# Methodology for PSA Uncertainty Estimation and Application in Risk-Informed Decision-Making

*O. Kukhotskyi[1], T. Iešmantas[2]*

*1 State Enterprise "State Scientific and Technical Center for Nuclear and Radiation Safety" (SSTC NRS), 35-37 V.Stusa Street, 03142, P.O. Box 124, Kyiv, Ukraine*

*2 Lithuanian Energy Institute (LEI), 3 Breslaujos Street, LT-44403, Kaunas, Lithuania*

**Abstract:**
Uncertainties are very important in risk analysis and should be considered in the decision-making process. This paper proposes the methodology for estimation of PSA uncertainties in risk-informed decision-making. The methodology allows solving the complex task of identifying the sources of uncertainties, assessing their range, and providing an approach for consideration of PSA results with uncertainties in combination with other factors underlying risk-informed decision-making. The levels of uncertainties are proposed to be classified using the variation factor. The authors applied the developed methodology to assess alternatives of post-Fukushima safety measures.

## 1 INTRODUCTION

Nowadays, risk assessment as a tool in support of decision-making is being increasingly used, particularly in such high-consequence technology as nuclear energy. Risk assessment deals with situations in uncertainty that is an inherent part of any modeling. The correspondence between a model and reality is always incomplete to some extent.

Although the concept for treatment of uncertainties in risk–informed decision-making [1] has been discussed and examined quite extensively, it is still relevant today and needs to be adopted for practical applications. The outcomes of several projects (e.g. ASAMPSA_E [2]) initiated after the Fukushima-Daiichi accident identified important sources of uncertainties in PSA (frequency of hazards, component fragility evaluation, etc.). The treatment of uncertainties has been recognized as an important problem for PSA with regard to decision-making. Hence, uncertainties have to be systematically identified and classified, assessed by mathematical approaches, and propagated through the steps of the risk assessment procedure onto the risk measures until the decisions are made.

The main objective of this paper is to provide a view on the methodology of PSA uncertainty estimation with an emphasis on classification of uncertainty level and application in risk-informed decision-making. The methods for uncertainty assessment are presented in a concise manner to allocate more space for practical examples.

## 2 TYPES AND SOURCES OF PSA UNCERTAINTIES

In the risk assessment context, it is useful to distinguish between "aleatory" and "epistemic" uncertainties [1].

We are talking about an aleatory uncertainty when the events or phenomena being modeled are characterized as occurring in a "random" or "stochastic" manner.

An epistemic (or state-of-knowledge) uncertainty is associated with the analyst's confidence in the prediction of the PSA model itself. This type includes parameter uncertainties, model uncertainties, and completeness uncertainties. Parameter uncertainties relate to the uncertainty in the computation of input parameter values used to quantify the probabilities of basic events in PSA. Model uncertainties are often related to assumptions behind the model. Completeness uncertainties are due to the portion of risk that is not explicitly included in PSA.

We think this categorization is helpful in explanation of the problem and may improve the transparency of uncertainty analyses. The distinction of various types of uncertainties can be used in a decision-making situation in order to identify the most suitable measures to reduce uncertainties. Examples of different types and sources of uncertainties are presented in Table 1 based on the authors' experience.

Table 1 - Examples of different types and sources of uncertainties

| Types and Sources of PSA uncertainties | | | |
|---|---|---|---|
| **Aleatory** | **Epistemic** | | |
| | **Parameter uncertainty** | **Model uncertainty** | **Completeness uncertainty** |
| *Random behavior* | *Values of parameters (fixed but poorly known)* | *Assumptions* | *Limitations* |
| Example:<br>• probability that a safety/relief valve sticks open after n-demands | lack of plant-specific data | imperfect knowledge on physical phenomena | limitation of PSA models |
| | deficiency of methods and/or data on hazard frequency | simplifications for constructing a manageable logic model of the plant | lack of resources |
| | imprecisely defined human errors and common cause failures | different models may be used for same processes | lack of knowledge (unknown unknowns) |

## 3 METHODS FOR ESTIMATION OF DIFFERENT TYPES OF UNCERTAINTIES

The uncertainty analysis aims at determining the uncertainty in results that derives from uncertainty in inputs. Many methods have been developed for arriving at aleatory models such as reliability block diagram, fault tree analysis, event tree analysis, Markov models, failure modes and effects analysis, and stochastic simulation. There are several mathematical methods that may be find in the literature for propagating epistemic uncertainties such as: analytical methods (method of moments), discrete probability distributions, sampling methods, interval arithmetic, fuzzy sets, probability bounds and Dempster–Shafer Theory (evidence theory). The methods differ from each other, in terms of characterizing the input parameter uncertainty and in kind of propagation from parameter level to model output level. Comprehensive overview of the methods is presented in [3]. Below we discuss the methods used for practical applications.

*Parameter uncertainty*

In PSA for a particular NPP, experts often have to resort to data outside their own power plant. This is because failures of many components are rare for a single power plant. Thus, relying solely on small-sample results leads to very high uncertainty levels in PSA risk measures, which makes the PSA results almost useless. On the other hand, since the designs and operating protocols are similar, it is feasible to look for data from other power plants and use them to reduce the uncertainty levels in PSA risk measures. A careful use of these different types of information sources would reduce the uncertainty levels in estimates.

Bayesian analysis is a natural framework to analyze different kinds of data. It is a relatively simple way to join different kinds of data and estimate the uncertainty levels for PSA model parameters. There are three main steps in Bayesian analysis: likelihood specification, prior distribution specification, and posterior calculation. The Bayesian analysis results in a posterior distribution for unknown model parameters and, therefore, provides a reliable level of uncertainty.

Several types of data are most often encountered: plant-specific data – taken from historical records for a specific power plant and generic data – gathered from another power plant of the same design. If the plant-specific sample for a particular component is large, then one should not add other data from different power plants. If there are no data at all for some component or system, then PSA analysis must rely on generic data. If, however, the plant specific sample is small and there are generic data available, then these two sources can be combined to decrease the uncertainty level about unknown PSA model parameters. In our application, we have only one data point for a mobile diesel generator and a mobile pump. However, there is a considerable scope of information on reliability of diesel generators and pumps in general. Thus, to support the PSA analysis, we collected failure rate estimates from various data sources and combined them with plant-specific data. The so-called empirical Bayes method [4, 5] can be used; however, it results in double use of data. We recommend (and did so in the calculation), looking at all of the collected estimates as a single data sample and performing full Bayesian analysis with non-informative prior distribution.

*Model uncertainty*

Sensitivity analysis techniques may be used to estimate the model uncertainty. Generally, sensitivity analyses are conducted by: (a) defining the model and its independent and dependent variables, (b) assigning probability density functions to each input parameter, (c) generating an input matrix through an appropriate random sampling method, (d) calculating an output vector, and (e) assessing the influences and relative importance of each input/output relationship. The literature contains details on the types of sensitivity analyses utilized for various modeling situations [6].

*Completeness uncertainty*

To estimate the completeness uncertainty, the analyst may add elements ('black box') of assumed limitation to the PSA model [3], [7]. It is the simplest way to connect inputs to output through the calculation code. It treats the system as a 'black box' so it does not explicitly use knowledge of the internal structure. We may be uncertain about the value or state of various inputs. These inputs include parameters of the new elements that form the boundary of the possible range of values. The value or status of output(s) would then be uncertain due to input uncertainties, as well as other sources of uncertainties besides the known inputs.

## 4 CONSIDERATION OF UNCERTAINTIES IN RISK-INFORMED DECISION-MAKING

### 4.1 Classification of uncertainty level

We propose to use the concept of variation factor for classification of uncertainty levels. This term was first used by K. Pearson in 1985 [8] as a dimensionless measure of dispersion of a random distribution. The variation factor for the purposes of uncertainty level classification is defined as follows:

$$K_V = \frac{\sigma}{|\mu|} \cdot 100\ \%, \tag{1}$$

where $\sigma^2$ is variance and $\mu$ is mathematical expectation of a random variable (in general, $\mu$ can be either positive or negative).

Having investigated the dispersion characteristics of a random variable, the authors developed the classification (scale) of uncertainty levels based on variation factor values (Table 2). Using this scale, one can set levels of uncertainties for both probabilistic and deterministic assessment.

Variation factor $K_V$ and, consequently, the level of uncertainty for probabilistic assessment should be defined based on the values of $\sigma^2$ and $\mu$ calculated using the PSA model.

Table 2 - Classification of uncertainty levels

| Class of uncertainty | Variation factor $K_V$ | Level of uncertainties |
|---|---|---|
| **Deterministic value** | $K_V = 0$ | Zero |
| **Random variable with finite variance** | $0 < K_V \leq 20\ \%$ | Low |
| | $20 < K_V \leq 50\ \%$ | Average |
| | $K_V > 50\ \%$ | High |
| **Random variable with infinite variance** | $K_V \to \infty$ | Extremely high |

For deterministic assessment, assuming uncertainty level for the final result and knowing its point value, it is possible to calculate the variance and to reconstruct a function of resultant distribution.

Such a transition from an expert judgement to a numeric characteristic of a random variable makes it possible to check compliance with specified criteria taking into account uncertainties in their values.

### 4.2 General procedure for making decisions on a set of acceptance criteria considering uncertainties

The classical integrated risk-informed decision-making (RIDM) process [1], [9] was supplemented by the uncertainty considerations and presented in Figure 1.

The uncertainty arises in two steps of RIDM:

- verifying the compliance of each alternative with an acceptance criterion;
- selection of the optimal/best decision.

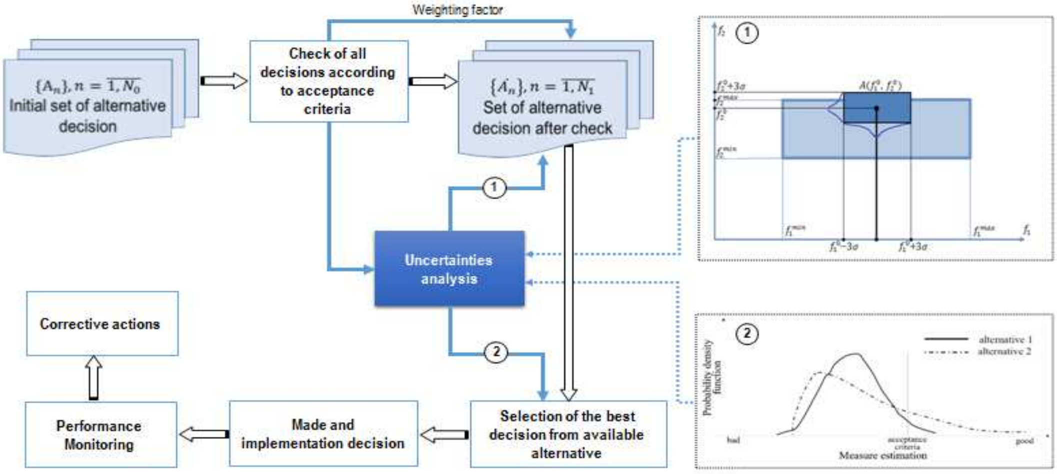


Figure 1 - RIDM process supplemented by uncertainty considerations

Comments on the RIDM process:

- The manner in which the mandatory requirements and the deterministic, probabilistic and other insights are weighted depends on the particular issue being addressed. In most cases the deterministic and probabilistic insights are in agreement (e.g. modification that improves the defense-in-depth will also lead to reduction in the risk). In other cases, greater weight is to be given to more conservative (deterministic) insights. The relative weights given to deterministic and probabilistic insights reflect the regulatory body's confidence in PSA.
- As can be seen from Figure 1 (1), when passing from point estimate of decision $A(f_1^0, f_2^0)$ to the interval estimate ($\{A_n\}$ – is a set of alternative decisions), its uncertainty area can exceed acceptance criteria, which shall be taken into account in making a decision. In this case, the following condition shall be fulfilled for each assessment of the decision (probabilistic and deterministic) $f_l^0 \pm 3\sigma_l \in [f_l^{\min}, f_l^{\max}]$, $l=\overline{1,L}$, set of acceptance criteria. In the process of such check, some of the alternative decisions are rejected, and as a result we have a truncated set of alternatives $\{\tilde{A}_n\}, n=\overline{1,N_1}$.
- The best decision from available alternatives is selected using the main three factors: validations of the decision compliance with the acceptance criteria (including '3σ'), results of the assessment by weighing factors and uncertainty class ($K_V$).

## 5 PRACTICAL APPLICATION FOR POST-FUKUSHIMA SAFETY MEASURE

In response to the 2011 Fukushima nuclear accident, safety re-assessments ('stress tests') were carried out at all EU nuclear power plants (Ukraine also joined the EU initiative on a voluntary basis). Different safety measures were on the table for consideration to ensure that the main safety functions would be performed in various hazards for VVER units. To validate the proposed methodology, we analyzed two options for long-term decay heat removal from the core: (1) feed the steam generator and restore service water supply from a mobile diesel-driven pump (MDP) accompanied with a 0.4 kV 'small' mobile diesel generator (MDG); (2) restore emergency power supply of one safety train with 6.3 kV 'big' mobile diesel generator.

The PSA model for generic VVER-1000 (SAPHIRE) developed by SSTC NRS was used for modelling [10]. The PSA model includes 14 event trees (ET), 168 fault trees (FT), and 581 basic events (BE). We modified the PSA model to estimate impact of both measures on the core damage frequency.

### 5.1 Parameter uncertainty (Bayesian assessment of reliability data)

Bayesian inference was used for estimation of the failure rate of mobile equipment. We have collected specific and generic data from various sources such as technical specifications for mobile equipment and available reliability databases for similar equipment. The generic data were failure rate mean or mode with either 0.05 and 0.95 quantiles, or error factor. The distribution in all cases was lognormal. Thus, for every data entry we can calculate lognormal distribution parameters $\mu$ and $\sigma$. Whenever the quantiles were present, lognormal distribution parameters were calculated by the following equations:

$$\sigma = \frac{1}{\Phi^{-1}(p_1) - \Phi^{-1}(p_2)} log\left(\frac{F^{-1}(p_1)}{F^{-1}(p_2)}\right)$$
$$\mu = F^{-1}(p_1) - \sigma \cdot \Phi^{-1}(p_1) \quad (2)$$

where $\Phi^{-1}(p)$ is a $p$-quintile of standard normal distribution, $p_1=0.05$ and $p_2=0.95$, $F^{-1}(p)$ are $p$-quintile of lognormal distribution.

In this way, we converted each entry of initial data to the parameters of lognormal distribution, i.e. two samples of parameters $\mu$ and $\sigma$ were obtained. Each set was treated as realizations of Gaussian random variables (first taking logarithms of sigma parameter) and Bayesian estimation procedure were carried out. Because only failure rate expectations were given for MDG and MDP, these specific entries could only be used to estimate $\mu$ parameter, but not $\sigma$. Posterior point estimates of mean and standard deviations for failure rates of the mobile diesel generator and mobile pump are provided in Table 2. Posterior predictive distributions for failure rates of the mobile diesel generator are presented in Figure 2.

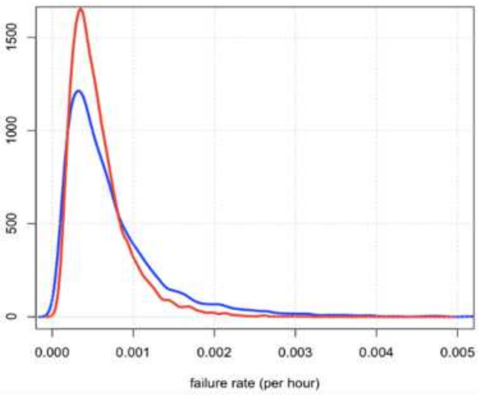


Figure 2 - Posterior predictive distribution for failure rate (blue line – failed to run mode, red line – failed to start)

| Equipment | Initial data for estimation (number of entries) | | Bayesian point estimates | | | |
|---|---|---|---|---|---|---|
| | | | Failed to run, 1/hr | | Failed to start, 1/hr | |
| | Failed to run | Failed to start | λ | σ | λ | σ |
| **MDG** | 9 | 12 | 7.37E-4 | 6.7E-4 | 5.76E-4 | 3.7E-4 |
| **MDP** | 1 | 5 | 3.3E-4 | 1.1E-3 | 1.2E-4 | 2.0E-4 |

Table 2 - Posterior point estimates of mean and standard deviations for failure rates

### 5.2 Model uncertainty (human reliability analysis (HRA))

Current HRA methodologies that are commonly used in the nuclear power industry are not designed to accommodate the evaluation of some tasks associated with the use of portable equipment, such as retrieving equipment, and temporary power and pipe connections. These assumptions are a huge source of model uncertainty.

The method for estimating the component of the human error probability (HEP) associated with the deployment of portable equipment [14] was used to consider the model uncertainty. This method is intended for application to a variety of hazard risk assessments. The method is a simplified process that applies adjustment factors to represent the impact of performance factors (PFs) on a hazard-specific basis on a base HEP. The impacts of each PF are tracked in an HRA decision tree and the combined impact of all decision branches, which characterize the implementation conditions for the site being evaluated and determine the scenario-specific HEP. We have developed an HRA decision tree for an external hazard (earthquake). The decision tree presented in Figure 3 addresses the conditions that were anticipated to be the most relevant to mobile equipment deployment in external hazard conditions. Available time window within which the action must be performed to achieve the function provided by the mobile equipment was considered. For example, this time was measured from the instant the hazard impacts the plant to the instant at which the MDP must be delivering water to its loads.

### 5.3 Completeness uncertainty (limitation of the PSA model)

Tabular functions were used to set the input parameters for new basic events ('black box') added to the fault trees presenting the equipment performing safety functions in case of hazards. The added basic events cover the existing modelling limitations for passive elements in PSA (e.g. pipe connections for MDP, feeding line, flexible hoses) that also may be affected by the hazards. Existing fragility curves were considered to estimate the parameters.

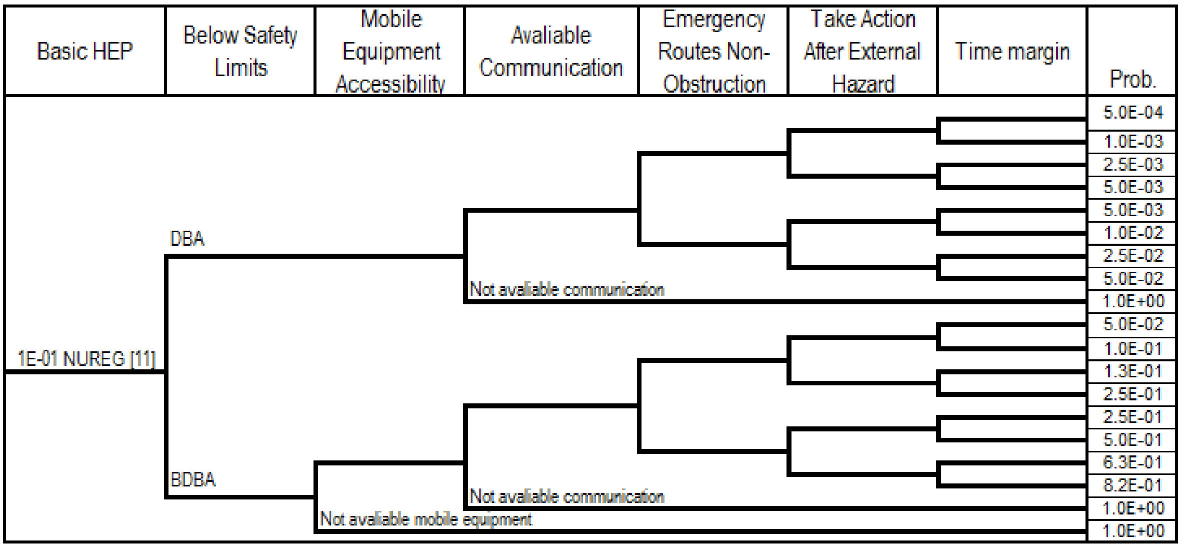


Figure 3 - Human Reliability Analysis decision tree

## 5.4 Results of calculations and decision- making

The modified PSA models were run repeatedly with different assumptions. As a result of calculations, the value of point estimation, mean and standard deviation, and probability density function (PDF) were obtained. PDF for each calculation of both alternatives shown in Figure 4.

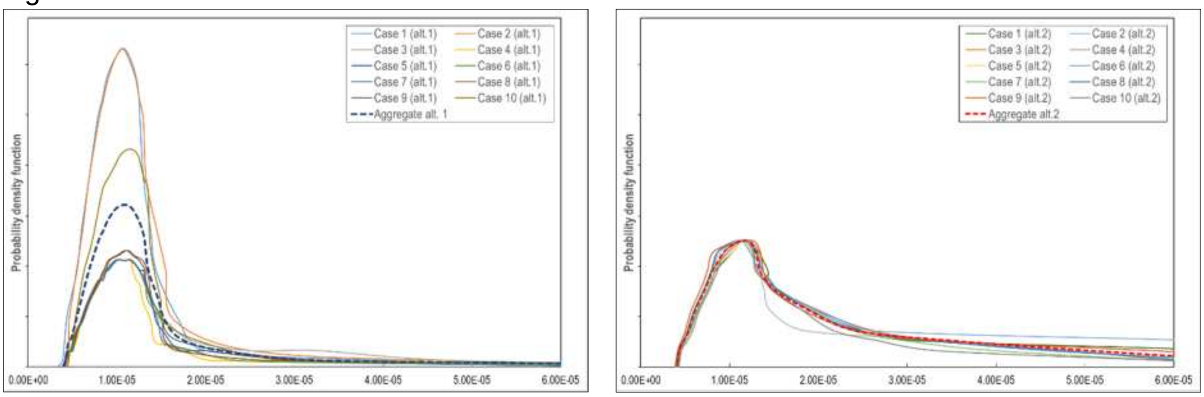


Figure 4 - Probability density function for both alternatives

Then the results were processed and aggregate functions were obtained with the mean and standard deviation for both options (Figure 5).

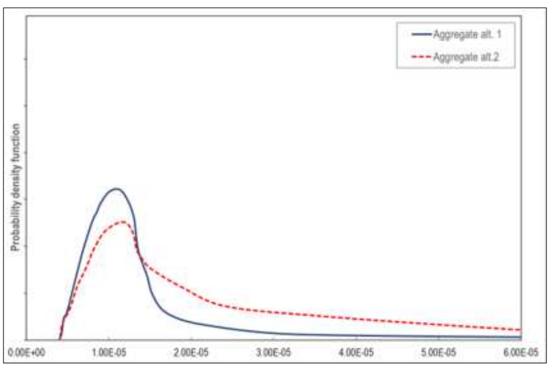


Figure 5 – Resulting probability density function for both options

As shown in Figure 5, the mean values for both alternatives satisfy the safety criteria (CDF) 1.0E-04 1/year for existing NPPs, including ‘margin’ of 3σ [12], [13]. CDF for alternative (1) less than for alternative (2). Moreover, the estimated $K_v$ for both alternatives show *average* level of uncertainty for alternative (1) and *high* for alternative (2) according to the proposed scale. High-level uncertainty of alternative (2) is caused by huge sources of uncertainties:

estimation of HEP, difficulties with transportation and deployment of ‘large’ MDG, reliability of one safety train after hazards etc. Therefore, on the basis of our calculations, we proposed option (1) as the best decision.

## 6 CONCLUSIONS

In this paper, we have presented our view on the methodology for estimation of PSA uncertainties and practical treatment of uncertainties in risk-informed decision-making. Our starting point is that PSA should provide evidence behind the results obtained. This is important because the role of risk assessment in making decisions is increasing, so the uncertainties of analyses should be clearly understood and properly considered.

We emphasize the need of an extensive qualitative analysis for all types of uncertainties that are recognized. There are different mathematical methods for estimation and propagation of aleatory and epistemic uncertainties. Having examined the dispersion characteristics of a random variable, we developed the classification (scale) of uncertainty levels based on variation factor values, which can be used both for probabilistic and deterministic assessment.

The classical integrated RIDM process was supplemented by uncertainty considerations. We assume that uncertainty arises during RIDM when compliance of each alternative is verified against an acceptance criterion and selection the best decision among alternatives. The proposed approach was applied to analyze alternatives of post-Fukushima safety measures to ensure the heat removal from the core in the events of hazards.

We believe that research in this area should be continued to ensure confidence in the PSA results and to provide a solid ground for risk-informed decision-making.

**References:**


1. Guidance on the Treatment of Uncertainties Associated with PRAs in Risk-Informed Decision-Making (NUREG-1855). Technical Report, US Nuclear Regulatory Commission, Washington, D.C.
2. Lessons of the Fukushima Daiichi Accident for PSA. ASAMPSA_E. Technical Report ASAMPSA_E / WP30 / D30.2 / 2015-08. Reference IRSN PSN-RES/SAG/2015-00025.
3. Enrico Zio and Nicola Pedroni, Methods for Representing Uncertainty. A Literature Review.
4. George Casella. An Introduction to Empirical Bayes Data Analysis. American Statistician 39:83-87. 1985.
5. L. Carlson et al., T-Book-Reliability Data of Components in Nordic Nuclear Power Plants', ATV Office, Vattenfall AB, S-162, 87 Vallingby, Sweden, 1987.
6. A Review of Techniques for Parameter Sensitivity Analysis of Environmental Models. Environmental Monitoring and Assessment. Kluwer Academic Publishers. 1994.
7. V. Kreinovich, S. Ferson. A New Cauchy-Based Black-Box Technique for Uncertainty in Risk Analysis. University of Texas at El Paso, 2-1-2003.
8. Pearson, Karl. (1895), “Skew Variation in Homogeneous Material”, Philosophical Transactions of the Royal Society of London, A, Vol. 186, pp. 343-414.
9. Framework for an Integrated Risk Informed Decision Making Process, Report by the International Nuclear Safety Group, Vienna, International Atomic Energy Agency, 2011, 24 p. (INSAG Series, ISSN 1025–2169; No. 25; ISBN 978–92–0–114110–1).
10. Scientific and Research Work. Development of a PSA model for generic VVER-1000 (SAPHIRE). Model and Technical Description. SSTC NRS. Ukraine, 2010.
11. A. Kolaczkowski et. al (U.S. Nuclear Regulatory Commission). “Good Practices for Implementing Human Reliability Analysis”. NUREG-1792. April, 2005.
12. O. Dybach. Assessing Probability of Exceeding the Safety Criteria According to Probabilistic Safety Analysis. Nuclear and Radiation Safety, Kyiv, No.4 (64), 2015.
13. O. Dybach. Consideration of Probabilistic Assessment Uncertainties in Risk-Informed Decision-Making. Nuclear and Radiation Safety, Kyiv, No.1 (70), 2016.

14. Don E. MacLeoda*et al.Simplified Human Reliability Analysis Process for Emergency Mitigation Equipment (EME) Deployment. Probabilistic Safety Assessment and Management PSAM 12, June 2014. Honolulu, Hawaii.