Bayesian estimator of human error probability based on human performance data

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Abstract: A Bayesian method for estimating human error probability (HEP) is presented. The main idea of the method is incorporating human performance data into the HEP estimation process. By integrating human performance data and prior information about human performance together, a more accurate and specific HEP estimation can be achieved. For the time-unrelated task without rigorous time restriction, the HEP estimated by the common-used human reliability analysis (HRA) methods or expert judgments is collected as the source of prior information. And for the time-related task with rigorous time restriction, the human error is expressed as non-response making. Therefore, HEP is the time curve of non-response probability (NRP). The prior information is collected from system safety and reliability specifications or by expert judgments. The (joint) posterior distribution of HEP or NRP-related parameter(s) is constructed after prior information has been collected. Based on the posterior distribution, the point or interval estimation of HEP/NRP is obtained. Two illustrative examples are introduced to demonstrate the practicality of the aforementioned approach.

Keywords: human error probability (HEP), human performance data, human reliability, probabilistic safety assessment, Bayesian approach.

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1. Introduction

System safety may be degraded by human errors seriously. Some catastrophic accidents and/or incidents, such as three mile island and piper alpha accidents, were caused by human errors. Therefore, to keep system safe, it is necessary to assess the human-related risk, namely, to analyze the human error and its consequences. Nowadays, the human reliability analysis (HRA) has been one of indispensable parts of the probabilistic safety assessment (PSA) project [1].

PSA is quantitative in nature and has the ability to provide dangerous scenarios’ probabilities. Therefore, HRA methods must be able to estimate human error probability (HEP) to satisfy PSA. The topic on HEP quantification has attracted many researchers’ attention from the 1960’s. Various HRA methods, such as technique for human error rate prediction (THERP) [2], human error assessment and reduction technique (HEART) [3], and cognitive reliability and analysis method (CREAM) [4], were presented, and most of them are able to quantify HEP. In recent years, some new methods were designed [5–8]. Moreover, some researchers show interests in some aspects about HEP estimation, such as the analysis of dependence between human actions or human failure events [9]. The aforementioned HEP quantification methods belong to the category of HRA cum the performance shaping factor (PSF). The term PSF refers to the characteristic of context or operator influencing task performance. In the category of HRA cum PSF, HEP may be less specific [10].

According to [11], there are task-defined, time-defined and context-defined HRA methods. In task-defined methods, HEP is determined just by the task. THERP is the most representative task-defined method, and human-related tasks are grouped according to their common characteristics about it. In fact, each group is the generic description of the common task as well as its HEP. The specific task is matched with one of the generic descriptions, and then the HEP is determined accordingly. Finally, HEP must be adjusted by some PSFs, such as the level of training and experiences, and the quality of human-machine interface.

In time-defined methods, HEP is determined only by the time available. It has been shown that operator’s response time has a lognormal or Weibull distribution [12]. The form of the human error is non-response made within the
minimum time available, so HEP is non-response probability (NRP). NRP at time $T$ is calculated by

$$\text{NRP}(T) = \int_{-T}^{\infty} f(t)dt$$  \hspace{1cm} (1)

where $f(t)$ is the probability density function (PDF) of the response time. Obviously, NRP is becoming smaller as the time available gets longer. Finally, NRP is zero with infinite time available. It means that an operator has the ability to make proper response with probability 1.

The implicit idea of context-defined methods is that the human error is forced by the context [13]. Therefore, it can be concluded that HEP is determined by context. The context means the surroundings of the operator and can be divided into various human performance-related factors. CREAM, holistic decision tree [11] and a technique for human event analysis (ATHEANA) [14] are three representatives of context-defined methods.

These methods have been applied to the PSA of many engineering systems successfully. However, there are still some problems unsolved. Firstly, for different tasks with the same generic description or under the same context, there are no differences among their HEPS. It is not always right obviously. Secondly, human performance data are not utilized appropriately during the process of HEP estimation. Similar with reliability data, human performance data are the number of error occurrences, or the response time. The prevailing viewpoint that human performance data are of little value for the extremely low error likelihood is a misleading. For example, in some situations, the operator executed a task 1 000 times repeatedly with only one error occurrence. Then, (1 000,1) belongs to human performance data certainly. But yet if the operator executed the task repeatedly without any error, do the zero-error data of (1 000,0) belong to human performance data or not? The answer is true. From the viewpoint of a statistician, there is no reason to reject the zero-error data from the process of HEP estimation. For one specific human-related task, human performance is reflected by human performance data directly. Therefore, human performance data must be incorporated into the HEP estimation process by an appropriate means.

A novel procedure for HEP estimation is presented in this paper. The idea of a Bayesian approach is introduced to assist the HEP estimation. According to the Bayesian procedure, the data about human errors and other information are integrated to get a more specific and accurate HEP. In the following sections, the Bayesian approach will be overviewed briefly, and then the procedure of the HEP estimation is discussed in detail, and the advantages, disadvantages and the potentials of practical application of the novel procedure are discussed finally.

2. Brief overview on Bayesian approach

Bayesian approach is a data analysis tool derived from the principles of Bayesian inference [15]. The well-known Bayesian formula is

$$\pi(\theta|\text{data}) = \frac{f(\text{data}|\theta)\pi(\theta)}{\int f(\text{data}|\theta)\pi(\theta)d\theta}$$  \hspace{1cm} (2)

where $\text{data}$ is the observed data from the field study or simulator experiments, which is conditioned independent and identically-distributed. It is sampled from the population $X$. $\theta$ is the parameter (or vector) of the PDF of $X$, $\Theta$ is the space of parameter $\theta$, $\pi(\theta)$ and $\pi(\theta|\text{data})$ are the prior and posterior density function of $\theta$ respectively, and $f(\text{data}|\theta)$ is the joint density function of $\text{data}$. There are no differences between the form of $f(\text{data}|\theta)$ and the likelihood function $L(\theta|\text{data})$. As can be seen from (2), $\pi(\theta|\text{data})$ is proportional to the product of $\pi(\theta)$ and $f(\text{data}|\theta)$, namely, $L(\theta|\text{data})$. Therefore, it can be concluded that the posterior information on the parameter (or vector) $\theta$ is the synthesis of observed data and prior information.

The Bayesian approach has been widely used in reliability engineering and PSA for parameters estimation [16,17]. However, there are only a few works on the application of the Bayesian approach to HEP quantification. In [10], the feasibility of the employment of the Bayesian method in HRA was demonstrated. However, the detailed HEP quantification process via the Bayesian approach is lack.

3. Procedure of HEP estimation via Bayesian approach

In some Bayesian reliability assessment methods, observed data (e.g., field data) are collected to construct the likelihood function, and other data (e.g., historical data or expert judgments) are used as prior information sources to assist the construction of prior distribution. Similarly, the prior distribution of the parameter about HEP should be constructed based on the prior data, and the likelihood function is based on human performance data. They are integrated to get a more accurate and specific HEP. The Bayesian HEP estimation procedure shown in Fig. 1 includes five steps, which are prior information collection, prior distribution of the parameter(s) of HEP/NRP construction, human performance data collection and its likelihood function construction, posterior distribution of the parameter(s) of HEP/NRP construction, and derivation of HEP/NRP estimation, respectively.

The term human reliability is usually defined as the probability that an operator will correctly perform some
As mentioned above, Bernoulli human performance data belong to the category of Bernoulli success/failure data. There exist two kinds of human performance data, which are error occurrences and opportunities to perform tasks. The time-unrelated task is restricted by time available rigorously. And human performance data are like lifetime data, which are operator’s response or non-response time.

### 3.1 HEP assessment under the time-unrelated task

As mentioned above, Bernoulli human performance data \((n, e)\) are collected under the time-unrelated task, where \(n\) is the number of opportunities to error occurrences, and \(e\) is the number of error occurrences. The HEP is used as the prior mean value of \(e\) with respect to \(n\) for many tasks because there are not many opportunities to carry them out repeatedly. Moreover, \(e\) may be zero because of the high likelihood of human error, and then the HEP is zero. It is not reasonable to accept a zero-HER as the HEP obviously. Therefore, the prior information should be collected and utilized to adjust the HER.

#### 3.1.1 Collection of prior information and human performance data

As mentioned above, some HRA methods (e.g., THERP and CREAM) have been applied to many different engineering systems successfully. They are aggregations of the knowledge and experiences of a large number of scientists and engineers, and are of great engineering value. Therefore, the HEPs estimated by them are collected as prior information. That is to say, the prior HEP is obtained by some existing methods firstly. Sometimes, the prior HEP can also be elicited by expert judgments.

Human performance data can be collected from simulators or real systems. The former is named as simulation data, and the latter is field data which can be acquired by observing the process of task performance, or can be extracted from historical accident/incident materials.

#### 3.1.2 Construction of prior distribution

For Bernoulli data \((n, e)\), the number of error occurrences \(e\) has a binomial density function as follows:

\[
f(e, n; \lambda) = C^n_e \lambda^e (1 - \lambda)^{n-e}. \tag{3}
\]

It is reasonable to assume that \(\lambda\) has a beta prior density function \([10]\). Therefore, we can say its posterior density function is beta according to the principle of the conjugate family. The beta density function is

\[
\pi(\lambda; \alpha, \beta) = \frac{\Gamma(\alpha + \beta)}{\Gamma(\alpha)\Gamma(\beta)} \lambda^{\alpha-1} (1 - \lambda)^{\beta-1}
\]

\[
0 \leq \lambda \leq 1, \quad \alpha > 0, \quad \beta > 0. \tag{4}
\]

The prior HEP is used as the prior mean value of \(e\). It is assumed that there are no prior information sources other than it. Therefore, the prior density function of \(\lambda\) can be constructed according to the principle of constrained non-informative (CNI) distribution \([18]\). \(\lambda\) has a CNI prior density function as follows:

\[
\text{CNI,Beta}(\lambda) = \frac{c \exp(b\lambda)}{\sqrt{\lambda(1 - \lambda)}}, \quad 0 < \lambda < 1 \tag{5}
\]

where \(c\) and \(b\) are the parameters of the informal beta density function. Thus, we have

\[
\int_{0}^{1} \lambda \frac{c \exp(b\lambda)}{\sqrt{\lambda(1 - \lambda)}} d\lambda = \lambda_{\text{prior}}. \tag{6}
\]

The integral of the probability distribution function is 1. We have

\[
\int_{0}^{1} \frac{c \exp(b\lambda)}{\sqrt{\lambda(1 - \lambda)}} d\lambda = 1. \tag{7}
\]

In theory, \(b\) and \(c\) can be got by working out (6) and (7) jointly. Unfortunately, the two equations are not analytically traceable and must be solved numerically. The relationship between \(\lambda_{\text{prior}}\) and the two parameters was figured out in \([18]\). As an informal beta function, \(\text{CNI,Beta}(\lambda)\) is not suitable for Bayesian inference. Therefore, it should be modified as a formal beta function by using the moment-matching principle as follows:

\[
\begin{align*}
\int_{0}^{1} \lambda \frac{c \exp(b\lambda)}{\sqrt{\lambda(1 - \lambda)}} d\lambda &= \lambda_{\text{prior}} = \frac{\alpha}{\alpha + \beta} \\
\int_{0}^{1} \lambda^2 \frac{c \exp(b\lambda)}{\sqrt{\lambda(1 - \lambda)}} d\lambda &= \frac{\alpha \beta}{(\alpha + \beta)^2(\alpha + \beta + 1)}
\end{align*}
\tag{8}
\]
where the two equations are the first and the second order moments respectively, and $\alpha$ and $\beta$ are the parameters of the prior beta density function $\text{Beta}(\lambda; \alpha, \beta)$.

3.1.3 Posterior density function construction and HEP assessment

As mentioned above, $\lambda$ has a posterior beta distribution. The differences between prior and posterior distribution only exist in the two parameters. The posterior parameters of $\alpha_1$ and $\beta_1$ can be determined easily with human performance data $(n, e)$ as follows:

$$
\alpha_1 = \alpha + e, \quad \beta_1 = \beta + n - e. \quad (9)
$$

Usually the posterior mean value of $\lambda$ is adopted as the final point estimation of HEP, i.e.,

$$
\overline{\text{HEP}} = E^{\text{Beta}(\lambda; \alpha_1, \beta_1 | n, e)}(\lambda) = \frac{\alpha_1}{\alpha_1 + \beta_1} = \frac{\alpha + e}{\alpha + \beta + n} \quad (10)
$$

where $\text{Beta}(\lambda; \alpha_1, \beta_1 | n, e)$ is the posterior density function of $\lambda$. $E^{\text{Beta}(\lambda; \alpha_1, \beta_1 | n, e)}(\lambda)$ means to evaluate the mean value of $\lambda$ with $\text{Beta}(\lambda; \alpha_1, \beta_1 | n, e)$. The confidence interval of HEP can be estimated accordingly. For example, 95%-fractile of $\lambda$ can be used as the upper bound and 5%-fractile as the lower bound of HEP’s confidence interval, respectively. The $p$-fractile of $\lambda$, $\lambda_p$, can be derived from the following equation or by some mathematical tools (e.g., Matlab).

$$
\int_0^{\lambda_p} \text{Beta}(\lambda; \alpha_1, \beta_1 | n, e) d\lambda = p
$$

3.1.4 Case study

The diesel engine is one of the most important subsystems of the diesel electric submarine. It provides power for the electromotor to generate electricity. The warm operation, namely, to rotate the engine manually at low speed for some minutes, must be executed before starting up the engine. Otherwise, the engine might be injured after startup. Sometimes, the operator may start up the engine without the warm operation. It belongs to the error of “forgetting the warm operation”, and is matched with “Omitting a step or important instruction from a formal or ad hoc procedure” in THERP, with the nominal HEP of 0.003 and the error factor (EF) of 3 [2]. The work context of the submarine is little supportive to human performance. Therefore, it is reasonable to adopt the upper bound as prior HEP, which is the product of nominal HEP and EF. From some statistical materials, we collect human performance data (511, 6), and it means that there are 511 identical operations and 6 error occurrences.

According to the above procedure, the prior density function $\text{Beta}(0.484 6, 53.359 8)$ and posterior density function $\text{Beta}(6.484 6, 558.359 8)$ is obtained. Based on the posterior density function, we get the final HEP point estimation

$$
\overline{\text{HEP}} = \frac{6.484 6}{6.484 6 + 558.359 8} = 1.15 \times 10^{-2}.
$$

The curves of prior and posterior density functions are shown in Fig. 2. The final HEP estimation, namely, the posterior mean value of HEP is moved to the right of the prior meaning value of HEP because of introduction of human performance data (511, 6). If 5% and 95% fractiles are used as the lower and upper bounds of the HEP confidence interval, then the final HEP interval estimation is $[5.20 \times 10^{-3}, 1.97 \times 10^{-2}]$.

3.2 NRP assessment under the time-related task

Under the time-related task, the operator must make proper response to some emergency situations within a required minimum of time. Therefore, HEP is the NRP within time $t$ NRP($t$).

As mentioned above, the response time $t$ has a Weibull or lognormal density function, and there are minor differences on the goodness-of-fit between the two distributions. In reliability engineering, the lifetime data having a Weibull distribution means that the system must fail as time approaches infinity. Similarly, the response time having a Weibull distribution means that the operator has the ability to make correct decision with probability of 1 as time approaches infinity, namely, NRP($\infty$) = 0.

The density function of 3-parameters Weibull distribution is

$$
\text{pdf}(t | \alpha, \beta, \mu) = \frac{\beta}{\alpha} \left( \frac{t - \mu}{\alpha} \right)^{\beta - 1} \exp \left[ - \left( \frac{t - \mu}{\alpha} \right)^{\beta} \right] \quad (11)
$$
where $\alpha > 0$ is a scale parameter, $\beta > 0$ is a shape parameter, and $\mu$ is a location parameter, namely, minimum response time. The operator must collect information pertinent to the situation before the suitable decision is made, and is unable to make response at the time $t = 0$. That is to say, the minimal response time is greater than zero, and it can be estimated by analyzing the task or interviewing with the operator. Once the minimal response time $\mu$ is known, the 3-parameters Weibull distribution will be simplified to a 2-parameters distribution. Without loss of generality, let $\mu$ be zero, and then the NRP at time $t$ is

$$NRP(t) = \exp \left[ - \left( \frac{t}{\alpha} \right)^{\beta} \right].$$  \hspace{1cm} (12)

Similar with the hazard function, the response function (RF) of the operator can be defined as

$$RF(t) = \frac{\beta}{\alpha} \left( \frac{t}{\alpha} \right)^{\beta - 1}. \hspace{1cm} (13)$$

It is either the number of operators who made proper responses or the number of proper responses made by an operator.

As can be seen from (12), the curve of NRP($t$) is determined by both $\alpha$ and $\beta$. As it is difficult to construct the distribution of NRP directly, the joint distribution of $(\alpha, \beta)$ is discussed instead. In the engineering application, the information (e.g., average or minimum response time) is easy to collect. However, it is not suitable to be the prior information of $(\alpha, \beta)$. Therefore, the parameters $(\alpha, \beta)$ must be transformed. According to [19], the Weibull density function (12) can be modified as one function in the form of $(t_R, \beta)$ by replacing $\alpha$ with the specified response time $t_R$.

$$pdf(t_R|\beta) = \begin{cases} A_0 \exp[-(a_0 t_R)^{-\beta}], & \beta \leq 1 \\ A_1 \exp[-(a_1 t_R)^{-\beta}], & \beta > 1 \end{cases} \hspace{1cm} (16)$$

where

$$a_0 = \frac{\Gamma(\beta^{-2} - \beta^{-1})}{t_{R,prior} \Gamma(\beta^{-2})}, \quad a_1 = \frac{\Gamma(1 - \beta^{-1})}{t_{R,prior}},$$

$$A_0 = a_0^{-\beta^{-1}} \beta t_{R}^{-\beta^{-1}+1}, \quad A_1 = a_1^{-\beta^{-1}} \beta t_{R}^{-\beta^{-1}+1}$$

and $t_{R,prior}$ is the prior mean value of the specified time $t_R$.

$\beta$ has a uniform distribution, and the density function is

$$pdf(\beta) = \frac{1}{\beta_2 - \beta_1}, \quad \beta_1 \leq \beta \leq \beta_2. \hspace{1cm} (17)$$

Then, the joint prior density function of $(t_R, \beta)$ is

$$pdf(t_R, \beta) = pdf(t_R|\beta)pdf(\beta) = C_0 I_{[0,1]}(\beta) + C_1 I_{(1,\infty)}(\beta) \hspace{1cm} (18)$$

where

$$C_0 = \frac{a_0^{-\beta^{-1}} \beta t_R^{-\beta^{-1}+1} \exp[-(a_0 t_R)^{-\beta}]}{(\beta_2 - \beta_1) \Gamma(\beta^{-2})},$$

$$C_1 = a_1^{-\beta^{-1}} \beta t_R^{-\beta^{-1}+1} \exp[-(a_1 t_R)^{-\beta}]) \frac{1}{(\beta_2 - \beta_1)}.$$

and $I_A(x)$ is the indicator function as follows:

$$I_A(x) = \begin{cases} 1, & x \in A \\ 0, & x \notin A \end{cases} \hspace{1cm} (19)$$

### 3.2.2 Determination of posterior joint distribution of $(t_R, \beta)$

After constructing the prior distribution $(t_R, \beta)$, human performance data, namely, the response or non-response time should be collected or recorded to construct the likelihood function, then the density function of $(t_R, \beta)$. Just like the lifetime data of technical systems, the response time is the time when the operator makes the proper response exactly, thus it belongs to complete data. Sometimes, the operator does not make any responses at all before the task is stopped or the time available is exhausted. Then, the stop time or time available is recorded.
as the non-response time and belongs to the censored data. The likelihood function of complete data is

\[ L(t_{\text{complete}}|t_R, \beta) = (K'\beta)^n X_\beta \exp(-K'\xi_\beta) \]  
(19)

where \( t_{\text{complete}} = (t_1, t_2, \ldots, t_n) \) is the response time data, \( K' = K/(t_R)^a \), \( K = -\ln(\text{NRP}_0) \), \( X_\beta = \prod_{i=1}^n t_i^{\beta-1} \), and \( \xi_\beta = \sum_{i=1}^n t_i^\beta \).

The likelihood function of censored data is

\[ L(t_{\text{censored}}|t_R, \beta) = \prod_{i=1}^n P(t \geq t'_i) = \frac{t_R^{-\beta} \sum_{i=1}^n (t'_i)^\beta}{\text{NRP}_0} \]  
(20)

where \( t_{\text{censored}} = (t'_1, t'_2, \ldots, t'_n) \) is the non-response time data.

Assume that \( t_{\text{data}} \) includes both complete and censored data, the likelihood function \( L(t_{\text{data}}|t_R, \beta) \) is exactly the product of \( L(t_{\text{complete}}|t_R, \beta) \) and \( L(t_{\text{censored}}|t_R, \beta) \) as follows:

\[ L(t_{\text{data}}|t_R, \beta) = L(t_{\text{complete}}|t_R, \beta)L(t_{\text{censored}}|t_R, \beta). \]

The joint posterior density function of \((t_R, \beta)\) can be obtained as follows according to the Bayesian formula (2).

\[ \text{pdf}(t_R, \beta|t_{\text{data}}) = \frac{F(t_R, \beta|t_{\text{data}})}{\int_{\beta} \int_{t_R} F(t_R, \beta|t_{\text{data}})dt_R d\beta} \propto F(t_R, \beta|t_{\text{data}}) \]  
(21)

where \( F(t_R, \beta|t_{\text{data}}) = \text{pdf}(t_R, \beta) L(t_{\text{data}}|t_R, \beta) \) and the terms of \( \text{pdf}(t_R, \beta) \) and \( L(t_{\text{data}}|t_R, \beta) \) are shown as formulas (18) and (19), respectively. It is not analytically traceable and must be solved numerically. The Markov Chain Monte Carlo (MCMC) algorithm is an appropriate tool to take samples of \((t_R, \beta)\) from \( \text{pdf}(t_R, \beta|t_{\text{data}}) \). The statistical characteristics of \((t_R, \beta)\) can be derived from the samples directly. Therefore, the point and interval estimations of \( \text{NRP}(t) \) can be calculated as the function of \((t_R, \beta)\) easily. One simple way is to substitute the estimations of \((t_R, \beta)\) into (15).

3.2.3 Case study

Abnormal sound is a typical symptom of the injured diesel engine of the submarine. As soon as the operator hears the abnormal sound, one must try to look for the probable cause and deal with it in time. At the simulator, the scenario is simulated to train the operator. On one class, 16 trainees are asked to handle the scenario, and the response time is recorded as

\[ t_{\text{data}} = \{14, 17, 18, 23, 30, 32, 35, 37, 42, 43, 49, 52, 57, 58, 61\}. \]

The trainees attend the train class at the same time, and are trained by the same teacher. Therefore, the individual differences on the level of training and experiences among them are minor and can be neglected.

In order to handle the scenario, the trainees must observe and collect various signals or indicators guided by the emergency operation procedure (EOP). Limited by the psychological and physical abilities, trainees are unable to make proper response in 10 min usually. That is to say, the minimum response time is about 10 min. However, if the abnormal scenario is not handled in 100 min correctly, the safety protection system will be triggered automatically to shut up the diesel engine. At the simulator, the platform will be locked. The abnormal event of the safety-critical submarine must be handled as quickly as possible. Therefore, it is reasonable to assume that the NRP to abnormal sound is less than 1/1 000 to ensure the safety of the submarine. Then \( t_R \) can be specified as the maximum time available, and \( \text{NRP} \) at \( t_R = 1 \times 10^{-3} \). Then we have \( \text{NRP}_0 = 1 \times 10^{-5} \) and \( t_{R,\text{prior}} = 90 \).

The maximum time available minus the minimum response time is \( t_{R,\text{prior}} \). The likelihood function and posterior density function are acquired by (19) and (21), respectively. The samples of \((t_R, \beta)\) are taken from the posterior density function by using the MCMC algorithm. It must be pointed out that the minimum response time should be subtracted from the recorded response time.

The lower and upper limits of \( \beta \) are 0.8 and 2, respectively. The data come from the experimental results of Qinshan plants, international atomic energy agency (IAEA) and operator reliability experiments (ORE) (see Table 4 in [20]). Thus, the prior density function of \( \beta \) is

\[ \text{pdf}(\beta) = \frac{5}{6}, \quad 0.8 \leq \beta \leq 2. \]

Then the joint prior density function of \((t_R, \beta)\) can be determined by (21) easily. After the work of sample taking of \((t_R, \beta)\) is completed, the mean values of \( t_R \) and \( \beta \) are calculated, which are 108.486 5 and 1.5, respectively. And the confidence limits of \((t_R, \beta)\) can also be obtained easily. For example, the 90% confidence limits of \((t_R, \beta)\) are [83.114 7, 140.719 0] and [1.495 4, 1.504 7], respectively. The trace plots of the samples of \((t_R, \beta)\) are shown in Fig. 3. By substituting the estimations of \((t_R, \beta)\) into (15), we obtain the estimation of the time curve of NRP, including the point and interval estimations (see Fig. 4).
4. Conclusions and outlook

A Bayesian approach for estimating HEP by incorporating human performance data is presented. Using the methods in the category of HRA cum PSF, different tasks may have the same HEP. That is to say, the differences existing among these tasks are overlooked by these methods. Then, the answer that can reflect the differences among different tasks is human performance data. If human performance data of a task are collected and utilized to assist the HEP estimation process, a specific HEP estimation will be given to it.

In the aforementioned approach, Bayesian thinking is introduced to make use of various information sources. Under the time-unrelated task, the prior information is derived from the existing HRA methods or expert judgments. The prior HEP is viewed as the prior mean value of HER. Therefore, the prior density function, likelihood function, and posterior density function of HER can be constructed successively. Under the time-related task, the prior information includes the expected value of specified time \( t_R \) and the corresponding NRP\(_0\) at \( t_R \). The MPBE is introduced to construct the joint posterior distribution density of NRP-related parameters. Based on the posterior density function of HER or NRP-related parameters, the point or interval estimation of HEP or NRP can be obtained easily by analytical or numerical means.

One of the main difficulties lies on the complex calculation process perhaps. It is also the main problem faced by the Bayesian approach. Compared with the benefit of the approach, the complexity of the calculation is acceptable. Moreover, the numerical algorithms (e.g., MCMC algorithm) can be used to overcome the difficulty to some extent. There have been many software packages for Bayesian inference, such as WinBUGS, R and Matlab. The authors have developed a software package for the aforementioned procedure by using Matlab. The point and interval estimations of HEP/NRP can be worked out quickly.

The other difficulty is the way of human performance data utilization and collection. In theory, field data are more valuable than simulation data, but they are far more difficult to obtain. For example, the likelihood of some dangerous scenario in the safety-critical systems is very low. The operator has few even or no opportunities to handle it on the real system. Thus, the operator has to be trained at the simulator. Therefore, the size of simulation data may be large. In the presented approach, simulation data and field data are treated without difference. Strictly speaking, it is a little problematic. However, with the development of the techniques of simulation and virtual reality, the differences between reality and simulator are less and less. Therefore, we can get highly reliable simulation data. It is practically reasonable to treat the highly reliable simulation data and field data without differences.

HEP estimation is an open problem. The presented approach is far from perfect. In the future, the following two problems will be emphasized at first.

(i) The validation of the approach

As an engineering approach, it must be validated by the engineering application. It has been applied to the PSA project of the submarine, and the engineering practicality has been validated preliminarily. It will be applied to as many systems as possible to uncover the latent problems. With more and more problems are uncovered and corrected, the approach will be more and more practical.
and reliable.

(ii) The collection of human performance data

It is important to collect as many data as possible to make the estimation of HEP/NRP more reliable. A great amount of data are lost because of absence of a simple and systematic report and record system. Therefore, a systematic human performance data base is necessary, e.g., the NRC’s human event repository and analysis (HERA) system [21]. The human performance data base has been constructed to collect and store data from various engineering domains by the authors.

References


Biographies

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