onboard sensors and used to determine the optimal way of the robot from one point to another. Algorithms for path planning of Autonomous Underwater Vehicles (AUVs) and Unmanned Aerial Vehicles (UAVs) based on Gaussian Processes (GP) and Partially Observable Markov Decision Process (POMDP) [10,11] aim to balance the exploration/exploitation trade-off for mapping purposes, covering requirements 1 (*Large number of locations*), 5 (*Availability of knowledge*) and 3 (*Sequential information*), assuming spatial correlations, without explicit causality as discussed in 2 (*Causally dependent information*). In fact, information in the event of a crisis is often not only spatially, but also causally dependent. Furthermore, the integration of a priori expert knowledge may be difficult in this approach.

Specific approaches for sequential information collection are for example proposed by [12,13]. [13] describe a multi-agent sequential problem in which the cooperation of a UAV and a helicopter in forest fires is optimised. Here, the UAV collects information and the helicopter works in firefighting. Both decide at which points to act depending on the jointly determined policy and available information. The decision on the next step is made sequentially, whereby Bayesian beliefs are used to assess the current situation. The approach enables the effects of decisions made on subsequent information procurement to be taken into account. Closely related, [12] propose a method for ad-hoc information gathering for emergency storm response. In this approach, a vehicle is used to gather information for emergency operations on power grids. The information is integrated using Bayesian beliefs. An ad-hoc Monte Carlo Tree Search (MCTS) algorithm is used to weight the exploration and exploitation for optimised information extraction based on the current information and to efficiently plan the necessary repairs. Both methods cover most of the relevant requirements, but do not explicitly consider Bayesian networks to model various levels of causal connections between the belief components with respect to the current state of the system identified as requirement 2 (*Causally dependent information*).

1.2. Contribution of this work

In a study, Schneider et al. [14] propose a new approach based on the combined application of Bayesian networks for information processing and an MCDA method for deciding on the next step to be taken by an autonomous support vehicle. We further develop this approach in this study to fulfil the six requirements identified in Section 1 by combining knowledge model based on a Bayesian network and a route optimisation based on MCDA methods. The knowledge model that the robotic support system is equipped with represents its awareness of the structure of the building in which it is located and the current known scenario-specific state there. The Bayesian network used for this purpose enables the integration of causally dependent information and was set up in a way here, that facilitates the easy adaptation of the Bayesian network to any realistic building structure with multiple rooms. At the same time, it supports sequential decision-making based on the structure of the building, as the MCDA used for this can access the current knowledge model in every step of the route finding process. In addition, we introduce the decision criterion of distance to optimise route finding under time constraints of requirement 1 (*Large number of locations*). Lastly, the structure of the knowledge model makes it easier to integrate expert knowledge.

2. Methods

2.1. Bayesian networks

Bayesian networks (BN) are renowned for their flexibility and efficiency in modelling a wide array of stochastic phenomena, enabling the representation of complex probabilistic relationships in a structured and understandable manner and allowing for the exploration of cause–effect relationships. Thus, they offer a method for representing complex interdependencies between variables by capturing the probabilistic relationships that govern their interactions.

Bayesian networks are based on Bayes' formula, which quantifies the probability that an event, say A, will occur in the presence of another event, say B, thus implying probabilistic inference across the network, relying on specific causal relationships. In particular,

$$\mathbb{P}(A|B) = \frac{\mathbb{P}(B|A) \cdot \mathbb{P}(A)}{\mathbb{P}(B)}, \tag{1}$$

where $\mathbb{P}(A|B)$ is the conditional probability of the event A given B, $\mathbb{P}(B|A)$ is the conditional probability of the event B given A, while $\mathbb{P}(A)$ and $\mathbb{P}(B)$ are the probabilities of the two events, respectively.

Given a set of variables, we represent them in a Bayesian network starting from a causal structure. Each node in the resulting Directed Acyclic Graph (DAG) corresponds to a variable and each link to a directed causal relationship. In this application, we do not infer the causal structure from data, but we manually construct the DAG according to the characteristics of the application domain. The next necessary components are the Conditional Probability Distributions (CPDs): practical quantification of the probability of the outcome of a variable given the values of its parents in the network. Specifically, for a random variable X with parents $\mathsf{pa}(X)$, we denote $\mathbb{P}(X|\mathsf{pa}(X))$ the conditional effects of $\mathsf{pa}(X)$ on X, thus probabilistically quantifying the correspondent causal influence within the network. In the case of a discrete probability distribution, CPDs can be explicitly represented by tables. However, the number of entries follows the number of possible state combinations of parent nodes, thus increasing exponentially with the number of parent nodes and requiring a proportional number of parameters. One solution for reducing this potential combinatorial explosion and thus reducing the computational effort is the technique of *parent divorcing* [15].

2.2. Multi-criteria decision analysis

Within the realm of decision making, the field of Multi-Criteria Decision Analysis (MCDA) describes methods that have been developed for situations in which multiple criteria need to be considered in the process of selecting one out of multiple alternatives. Among the numerous methods that exist to perform MCDA (cf. [16] for a review on MCDA methods), the subfield of multi-attribute decision making (MADM) focuses on situations where the alternatives are discrete.

Here, we apply the MADM method called PROMETHEE II, from the family of *preference ranking organisation method for enrichment evaluation* (PROMETHEE), first introduced by [17]. Such methods have been applied in various fields such as health care, banking, and investments [18]. PROMETHEE II allows for a complete ranking of alternatives based on pairwise comparisons (cf. [18] for a detailed summary). Specifically, pairs of alternatives are compared with respect to each decision criterion $j \in \{1, \dots, J\}$. Afterwards, the results of these comparisons are aggregated such that all alternatives are ranked in order of preference.

For each criterion $j \in \{1, \dots, J\}$, the deviation between a pair of alternatives is defined as:

$$d_j(a_i, a_x) = g_j(a_i) - g_j(a_x), \tag{2}$$

with a_i being the value of alternative i and $g_j(a_i)$ representing a_i evaluated according to criterion *j*. This deviation d_j between pairs of alternatives for criterion *j* is then used to determine the preference among the pair of alternatives $P_j(a_i, a_x)$. For each criterion *j*, a separate preference function P_j needs to be defined. A limited number of different types of preference functions are usually applied in this step. A general overview can be found in [18]. The preference functions employed in this work are shown in Fig. 3. The parameterisation of preference functions is a required input from the decision maker or the stakeholder. Another important input that these groups need to provide is a set of weights $\Omega = \{\omega_1, \dots, \omega_j, \dots, \omega_J\}$ that assigns a weight to each of the j decision criteria. Based on the pairwise comparison of alternatives and the criteria weights, a "net outranking flow" ϕ^{net} is calculated for each alternative:

$$\phi^{net}(a_i) = \frac{1}{n-1} \sum_{j=1}^{J} \sum_{a_x \in A} \left[P_j(a_i, a_x) - P_j(a_x, a_i) \right] \omega_j, \tag{3}$$

with $\phi^{net}(a_i) \in [-1, 1]$. The alternative with the highest value of ϕ^{net} is preferred.

2.3. Proposed strategy

In this study, we further develop the approach of Schneider [14] and introduce a robotic system equipped with knowledge models that represent its awareness about the building structure and the current state of the building in which it is deployed. A Bayesian Network [19] is used to model this knowledge in the form of the scenario-specific dependencies between relevant factors. For example, measuring elevated temperatures in one room of the building is considered as an indicator for a fire in the vicinity of this room and thus increases the probability (i.e. belief of the robot) of finding a fire in a neighbouring room. Therefore, requirement 2 (*Causally dependent information*) is fulfilled in a scenario-specific manner. Furthermore, the Bayesian Networks allows expert knowledge to be taken into consideration (requirement 4. *A priori expert knowledge*) by representing their opinions about the state of a system as prior beliefs in the network.

We assume that navigating the building (including the detection of unforeseen obstacles, etc.) is automatically performed by the robot at constant speed and we do not take details of these processes into consideration here. Instead, we focus on the strategic optimisation of the route through the building, i.e., answering the question which room or section of the building to visit next based on the information available in the actual situation (requirement 1. *Large number of locations*).

In order to fulfil requirements 5 (*Availability of knowledge*) and 6 (*General applicability*), we follow a relatively simple yet robust approach: PROMETHEE II, as described by [18,20] is applied as a multi-criteria decision making (MCDM) algorithm. This algorithm allows for the consideration of differing (and even opposing) optimisation criteria to be considered when selecting the next Point Of Interest (POI) to visit. We consider a fire in a building as an application example. Here, it is interesting to collect different types of information during the limited time interval that is available for situation reconnaissance: it might be interesting to search for humans who are still in the building, to search for potential threats such as burning hazardous materials or to check the accessibility of emergency exits in the building.

Depending on the situation, different experts or stakeholders might have different preferences among these criteria. MCDM-algorithms such as PROMETHEE II allow for the consideration of these preferences during the decision-making process. The decision criteria and stakeholder preferences will likely always be scenario-specific. However, it is possible with relatively little effort to parameterise this approach for a selected number of likely scenarios in advance, therefore making it easily adaptable.

Combining a Bayesian Network knowledge model with an MCDA-algorithm that has been parameterised by experts creates the opportunity to perform well-informed sequential decisions as part of a continuous route optimisation, while continuously updating the knowledge model based on newly available sensor information. This approach ensures an efficient collection of information in a given limited time

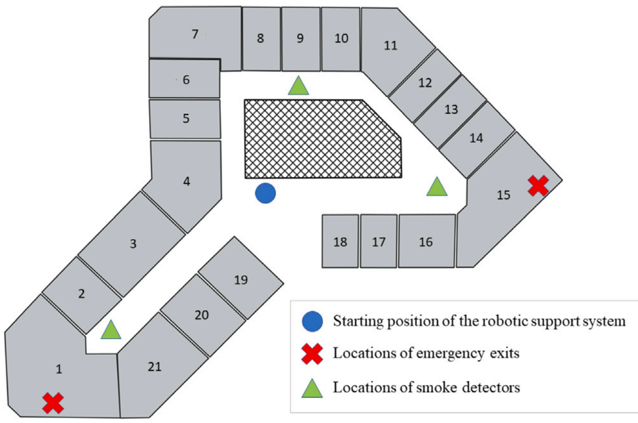

Fig. 1. Floor plan of the building that serves as an application example. The grey areas numbered from 1 to 21 are the rooms of the building. The shaded area in the centre represents utilities such as stairways which do not need to be inspected by the robotic support system.

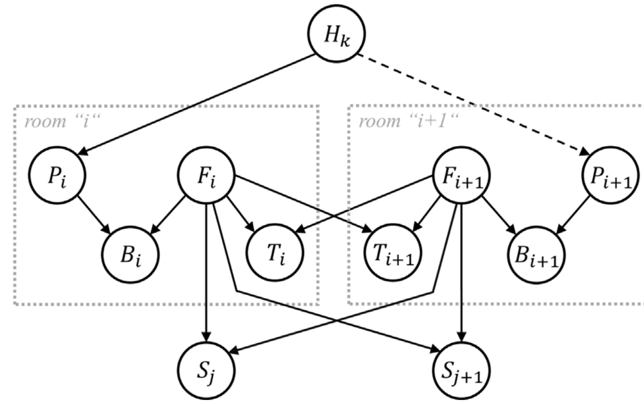

Fig. 2. Schematic illustration of nodes and edges of the Bayesian Network for two neighbouring rooms. Meaning of nodes: H_k: belief of expert k on the locations of hazardous materials, P_i: presence of hazardous material, F_i: presence of fire, B_i: burning hazardous material, T_i: room air temperature, S_j: state of smoke detector.

period during an emergency situation. Details about the combined application of a Bayesian Network and PROMETHEE II as an MCDM algorithm for optimised situation reconnaissance in an application example are described in Sections 3.1.2 and 3.1.3.

3. Evaluation

3.1. Application example

In order to evaluate the suitability of our combination of Bayesian networks and PROMETHEE II for the optimisation of an information gathering process, we simulate and analyse the route-optimisation process of an autonomous robotic support system in a realistic building in the aftermath of a fire outbreak.

3.1.1. The building structure and the emergency situation

We examine the information gathering process on one complete floor of a building which comprises 21 rooms (cf. Fig. 1). There are three smoke detectors installed in different parts of the floor and two emergency exits, located in room *1* and room *15*. As some of the 21 rooms are used as laboratories, it is possible that hazardous materials, which might pose serious threats to emergency personnel in case of fire, are present in the building. We assume that any personnel present in the building immediately leaves the building as soon as a fire alarm is triggered. Therefore, the presence of humans in the building is not expected during the information gathering process.

In each of the two examined scenarios, one or multiple smoke detectors have been triggered and fire fighters have been informed in order to search for fires in the building. Since smoke can spread relatively easily through the corridors, it is not trivial to limit the set of suspected rooms which potentially are on fire and thus might have triggered the smoke detector. Multiple experts who are familiar with the building have different opinions about possible locations of hazardous materials within the building. The initial situation is therefore characterised by uncertainty about the existence and location of fire, the existence and location of hazardous materials and the accessibility of the emergency exits.

The autonomous robotic support system that serves as a mobile sensor platform arrives a few minutes prior to human fire fighters and is assigned to gather as much valuable information as possible about the situation before the fire fighters arrive. Therefore, it operates under time constraints and the examination of all 21 rooms is not feasible.

3.1.2. The autonomous robotic support system

The autonomous robotic support system is equipped with two sensor systems: A temperature sensor that can measure the local air temperature in the immediate surrounding of the robot and a sensor to detect the local presence of hazardous materials. To conduct these measurements, the robot must stop for a short time. Furthermore, it possesses some relevant information about the floor plan of the building (cf. Fig. 1) which are required for the given task: it has access to data on all distances which are required to determine the distance from its current position to the next Point Of Interest (POI) along feasible routes; based on room identifiers, it can process input from experts regarding suspected locations of hazardous materials; the positions of all three smoke detectors and of the two emergency exits are known as well.

A Bayesian network serves as a knowledge model of the situation (cf. Fig. 2). It is tailored to scenarios involving fire and the potential presence of hazardous materials inside buildings. Each room i is represented by four nodes of which nodes T_i (room air temperature) and P_i (presence of hazardous material) can be measured by the robot's sensors as soon as the robot enters the respective room. The values of the variables F_i (presence of fire) and B_i (burning hazardous materials) cannot be measured, but only determined through inference based on values of the other nodes in the network. The other nodes of the Bayesian network consist of the states of the smoke detectors (nodes S_j and S_{j+1} in Fig. 2), which are influenced by the states of the *fire* nodes and nodes H_k, representing the belief of expert k on the locations of hazardous materials. The latter nodes are only connected to the P_i node of room i, if one of the experts suspects the presence of hazardous materials in room i (as indicated by the dashed line in Fig. 2).

As described in Section 2.1, the structure of a node's CPD depends on the number of parent nodes and the number of their potential states. In order to avoid combinatorial explosion when defining the CPDs of the smoke detector nodes, rooms that are relatively far away from one detector (i.e. within the "zone" of another smoke detector) are grouped together by parent divorcing. Therefore, the state of each smoke detector is modelled to depend on the presence of fire in each individual room, which is close to this particular smoke detector, and on the presence of fire in each of the groups of rooms that are located closer to another smoke detector. According to the positions of smoke detectors, the rooms are grouped as follows: group *1* consists of rooms (1, 2, 3, 4, 19, 20, 21), group *2* comprises rooms (5, 6, 7, 8, 9, 10, 11) and group *3* contains rooms (12, 13, 14, 15, 16, 17, 18).

3.1.3. The route optimisation task

When applying MCDA techniques to the route optimisation task, multiple criteria can be considered during the determination of the optimal next room to visit: (1) For fire fighters, it is valuable to know whether or not there are burning hazardous materials in any of the rooms. (2) Fire fighters need to know whether at least one of the emergency exits is accessible. If one emergency exit has been identified as being accessible, this criterion can be considered fulfilled and excluded from the list of optimisation criteria for the rest of the route optimisation task. (3) As much information as possible should be gathered during the limited time period which is available to the support system before the fire fighters arrive. Therefore, the number of visited rooms should be maximised, i.e. minimising the travelled distance.

Depending on the current position of the robot, all available alternatives (i.e. rooms that have not yet been visited by the robot) are evaluated based on these three criteria. That means that for each room i the following quantities are determined: the distance to the current position of the robot, the distance to the closest emergency exit, and the probability of B_i. B_i is interpreted as a preference percentage value based on the probabilities of fire (node F_i) and the presence of hazardous materials (node P_i). In particular, node B_i implicitly balances the decision maker's interest in exploring rooms with both fire and hazardous materials or either one of the two. In fact, although our primary interest is to discover rooms where both conditions occur, exploring rooms where fire or hazardous materials is likely to be present can be profitable in terms of improving the belief on the state of the system, thus balancing exploration and exploitation. Given maximum priority in case of burning hazardous materials ($\mathbb{P}(B_i|P_i = \text{True}, F_i = \text{True}) = 100\%$), such a balance is weighted by conditional probabilities $\mathbb{P}(B_i|P_i = \text{True}, F_i = \text{False})$ and $\mathbb{P}(B_i|P_i = \text{False}, F_i = \text{True})$.

The belief about the state of the system is updated after each new sensor measurement in a visited room. Therefore, the optimisation task can be characterised as a sequential decision problem. That means that it is not sufficient to optimise the route through the building only once in the beginning. The solution to this optimisation problem also depends on the relative weights that each of the decision criteria is given by the decision maker. As described in Section 2.2, we apply PROMETHEE II as the MCDA method, showing how different weight parameterisations (cf. Table 6) affect the determined optimal path through the building.

In all scenarios considered, the robot starts at the entrance to the floor (cf. Fig. 1) and then follows a sequence of actions in a loop:

1. employ the new collected evidence to update probability estimations (i.e. states of the nodes) in the Bayesian network;
2. perform MCDA to determine next POI to visit;
3. move to the next POI;
4. measure temperature and presence of hazardous materials;
5. go to 1.

Actions 4, 1 and 2, which are executed for each visited POI, require a total of 3 time units. Furthermore, it is assumed that the dynamics of fire and smoke are slow compared to the time interval considered here. Accordingly, the position of fire and smoke are assumed to be static (i.e. no further spreading of fire or smoke during the operation of the robot). For this reason and due to time constraints, it is not reasonable to visit the same POI twice. Therefore, each POI, which has been visited, is eliminated from the list of potential next POIs to select from.

3.2. Model set-up and parameterisation

Setting-up the structure of the Bayesian network (cf. Fig. 2) for this specific application example requires information about the number of rooms, the locations of emergency exits, the adjacency of rooms (edges from F_i to T_{i+1}), location of rooms with respect to smoke detectors (edges from F_i to S_j and S_{j+1}) and experts' belief about potential locations of hazardous materials (edges from H_k to P_i). The specification of the Bayesian network is completed by defining conditional probability distributions (CPD) for each type of node in the network.

Table 1
Conditional probability distribution of the temperature in room i (node T_i), given left- and right hand-side neighbours.

Room	Fire (True or False)							
Room $i-1$	True	True	True	True	False	False	False	False
Room $i+1$	True	True	False	False	True	True	False	False
Room i	True	False	True	False	True	False	True	False
$\mathbb{P}(T_i = \text{H})$	1 - σ_T	0.3	1 - σ_T	0.3	1 - σ_T	0.3	1 - σ_T	0
$\mathbb{P}(T_i = \text{M})$	σ_T	0.7	σ_T	0.7	σ_T	0.7	σ_T	σ_T
$\mathbb{P}(T_i = \text{L})$	0	0	0	0	0	0	0	1 - σ_T

Table 2
Conditional probability distribution of the presence of hazardous materials in room i (node P_i) when pointed out by an expert as possible location.

Expert suspects haz.mat.	True	False
$\mathbb{P}(\text{P}_i)$	0.8	0.1

Table 3
Conditional probability distribution of node B_i, interpreted as visiting priority for room i.

Fire (True or False)	True	True	False	False
Hazardous material (True or False)	True	False	True	False
$\mathbb{P}(\text{B}_i)$	1 - σ_B	0.5	0.3	σ_B

Each temperature node (T_i in Fig. 2) is dependent on the fire node of the room itself and of adjacent rooms. Its CPD is shown in Table 1. The values of the temperature variable are clustered into three distinct intervals: low ("L"), medium ("M"), and high ("H"). The probability of a measurement error when no alterations due to fires are occurring is set to 0.1% ($\sigma_T = 0.001$).

The probability assigned by the knowledge model of the support system for the presence of hazardous materials in room (P_i, in Fig. 2) depends on the experts' belief about potential locations of any such material (H_k in Fig. 2). If any expert assumes hazardous materials to be present in a room, the correspondent probability increases to 80% (cf. CPD in Table 2), otherwise it is set to 10%.

The occurrence of burning hazardous materials in a room (B_i in Fig. 2) depends on the presence of hazardous material (P_i) and the presence of fire (F_i). Moreover, the state of this variable is used as one of the criteria for route optimisation. It follows that entries of its CPD (Table 3) are interpreted as priorities and implicitly weighted, as discussed in Section 3.1.3. An additional parameter σ_B, set to 0.01, is employed as interpretation error.

Detectors can be triggered by a fire in any of the rooms, but a fully connected CPD would incorporate 2^{21} combinations. To limit the size of the CPD for smoke detector nodes (S_j in Fig. 2), the number of parent nodes is reduced. Therefore, the CPD depends only on a limited set of rooms in the vicinity of the respective smoke detector and on the status of the two other clusters of rooms that generate a more uncertain effect due to the increasing distance (i.e. given an active cluster, its effect on the detector is set to 0.8). Hence, the number of combinations drops to 2^{7+2}. Table 4 shows the CPD for smoke detector 2, while Table 5 displays the dependency of the state of cluster 2 on the *fire* nodes of the set of rooms that are close to smoke detector 2 as an example. The additional parameter σ_D represents the false alarm probability, here set to 1%.

Further input required from experts or the decision maker in order to set up and parameterise the method are the preference functions for each decision criterion and the corresponding criteria weights. Preference functions resemble the degree to which one alternative is preferred over another, represented as a function of the deviation between these

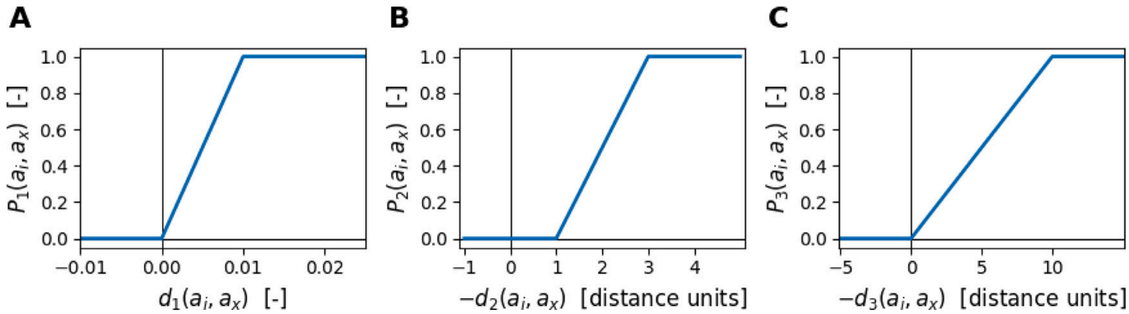

Fig. 3. Preference functions for the three decision criteria. The x-axes of criteria *2* and *3* display the negative deviation $d_j(a_i, a_x)$ between pairs of alternatives, since these criteria are to be minimised.

Table 4
Conditional probability distribution of detector node S_2.

Room	Fire (True or False)						
Room 5	True	False	…	False	False	False	False
⋮	⋮	⋮	…	⋮	⋮	⋮	
Room 11	True	True	…	False	False	False	False
Clusters	Smoke spread (True or False)						
Clust 1	True	False	…	True	False	True	False
Clust 3	True	False	…	True	True	False	False
ℙ(detector ON)	1	1	…	1	0.8	0.8	0
ℙ(detector OFF)	0	0	…	0	0.2	0.2	1 -σ_D
ℙ(detector FP)	0	0	…	0	0	0	σ_D

Table 5
Conditional probability distribution for cluster 2.

Room	Fire (True or False)			
Room 5	True	False	…	False
⋮	⋮	⋮	…	⋮
Room 11	True	True	…	False
ℙ(cluster ON)	1.0	1.0	…	0.0
ℙ(cluster OFF)	0.0	0.0	…	1.0

Table 6
Two different sets of weights to be assigned to the three decision criteria. Each set yields a different solution to the route optimisation task for information gathering.

Weights of decision criteria	Ω_1	Ω_2
Criterion "probability of burning hazardous material"	0.125	0.1
Criterion "distance to potential next POI"	0.075	0.05
Criterion "distance to next emergency exit"	0.8	0.85

alternatives (cf. Eq. (2)). The decision maker needs to select the type of preference function and the individual parameter values. Thus, for each criterion ranges are defined, in which deviations between alternatives are insignificant or in which one alternative is strongly preferred over the other. The preference functions of the three criteria used in our case study are shown in Fig. 3.

The MCDA framework employed here offers the advantage that decisions can easily be evaluated from the perspective of different stakeholders. In PROMETHEE II, this is achieved via criteria weights which are assigned to each criterion by the respective stakeholder. Table 6 contains two sets Ω_s, $s \in \{1, 2\}$ of different criteria weights, which we use in our application example to illustrate the effect that these weights have on the outcome of the route optimisation. Here, the values of each set of weights add up to one. However, this is not strictly necessary.

4. Results

The path of the autonomous robotic support system through the building is computed for two different scenarios. In each scenario, the two sets of criteria weights (Ω_1, Ω_2) introduced in Section 3.2 (cf. Table 6) are tested.

4.1. Scenario 1

In scenario 1, there is a fire located in room 11. This fire leads to increased temperatures in the neighbouring rooms 10 and 12. Hazardous materials are present in rooms 9, 11, and 17. However, this information is initially not known to the robotic support system and should be obtained during the information gathering process. The only information that serves as initial input to the knowledge system concerns the position of the two smoke detectors that have been triggered (smoke detectors close to rooms 9 and 14), the two sets of rooms in which two experts suspect hazardous materials (expert 1: rooms 9, 12, and 17; expert 2: rooms 10 and 18), and the need to check whether one of the two emergency exits (in rooms 1 and 15) is accessible. The starting point of the robotic support system is marked with a blue dot in Fig. 1. Resulting routes for scenario 1 and resulting observations are summarised in Table 7 for both preference sets Ω_s, $s \in \{1, 2\}$.

The time required by the robotic system to detect the burning hazardous materials is almost identical for Ω_1 and Ω_2 (90 and 93 time units). This information is reflected in Table 7 by observations *high temperature* and *presence of hazardous material*. To obtain it, the system performs one more step on its route for Ω_1 with five steps than for Ω_2 with four steps. When using Ω_1, all locations of hazardous materials are detected more quickly (108 instead of 155 time units) and the process takes one step less overall. After 123 (Ω_1) or 155 time units (Ω_2), no further increase in information is to be expected. This corresponds to seven steps for both preference sets Ω_s, $s \in \{1, 2\}$.

Effects of the different weightings for the preference sets Ω_1 and Ω_2 are distinguishable during the exploration. As the criterion "distance to the nearest emergency exit" is weighted higher in Ω_2, the robotic support system first heads for the nearest room with an emergency exit (room 15). Since the emergency exit can be used, this criterion is then disregarded for further route planning. For this reason, the support system no longer prioritises the second room with an emergency exit (room 1). In contrast, when using Ω_1, the robotic support system first heads for rooms in which dangerous material is expected according to previously known expert opinion (steps 1 and 2), as this criterion has a higher relative weight in Ω_1. However, since there are no hazardous materials in room 18, contrary to the information provided by expert 2, the influence of expert 2's opinion is devalued in the further course

Table 7
Explored rooms and observations in scenario 1.

Preference set Ω_1					Preference set Ω_2			
Route			Observations		Route		Observations	
Step	Current room	Elapsed time	Temp.	Haz.mat.	Current room	Elapsed time	Temp.	Haz.mat.
0	0	0	L	none	0	0	L	none
1	18	13	L	none	15	30	L	none
2	17	29	L	present	10	61	M	none
3	15	54	L	none	9	75	L	none
4	12	76	M	none	11	93	H	present
5	11	90	H	present	12	107	M	present
6	9	108	L	present	17	139	L	none
7	10	123	M	none	18	155	L	present
8	6	144	L	none	5	180	L	none
9	7	158	L	none	7	198	L	none
10	5	176	L	none	6	212	L	none
11	8	194	L	none	8	226	L	none
12	13	224	L	none	13	256	L	none

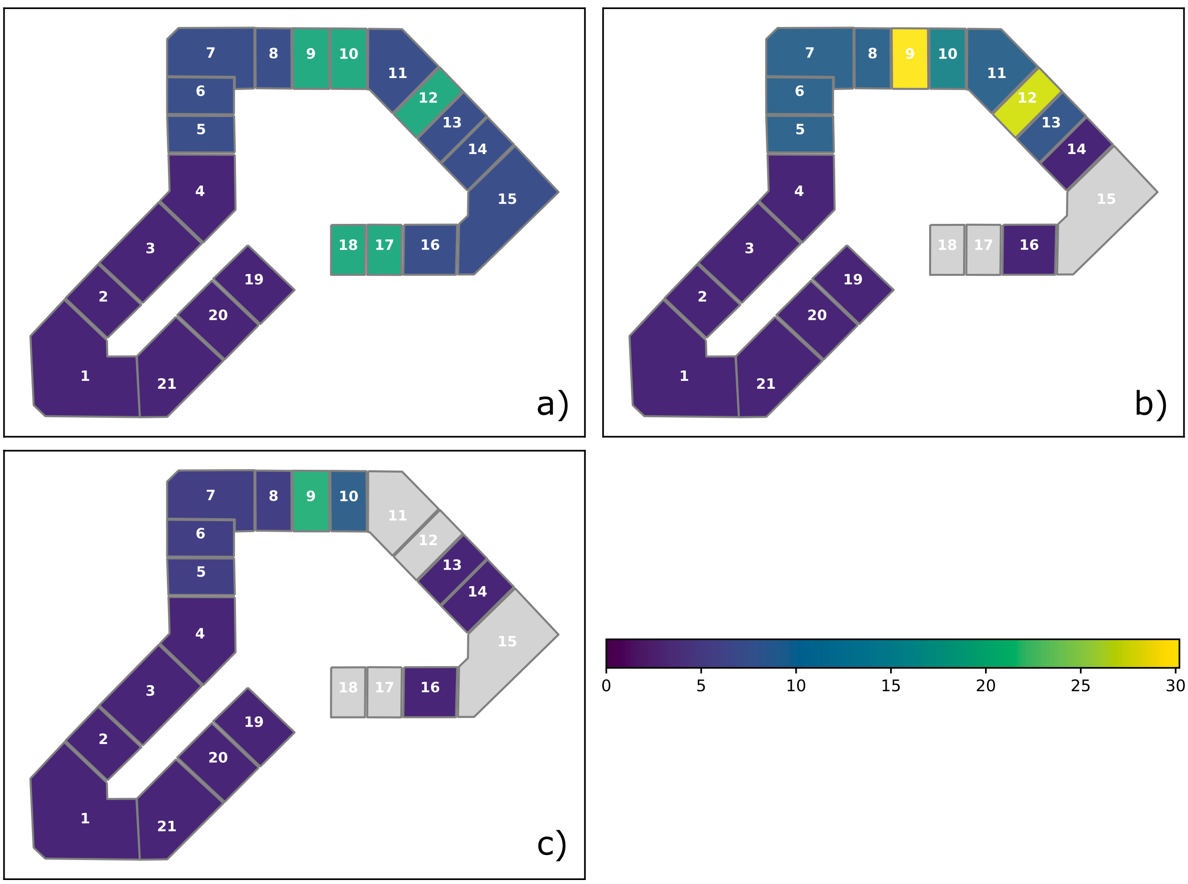

Fig. 4. Graphical representation of Bayesian preferences of the individual rooms $\mathbb{P}(B_i)$ for scenario 1 with weight set Ω_1 in the initial state (a), after checking the emergency exit in room 15 (b), and after 100 time units (c). These values are the same as those shown in Table 8. The rooms that have already been visited by the robot are indicated by grey colour.

of route finding. When material is found in room 17, as expected by expert 1, the belief in the predictions of expert 1 is strengthened.

In the further process, the influence of the different criteria weights of Ω_1 and Ω_2 becomes visible. In some cases, the rooms with the highest Bayesian preference $\mathbb{P}(B_i)$ are not selected for the next step, as the criterion of distance to the current location has priority. This can be seen, for example, in steps 1 and 3 in Table 8, in which the Bayesian preferences for all individual rooms and the distance from the current location are listed for Ω_1 up to step 6. In step 1, the Bayesian preference (i.e. interest in exploring the probability of burning hazardous materials) is higher for room 12 ($\mathbb{P}(B_{12}) = 18.8\%$) than for room 17 ($\mathbb{P}(B_{17}) = 13.6\%$). Nevertheless, room 17 is selected for the exploration in the next step, as the distance of 3.9 units is significantly lower than to room 12 (9.8 units). The same phenomenon is observed in step 3. Here, the Bayesian preference is higher for room 9 ($\mathbb{P}(B_9) = 30.2\%$) than for room 12 ($\mathbb{P}(B_{12}) = 28.3\%$), but again the closer room is selected for the next exploration step. Here, the distance to room 9 (9.4 units) is larger than the distance to room 12 (5.7 units). After the selected room has been visited, it is eliminated from the list of potential next locations (indicated by the "-" signs in Table 8).

Fig. 4 graphically shows Bayesian preferences for scenario 1 with weights of set Ω_1 at the initial state (a), after checking the emergency exit (b) and after 100 time units (c). Initially known knowledge of experts 1 and 2 is visible in (a), where rooms close to active detectors

Table 8
(Bayesian preference (%) | Distance) for scenario 1, Ω_1, step 0-6. Emergency exits in red colour.

Room	Step (time)						
	0	1 (13)	2 (29)	3 (54)	4 (76)	5 (90)	6 (108)
Room 1	3.1 | 9.1	3.1 | 11.5	3.1 | 12.8	3.1 | 16.5	3.1 | 18.0	3.1 | 17.0	3.1 | 14.5
Room 2	3.1 | 7.9	3.1 | 10.3	3.1 | 11.6	3.1 | 15.4	3.1 | 16.9	3.1 | 15.8	3.1 | 13.4
Room 3	3.1 | 5.3	3.1 | 7.7	3.1 | 9.0	3.1 | 12.7	3.1 | 14.3	3.1 | 13.2	3.1 | 10.8
Room 4	3.1 | 3.8	3.1 | 6.2	3.1 | 7.5	3.1 | 11.3	3.1 | 12.8	3.1 | 11.7	3.1 | 9.3
Room 5	7.4 | 3.3	8.2 | 6.5	8.7 | 7.9	9.9 | 11.6	4.5 | 9.2	5.6 | 8.1	5.6 | 5.7
Room 6	7.4 | 4.7	8.2 | 8.0	8.7 | 9.3	9.9 | 11.7	4.5 | 8.0	5.6 | 6.9	5.6 | 4.5
Room 7	7.4 | 5.1	8.2 | 8.3	8.7 | 9.7	9.9 | 12.1	4.5 | 8.4	5.6 | 7.3	5.6 | 4.9
Room 8	7.4 | 5.3	8.2 | 8.5	8.7 | 9.8	9.9 | 10.5	4.5 | 6.8	5.6 | 5.7	3.1 | 3.3
Room 9	18.4 | 6.3	19.3 | 9.6	28.6 | 10.9	30.2 | 9.4	18.2 | 5.7	19.4 | 4.7	–
Room 10	18.4 | 7.4	12.2 | 10.6	12.8 | 11.3	14.1 | 8.3	8.4 | 4.6	9.5 | 3.6	6.9 | 3.3
Room 11	7.4 | 8.8	8.2 | 11.1	8.7 | 9.9	9.9 | 7.0	32.7 | 3.3	–	–
Room 12	18.4 | 9.8	18.8 | 9.8	27.7 | 8.6	28.3 | 5.7	–	–	–
Room 13	7.4 | 9.2	7.7 | 8.6	7.9 | 7.4	8.4 | 4.5	25.2 | 3.2	3.1 | 4.5	3.1 | 6.9
Room 14	7.4 | 7.7	7.7 | 7.1	7.9 | 5.9	3.1 | 3.0	3.1 | 5.1	3.1 | 6.4	3.1 | 8.8
Room 15	7.4 | 8.3	7.7 | 7.7	7.9 | 6.5	–	–	–	–
Room 16	7.4 | 6.0	7.7 | 5.4	3.1 | 4.2	3.1 | 5.0	3.1 | 7.1	3.1 | 8.4	3.1 | 10.9
Room 17	18.4 | 4.5	13.6 | 3.9	–	–	–	–	–
Room 18	18.4 | 3.2	–	–	–	–	–	–
Room 19	3.1 | 4.3	3.1 | 6.6	3.1 | 8.0	3.1 | 11.7	3.1 | 13.2	3.1 | 12.1	3.1 | 9.7
Room 20	3.1 | 6.1	3.1 | 8.5	3.1 | 9.8	3.1 | 13.5	3.1 | 15.0	3.1 | 14.0	3.1 | 11.5
Room 21	3.1 | 8.2	3.1 | 10.6	3.1 | 11.9	3.1 | 15.6	3.1 | 17.1	3.1 | 16.1	3.1 | 13.7

Table 9
Explored rooms and observations in scenario 2.

Preference set Ω_1					Preference set Ω_2			
Route			Observations		Route		Observations	
Step	Current room	Elapsed time	Temp.	Haz.mat.	Current room	Elapsed time	Temp.	Haz.mat.
0	0	0	L	none	0	0	L	none
1	18	13	L	none	15	30	H	none
2	17	29	L	present	1	88	L	none
3	15	54	H	none	18	129	L	none
4	1	112	L	none	16	150	M	none
5	9	164	L	present	12	177	M	none
6	12	187	M	present	13	191	M	none
7	13	199	M	none	14	207	H	none
8	14	215	H	none	17	230	L	present
9	10	244	M	none	9	269	L	present
10	11	259	H	present	10	283	M	none
11	8	281	L	none	11	298	H	present
12	6	296	L	none	8	320	L	none

have higher priority and the experts' suggestions regarding locations of hazardous materials are added to rooms via the Bayesian network structure. In (b), room 10 has lost priority due to the incorrect suggestion on room 17 from the expert who indicated it, while the neighbours of the already explored rooms have low priority due to the measured low temperature. After 100 time units only room 9 – which, in fact, contains hazardous materials – has a high priority.

4.2. Scenario 2

In scenario 2, the fire has spread over three rooms (11, 14, and 15), leading to increased temperatures in the neighbouring rooms 10, 12, 13, and 16. All other boundary conditions (rooms containing hazardous materials, triggered smoke detectors, beliefs of experts about locations of hazardous materials, position of emergency exits and starting point of the robotic support system) are identical to the ones presented in scenario 1. It should be noted that the emergency exit in room 15 is blocked by the fire. Table 9 shows the paths of the robotic support system for scenario 2 using Ω_1 and Ω_2.

The gathering of the most important information takes significantly longer in this scenario than in scenario 1 (see Section 4.1). The reason for the longer time required in both variants is the non-accessibility of the emergency exit in room 15. This means that the criterion "distance to next emergency exit" is included further in the route planning until the robotic support system explores the second emergency exit in room 1. Thus, the criterion of distance optimisation is less important overall. When using Ω_1, the robotic support system requires ten steps or 259 time units until the accessibility of the emergency exits is checked, the hazardous materials are detected and the fire is localised. For Ω_2, the system requires 298 time units and eleven steps for these tasks. For this preference set, the robotic support system accepts longer distances to check the accessibility of the emergency exits, as the weighting of this criterion is higher than for Ω_1.

This is shown by the fact that, in contrast to Ω_1, the emergency exit in room 1 is explored directly in step 2 when using Ω_2 as soon as the system has detected the non-accessibility of the emergency exit in room 15 in the first step (cf. Table 9). Due to the more dominant distance optimisation in Ω_1, the robotic support system first explores the closer room 18 and room 17, in which the system detects existing dangerous material (cf. Table 9) and only reaches the unavailable emergency exit in room 15 in step 3. The second emergency exit in room 1 is then checked immediately in the following step, analogous to Ω_2. The resulting time advantage for Ω_2 is $112 - 88 = 24$ time units. This time advantage is then reversed for the collection of all information in $298 - 259 = 39$ time units in favour of Ω_1.

After the available emergency exit in room 1 has been localised, the criterion of the accessibility of emergency exits is dropped for Ω_1 and Ω_2 in the further course of the exploration route. Due to the distance optimisation, the route for both preference sets is then similar. For Ω_2, room 18 and room 17, already explored at the beginning of Ω_1, are also explored in the course of the exploration route. Apart from that, the order of the information discovery is otherwise identical for Ω_1 and Ω_2.

5. Discussion

The presented approach aims to achieve improved ad-hoc situation awareness in emergency situations by using an autonomous robotic support system. To optimise the deployment route of the system in terms of rapid information gain, we propose a combination of Bayesian networks and the MCDA method PROMETHEE II. The results presented in Section 4 show the properties of the proposed algorithm for optimised route finding. In particular, with regard to its suitability for use with an autonomous robotic support system in emergency situations, a detailed consideration of these results is useful, taking into account the requirements 1–6 identified in Section 1.

The route calculated by the system in the application examples is optimised for exploration using MCDA in combination with a Bayesian network, where the weighting of the MCDA criteria enables a balancing of the different types of information to be obtained and the minimisation of the route length (cf. Section 4.1, Table 8). As stated in requirement 1 (*Large number of locations*), the approach is able to utilise the limited time efficiently while taking existing information into account. Causal and spatial dependencies of data for the formation of higher-level information (requirement 2. *Causally dependent information*) are also considered in the proposed procedure. For the application example, the information on the smoke detectors is clustered via parent divorcing in the Bayesian network presented in Section 3.1.2. This method achieves a simplified representation of the physical phenomenon of smoke propagation. For temperature propagation, the information from neighbouring rooms is included, which takes into account their spatial dependency.

Requirement 3 (*Sequential information*) is addressed by incorporating the information from newly explored rooms into the Bayesian network based knowledge model by updating the probabilities after each step (see Section 3.1.3). The decision on the next step made by MCDA is then based on the current belief of the systems' state. This behaviour can be observed in Table 8: Here, the Bayesian preference for exploring the rooms in the application example changes at each step. The proposed approach also takes into account the requirement to consider a priori expert knowledge (4. *A priori expert knowledge*). In the treated application example, the assumptions made by experts about the presence of hazardous materials are directly integrated into the knowledge model as a prior (cf. Fig. 2). These assumptions integrated via the node H_k thus influence the route finding decisions. This becomes particularly clear in the calculated routes for Scenario 1 in Section 4.1. Here, the robotic support system for Ω_1 initially (steps 1 and 2) explores the rooms in which the experts suspect hazardous materials (cf. Table 7). Additionally, we demonstrate how the evaluation of the expert knowledge provided is implemented via inference in the Bayesian network. In this case, the significance of the a priori information decreases if it cannot be confirmed by exploration.

In principle, the proposed simple structure of the decision logic is easily adaptable. As soon as a suitable knowledge model based on a Bayesian network for relevant information in the current scenario and a spatial plan of the concerned locations are available, it can be used in combination with an autonomous robotic support system. It should be noted here that the general approach allows to create a suitable Bayesian network in advance only based on the relevant information. The system then requires little additional initial information to be ready for use. In particular, due to the simple logical mapping of physical phenomena in the Bayesian network, complex tailored simulations are not needed. Taken together, these properties fulfil the requirements 5 (*Availability of knowledge*) and 6 (*General applicability*).

Overall, the approach addresses the requirements identified in Section 1. Here we try to balance effort and accuracy. We show that a Bayesian network and a connected MCDA can be used to optimise a route with little initial information. In particular, a sequential strategy was implemented that incorporates existing information into the route planning at each step. It should be noted here that the approach presented was only tested in the scenarios presented with the preference sets (Ω_1, Ω_2). Application in more complex scenarios could provide further insights regarding the flexibility of the approach for different application examples. This also applies to possible limitations, whereby two points in particular should be emphasised here. First, we are not dealing with the details of the technical solution for the robotic system, i.e. we are assuming autonomous navigation. Thus, we assume that the map is known to the robotic system and unknown obstacles must be overcome with the help of its onboard navigation system. Second, we do not take into account the temporal dynamics of physical hazards and crisis situations. In particular, this means that state information can change quickly, causing older information to quickly lose its relevance for exploring the current situation. Although this is less relevant for this very short-term focused approach for rapid information gain, it would be important for longer explorations. A first solution could be the use of soft evidence methods in the proposed Bayesian network. Here, the degree of belief, which determines the influence of information in the Bayesian network, could be used to integrate the decreasing relevance of obtained information over time.

6. Conclusion

We have presented a novel approach for route optimisation of support systems for situational awareness in emergency situations. In order to meet the special constraints imposed by this scenario, we have combined the widely used methods of Bayesian networks and MCDA, in specific PROMETHEE II. In particular, the approach allows the sequential consideration of limited available data in the case of rapid availability in an emergency. In this way, the limited time window available between alerting and the arrival of emergency services can be optimally utilised.

To develop the approach, we first identified six requirements based on the application example of an autonomous robotic support system for rapid information gathering in the event of a crisis, also discussing the pros and cons of existing approaches. It turns out that the rapid availability of the overall system, the sequential consideration of limited information and its causal dependency, as well as the inclusion of a priori existing expert knowledge are of great importance. Based on these findings, we introduced our alternative solution combining Bayesian Networks and the MCDA method PROMETHEE II. We evaluated it in two selected scenarios, where the approach is presented in detail.

For the evaluation, we simulated the two scenarios and the resulting behaviour of the robotic support system for two sets of criteria weights (Ω_1 and Ω_2). The results confirm that the requirements can be fully addressed. Specifically, the developed solution can easily be adjusted to reflect the scenario-dependent priorities of the decision maker regarding the exploration task. The robotic support system then does not follow a rigid pre-defined route, but adjusts its information-gathering activities based on all the momentarily available information. Due to the limitations discussed in Section 5, especially the requirement of an operational system capable of autonomous navigation and the non-consideration of the temporal development of emergency situations, the application potential should be analysed for more complex scenarios. Nevertheless, the presented approach shows great potential in route optimisation for creating short-term ad-hoc situation awareness in emergency situations.

CRediT authorship contribution statement

Daniel Lichte: Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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