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Bayesian Reasoning in Managerial Decisions on the Choice of Equipment for the Prevention of Industrial Accidents

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The managerial problem of the choice among alternative protective equipment used to prevent industrial (technological) accidents is considered. The choice takes into account potential failures of the equipment or, conversely, the equipment reliability. Such failures can substantiate contributors to escalations of industrial accidents. The problem of the choice is formulated in the form of a multi-attribute selection.

The probability of failure of alternative equipment sets is used as an attribute of the selection problem. An estimation of this probability by means of Bayesian statistical theory is considered. Bayesian prior and posterior distributions are applied as an estimate of failure probability. These distributions are incorporated in the selection problem as uncertain attributes. Development of prior distributions of individual alternatives is discussed in detail. The prior and posterior distributions are treated as measures of the epistemic uncertainty (state-of-knowledge) related to unknown values of failure probabilities.

The modelling of uncertainty related to the failure probability corresponds to the classical Bayesian approach to risk assessment. It is suggested to apply the uncertain failure probabilities to developing risk profile for each of the alternative equipments and to incorporate the risk profile to the multi-attribute decision making.

The epistemic uncertainty in the failure probabilities and elements of risk profile is quantified by means of Bayesian statistical theory. It is shown that this uncertainty can be reduced by applying Bayesian updating procedure when new data on equipment failures is obtained. Probable cases of the application of this procedure are discussed. This discussion relates the acquisition of the new statistical evidence used for Bayesian updating to the moments, at which managerial decisions are made.

It is suggested to solve the problem of the multi-attribute selection with uncertain attributes by means of uncertainty propagation. This propagation is accomplished by means of Monte Carlo simulation. The epistemic uncertainty related to the attributes is transformed into a discrete distribution of epistemic uncertainty. Probability masses of this distribution express the chance of individual alternatives to be selected as the best one. The result of this selection will be the alternative with the largest epistemic weight.

The potential field of the application of the proposed approach is the management of technological risks present in many industrial facilities and non-industrial installations (dwellings, offices, public places) which are subjected to the hazard of accidents. The approach proposed in the paper allows to make managerial decisions which take into account the reliability of protective equipment. In addition, this approach will allow to utilize data on equipment failures encountered in the past. Such data is usually scarce and expensive. The Bayesian framework is best suited for the application of such data.

Keywords: *Bayesian approach, accident, protective equipment, failure, multi-attribute selection.*

Introduction

The construction and exploitation of many industrial installations and transportation facilities involve hazards, the potentiality of which can range between common occupational accidents and devastating disasters (major accidents) (Babinec, Ivanek, 2005; Hola, 2007; Mitropoulos, Abdelhamid, Howell, 2005; Xinzheng, Ning, Jianjing, 2004, Vaidogas, 2006). 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 and other accidents caused by extreme natural phenomena, equipment failures, or human errors. Cost of such accidents can be very high (Khan, Amyotte, 2007; Fewtrell, Hirst, 1998; Venart 2004, 2007).

In European Union, most industrial installations require mandatory risk assessment and development of preventive measures (European Council, 1996). Nevertheless, the MARS database records that, approximately 30 major accidents happen each year within the industry sectors covered by the Seveso 2 directive (ETPIS 2007). These accidents are not major contributors to the overall statistics but have a major impact on industry and society and thus on sustainable development (Casal, 2008; Vaidogas, Juocevičius, 2008). As a consequence, quantitative risk assessment (QRA) and risk management have to take a proper account of multiple hazards which threaten critical installations and can develop into major accidents. The risk management is often performed in relation to a QRA (Kumamoto, Henley, 1996). The phase of QRA is more formal and objective than the management phase, which is based on judgement and heuristics and so is more qualitative and subjective (Rutkauskas, 2008; Startienė, Remeikienė, 2007).

Risk management is based on safety culture, quality management and proved engineering practices (IAEA, 1988). The process of risk management includes accident prevention (or failure prevention & propagation prevention) and accident management (or onsite and offsite consequence mitigation). As Kumamoto and Henley (1996) have put it, failure prevention is similar to prevention of infection with a disease, propagation prevention corresponds to outbreak prevention, and accident management resembles treatment and recovery after outbreak. If the propagation prevention works successfully, perturbations of technological process and incipient failures of production equipment will develop into a serious situation and yield an accident. Abnormal occurrences, ranging from minor disturbances to unlikely accident sequences, will not cause serious consequences, if measures of propagation prevention remain healthy and operate correctly. These measures include equipment which is installed to carry out a specific preventive function: to extinguish fire, to protect by means of physical barrier, to provide tolerance for failures etc.

If protective equipment fails to carry out its function when demanded or abnormal occurrence develops to events beyond the design basis of the equipment, the accident sequence continuous to develop and may lead to serious consequences. Therefore, a crucial part of manager's overall effort in reducing technological risk should be acquisition and implementation of reliable, safe, and effective protective equipment (Hadad, Laslo, Ben–Yair, 2007; Kazlauskienė, Christauskas, 2007; Vaidogas, 2007). Such equipment is usually produced and offered by some number of competing manufacturers able to assure different levels of reliability. Therefore the manager responsible for the plant safety will often face the problem of the choice among several alternative arrangements (types) of protective equipment or, briefly, among several alternatives.

The larger are consequences of protective equipment failure the stronger can be the influence of its reliability on the choice of particular alternative arrangement. Quantitatively, the reliability-oriented choice can be expressed as a problem of multi-attribute selection (MAS) (Vaidogas, Zavadskas 2007; Vaidogas, Zavadskas, Turskis, 2007). One of the main problems of such selection is the estimation of failure probability of the alternatives. Accidents demanding the operation of protective equipment are relatively rare events. Failures of the equipment to operate on demand are even more rare events. Therefore the main practical approach to the estimation of the failure probability is the Bayesian approach to QRA (e.g. Aven, 2003; Aven, Pörn, 1998; Kelly, Smith, 2009). If the problem of the multi-attribute selection has to take into account the failure probability or related characteristics (e.g. total cost or total benefit), this approach can be used for estimating this probability in terms of an epistemic uncertainty distribution. The present paper considers how to develop this distribution in the framework of QRA and to apply it in the general context of MAS.

Industrial accident

The exposure to hazards during construction, installation, calibration, testing and exploitation of hazardous facility may vary considerably and depend on individual industry. However, the construction and installation phases are usually less organised and stable processes 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.

The exposure to hazards during construction and installation 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. One the other hand, the time of exposure to hazards during exploitation of hazardous facility exceeds by far the exposure time during construction.

An accident happens as a sequence of adverse events which escalate into a harmful event (process) directly causing catastrophic consequences (e.g. Høiset, Hjertager, Solberg, Malo, 2000; Kaszniak, Holmstrom 2008; Skelton, 2001). An accident sequence is called a scenario. QRA uses, among other things, event tree and fault tree techniques to identify possible accident scenarios and consequences. Figure 1 shows a number of such scenarios 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 event tree given in Figure 1 demonstrates the negative contribution of individual protective equipment failures and combinations of these failures to accident escalation.

An "embedding" of the protective equipment failures in the logical modelling of accident scenarios allows to answer three questions:

1. Are there any accident scenarios which require installation of protective equipment?
2. What specific equipment is necessary to prevent propagation of the accident?
3. What is the role of protective equipment failures in individual scenarios of accident, especially, in potential critical escalation leading to catastrophic consequences?

These questions arise due to the simple fact that components of the protective equipment are not fail-safe technical objects. There are numerous examples when these components failed to work on demand and so contributed to consequences of major accidents. The disaster on board the offshore platform Piper Alpha in 1988 is a sad and impressive example of such an accident (e.g. Paté-Cornell, 1993). Managerial decisions concerning the acquisition installation and exploitation of this equipment should take into account this possibility of the protective equipment failure.

Failures of equipment used for accident prevention

The major accident can cause multiple casualties and considerable damage to structural and non-structural property. A proper planning of construction and

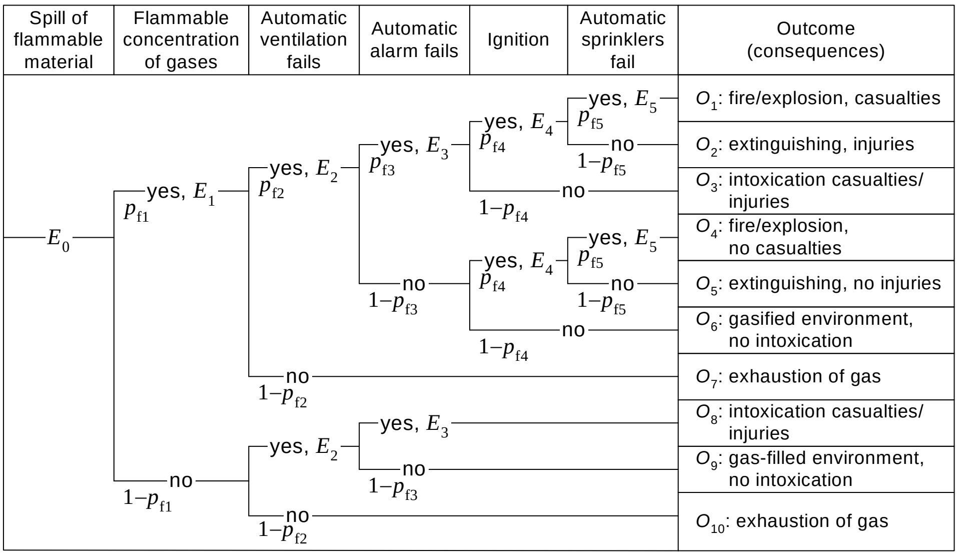

Figure 1. Scenarios of an accident initiated by a spill of flammable material in a tunnel

exploitation process and organisation of dangerous production operations requires recognising, controlling, and, if possible, eliminating hazards. If a complete elimination is impossible, automatic protective equipment must be installed to stop a possible propagation of an accident and/or protect against a disastrous physical phenomenon, if this takes place. Obvious and often used 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 the case where the production process involves the potentiality of a major accident, the role of protective equipment protecting against this accident becomes critical. It is natural to expect that in the 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 facilities serve as an illustration of this problem (Hauptmanns, Marx, Grünbeck, 2008; Kala, 2008; Rasbach, Ramanchandran, Kandola, Watts, Law, 2004: 236; Siu, Apostolakis, 1988).

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 Figure 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 failures E_k and the very possibility of such failures raise the problem of reliability. Although usually explicit measures of reliability (probability of fail-safe service) are not known for users of the equipment, everyone expects that his/her equipment has a sufficiently high level of reliability. Failures of protective equipment, E_k, can be critical. Therefore decisions concerning, acquisition, installation, and running of this equipment should take into account explicit measures expressing its reliability.

Generally the reliability is expressed through 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 to three typical failure modes (Kumamoto, Henley, 1996: 60 and 62):

- Demand unavailability (epressed by conditional probability that equipment will not start to operate given an emergency/accident; demand failure, E_{k1}).
- Failure to work in the course of emergency / accident after equipment starts operate (run failure, E_{k2}).
- Equipment does 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}).
- Unavailability due to maintenance and testing, E_{k4}.

The above list of failure modes is not 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:

$$p_{fk} = P(E_k \mid E_{k-1} \cap E_{k-2} \cap \ldots) = \\ = P\left(\bigcup_{l=1}^{3} E_{kl} \mid E_{k-1} \cap E_{k-2} \cap \ldots \right) \qquad (2)$$

where E_{k-1}, E_{k-2}, … are events preceding the failure event E_k. The first of them generates the demand for protective equipment. For instance, E_{k-1} means “spread of fire in tunnel under construction” (Figure 1).

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 choice of specific equipment into a non-trivial task.

Choice among alternative sets of protective equipment

When the manager has to choose specific protective equipment, many, sometimes contradictory, attributes characterising this equipment must be considered simultaneously. The field of management science has long dealt with the problem of this kind. They developed MAS also known as multi-criteria decision making and abbreviated to MCDM (e.g. Triantaphyllou 2000, Zavadskas, Liias, Turskis, 2008).

Applications of MAS methods in real world problems are numerous and in very different fields (e.g. Figuera, Greco, Ehrgott, 2005: part VII). These applications include a combined use of MAS and risk analysis methods (Pires, de Almeida, Lemos, 2005; Vaidogas, 2008). We think that methods of MAS can be applied to problems where a decision-maker must evaluate, rank, or classify alternative protective 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 protective equipments (alternatives, in brief) can be represented by the vector $\boldsymbol{a} = (a_1, a_2, \dots , a_i, \dots , a_m)^{\mathrm{T}}$. 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 $\boldsymbol{c}_i = (c_{i1}, c_{i2}, \dots , c_{ij}, \dots , c_{in})$, 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

$$\mathbf{C} = [\boldsymbol{c}_1, \dots, \boldsymbol{c}_i, \dots, \boldsymbol{c}_m]^{\mathrm{T}} \quad (3)$$

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 $\mathbf{C}$.

Formally the alternative protective 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 criticality of equipment failures may require to introduce a specific attribute c_{ij} into the MAS problem. In the simplest case, such attribute can be the failure probability $p_{\mathrm{f}ki}$, which is estimated for the ith alternative a_i:

$$\boldsymbol{c}_i = (p_{\mathrm{f}ki}, c_{i2}, \dots , c_{ij}, \dots , c_{in}) \quad (4)$$

The failure probability can be introduced into the MAS problem indirectly, that is, through the utility function specified for the alternatives a_i (Vaidogas, Zavadskas, 2007; Vaidogas, Zavadskas, Turskis, 2007). The non-probabilistic attributes $c_{i2}, c_{i3}, \dots , c_{in}$ 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 $p_{\mathrm{f}k}$. The influence of these probabilities on system performance can be expressed by risk profile widely used in the field of QRA (Kumamoto, Henley, 1996). Components of risk profile can be applied to specify MAS attributes (Vaidogas, 2008). For instance, the risk profile related to the accident represented by the event tree shown in Figure 1 will take on the form

$$\text{Risk} \equiv \{(Fr(O_j), S_j), j = 1, 2, \dots , 10\} \quad (5)$$

with

$$\begin{cases} Fr(O_1) &= Fr(E_0)\,p_{\mathrm{f}1} p_{\mathrm{f}2} \cdot \ldots \cdot p_{\mathrm{f}5} \\ Fr(O_2) &= Fr(E_0)\,p_{\mathrm{f}1} p_{\mathrm{f}2} p_{\mathrm{f}3} p_{\mathrm{f}4}(1-p_{\mathrm{f}5}) \\ \quad\vdots & \\ Fr(O_{10}) &= Fr(E_0)(1-p_{\mathrm{f}1})(1-p_{\mathrm{f}2}) \end{cases} \quad (6)$$

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

$$\overline{S}(p_{\mathrm{f}1}, p_{\mathrm{f}2}, \dots, p_{\mathrm{f}5}) = \sum_{j=1}^{10} Fr(O_j) S_j \quad (7)$$

The latter value can be used as an MAS attribute. If, say, the problem is too choose among alternative sprinkler systems a_i, which can fail on demand with the probabilities $p_{\mathrm{f}ki}$, the MAS can be carried out using the attribute vector

$$\boldsymbol{c}_i = (\overline{S}(p_{\mathrm{f}1}, p_{\mathrm{f}2}, \dots, p_{\mathrm{f}5i}), c_{i2}, c_{i3}, \dots, c_{in}) \quad (8)$$

The above vector expresses the contribution of the failure probability $p_{\mathrm{f}5}$ 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 $p_{\mathrm{f}ki}$ (i = 1, 2, … , 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 $p_{\mathrm{f}ki}$ are usually not known in advance. An estimation of them can be a difficult problem.

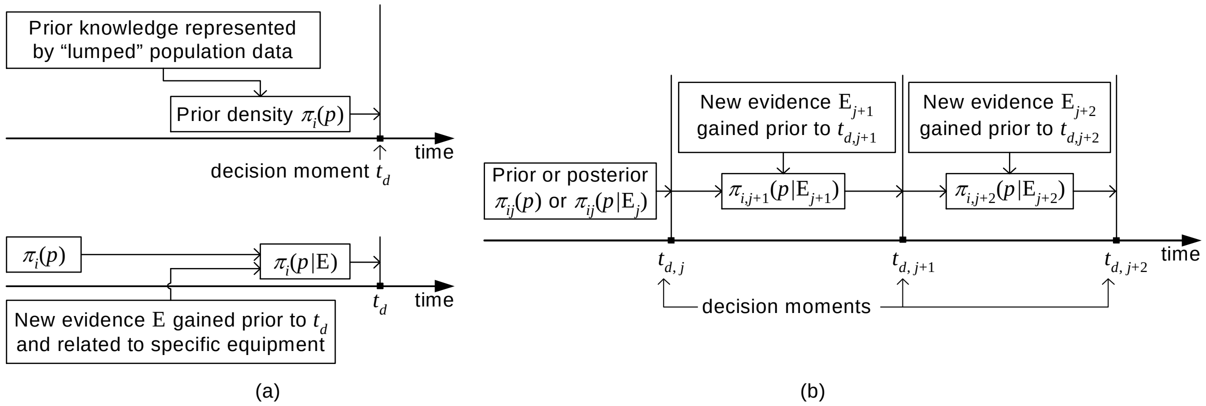

Figure 2. Availability of the evidence E for the Bayesian updating of the equipment failure probabilities at the moment(s) of decision-making (multi-attribute selection): (a) in case where decision is made only once; (b) in case of repetitive decisions

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 probability distributions quantifying the epistemic uncertainty in true, albeit unknown values of p_{fki}. Such an approach is called the classical Bayesian approach to QRA (Aven, Pörn, 1998). 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 (Vaidogas, Hayashi, 2007).

In case where the alternative a_i is characterised by uncertain failure probability p_{fki}, the uncertainty in p_{fki} can be expressed by a Bayesian prior probability density function $\pi_i(p)$ ($p \in [0, 1]$). This density can be updated to a posterior density $\pi_i(p \mid \mathrm{E})$ when new evidence E is obtained (e.g. Siu, Kelly, 1998; Shafaghi, 2008). This is a standard procedure based on the Bayes's theorem:

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

where $L(\mathrm{E} \mid p)$ 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 $\pi_i(p)$ and $\pi_i(p \mid \mathrm{E})$ ($i = 1, 2, \dots, m$). The solution will be based on sampling values of p_{fki} from the probability distributions represented by $\pi_i(p)$ or $\pi_i(p \mid \mathrm{E})$ and determining the best alternative a^* corresponding to the current sampled probability values. The sampling should be carried out using a Monte Carlo simulation. After it is repeated a sufficiently large number of times, the best alternative can be chosen using the following criterion (Vaidogas, Hayashi, 2007):

$$a^* = a_i, \text{ where } i = \operatorname{argmax}\{Fr_1, Fr_2, \dots, Fr_m\} \qquad (10)$$

where $Fr_1, Fr_2, \dots$ are the frequencies of choosing the corresponding alternatives $a_1, a_2, \dots$ as the best ones.

Bayesian analysis in specifying input information for the choice of equipment

Developing appropriate prior densities $\pi_i(p)$ can be the most controversial part of MAS. However, after $\pi_i(p)$ has been specified, the further analysis can proceed according to formal steps represented by the expressions (9) and (10). Developing the prior distributions $\pi_i(p)$ deserves a thorough review. However, such a review is beyond the scope of the present paper. This section will provide only a short discussion about the densities $\pi_i(p)$ and $\pi_i(p \mid \mathrm{E})$.

The operation of protective equipment represented by a_is commonly occurs as a Bernoulli process which generates failures F and successes S of the equipment to operate on demand. This process is described by a binomial distribution. The failure probability p_{fki} is interpreted as a parameter of this distribution. The binomial model is appropriate if the equipment failure events F are independent and there is no aging of this equipment, that is, p_{fki} remains constant over time. The protective equipment is normally operated for a short time during an accident progression. Therefore this equipment normally is not subjected to the intensive and long-lasting wear which takes place in the case of constantly operated equipment. Thus the aging of protective equipment may be considered negligible, at least preliminary.

In the case of the binomial model, the natural prior density $\pi_i(p)$ is a beta density. Lognormal distribution can be used as $\pi_i(p)$ if the failure probability p_{fki} is very small and the tail truncation above $1 - p_{fki}$ has a negligible effect. Siu and Kelly (1998) and Kelly and Smith (2009) suggest recipes for developing $\pi_i(p)$ depending on the availability of information on possible values of p_{fki}.

The new evidence E related to the alternative a_i and used for the updating of the prior distribution $\pi_i(p)$ may have at least three forms

$$\mathrm{E} = \{r \text{ failures in } n_d \text{ demands}\} \qquad (11a)$$

$$\mathrm{E} = \{(r_1, n_{d1}), \dots, (r_l, n_{dl}), \dots, (r_k, n_{ds})\} \qquad (11b)$$

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

Alternative a_i	Recorded evidence $E_i = \{r_i$ failures in n_{di} demands$\}$		Parameters of posterior distribution $\pi_i(p \mid E_i)$		95[th] 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

$$E = \{F, S, S, F, S, S, S, \ldots\} \quad (11c)$$

Where r_l is the number of failures and n_{dl} is the number of demands at a specific situation or environment l (e.g. fire scenario l, operating conditions l, or the maintenance practice l). The evidence (11b) comes from s different sources and can be applied for developing the hierarchical prior distribution. The evidence (11c) is a unique sequence of successes and failures recorded during the observation of specific equipment during accidents and near misses (undeveloped accidents). Accidents demanding particular protective equipment are relatively rare events. Therefore, the size of the evidence (11) may be relatively small.

The updating of $\pi_i(p)$ with a specific form of the evidence (11) is a formalised procedure which can be carried out almost automatically with greater or lesser computational effort. Managerial decisions concerning the choice of the alternative a_i will depend on the availability of the evidence E at the decision moment t_d. The manager may face the following cases:

1. The decision concerning the choice among the alternatives a_i is made only once with or without the new evidence E (Figure 2a).

2. The decision is a repetitive process, during which the new evidence E can be obtained between successive decision moments (Figure 2b).

In the first case, the updating of $\pi_i(p)$ will be a single act, whereas the second case will occur as an iterative process. The prior distribution $\pi_{ij}(p)$ will represent the manager's knowledge prior to the evidence E_{j+1}. The posterior distribution $\pi_{i,j}(p \mid E_{j+1})$ obtained with E_{j+1} will serve as a prior distribution for the next updating with the new data E_{j+2}.

An example of the first case is the decision concerning a_is which represent typical or unique protective equipment which will hardly be acquired (leased) once again in the near future of decision-maker's company. The protective equipment installed in the new plants running the same hazardous technology and built one after another during business expansion may serve as an example of the second case.

An acquisition of the new evidence E can be a problematic and costly process. The potential source of E is the equipment-specific data contained in various databases. Ayyub (2003) and Vaidogas (2007) provide a review of these databases. As the evidence (11) consists of highly specific raw data, in-house failure databases developed by companies running or manufacturing the equipment under consideration is the probable source of this data. If an in-house database is not available, data on similar equipment should be used. Such data can be found in plant failure databases. Sometimes government regulatory agencies require that companies under their purview report failures and accidents to them in a standardised form. In these cases, the centralised databases (e.g. fire accident databases), can be valuable source for the acquisition of E.

Example

Consider the automatic protective equipment "k" (e.g. sprinkler system) 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 the alternative i, $p_{fki} = P(E_{k1}| \cdot)$, will be interpreted as a parameter of a binomial distribution. This distribution quantifies the conditional probability of observing r failures in n_d demands:

$$P(r \text{ in } n_d \mid p_{fki}) = \frac{n_d!\,(p_{fki})^r}{r!(n_d - r)!}(1 - p_{fki})^{n_d - r} \quad (12)$$

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 $\pi_i(p)$. A convenient form of $\pi_i(p)$ is the beta distribution with parameters α_{0i} and β_{0i} (Congdon, 2001).

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 (Siu, Kelly, 1998). 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 α_{0i} = 2 and β_{0i} = 10 (Figure 3).

The prior will be updated using alternative-specific evidence E_i given in Table 1 and consisting of the recorded values of the numbers of demands and failures:

$$E_i = \{r_i \text{ failures in } n_{di} \text{ demands}\} \quad (13)$$

These sets of evidence 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 evidence (13), the likelihood function $L(E_i \mid p)$ is expressed by the Eq. (12). If the beta distribution with the parameters α_{0i} and β_{0i} is used as a prior of p_{fki}, the posterior distribution will also be a beta distribution with the parameters calculated by the following formulas (Congdon, 2001: 29):

$$\begin{cases} \alpha_{1i} = \alpha_{0i} + r_i \\ \beta_1 = \beta_{0i} + n_{di} - r_i \end{cases} \qquad (14)$$

The three sets of evidence E_i yield three posterior beta distributions $\pi_i(p \mid E_i)$ with densities shown in Figure 4. These distributions are different for all three alternatives a_i and so they can be used as uncertain attributes of MAS.

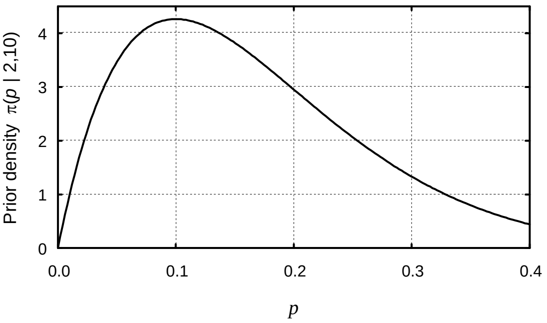

Figure 3. Prior density $\pi_i(p \mid 2, 10)$ for all alternatives

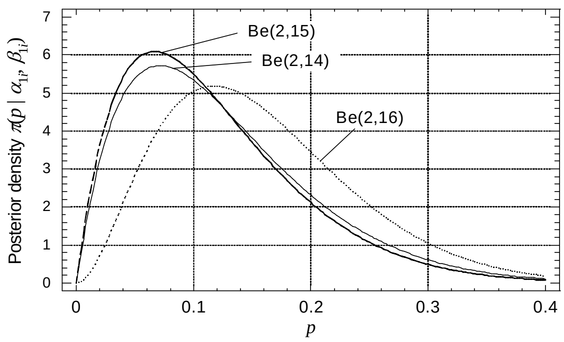

Figure 4. Posterior densities $\pi_i(p|\alpha_{1i}, \beta_{1i})$ (i = 1, 2, 3)

Conclusions

Problem of a managerial decision concerning the choice of equipment used for a prevention of industrial accidents has been considered. The choice was formulated as a selection among alternative arrangements/types of protective equipment. The choice was implemented by applying mathematical methods of multi-attribute selection (multi-criteria decision-making). The emphasis was on specifying reliability-oriented part of input information for the multi-attribute selection.

The main idea of the paper was that the multi-attribute selection should include attributes which account for the possibility of failure of the protective equipment. A failure probability is the main example of such safety-related attributes. They can be uncertain in the epistemic sense. The epistemic uncertainty in the safety-related attributes was quantified by applying Bayesian analysis. This analysis yields prior or posterior probability distributions which can be used as input information for the multi-attribute selection.

A development of appropriate prior distributions for the alternatives under comparison can be the most resource-intensive part of specifying the input information for a multi-attribute selection problem. The development and updating of the prior distribution will require a delicate handling of available historic data on equipment failures and extensive use of expert judgements. However, after this information is received, the prior can be updated and selection problem solved almost automatically by applying rules of Bayesian reasoning and formal methods multi-attribute selection.

The decision-making which, among other things, takes into account uncertain failure probabilities is far from the current managerial practice. However, failures of the equipment to perform its protective function may lead to major accidents. The potentiality of such accidents will require to abandon the intuitive assessment of the reliability of protective equipment. The decision-making based on formal measures characterising the fail-safe behaviour can be the proper step towards managing risks of hazardous industrial facilities.

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Bajėso požiūris į vadybinius sprendimus pasirenkant saugos įrangą technologinėms avarijoms išvengti

Santrauka

Straipsnyje nagrinėjama problema, kaip pasirinkti technologinę saugą užtikrinančią įrangą (saugos įrangą) iš kelių alternatyvių įrangos variantų. Pagrindinis akstinas taip pasirinkti yra saugos įrangos gedimai. Jie atsiranda kartkartėmis ir gali sukelti sunkų technologinių avarijų eskalavimą. Pasirinkimo problema formuluojama matematiniu daugiakriterinės atrankos uždaviniu. Šis uždavinys matematiškai išreiškia vadybinę sprendimo priėmimo problemą. Straipsnio tikslas - susieti saugos įrangos patikimumo (gedimo tikimybės) vertinimą su daugiakriterine atranka.

Alternatyvių saugos įrangos variantų gedimo tikimybė yra laikoma atrankos kriterijumi (atributu). Nagrinėjama, kaip vertinti šią tikimybę pasitelkiant Bajėso statistinės teorijos priemones. Apriorinis ir aposteriorinis Bajėso skirstiniai laikomi gedimo tikimybės įverčiais. Detaliai aptariamas šių skirstinių parinkimas. Tariama, kad saugos įrangą sudaro techniniai komponentai, kurie normaliomis sąlygomis yra laukimo būsenos ir turi veikti kilus pareikalavimui (plėtojantis technogeninei avarijai). Toks įrangos darbo pobūdis yra aprašomas binominiu tikimybiniu skirstiniu. Pagrindžiant jo taikymą teigiama, kad saugos įrangos senėjimo procesas nėra intensyvus ir bent preliminariai jį galima ignoruoti. Binominio skirstinio parametras – gedimo pareikalavus tikimybė – laikomas epistemine prasme neapibrėžtu dydžiu. Nagrinėjama, kaip šį neapibrėžtumą kiekybiškai išreikšti aprioriniu skirstiniu. Rodoma, kaip atnaujinti tą skirstinį taikant Bajėso teoremą ir taip gauti aposteriorinį skirstinį. Apriorinis ir aposteriorinis skirstiniai yra įtraukiami į atrankos problemą juos laikant neapibrėžtais atributais. Šie skirstiniai kiekybiškai išreiškia episteminį neapibrėžtumą, kuris gali būti sumažintas gaunant naujos informacijos apie įrangos gedimus.

Straipsnyje taikomas neapibrėžtumų modeliavimas atitinka rizikos analizės metodologiją, kuri vadinama klasikiniu Bajėso požiūriu į rizikos vertinimą. Jo esmė yra ta, kad gedimo tikimybės yra laikomos fizinėmis saugos įrangos charakteristikomis, kurių tikslios reikšmės nebūna žinomos. Jas vertinti būna sunku, nes įrangos gedimai yra reti ir šias tikimybes išreikšti santykiniu gedimo dažniu yra problemiška. Duomenų apie gedimus paprastai būna surinkta mažai ir pasikliautinieji intervalai, skaičiuojami klasikinės statistikos metodais, būna nepriimtinai platūs. Todėl straipsnyje gedimo tikimybes siūloma nusakyti ne intervalais, o tikimybiniais skirstiniais. Atliekant daugiakriterinę atranką, šie skirstiniai yra parenkami kiekvienam alternatyviam saugos įrangos variantui.

Straipsnyje rodoma, kad neapibrėžtas gedimo tikimybes galima naudoti skaičiuojant kiekvieno saugos įrangos varianto rizikos profilį. Šis rizikos matas įtraukiamas į daugiakriterinės atrankos uždavinį. Tai atliekama nustatant avarijos, kurią turėtų užkirsti saugos įranga, pasekmes ir apskaičiuojant tų pasekmių sunkumo matus. Taip gaunama vidutinė kiekvieno varianto rizika, kuri yra laikoma vienu iš lyginamų variantų

atributų. Siūloma tiek gedimo tikimybę, tiek vidutinę riziką naudoti kartu su įprastiniais atrankos atributais: kaina, priežiūros išlaidomis, techninėmis charakteristikomis (pvz., našumu).

Tiek saugos įrangos gedimo tikimybės, tiek alternatyvių įrangos variantų rizikos profilio elementai laikomi epistemine prasme neapibrėžtais dydžiais. Rodoma, kad jų neapibrėžtumas gali būti sumažintas pasitelkiant Bajėso atnaujinimo procedūrą. Atnaujinimą galima atlikti gavus naujų duomenų apie įrangos gedimus. Detaliai aptariama, kaip šie duomenys turi būti surinkti, kad jie tiktų apriorinio tankio atnaujinimo procedūrai. Pateikiami trys naujų duomenų išreiškimo pavidalai: (a) gedimų skaičius per stebėtą pareikalavimų skaičių; (b) gedimų ir pareikalavimų skaičiai, užfiksuoti eksploatuojant saugos įrangą įvairiomis sąlygomis, bei (c) unikali gedimų ir sėkmingų startavimų seka, užfiksuota per tam tikrą pareikalavimų skaičių.

Trumpai aptariama, kur reikia ieškoti duomenų apie saugos įrangos gedimus. Galimu duomenų šaltiniu yra laikomos gedimų duomenų bazės, kurias kuria ir papildo saugos įrangą gaminančios ir eksploatuojančios įmonės. Kitu duomenų šaltiniu laikomos duomenų bazės, kuriose kaupiama informacija apie analogiškos ir panašios įrangos eksploatavimo istoriją. Teigiama, kad dar vienas duomenų šaltinis yra duomenų bazės, kurias kaupia valstybės kontrolės organizacijos. Šios organizacijos reikalauja pateikti standartizuotas ataskaitas apie gedimus ir avarijas, įvykstančius jų prižiūrimose įmonėse. Tų ataskaitų informacija yra kaupiama duomenų bazėse, kurios gali būti patikimas duomenų šaltinis vertinant saugos įrangą. Tokios bazės pavyzdys yra bazė, kurioje kaupiami duomenys apie gaisrus ir nelaimingus atsitikimus, įvykstančius pramonės įmonėse.

Straipsnyje aptariami du atvejai, susiję su Bajėso atnaujinimui naudojamos informacijos gavimu.

Pirmuoju atveju daugiakriterinė atranka vykdoma tik vieną kartą. Ji grindžiama arba tik aprioriniais skirstiniais, arba aprioriniais skirstiniais ir nauja informacija, kurią pavyksta sukaupti iki sprendimo priėmimo momento. Antruoju atveju sprendimai apie saugos įrangos pasirinkimą yra priimami keletą kartų.

Tarp gretimų sprendimų praeina tam tikri laiko tarpai. Per šiuos laiko tarpus gali būti gauta nauja informacija ir atliekamas Bajėso atnaujinimas. Taip susiformuoja iteratyvus procesas, kuriame aposteriorinis skirstinys, naudotas paskutiniojo pasirinkimo procese, yra naudingas kaip apriorinis einamojo pasirinkimo procese. Toks pasikartojantis saugos įrangos pasirinkimas gali būti atliekamas statant vis naujas įmones, kuriose yra taikoma ta pati pavojinga gamybos technologija.

Daigiakriterinės atrankos uždavinį su neapibrėžtais atributais siūloma spręsti epistеminio neapibrėžtumo propagavimo būdu. Jį reikia atlikti taikant Monte Karlo modeliavimą. Atliekant tokį propagavimą, epistеminio neapibrėžtumo matai, susiję su pavieniais atributais, yra transformuojami į diskretųjį epistеminį skirstinį. Jo tikimybiniai svoriai išreiškia pavienių atrankos variantų šansą būti išrinktais geriausiuoju variantu. Atrankos rezultatas bus variantas su didžiausiu tikimybiniu-epistеminiu svoriu. Toks atrankos kriterijus atspindi pasirinkimo pagal didžiausią sėkmes tikimybę principą.

Galima siūlomo metodo taikymo sritis yra technologinės rizikos valdymas. Jo prireiks eksploatuojant tiek pramoninius objektus, tiek ir gyvenamuosius namus, įstaigų pastatus, viešųjų renginių vietas. Siūlomas metodas padės atsižvelgti į saugos įrangos patikimumą, o ne tik į kainą ir eksploatacines charakteristikas. Kartu siūlomas metodas leis racionaliai išnaudoti ribotus ir dažnai brangius statistinius duomenis apie saugos įrangos gedimus. Bajėso atnaujinimo procedūra tam gerai tinka.

Raktažodžiai: *Bajėso požiūris, technologinė avarija, saugos įranga, gedimas, daugiakriterinė atranka.*

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