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# A Probabilistic Approach to Dynamic Risk Scenario Identification

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Situation awareness is crucial for decision makers during an emergency. An efficient knowledge management can enhance situation awareness by providing information about the most relevant factors of the situation. Scenario analysis, based on morphological analysis, represents a structured method that can support the identification of such factors. Various studies based on this method have already been presented in the literature, e.g. as a method to strategically enhance disaster preparedness. In this paper, we introduce an approach that allows us to analyze current information in order to dynamically identify an emerging risk scenario. First, morphological analysis is applied to construct a scenario space. Second, in order to quantify the relations between scenario-factors, a Bayesian network model is implemented. For identification of the scenario, current information about the scenario-factors are needed. Information can be gathered from different sources, e.g. sensors or observations by emergency personnel and processed in the Bayesian network model to calculate the posterior probabilities of the parameters in the model. We illustrate the approach for risk scenario identification by applying it to an example in the context of emergency management. To conclude, we discuss the benefits and limitations of this approach as a knowledge management tool for enhancing situation awareness.

*Keywords*: Scenario Analysis, Emergency Management, Scenario Identification, Risk Scenario, Situation Awareness, Bayesian Network, Morphological Analysis.

## 1. Introduction

A wide variety of relevant information - described as factors in scenario analysis - can be important to enhance situation awareness in emergency management. Key information often exceeds knowing the cause of disruptions (e.g. natural or man-made hazards) but also includes knowledge about aspects such as the number of civilians affected or the availability of emergency response resources. The variety of these factors make it difficult to conduct a uniform and comprehensive scenario analysis. In order to enhance situation awareness, information about the current situation must be collected and processed (Endsley, 1988). The diversity of information sources (e.g. sensors or emergency personnel) and the volume of information they supply, make it difficult to get a quick picture of the situation (Endsley, 1995). Additionally, incoming information may be noisy, uncertain, fragmentary, or difficult to confirm immediately (Comes et al., 2011). Scenario-based approaches can help a decision maker to structure all this information and allow an estimation of possible future developments. For this purpose, current information can be compared to scenarios from the model to allow an assignment of the current situation to a specific scenario (Comes et al., 2011). In this way, situation awareness can be enhanced. According to the most widely cited and accepted definition by Endsley (1995), situation awareness is defined as "*the perception of elements in the environment within a volume of time and space, the comprehension of their meaning, and the projection of their status in the near future*". The essence of this definition is the division of situation awareness in three sequential levels: *perception*, *comprehension*, and *projection*.

In this paper, we present a probabilistic approach to dynamic risk scenario identification. Based on incomplete information regarding the present situation, this approach enables the calculation of probabilities for all possible outcomes within a comprehensive scenario space, which is initially constructed using morphological analysis (MA). It is dynamic in the sense that it allows for the continuous integration of new observations as soon as they are available, whereby the information is processed using a Bayesian network (BN) approach. In the following, we first present MA and BN as the two main methodologies. We then introduce our approach and demonstrate it in the context of emergency management. In conclusion, the benefits and limits of this approach are outlined.

## 2. Methodology

In the following, morphological analysis and Bayesian networks as main methodologies of the approach are introduced. Combining MA and BN enables scenario probability estimation and scenario identification based on observations.

### 2.1. *Morphological Analysis*

Environmental changes, uncertain socio-technical developments, or socio-political unrest have strengthened the interest in scenario analysis, from both, a theoretical and an applied point of view (Tourki et al., 2013). According to Gausemeier et al. (1998), a scenario is defined as "*a generally intelligible description of a possible situation in the future, based on a complex network of influence-factors*". Scenario analyses are applied in several fields, such as threat analysis (Lichte et al., 2020; Witte et al., 2020; Conrado and de Oude, 2014), risk analysis (López-Silva et al., 2015), resilience management (Lichte et al., 2022), and also in emergency management (Comes et al., 2012; Schätter, 2014).

While other scenario development techniques struggle when dealing with rare events and cases with a multiplicity of possible futures (Kwakkel et al., 2013), MA enables modeling of such events (Johansen, 2018). MA provides a structured method that ensures consistency and relevance in scenario development (Johansen, 2018) and aims at investigating the total set of possible relationships or configurations contained in a given problem complex (Ritchey, 2011).

In order to set up the scenario space, i.e. conducting MA, relevant scenario-factors concerning the analysis objective are collected. In a next step, factor states are identified, which should describe every possible outcome of the respective scenario-factor. A scenario is thus defined as a specific combination of factor states each describing one scenario-factor. The scenario space includes all consistent factor state combinations, i.e. all consistent scenarios. For a vivid representation and organization of the scenario space, the so-called morphological box is often set up. This box comprises all solutions that can be constructed on the basis of the scenario-factors (Johansen, 2018). All scenario-factors are listed in the top row and their states in the columns below the respective factor (Johansen, 2018). For more examples of how to create a morphological box for scenario analysis, see Witte et al. (2020) or Schneider et al. (2021).

### 2.2. *Bayesian Networks*

BNs are composed of nodes, representing system variables as probability distributions, and edges representing their probabilistic dependencies (Ben-Gal, 2008; Ramírez-Agudelo et al., 2020). Nodes can be either dependent or independent. Figure 1 shows an exemplary BN. In this example, the node *X* represents an independent node, which is described via marginal probabilities. The nodes *Y* and *Z*, on the other hand, are depended nodes. For each dependent node, Conditional Probability Tables (CPT) are assigned, containing one probability value for every possible combination of child and parent states (Ramírez-Agudelo et al., 2020; Murphy, 2012). Thereby, conditional probabilities follow the Bayes rule shown in Eq. (1). Node $X$ represents the parent node with its marginal probability $P(X)$, whereas node $Y$ represents the associated child node with its prior estimate $P(Y)$. $P(X|Y)$ represents the likelihood, which is the conditional probability of $X$ given $Y$. The posterior distribution, which is the probability of $Y$ given $X$, is represented as $P(Y|X)$.

$$P(Y|X) = \frac{P(X|Y) \cdot P(Y)}{P(X)} \tag{1}$$

Assuming a BN with the structure $(N, E)$, whereby $N$ represents the random variables (i.e.

nodes) $N = \{n_1, n_2, ..., n_M\}$ of the BN and $E$ represents the edges with conditional dependent probabilities between the nodes, $Par(n_i)$ denotes the set of parent nodes of the random variable $n_i$. Nodes that are not listed within this set are conditionally independent of $n_i$. In order to calculate the joint probability distribution of a BN with $M$ nodes, the chain rule can be applied (see Eq. (2)).

$$P(N) = \prod_{i=1}^{M} P(n_i|Par(n_i)) \qquad (2)$$

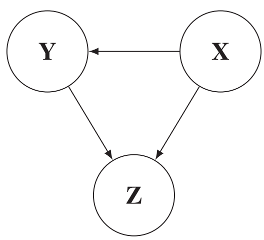


Fig. 1. Example of a BN with three nodes.

#### 2.2.1. *Pomegranate*

For the implementation of the BN model, the Bayesian network class of the machine learning package *pomegranate* (Schreiber, 2018) has been used. It is an open source package that works in *Python* and is implemented in *Cython* to speed up the calculations.

## 3. Approach

In the following, the approach of a scenario-based model is presented that should enable dynamic scenario identification based on current observations. It is important to note that the following explanations only refer to this illustrative example. For scenario construction, MA is applied. The goal of scenario construction is to set up a comprehensive scenario space including relevant scenario-factors to enhance situation awareness in case of an illustrative emergency situation. In a next step, the scenario space is extended by a BN that quantifies scenario-factor dependencies. This enables reasoning about scenario-factors for which observations are still missing.

### 3.1. *Model Development*

#### 3.1.1. *Scenario Construction*

To illustrate our approach, an exemplary scenario space is constructed that incorporates scenario-factors that are relevant in an emergency situation. The selection of scenario-factors is based on the procedure for situation assessment described in the German fire department regulation 100 (FwDV100). In addition to the cause and type of damage, the availability of emergency personnel as well as the availability of necessary resources for emergency response are relevant scenario-factors. Another relevant scenario-factor is the time of day, which provides an indication on whether people are present (at the place of emergency). Thus, the considered scenario-factors are: *Time of Day, Damage Cause, Damage Type, Availability of Emergency Resources*, and *Availability of Emergency Personnel*. It should be noted that the chosen example only serves an illustrative purpose and does not claim to be exhaustive.

For each scenario-factor, factor states must be defined that should fully describe each relevant outcome. Thereby, a trade-off must be made between the resolution of factor state descriptions, i.e. the amount of factor states, and the complexity of the analysis. For example, the factor states of the scenario-factor *Time of Day* could be represented by a continuous time scale. This would allow a detailed description of this factor, but would also enhance the complexity of the analysis. Alternatively, specifying whether the hazard is to be expected during or outside regular working hours could be sufficient and would minimize the complexity of the analysis. In general, if a high resolution of the factor-states is not necessary, larger intervals should be considered. Within the presented example, a small number of scenario-factors and a broad scale description of factor states (two to four states) is selected to keep the complexity at a minimum. Table 1 shows the respective morphological box as introduced in Section 2.1 including the five scenario-factors and their factor states. In this example, the scenario space consists of 96 scenarios.

Table 1. Morphological box of the analysis.

| Time of Day | Damage Type | Damage Cause | Emergency Resources | Emergency Personnel |
|---|---|---|---|---|
| During Working Hours | Personal Injury | Natural Hazard | Immediate Availability | Immediate Availability |
| Outside Working Hours | Material Damage | Accident | Delayed Availability | Delayed Availability |
| | Both | Human Intent | | |
| | No Damage | | | |

### 3.1.2. *Scenario-Factor Dependencies*

After construction of the scenario space, scenario-factor dependencies are quantified. First, the directed dependencies between the scenario-factors are determined. Figure 2 shows the assumed network of the illustrative example after this step. In a next step, marginal and conditional probabilities are determined, e.g. by means of expert knowledge, historical-, or simulated data. In order to simplify the specification of marginal and conditional probabilities in the example, a seven-step scale (see Table 2) has been used by the authors, enabling a translation of qualitative statements into quantitative probabilities.

Table 2. Seven step scale for probability quantification.

| Qualitative Statement | Quantitative Probability Value |
|---|---|
| Impossible | 0.00 |
| Very unlikely | 0.167 |
| Unlikely | 0.333 |
| Indifferent | 0.500 |
| Likely | 0.667 |
| Very likely | 0.833 |
| Certain | 1.00 |

As a result of this step, the BN is set up, consisting of nodes that represent the scenario-factors and probabilistic quantification of scenario-factor dependencies. By means of Eq. (2), scenario probabilities can be calculated. A scenario is defined as inconsistent if $P(Scenario_i) = 0$.

## 3.2. *Scenario Identification*

For scenario identification, the scenario-based model is used dynamically, i.e. it is updated every time new observations regarding scenario-factors are available. These observations can originate from e.g. sensors, emergency personnel, or social networks. Given a new observation about a scenario-factor, posterior probabilities can be calculated improving the estimation of other scenario-factors that are not yet confirmed. Thus, a probabilistic estimation of the current overall scenario can be made and thereby situation awareness enhanced.

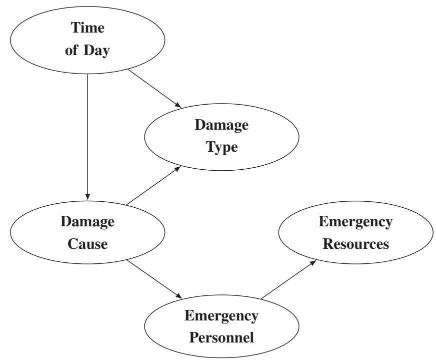


Fig. 2. Bayesian network of illustrative example.

### 3.2.1. *Observations*

During the emergence of a risk scenario, observations about relevant aspects of the situation, i.e. scenario-factors, are gathered. These observations can state, e.g. whether a factor state is confirmed, can be excluded, or is sighted. The obtained information by these observations can be processed in the model to update beliefs about scenario-factors whose status has not been observed yet. Additionally, the reliability of the observation should be considered. For example, an unconfirmed report from the public and a report of a survey team should be evaluated differently. Table 3 shows an exemplary sequence of consecutive observations in the context of the illustrative example.

## 4. Results

In the following, we demonstrate our approach based on the exemplary sequence of consecu-

Table 3. Examplary sequence of observations.

| Observation Number | Scenario-Factor | Factor State | Status |
|---|---|---|---|
| 1. | Time of Day | During Working Hours | Confirmed |
| 2. | Damage Cause | Human Intent | Excluded |
| 3. | Damage Cause | Natural Hazard | Confirmed |
| 4. | Damage Type | No Damage | Excluded |
| 5. | Damage Type | Personal Injury | Excluded |
| 6. | Damage Type | Material Damage & Personal Injury (Both) | Confirmed |
| 7. | Emergency Personnel | Delayed Availability | Confirmed |
| 8. | Emergency Resources | Immediate Availability | Confirmed |

tive observations shown in Table 3. From the scenario space with a total of 96 scenarios, 60 scenarios are initially identified as consistent, i.e. $P(Scenario_i) \neq 0$. Figure 3 shows how the number of consistent scenarios decreases with each observation. In the following explanations of the results, it is important to note that these are only illustrative examples.

Figure 4 shows the probability of the consistent scenarios after each observation. Given a new observation, posterior probabilities are calculated using the implemented probabilistic BN model. Updated scenario probabilities are calculated by means of Eq. 2. After confirmation of two scenario-factors (see the third observation in Table 3), which is 40% of the scenario-factors, the number of consistent scenarios has already decreased to 12 scenarios, which is 20% of the initial number (see Figure 3). The actual scenario (scenario 1 in Figure 4) that is identified based on the observations shows a prior probability of 2.42% (given zero observations). The least probable consistent scenario shows a prior probability of 0.06%, whereas the most probable consistent scenario shows a prior probability of 8.37% (see Figure 4 given zero observations). Due to the large number of scenarios, the actual scenario is highlighted within Figure 4. In addition, the scenarios (see Table 4) that show the highest probability at least once in the sequence of observations are highlighted. The remaining scenario probabilities are represented by dotted lines. The results after each observation show that the probability of the actual scenario is constantly increasing. Given the sixth observations the actual scenario is already the most probable with a probability of 60%. This trend continues after the following three observations and after the eighth observation, the actual scenario is identified, i.e. $P(Scenario_1 = 1)$. It should be noted that the number of observations does not represent a direct time reference. Observations can for instance occur simultaneously, at different times, or sometimes be difficult to determine and therefore occur later in time. The approach is not intended to replace the need for observations, but to improve an estimate of the overall scenario until all scenario-factors have been observed.

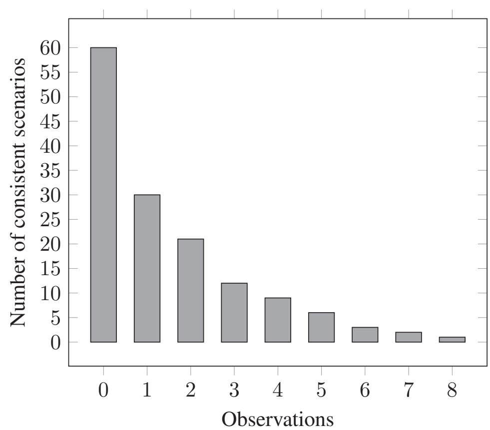


Fig. 3. Number of consistent scenarios after each observation.

## 5. Discussion

The chosen illustrative example is only composed of a small number of scenario-factors and a broad scale description of factors states. This limits the

Table 4. Exemplary highlighted scenarios.

| Scenario *i* | Time of Day | Damage Type | Damage Cause | Emergency Resources | Emergency Personnel |
|---|---|---|---|---|---|
| Scenario 1 | During Working Hours | Both | Natural Hazard | Delayed Availability | Immediate Availability |
| Scenario 2 | During Working Hours | Material Damage | Natural Hazard | Delayed Availability Availability | Immediate Availability |
| Scenario 3 | During Working Hours | Personal Injury | Natural Hazard | Delayed Availability | Immediate Availability |
| Scenario 4 | During Working Hours | Personal Injury | Accident | Immediate Availability | Immediate Availability |
| Scenario 5 | Outside Working Hours | Material Damage | Natural Hazard | Delayed Availability Availability | Immediate Availability |

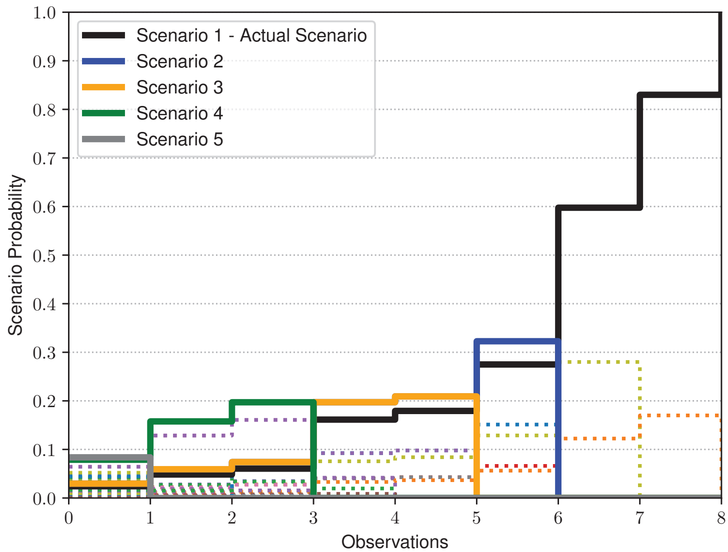


Fig. 4. Scenario probabilities after each observation.

complexity of the analysis. Nevertheless, the presented example shows the feasibility of the approach for scenario identification and illustrates an exemplary procedure for setting up the model. The results of the identification based on the exemplary sequence of observations show that an estimation of the actual scenario can be made, based on the probabilities calculated by means of the BN. Given a new observation, posterior probabilities of scenario-factors, that are not yet confirmed, can be calculated. This allows an estimation of these unconfirmed scenario-factors and thus an estimation of the probability of the overall scenario.

Accordingly, the presented approach is a first step towards a model to enhance situation awareness. For scenario construction, morphological analysis has been applied. This methodology ensures comprehensiveness in scenario-factor description (due to the use of factor states) and can be easily extended by adding more scenario-factors. The scenario-factors considered in the analysis can be both qualitative and quantitative in nature, but modeled in a uniform manner. For setting up the scenario space, i.e. collecting relevant scenario-factors, consultation of domain experts is required. It must be noted that the information and preference of different experts may vary. Therefore, the results of collaborative work should be agreed upon by all experts involved. Both the description of the scenario-factors and the factor states should be comprehensive, easy to understand, and expressed in such a way that no misunderstandings can arise. Thus, the construction of the scenario space is intended to provide a knowledge base of all relevant factors that are important to increase situation awareness in an emergency situation. In the event of an emerging or developing risk scenario, the scenario-factors can support the efficiency in getting a quick picture of the situation by gathering information about these factors.

Combining MA and a BN enables an estimation of scenario-factor probabilities about which information are not yet available as well as about the overall scenarios. This contributes to the enhancement of situation awareness by enabling the assessment of the overall picture of the situation beyond the current status of available observations. The quality and availability of the data for setting up the BN represents one of the strongest limitations of the approach. Emergency situations are often rare event scenarios, which is why there is a strong potential lack of historical data. This fact strengthens the need for combining various data sources in one model. Bayesian networks allow such combinations of data sources. Dependencies can be quantified based on beliefs (e.g. expert knowledge), as well as statistical data sources (e.g. historical data), both resulting in a uniform description within the BN. Thus, all available knowledge - knowledge about relevant scenario-factors, suitable division of factor states, and factor dependencies - can be captured within one model.

In addition to the information for building the model, the observations on the current situation may also be subject to uncertainties or contain contradictory statements. This must also be taken into account in the model to avoid misinformation. The exemplary sequence of observations in the example does not have any contradictory or uncertain information. Further analyses of different sequences should be conducted. In general, it is important to ensure that misinformation due to false certainty of results is avoided. The uncertainty and reliability of the information provided by the model should be appropriately assessed and additionally reported along with the model results.

## 6. Conclusion and Future Work

An approach for developing a scenario-based model to enhance situation awareness has been presented. An exemplary network that includes relevant factors in emergency management has been used as an illustrative example. For scenario construction, morphological analysis has been applied. For quantification of scenario-factor dependencies, a Bayesian network has been implemented. Within the approach, it is illustrated how a scenario can be identified based on observations about the current situation. Given new observations about scenario-factors, posterior probabilities of scenario-factors that are not yet confirmed, can be calculated. This process supports the enhancement of situation awareness by enabling an estimation of the actual scenario without current information about all scenario-factors.

The presented approach represents a knowledge management tool which can enhance situation awareness in three ways. *(1)* The collection of scenario-factors and the suitable division of factor states, represents the knowledge about relevant aspects of emergency situations for decision makers. Accordingly, already setting up the scenario space can enhance situation awareness as it requires an intensive preoccupation with potential emergency situations. *(2)* Collected knowledge, e.g. from domain experts, historical or simulated data, can be used to set up the BN and derive prior probabilities of scenarios from the scenario space. *(3)* Current observations about scenario-factors can be processed in the BN to estimate updated scenario probabilities.

Within future work, validation of the presented approach should be carried out in a real life use case using real data, where the outcome should be evaluated with both domain experts and potential end users. In a real life use-case, significantly more factors have to be considered, as well as a higher resolution of factor states. In addition, the effects of uncertainties in the data for model development, as well as uncertainties in the observations, should be analyzed in more detail.

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