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A framework to estimate task opportunities from the operational experience of domestic nuclear power plants

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ABSTRACT

Since one of the most important issues in operating socio-technical systems is to enhance their safety through reducing the likelihood of human errors, it is prerequisite to secure reliable human performance data clarifying when and why human operators make an error. In this regard, many researchers tried to calculate an HEP (Human Error Probability) from operational experience data based on its traditional definition (i.e., HEP = number of errors observed/number of task opportunities for error). Accordingly, most of existing HEPs mainly based on the number of task opportunities being estimated from routine or periodic tasks that are usually performed in a full power condition with fixed time intervals. In contrast, calculating an HEP for a task being conducted in an off-normal condition is relatively seldom because it does not happen with a fixed time interval. For this reason, in this study, a novel framework is proposed, which can be used to estimate the number of task opportunities in terms of off-normal tasks from the operational experience of domestic NPPs. Although the proposed framework still has a couple of limitations, it could be a good starting point not only to enrich the ability of HEP calculation from the operational experience data but also to provide a reference information for HEPs obtained from other sources of information (e.g., full-scope simulators).

1. Introduction

One of the most substantial issues in operating socio-technical systems, such as NPPs (Nuclear Power Plants), chemical/petrochemical plants, and commercial airplanes, is to secure their operational safety because any incidents and/or accidents could be catastrophic for the public health and living environment (List25, 2015). Therefore, it is natural that most organizations running such socio-technical systems want to continuously confirm whether or not their safety (or risk) level is acceptable or tolerable. In this regard, many kinds of risk quantification techniques have been developed for several decades, and a PSA (Probabilistic Safety Assessment) or PRA (Probabilistic Risk Assessment) is widely used especially in the nuclear sector (Mosleh, 2014; H. Kim et al., 2015; Lee et al., 2015; Duy et al., 2016).

The basic idea of the PSA technique is to quantify all the risk contributions of plausible initiating events that can lead the status of an NPP toward hazardous consequences (e.g., a core damage or a large release of radioactive material). In general, such initiating events are classified into internal events (e.g., the failure of safety critical systems) and external events (e.g., earthquake, typhoon, flood, and high wind). However, since the diverse spectrum of human actions is also attributable to the safety of the socio-technical systems (Akyuz, 2015; Evans, 2011; Hughes et al., 2015; Kim and Kim, 2015; Pasquale et al., 2015), it is indispensable to incorporate the likelihood of human errors (i.e., HEPs; Human Error Probabilities) to the framework of the PSA in a systematic manner (Vaurio, 2009; Farcasiu and Nitoi, 2015). To this end, not only HEPs but also other information including the effect of error-forcing contexts (e.g., PSFs; Performance Shaping Factors) on the associated HEPs should be available to HRA practitioners (for convenience, the term of *HRA data* is used hereafter for representing all kinds of data necessary for conducting an HRA).

For this reason, many researchers have spent huge amount of efforts in providing HRA data to HRA practitioners, of which the contents are collected from several sources of information such as (1) operational experience data based on event reports (e.g., maintenance reports, periodic test reports, near miss reports, and incident reports), (2) full-scope and/or partial-scope simulators, (3) laboratory experiments, (4) expert judgments, and (5) interviews with subject matter experts (Hirschberg and Dang, 1996; IAEA, 1998; Isaac et al., 2002; NEA, 2008). Of them, the use of simulators (especially full-scope simulators) is a main stream in collecting HRA data because they allow HRA practitioners to

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directly observe the variability of human performance with respect to diverse error-forcing contexts (IAEA, 1995a). In addition, if we recall the fact that most initiating events being considered in the PSA have an extremely rare frequency, it is unrealistic to obtain sufficient HRA data from other information sources except full-scope simulators (Chang and Lois, 2012; Lederman, 1988; Stanton, 2005). Subsequently, for several decades, many HRA databases have been developed on the basis of human performance data collected from full-scope simulators (Chang et al., 2014; Moieni et al., 1994; Park and Jung, 2007; Reece et al., 1994).

However, it should be emphasized that HRA data obtained from the operational experience of NPPs are needed in parallel with those from full-scope simulators due to a couple of issues. The first one is that the use of full-scope simulators is one of the alternating solutions because operational experience data are not sufficient for securing necessary HRA data. In other words, if the sufficient amount of reliable operational experience data (e.g., near miss or incident reports) is available, it is possible to secure more realistic HRA data reflecting actual working environments.

The second issue is the reality of HRA data collected from full-scope simulators. According to existing studies, it seems that the overall tendencies of human behaviors being observed from simulated situations properly reflect those from real situations (Gibson et al., 2006; Hirschberg and Dang, 1996; Park et al., 2004; Park and Jung, 2007; Takano and Reason, 1999). However, it is also true that the level of stress and/or reality to be felt by human operators under simulated situations is different from those of real situations. This means that it is still careful to directly use HRA data gathered from full-scope simulators because of a certain bias from the real situations (Criscione et al., 2012; IAEA, 1995a; NEA, 1988). In this case, if we are able to use HRA data observed from real situations (i.e., operational experience data), it can be used as reference information to clarify the difference and/or similarity of human performance data collected from full-scope simulators.

The last issue is that, from the point of view of conducting an HRA, HRA data pertaining to the performance of routine tasks under a full power condition (e.g., periodic tests and maintenances) are also necessary. For example, in terms of the PSA, the IAEA (1995b) has clearly stated that an HRA should quantify the likelihood of human errors with respect to the following three task types: (1) *Type A* task includes human actions associated with maintenance and testing that can degrade the availability of a certain component or system, (2) *Type B* task contains human actions directly resulting in the occurrence of initiating events (e.g., an unexpected reactor shutdown due to a human error in carrying out a periodic test procedure), and (3) *Type C* task involves various kinds of required actions institutionalized in AOPs (Abnormal Operating Procedures) and EOPs (Emergency Operating Procedures), which are crucial for responding and/or mitigating the progression of initiating events. In this regard, although full-scope simulators are very useful for collecting HRA data related to *Type C* tasks, it is still necessary for HRA practitioners to access those of *Type A* and *Type B* tasks, which are not able to sufficiently gather from the full scope simulators.

In this paper, in order to resolve the abovementioned issues, a novel framework is proposed, which allows us to systematically estimate the opportunity of *Type C* tasks from the operational experience of domestic NPPs. To this end, it is necessary to distinguish the category of off-normal tasks, of which their opportunity can be soundly estimated. In this regard, in total 193 incident reports that have been accumulated over 14 years (i.e., from January of 2002 to December of 2013) are reviewed in detail. As a result, it is revealed that the opportunity of *Type C* tasks can be reasonably estimated if an error has occurred during the performance of either abnormal tasks being described in AOPs or emergency tasks being prescribed in EOPs.

The structure of this paper is organized as follows. First, in order to clarify the background information of this study, the reason for estimating the opportunity of *Type C* tasks is described based on the characteristics of off-normal tasks in Section 2. After that, in Section 3, an underlying concept that should be considered in calculating the opportunity of *Type C* tasks is outlined. Next, a brief explanation on a novel framework is given in Section 4, which can be used to determine the opportunity of *Type C* tasks from the operational experience data of domestic NPPs. Finally, the contribution and limitation of this study are discussed with a concluding remark in Section 5.

2. Basic idea for HEP quantification

As briefly outlined in the previous section, it is important to collect HRA data from the operational experience data of NPPs. From this concern, a couple of HRA databases have been developed through an extensive review of operational experience data across diverse industrial sectors. Typical HRA databases include CAHR (Connectionism Assessment of Human Reliability), HERA (Human Event Repository and Analysis), and CORE (Computerized Operator Reliability and Error) (Hallbert et al., 2006; Kirwan et al., 1997; Sträter, 2000). More recently, Preischl and Hellmich (2013) calculated the HEPs of 37 tasks based on the operational experience data of German NPPs. In this regard, although several quantification techniques are available for quantifying HEPs based on operational experience data (Reer, 2004; Reer and Sträter, 2014), most of the existing HRA databases have quantified an HEP by using a very straightforward formula as given in Eq. (1):

$$\text{HEP of the } i\text{th task } (\text{HEP}_i) = \frac{m_i}{n_i} \tag{1}$$

Here, m_i and n_i denote the number of human errors observed from the performance of the ith task and the number of opportunities for the performance of the ith task, respectively. Actually, this formula is a direct reflection of the traditional assumption such that human operators will show similar HEPs if they have to accomplish identical tasks under a specific task environment (Fleishman and Buffardi, 1999; Li and Wieringa, 2000; Reason, 2000; Stassen et al., 1990). In this light, Preischl and Hellmich (2013) stated that "[...] if an individual is randomly selected from a population, the probability for making an error in performing a certain task under given conditions at a given point of time depends on the individual's error probability, and thus becomes uncertain. This uncertainty [...] can be modeled by considering HEP_i as a random variable with a distribution concentrated on the interval [0,1]" (p. 151). Therefore, if we are able to properly estimate the opportunity of a certain task (i.e., n_i) from operational experience data, it is strongly expected that the corresponding HEP can be calculated in a reliable manner. From this perspective, Table 1 exemplifies how to estimate a task opportunity from the operational experience data of a nuclear reprocessing plant (Taylor-Adams and Kirwan, 1997).

As can be seen from Table 1, an error has occurred because a human operator put radioactive materials into a wrong waste flask. Here, since there has been no such human error for four years of operation, the corresponding task opportunity can be estimated as: 20 (loading tasks/week) × 26 (weeks/year) × 4 (years) = 2080 loading tasks. This means that the HEP of the loading task can be calculated as 4.81E−4. Accordingly, it is promising to assume that the key step of an HEP quantification is to reasonably estimate a task opportunity (i.e., n_i). This means that the very first step is to distinguish the catalog of tasks, of which the opportunity can be properly estimated. To this end, the operational experience data of domestic NPPs, which are stored in a NEED (Nuclear Event Evaluation Database) are reviewed in detail.