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MANAGERIAL DECISIONS ABOUT ALTERNATIVE AUTOMATIC EQUIPMENT FOR DISASTER MANAGEMENT IN CONSTRUCTION

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ABSTRACT

The choice among alternative automatic equipment used to protect the construction site against major accidents is considered. Methods of multi-attribute selection are suggested to implement the choice. This includes attributes accounting for the possibility of failure of the automatic equipment (safety-related attributes). The epistemic uncertainty in the safety-related attributes is quantified by means Bayesian analysis. Prior or posterior probability distributions of safety-related attributes developed during this analysis are used as input data for the multi-attribute selection.

KEYWORDS

Disaster, automatic equipment, failure, multi-attribute selection, sprinklers, ventilation

1. INTRODUCTION

Construction of many industrial and transportation facilities involves hazards, the potentiality of which can range between common occupational accidents and disasters occurring on the construction site (major accidents) [1, 2]. Examples of the latter events are well-known: heavy fire, explosion, massive and sudden release or gradual leak of toxic materials, undetected release of flammable or explosive gases in closed environments, major failures of structures and geotechnical objects during in course of construction, accidents caused by extreme natural phenomena or human errors, say, overturning of tower crane.

The present paper considers the problem of how to protect the construction site against such accidents by installing and running automatic protective equipment. The problem is formulated as a choice among alternative types or arrangements of this equipment. This problem arises from the fact that protective equipment is produced and sold by competing companies which are able to assure different levels of reliability. It is shown how to implement the choice by applying formal methods of multi-attribute selection which includes uncertain probabilities of equipment failure.
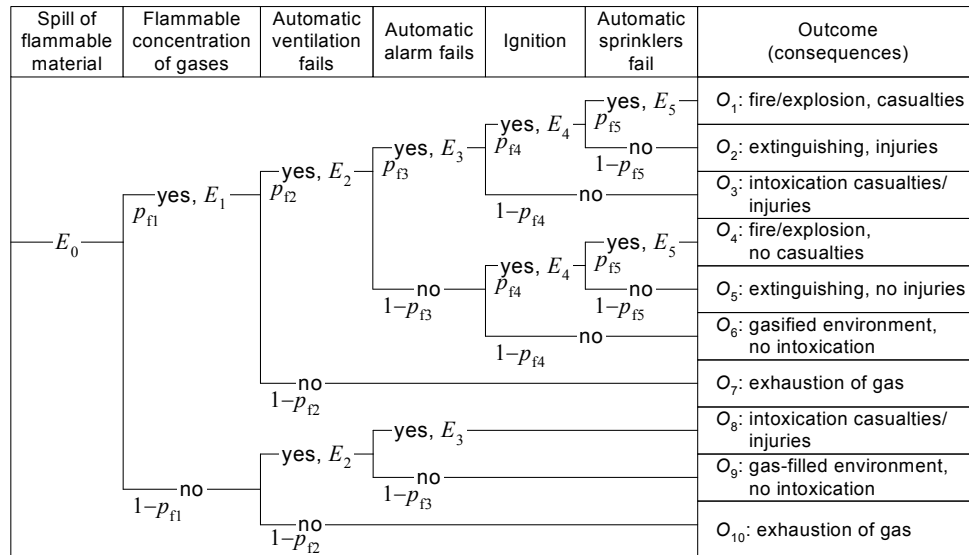
Spill of flammable material | Flammable concentration of gases | Automatic ventilation fails | Automatic alarm fails | Ignition | Automatic sprinklers fail | Outcome (consequences)

E_0 — yes, E_1 p_{f1} — yes, E_2 p_{f2} — yes, E_3 p_{f3} — yes, E_4 p_{f4} — yes, E_5 p_{f5} → O_1: fire/explosion, casualties
— no $1-p_{f5}$ → O_2: extinguishing, injuries
— no $1-p_{f4}$ → O_3: intoxication casualties/injuries
— no $1-p_{f3}$ — yes, E_4 p_{f4} — yes, E_5 p_{f5} → O_4: fire/explosion, no casualties
— no $1-p_{f5}$ → O_5: extinguishing, no injuries
— no $1-p_{f4}$ → O_6: gasified environment, no intoxication
— no $1-p_{f2}$ → O_7: exhaustion of gas
$1-p_{f1}$ no — yes, E_2 — yes, E_3 → O_8: intoxication casualties/injuries
— no $1-p_{f3}$ → O_9: gas-filled environment, no intoxication
— no $1-p_{f2}$ → O_{10}: exhaustion of gas

Figure 1. The possible scenarios of an accident initiated by a spill of flammable material during construction of a tunnel

2. DISASTER IN CONSTRUCTION

In many cases a disaster occurs as a result of a sequence of adverse events which escalate into a harmful event (process) directly causing catastrophic consequences. Fig. 1 shows a number of such sequences aggregated in an event tree diagram. They lead to consequences, some of which can be considered disastrous (consequences O_1 to O_4 and O_8).

The exposure to hazards during construction of facility is, naturally, much shorter than during its subsequent exploitation. However, construction is usually less organised and stable process than exploitation and so more predisposed to accidents. In addition, construction process can be prone to hazards which are not inherent in the later exploitation. Thus the risk related to construction stage can be higher than the one accompanying the exploitation.

3. THE PROBLEM OF AUTOMATIC EQUIPMENT FAILURE

The major accident can cause multiple casualties and considerable damage to structural and non-structural property. A proper planning of construction process and organisation of dangerous construction operations requires recognising, controlling, and, if possible, eliminating hazards. If a complete elimination is impossible, automatic equipment must be installed to stop a possible escalation into an accident and/or protect against a disastrous physical phenomenon, if this takes place. Obvious examples of such equipment are:

- Automatic detectors of heat, smoke, and toxic gases.
- Ventilators used to remove burning products or toxic gases.
- Automatic sprinklers.
- Automatic alarm systems.

In case where the construction process involves the potentiality of major accident, the role of automatic equipment protecting against this accident becomes critical. It is natural to expect that in case of an accident (early escalation of events which can end up in an accident) the protective equipment will not fail to perform its function. For many, this fail-safe behaviour is taken as granted. However, the possibility of failure is constantly present and is not always negligibly small. Failures of automatic sprinklers used in conventional buildings and

nuclear power plants serve as an illustration of this problem [3, 4].

In many cases, the worst-case scenario of an accident will be a result of a combination (sequence) of protective equipment failures. These are usually highly random, low-probability events. The sequence of the failure events E_2 to E_5 shown in Fig. 1 will result in the worst consequences O_1 expressed as

$$O_1 = \bigcap_{k=0}^{5} E_k \qquad (1)$$

The random nature of the equipment failure events E_k and the very possibility of such failure raises the problem of reliability. Although usually explicit measures of reliability (probability of fail-free service, say) are not known for users of construction machinery, everyone expects that his/he machines have a sufficiently high level of reliability. Failures of protective equipment, denoted in what follows by E_k, can be critical. Therefore decisions concerning its design, installation, and running should take into account explicit measures expressing the likelihood of failure.

Generally such measures are failure probability, availability, and reparability. The answer to the question, which measure should be used for decision-making, depends on the type of equipment and particular situation, in which the accident can take place. This measure can be related two three typical failure modes [7]:

- Demand unavailability expressing (conditional probability that equipment will not start to operate given an emergency/accident; demand failure, E_{k1}).
- Probability that equipment will fail to work in the course of emergency/accident after it starts operate (run failure, E_{k2}).
- Probability that equipment will not perform its protective function even if it is not in a failed-state (operation during complex events below the design basis of equipment, E_{k3}).

Clearly, the above list of failure modes is far from being exhaustive. However, one can write with some simplification that the probability of equipment failure, p_{fi}, is a probability that at least one of these failures will take place:

$$
\begin{aligned}
p_{fk} &= P(E_k | E_{k-1} \cap E_{k-2} \cap ...) \\
&= P\left(\bigcup_{l=1}^{3} E_{kl} \,\middle|\, E_{k-1} \cap E_{k-2} \cap ... \right)
\end{aligned} \qquad (2)
$$

where E_{k-1}, E_{k-2}, … are events preceding the failure event E_k. The first of them generates the demand to activate the protective equipment, for instance, E_{k-1} = "spread of fire in tunnel under construction".

The failure probability p_{fk} is a feature of the equipment used to characterise it along with technical and economic parameters. It can be considered a physical property of the equipment and used for its choice in cases where the possibility of failure is of concern.

The complexity of protective equipment, non-non-negligible possibility of its failure as well as a steady supply of equipment by different competing producers (lessors) turns the problem of the choice of specific set of equipment into a non-trivial task.

4. CHOICE AMONG ALTERNATIVE SETS OF AUTOMATIC EQUIPMENT

The choice of automatic equipment for protection against specific accident in construction can be difficult. Many, sometimes contradictory, attributes characterising the equipment must be considered simultaneously. The field of management science has long dealt with the problem of this kind. They developed multi-attribute selection (MAS) also known as multi-criteria decision making and abbreviated to MCDM (e.g. [5]).

Applications of MAS methods in real world problems are numerous and in very different fields (e.g. [8: part VII]). These applications include a combined use of MAS and risk analysis methods [9, 10]. We think that methods of MAS can be applied to problems where a decision-maker must evaluate, rank, or classify alternative automatic equipment by two or more relevant attributes. Examples of such alternatives are

- Equipment belonging to basic different types (e.g. wet-pipe sprinkler system, dry-pipe sprinkler system or deluge sprinkler system).

- Equipment of the same type and function produced and installed by different companies and having differed history of recorded failures (e.g. ventilation system sold by competing producers).
- Equipment with key components supplied by different producers capable to assure different levels of reliability.

A discrete set of alternative automatic equipments (alternatives, in brief) can be represented by the vector $\boldsymbol{a} = (a_1, a_2, \ldots, a_i, \ldots, a_m)^{\mathrm{T}}$. MAS can be used to determine the best alternative a^* or a subset of leading alternatives among the ones represented by components of $\boldsymbol{a}$.

The quality of a_i is evaluated by means of a row-vector $\boldsymbol{c}_i = (c_{i1}, c_{i2}, \ldots, c_{ij}, \ldots, c_{in})$, the components of which, c_{ij}, are attributes (characteristics) of a_i used for MAS. In terms of MAS, the element c_{ij} expresses impact of the ith alternative on the jth attribute. Data for solving an MAS problem is formulated as a $m \times n$ decision matrix

$$\mathbf{C} = [\boldsymbol{c}_1, \ldots, \boldsymbol{c}_i, \ldots, \boldsymbol{c}_m]^{\mathrm{T}} \tag{3}$$

Usually the values c_{ij} making up different columns of $\mathbf{C}$ are of different units. To facilitate an inter-attribute comparisons, the components c_{ij} are normalized. A normalized (dimensionless) decision matrix $\overline{\mathbf{C}}$ is obtained from $\mathbf{C}$.

Most methods of MAS select a^* with the normalised $\overline{\mathbf{C}}$ and not the initial $\mathbf{C}$ (examples of normalization formulas used to obtain $\overline{c}_{ij}$s from c_{ij}s may be found in the book [6]). The key element of each MAS method is the criterion, according to which a_is ranked and the best one, a^*, selected (MAS criterion, in short). Examples of MAS criteria are presented in, for instance, in the book [6].

The choice of a specific MAS criterion used to solve the specific problem of MAS can significantly influence its solution. However, the problem itself is set by generating the list of attributes represented by the components of the vectors $\boldsymbol{c}_i$.

Formally the alternative automatic equipment a_i can be considered as a typical industrial product characterised by usual attributes c_{ij}, say, purchase price or renting price, effectiveness (time for suppressing hazardous phenomenon), number of employees necessary to run or maintain the equipment, etc. However, the role in preventing a disaster and devastating consequences of the failure to perform the protective function may require to to introduce a specific attribute c_{ij} into the MAS problem. In simplest case, such attribute can be the failure probability p_{fki}, which is estimated for the ith alternative a_i, namely,

$$\boldsymbol{c}_i = (p_{fki}, c_{i2}, \ldots, c_{ij}, \ldots, c_{in}) \tag{4}$$

The failure probability can be introduced into the MAS problem indirectly, that is, through the utility functions specified for the alternatives a_i [9, 10]. The non-probabilistic attributes $c_{i2}, c_{i3}, \ldots, c_{in}$ can be ones used in the traditional MAS.

In many cases, the same safety system can include a set of equipments performing different functions and having different failure probabilities p_{fk}. The influence of these probabilities on system performance can be expressed by risk profile as it is used in the field of the quantitative risk assessment (QRA) [7]. Components of risk profile can be applied to specify MAS attributes [8]. For instance, the risk profile related to the accident represented by the event tree shown in Fig. 1 will take on the form

$$\text{Risk} \equiv \{(F(O_j), S_j), j = 1, 2, \ldots, 10\} \tag{5}$$

with

$$\begin{cases} F(O_1) &= F(E_0)p_{f1}p_{f2} \cdot \ldots \cdot p_{f5} \\ F(O_2) &= F(E_0)p_{f1}p_{f2}p_{f3}p_{f4}(1 - p_{f5}) \\ \quad \vdots \\ F(O_{10}) &= F(E_0)(1 - p_{f1})(1 - p_{f2}) \end{cases} \tag{6}$$

where $F(O_j)$ and S_j are the frequency and severity of the consequences O_j, respectively; $F(E_0)$ is the frequency of the initiating event E_0. Eqs. (5) and (6) imply that the risk is a function of the failure probabilities p_{fk} and so is the expected severity:

$$\overline{S}(p_{f1}, p_{f2}, \ldots, p_{f5}) = \sum_{j=1}^{10} F(O_j)S_j \tag{7}$$

The latter value can be used as MAS attribute. If, say, the problem is too choose among alternative sprinkler systems a_i, which can fail with the probabilities p_{f5i}, the MAS can be carried out using the attribute

$$c_i = (\overline{S}(p_{f1}, p_{f2}, \dots, p_{f5i}), c_{i2}, c_{i3}, \dots, c_{in}) \qquad (8)$$

The attribute vector (8) expresses the contribution of the failure probability p_{f5} to the system risk and so motivates to account for the influence of sprinklers on the system safety.

As long as estimates of the failure probabilities p_{fki} ($i = 1, 2, \dots, m$) are available, the MAS problem with the attribute vectors (4) or (8) can be solved by means of standard deterministic methods of MAS. Unlike other attributes, say, price or efficiency, the failure probabilities p_{fki} are usually not known in advance. An estimation of them can be a non-trivial task.

5. SELECTION WITH UNCERTAIN FAILURE PROBABILITIES

Failures of protective equipment are generally rare events backed by scarce historic data. In some cases experience data can by unavailable at all. In such a situation, the failure probabilities p_{fki} can be estimated using methodological means of QRA. In line with QRA, the probabilities p_{fki} can be uncertain in the epistemic sense. This means that the probabilities p_{fki} should be represented not by single-value estimates but by distributions quantifying the epistemic uncertainty in the true, albeit unknown values of p_{fki}. Such an approach is called the classical Bayesian approach to QRA [11]. It is based on the Bayesian statistical theory.

The solution of MAS problem will be still possible in the case where the probabilities p_{fki} are represented by epistemic uncertainty distributions. The best alternative a^* can be found by applying the procedure of a simulation-based uncertainty propagation [12].

In case where the alternative a_i is characterised by uncertain failure probability p_{fki} this can be interpreted and estimated as a distribution parameter. Uncertainty in p_{fki} is expressed by the Bayesian prior probability density function (p.d.f.) $\pi_i(p)$ which can be updated to posterior p.d.f. $\pi_i(p \mid E)$ when new

evidence E is obtained ($p \in]0, 1[$) (e.g. [15]). This is a standard procedure based on the Bayes's theorem:

$$\pi_i(p \mid E) \propto L(E \mid p)\ \pi_i(p) \qquad (9)$$

where $L(E \mid p)$ is the likelihood function. It quantifies the conditional probability of observing E given p or is proportional to this probability.

The MAS problem can be solved by applying both prior p.d.f.s $\pi_i(p)$ and posterior p.d.f.s $\pi_i(p \mid E)$ ($i = 1, 2, \dots, m$). The solution will be based on sampling values of p_{fki} from the probability distributions represented by $\pi_i(p)$ or $\pi_i(p \mid E)$ and determining the best alternative a^* corresponding to the current sampled probability values. The sampling should be carried out using Monte Carlo simulation. After it is repeated a sufficiently large number of times, the best alternative can be chosen using the following criterion [12]:

$$a^* = a_i, \text{ where } i = \operatorname{argmax}\{F_1, F_2, \dots, F_m\} \qquad (10)$$

where $F_1, F_2, \dots$ are the frequencies of choosing the corresponding alternatives $a_1, a_2, \dots$ as the best ones.

Developing appropriate prior p.d.f.s $\pi_i(p)$ can be critical and the least formal step of MAS. Generally developing prior distributions is considered the most controversial part of Bayesian analysis [13]. However, after $\pi_i(p)$ have been specified, the further analysis can precede using more formal steps represented by the expressions (9) and (10). Developing the prior p.d.f.s $\pi_i(p)$ and their updating by means of the theorem (9) depends on

- The physical nature of the failures represented by the probabilities p_{fki}.
- Statistical evidence related to the failure events E_k available prior to the new information E.
- The nature of equipment represented by the alternatives a_i and compared within MAS problem.

We think that a systematising review is necessary to list all the situations which the engineer may face when developing and updating the prior p.d.f.s $\pi_i(p)$. Such review is beyond the scope of the present paper. Therefore, the next section will deal with the demand unavailability of a_is.

6. EXAMPLE

Consider the automatic equipment "k" (sprinkler system, say) which can undergo only the demand failure E_{k1}: it will start or not start to operate given an emergency (e.g. fire). Three alternatives of the equipment, a_i ($i = 1, 2, 3$), will be compared. The failure probability of a_i, $p_{fki} = P(E_{k1}|\cdot)$, can be interpreted as a parameter of a binomial distribution [13]. This fits naturally for quantifying the conditional probability of observing r failures in n_d demands:

$$P(r \text{ in } n_d \mid p_{fki}) = \frac{n_d! \, (p_{fki})^r}{r!(n_d - r)!}(1 - p_{fki})^{n_d - r} \qquad (11)$$

In practice, a sufficiently large number of demands n_d is not available to calculate classical statistical point estimate r/n_d or sufficiently narrow confidence interval of p_{fki}. The value p_{fki} is uncertain in the epistemic sense and we need to develop the uncertainty distribution $\pi_i(p)$. As p_{fki} can have infinity of values between 0 and 1 and for the reason known in Bayesian analysis as conjugacy, a convenient prior for p_{fki} is the beta distribution with parameters α_{0i} and β_{0i} [14].

Information for developing the prior density $\pi_i(p|\alpha_{0i}, \beta_{0i})$ can be highly specific to the history of running equipment represented by a_i. If this history produced some data on failures of a_i, techniques for developing the so-called non-informative priors can be applied [13]. However, $\pi_i(p|\alpha_{0i}, \beta_{0i})$ can be informative prior, that is, reflect solely the engineer's belief concerning p_{fki}. In the present example, the same prior distribution will be used for all three a_is, namely, the beta distribution with $\alpha_{0i} = 2$ and $\beta_{0i} = 10$ (Fig. 2).

The prior will be updated using alternative-specific evidence E_i consisting of the recorded values of
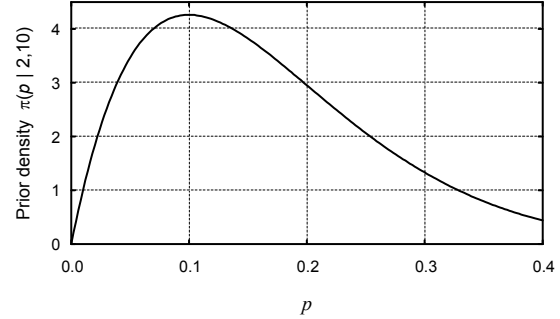
Figure 2. Prior density $\pi_i(p| 2, 10)$ for all alternatives

numbers of demands n_{di} and failures r_i (Table 1). This will yield three different posterior distributions $\pi_i(p \mid E_i) \equiv \pi_i(p \mid \alpha_{1i}, \beta_{1i})$ which can be used as input information for MAS.

For the binomial model (2), the new (latest) set of evidence E related to the alternative a_i has the form

$$E_i = \{r_i \text{ failures in } n_{di} \text{ demands}\} \qquad (12)$$

and the likelihood function $L(E \mid p)$ is expressed by the Eq. (11). The statistical evidence given by (12) is the history of demands and failures recorded for the alternative a_i. If the gamma distribution with the parameters α_{0i} and β_{0i} is used as prior p_{fki}, the posterior distribution will also be gamma one with the parameters calculated by the following formulas [16]:

$$\begin{cases} \alpha_{1i} = \alpha_{0i} + r_i \\ \beta_1 = \beta_{0i} + n_{di} - r_i \end{cases} \qquad (13)$$

The three sets of evidence E_i yield three posterior gamma distributions $\pi_i(p \mid E_i)$ with densities shown in Fig. 3. These distributions are different for all three alternatives a_i and so they can be used as uncertain attributes of MAS.

Table 1. Three alternative equipments with different histories of demands and failures

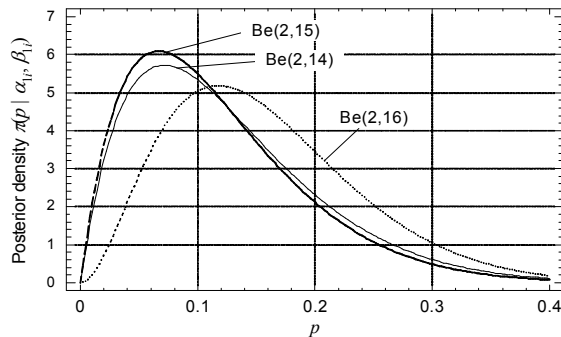| Alternative a_i	Recorded evidence $E = \{r_i$ failures in n_{di} demands$\}$		Parameters of posterior distribution $\pi_i(p \mid E_i)$		95th percentile of $\pi_i(p \mid E_i)$	Mode of $\pi_i(p \mid E_i)$
	n_{di}	r_i	α_{1i}	β_{1i}		
a_1	4	0	2	14	0.279	0.0714
a_2	5	0	2	15	0.264	0.0667
a_3	7	1	3	16	0.310	0.125

Figure 3. Posterior densities $\pi_i(p|\alpha_{1i}, \beta_{1i})$ ($i = 1, 2, 3$).

7. CONCLUSION

The problem of the choice among alternative types/arrangements of automatic protective equipment has been considered. This equipment is to be installed to protect the construction site against major accidents (disasters). The choice can be implemented by applying formal methods of multi-attribute selection (multi-criteria decision making). This selection should include attributes which account for the possibility of failure of the protective equipment, for instance, failure probability. Such attributes can be uncertain in the epistemic sense. The epistemic uncertainty in the safety-related attributes can be quantified by applying Bayesian analysis. This will yield prior or posterior probability distributions which can be used as input data for the multi-attribute selection.

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