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An Explorative Application Of The Task Reliability Index Framework For Human Reliability Data Collection

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Abstract

To enhance the empirical basis of probability estimates of human failure events in human reliability analysis, a framework for data collection and analysis has recently been proposed based on a task reliability index (TRI). In this framework, the TRI is obtained by combining two component measures of performance, addressing plant outcomes and task performance. These component measures are not fully operationalized at this time: this paper explores their potential operationalization, using an existing set of data collected in a nuclear power plant simulator. The aims are (1) to examine how the TRI could be operationalized based on the existing data set (2) to determine what other data would be needed to support a TRI-based data collection effort. Simulation records were scrutinized; the plant outcomes and operator behaviours were assessed in terms of (sub-)indices corresponding to the component measures. The insights obtained from this application were used to establish some assessment rules for the indices. Some practical issues of preparation and analysis for future simulation data collection are also identified.

Keywords: human reliability analysis, human reliability data, nuclear power plant, plant outcome index, simulator data, task performance index, task reliability index

1. Introduction

Human reliability analysis (HRA) aims to provide quantitative evidence for human performance in technical systems, to support risk-related system analysis and establish a reference point for the improvement of human–machine systems. Many experts, however, have indicated that the quantitative basis of HRA needs to be empirically validated: historically, judgment underlies significant parts of HRA while some of the data are possibly outdated, for instance, due to changes in human-machine interfaces and in the conduct of operations. To enhance the empirical basis of the human reliability estimates (so-called Human Error Probabilities, HEPs) used in the probabilistic safety assessments of nuclear power plants, various data collection campaigns have been carried out. The aims of these campaigns and the orientation of their collection methodologies can be roughly divided into (1) developing human error rates for basic, elementary tasks or (2) estimating failure probabilities directly at the human failure event (HFE) level. The first are parameters for HRA models and methods. The second correspond to HRA results for specific safety-critical crew tasks, such as those that would appear in a PSA.

Data for basic tasks has been collected mainly to validate or update the data underlying HRA methods (Jung et al., 2020; Chang et al., 2014; Hildebrandt and Fernandes, 2016; Park et al., 2020). Data for HFEs have been acquired to verify and update the outcomes of HRA applications, with holistic viewpoint (Groth et al., 2014; Bye et al., 2011; Liao et al., 2014; Park et al., 2017). These micro and macro data collection approaches can be considered complementary. On the one hand, microscopic data collection produces allows data aggregation and can support the quantification of diverse HFEs. On the other hand, macroscopic, HFE-level data addresses the overall performance, without resorting to the simplifying decomposition assumptions typical of HRA methods.

Data collection at the HFE level has not yet reached a maturity comparable to that at the basic task level. As examples of approaches at the basic task level, KAERI (Korea Atomic Energy Research Institute) established the

HuREX (Human reliability data extraction) framework (Jung et al., 2020), and the NRC (Nuclear Regulatory Commission) developed the SACADA (Scenario Authoring, Characterization, and Debriefing Application) system (Chang et al., 2014). In contrast, data collection at the HFE level is still explorative both concerning the performance features to collect and how to use this data to obtain HEPs. In general, ensuring a large amount of data at the HFE level is more difficult than at the detailed task level. In addition, HFE-level data has generally been collected by considering the success criteria considered in HRA, which may not necessarily align with how performance is assessed in the context of operator training. Furthermore, human performance at the HFE level includes the elements of complexity that the basic tasks approach intends to avoid: crew dynamics, crew-plant interactions, overall response strategies, and the like. The amount of qualitative information emerging from observations at the HFE level can go much beyond assessment of performance as success or failure. This suggests that a data collection method based on multidimensional and multi-level performance assessment could be more fruitful than the dichotomous performance evaluation of success or failure typical for basic tasks (Hallbert et al., 2014; Porthin et al., 2020).

The conceptual approach for the collection and analysis of HFE-level data based on the TRI, examined in this paper, can be found in Porthin et al. (2020, 2024). The approach combines plant outcome–oriented features, a typical measure of HRA, with cognition-oriented features, more common in human factors engineering, to form a task reliability index (TRI). The cognition-oriented or human-centered features are referred to as "task performance". Both the plant outcome index (POI) and the task performance index (TPI) are specified on a six-level scale. The POI is assessed based on the plant behaviour and in relation to the fulfilment of the HFE success criteria (e.g. how close relevant plant parameters are to the success criteria, or the safety margin maintained over the response). The TPI is assessed based on the acceptability of the crew performance in terms of acquired situation awareness as well as of resilience work behaviour (e.g. use of redundant information, proactive behaviour, information sharing). The POI and TPI results are combined into an overall TRI value through a matrix. Then, the TRI value from each observed performance (empirical record) enters a Bayesian update scheme.

The proposed approach by Porthin et al. (2024) is still conceptual; for practical application, operationalization of the index scales is one of the open issues. In response to this need, the present study applies the TRI concept to a set of simulator records from a nuclear power plant simulator, with a specific focus on exploring index operationalization. Using the HuREX data collected for an APR1400 plant, nine TRI scores at the HFE level were generated, and an HEP value was estimated based on the TRI scores. With the insight obtained from this case study, we derived evaluation rules for the POI and TPI, focused on HFE success criteria and observed deviations. It is important to mention that for the present paper the assessment of the indices is based on simulator records collected for the HuREX framework, independently on the TRI concept. Therefore, the evaluation was based on already available information, not necessary covering all aspects required for the TRI evaluation, and in particular concerning the TPI. Indeed, the application to HuREX records was intended as a first exploration for index operationalization, at least for the aspects covered by the available data.

2. Concept of data collection and analysis based on task reliability index

Figure 1 shows the framework for gathering TRI values as human reliability data and quantifying an HEP using them (Porthin et al., 2024). This framework can be implemented by various entities depending on the purpose and method of data collection. The implementation discussed here assumes that HRA/reliability data specialists work together with observers with expertise in plant operations (e.g., plant training staff); the tasks of the two groups are distinguished and represented in separate lanes. This framework has three phases, as follows. The preparation phase is the process of selecting the HFEs for which empirical data is to be collected and identifying the success criteria and the set of observables for index assessment. This phase provides important implications for how to observe operator behaviours and measure the POI and TPI observables. It is noteworthy that the two activities, the definition of HFEs in scenarios and the selection of observables, are carried out by the collaboration between the data analysts and the simulation observers. An interdisciplinary approach is required to consider the data collection purposes, ergonomic features, plant dynamics, simulator fidelity, time constraints, and so on (Kim, 2020).

In the data acquisition phase, simulator data and index observables are collected in each simulation run, corresponding to one observation of a crew in a given scenario. The simulator data includes the chronological logs (with plant parameters and components states) as well as observations made by the session observers (e.g. the trainers), and debriefing reports. Depending on the data to be analyzed, the event investigation records or various experiments can be employed as the simulator data for this acquisition. Protocols to organize the data will be developed in future work. During a data acquisition session, the observers would record plant outcomes, crew actions and other crew behaviours, which are subsequently used to assign POI and TPI values to that crew's performance of a given task (the HFE represents the failure of this task). Evaluation of the POI is based on plant metrics important to the HFE, meaning those that are associated with meeting the HFE success criteria. As shown in Table 1, the POI is rated on a scale of 1 to 6. In terms of the HFE success criteria, index values between 1 and 3 indicate failures, and values between 4 and 6 indicate successes. On the other hand, the TPI is intended to represent behavioural aspects such as situation awareness as well as resilient conduct of operation. As indicated in Table 2, the TPI is also rated on a scale from 1 to 6, where lower index values correspond to different degrees of performance inadequacy. Especially concerning the TPI, the development of behavioural markers and of the rating scale is an important aspect for practical applications and will be subject of investigation.

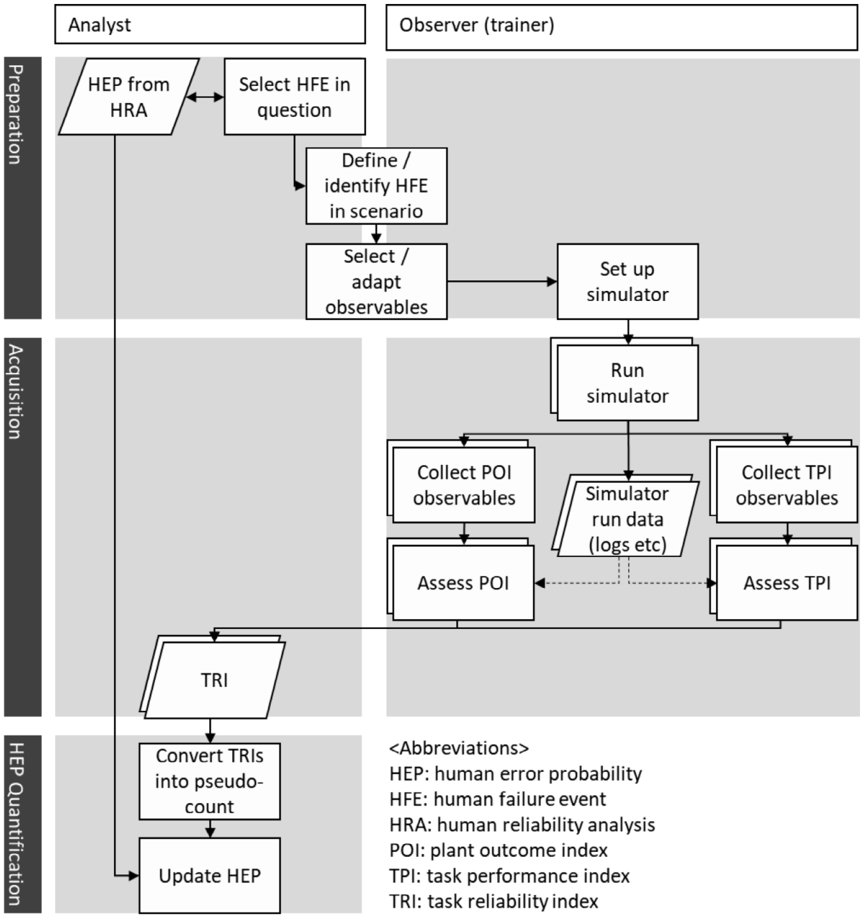

Fig. 1. Process of TRI-based data collection and analysis.

The POI and TPI, accounting for two different perspectives, would be converted into one TRI through a combination matrix, of the type shown in Table 3. Conceptually, the table shows that the different TRI "degrees of failure or success" correspond to combinations of performance on the two dimensions. Indeed, as an example, the use of the two dimensions allows to differentiate near failures concerning POI (e.g. with an index of 4), depending on the crew situation awareness (TRI ranging between 2 and 4). Simply put, a TRI of 4 would represent that the crew was in complete control of the situation, while operating close to the HFE success criteria. A TRI of 2 would represent that operation close to the success criteria was instead due to lack of awareness. A variety of similar considerations can be made on the basis of Table 3, not discussed here for brevity.

In the HEP quantification phase, a set of TRI values obtained from the empirical records is converted into a pseudo-failure count, representing corresponding partial evidence of failure. For example, a TRI of 1 means "full" failure, while a TRI of 6 is associated to the values of 0.001 (very low evidence of failure). A proposed scale for the partial evidences is given in Porthin et al. (2024). The total number of attempts is generally the number of empirical records. However, if the number of acquired TRI values is insufficient but provides strong evidence for the HEP, both the total number of attempts and the number of failures can be multiplied by an additional "weighting" factor. These pseudo-failure counts are incorporated into a Bayesian update scheme to reach the posterior HEP. The HEP posterior is usually estimated by combining the beta prior distribution with the numbers of attempts and failures, where its likelihood function is the binomial distribution (Kelly and Smith, 2011; Preischl and Hellmich, 2013). When the HEP prior is absent or weakly informative, Jeffreys prior (Jeffreys, 1946) or constrained prior (Atwood, 1996) can be used. For example, the mean posterior probability of the Bayesian update using a constrained prior can be computed by the following equation:

$$HEP_{posterior} = \frac{\alpha_{prior} + x}{\alpha_{prior} + \beta_{prior} + n} \quad , \tag{1}$$

where α_{prior} is 0.5 and β_{prior} is 0.5(1-HEP_{mean})/ HEP_{mean}. The x and n indicate the numbers of failures and attempts in the pseudo-failure counts, respectively.

Table 1. Scores in the plant outcome index (Porthin et al., 2024).

Index	Definition	Relation to success criteria	HFE outcome
1	Clearly failed	Most success criteria failed	Failure (criteria not fulfilled)
2	Failed	Some success criteria failed	
3	Failed, but close to success	Some success criteria failed, close to limits	
4	Succeeded, but close to failure	All criteria succeeded, some close to limits	Success (criteria fulfilled)
5	Succeed	Satisfies success criteria with some margin	
6	Clearly succeeded	Substantial margin to the success criteria	

Table 2. Scores in the task performance index (Porthin et al., 2024).

Index	Definition	Evidence of resilient performance	Acceptability in human factors
1	Clearly not acceptable	Shortcomings in multiple dimensions, failure to track critical safety functions	Not acceptable
2	Not acceptable		
3	Acceptability disputable, but probably not acceptable	Shortcomings in one dimension, e.g. lack of shared understanding within crew, omitted verification of plant response	
4	Acceptability disputable, but probably acceptable	Adequate performance. Minor issues observed	Acceptable
5	Acceptable		
6	Clearly acceptable	Good situation awareness throughout, optimal operational strategies, response exhibits resilient behaviors.	

Table 3. An example combination matrix determining TRI. Different options are under investigation (Porthin et al., 2024).

	POI					
TPI	1	2	3	4	5	6
1	1	1	1	2	2	3
2	1	2	2	2	3	3
3	1	2	3	3	3	4
4	1	2	3	4	4	5
5	2	2	3	4	5	5
6	2	2	3	4	5	6

3. Application of the data collection framework to simulator records

3.1. Empirical Data Acquisition

We applied the TRI-based framework to the simulator training records of the Korean APR1400 (Kim et al., 2021). The specific HFE is feed-and-bleed (F&B) operation during a loss of all feedwater accident. The HFE success criterion for the F&B event is that the operator (1) checks the depletion state of the steam generator (SG), (2) verifies the automatic opening state of the relief valve of the pressurizer, (3) turns on the power of the safety valve of the pressurizer in its cabinet, and (4) opens the safety valve. According to the procedure structure in the APR1400, the operators should follow the standard post-trip action procedure after the reactor trip, move to the diagnostic action procedure, select the loss of all feedwater procedure, and then transfer to the F&B procedure. The SG depletion time, which is the initial cue time of this HFE, was predicted by thermal-hydraulic analysis to be 25 min after the reactor trip, and the temporal success criterion of the safety valve opening was anticipated to be 65 min; accordingly, the time available for this event is 40 min. Using the HuRECA (Human Reliability Evaluator for Computer-based Control Room Action) method, the HRA practitioner obtained 4.94E-03 for the HEP of this event (Kim et al., 2018).

Information from 10 simulator records of the F&B event is contained in the APR1400 HuREX database. In this work, POI and TPI scores were evaluated and TRI values determined for nine simulation records (the tenth record was excluded because the session was stopped due to simulator issues). For all simulations of the F&B event, the scenario is an Anticipated Transient Without Scram (trip) with a failure of all feedwater systems. Since the reactor did not trip automatically, the complexity of the simulation scenarios increased and the SG depletion time was shortened.

In terms of measuring POI levels, all crews showed highly successful responses to the given accident. The time to open the safety valve ranged from 13 to 19.5 minutes. Although the time frame of the simulations is not the same as that in the F&B event covered by HRA, the operators' performance time was judged to be significantly shorter than the time available. As a result, the POI values for all nine simulator records were assessed to have a value of 6. Because most simulations were terminated by the trainer within a few minutes after opening the safety valve (i.e., the "bleed" task), no significant changes in the plant integrity parameters, such as peak cladding temperature, were found.

Regarding TPI, interestingly, values across the nine simulator records varied widely. Table 4 summarizes the number of deviations, their relevance to the HFE actions, the recovery for the relevant actions, and the TPI. Deviations in TPI were determined by the identification rule of an unsafe act in the HuREX framework (Jung et al., 2020). These deviations correspond to operator behaviours inconsistent with the instructions in the procedures, resulting in omission or commission errors in the equipment operation and procedure flow. But not all deviations were related to the actions required to achieve the HFE goals. Some operators momentarily missed opening the safety valve (e.g., in the fourth record) or energizing the safety valve (e.g., in the third record). Except for one case, all deviations related to the HFE were recovered within 5 min through the operators' own efforts, and the results of the operators' actions, as evaluated in the POI, met the success criteria for the HFE. In the fifth record, a crew error was recovered due to a hint presented by the trainer. Although there was still enough time in the accident situation and additional recovery attempts by the operators were predictable, the trainer's intervention is conservatively considered a recovery from failure and the performance is assigned a low TPI.

Table 4. TPI assessment for the nine simulator records.

Record index	Number of deviations	Relevance to the HFE actions	Whether related deviations were recovered	TPI
1	3	No relevance	N/A	5
2	5	No relevance	N/A	4
3	3	One deviation related	Recovered soon	4
4	4	One deviation related	Recovered soon	3
5	2	One deviation related	Recovered by trainer	2
6	3	No relevance	N/A	5
7	0	No relevance	N/A	6
8	2	No relevance	N/A	5
9	2	One deviation related	Recovered soon	4

Although deviations reflect operator's issues in situation awareness and decision making, they do not provide a complete picture of performances relevant for the evaluation of the TPI. As mentioned, complete operationalization of the measure will be subject of future work.

Based on the results of the POI and TPI measurements and using the matrix shown in Table 3, we acquired TRI scores as shown in Table 4. Following the Porthin et al. (2024) framework, the set of scores correspond to 0.181 failures occurring out of the nine simulations. By multiplying the failure and attempt numbers by 3, respectively, and applying Bayesian inference with a constrained prior with mean 4.94E-03 (Atwood, 1996), we obtained the posterior HEP of 8.14E-03.

3.2. Determination of plant outcome index and task performance index

As a result of examining the training plans and simulation records during the POI measurement, we derived determination rules for the POI based on three types of criteria. The first is operational criteria, which can be used to evaluate whether the operator appropriately performed the manipulations required by the HFE purpose. In the above application study, the act of supplying power to the safety valve or opening the valve is an example of this criteria type. If the operator behaviour does not meet any of the operational criteria, the POI should have a value in the failure region (i.e., between 1 and 3).

The second type is temporal criteria. Based on the time available derived from HRA or thermal-hydraulic analysis, it is possible to evaluate how well the required actions were performed within the time constraints. In the above application, a time available of 40 min was used as the reference point. The POI evaluator can estimate the size of the time margin through the ratio between the operator's performance time and the time available; the POI value is then a function of how low the ratio is ("distance" from 1). Obviously, it should be noted that the accident time predicted in HRA and the actual time flow in simulation may not be the same due to differences in malfunction inputs or thermal-hydraulic codes.

The third type is parameter criteria. As seen in the application example, final parameters such as peak cladding temperature can often be difficult to observe through simulation data. However, if the operational criteria require the act of manipulating parameters within a specific parametric range, the POI can be assessed by considering the parameter criteria. For example, if the pressurizer pressure needs to be reduced below 120 kg/cm2, the pressure value in the simulation can be evaluated to see how far from 120 it was during the simulation and at the conclusion. Depending on the traits of the parameter criteria, POI values can be evaluated binarily (e.g., cliff edge effect) or continuously.

Focusing on TPI, we developed determination rules based on deviation as assessed in the simulator records. First, a basic TPI is evaluated according to how the deviation results and recovery relate to the HFE success criteria. Table 5 shows the conditions for selecting the basic TPI value. For example, if a deviation is associated with the HFE but is quickly recovered and does not ultimately have a significant impact on the success of the event, the TPI is assigned a value of 4.

Table 5. Basic TPI determination rule based on the recovery and effect of deviations.

Deviation relevance with HFE	Recovery	Final effect on HFE outcome	TPI
Relevant	Delayed or no recovery	Significant effect	2
Relevant	Rapid recovery	Significant effect	3
Relevant	Delayed or no recovery	Insignificant effect	3
Relevant	Rapid recovery	Insignificant effect	4
Not relevant	—	No effect	5

Once the basic TPI is determined, the value is adjusted depending on how many deviations are found. The following shows the TPI adjustment rules according to the number of deviations.

- Many deviations were observed: subtract TPI by 2;
- Some deviations were observed: subtract TPI by 1;
- A few deviations were observed: no change;
- No deviation was observed: add 1 to TPI.

Specific reference points for the number of deviations can be determined depending on the complexity of the scenario, the nominal execution time, and the number of actions to be performed. In this application study, for instance, when four or five deviations were found, the TPI value was reduced by 1.

4. Discussion and future work

In this study, we applied the TRI concept on simulator records in the HuREX database and verified the feasibility of the operationalization. Via this application, assessment rules for the POI were established considering operation, time, and parameter constraints. In addition, determination rules for the TPI based on the effects of deviations and their observed numbers were derived. The TRI-based approach is useful to practically collect abundant data at the HFE level human reliability data. This framework allows simulation observers to initiatively generate key index values for securing data continuously, while also to interactively define and identify the key observables with data analysts for enhancing the significance of the obtained data. In addition, by evaluating performance and outcomes of HFEs, human reliability can be estimated from a comprehensive perspective. This exploratory study demonstrates that data acquisition based on TRIs is capable of evaluating human reliability from more diverse perspectives.

Some practical issues of preparation and quantification for future simulation data collections were also identified. To determine the POI, it is important to define success criteria before simulation runs or raw data collection. Therefore, it is important to thoroughly characterize the HFEs in question during the preparation phase and implement their characteristics into the simulator environment and scenario development. In particular, the temporal criteria must be precisely predicted in advance and compared with the time flows in the simulator. If the malfunction inputs in the simulator and the conditions assumed in the HRA application are different, a strategy to interpret this gap during the analysis of the data should be prepared.

To measure the TPI, this study employed the effect and number of deviations. Depending on who the measurer is (e.g., HRA expert, data collection specialist, or simulator trainer), deviations may be identified differently. Therefore, it is important to develop specific guidelines for the identification of deviations. Then according to the guidelines, reference points of the TPI adjustment rules should also be specified. Resilient behaviours of the crews should be a factor in determining the TPI. For example, cooperative attitude, compliance with three-way communication, and high awareness of procedure progression can be considered positive factors. In this study, these behaviours could not be assessed for the TPI measurement because the necessary detailed information on crew behavior was lacking. It is expected that future research will be able to strengthen the evaluation of such factors, in particular with the development of behavioural markers to aid observers to recognize evidence of emerging resilient behaviour. The SCORE (Supervisory Control and Resilience Evaluation) measure could be an example for assessing the human performance level from observations of human operators (Braarud et al., 2016).

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