The HERA Database –
Status and Outlook for Supporting HRA Applications

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Lack of suitable data for human reliability analysis (HRA) has been a key factor affecting the reproducibility in predicting human error probabilities (HEP) in probabilistic risk assessment (PRA) applications. A data framework has been developed in the U.S. Nuclear Regulatory Commission (NRC) to support better HEP predictions. For best use of simulator data, the collection and exchange of simulator data for HRA should be discussed as part of an overall HRA data program. This paper discusses simulator data collection from the view of the data framework. The Human Event Repository and Analysis (HERA) system [1, 2] is an import tool for the NRC to support the data framework. The HERA operational experience of the past few years has identified several areas of improvement, and there are ongoing activities to enhance the HERA methodology and tool to support better HEP predictions.

Section 1 provides an overview of the data framework. Section 2 discusses the three key elements of the framework: data sources, data repository, and use of data. These three elements are discussed in a reversed order. The discussion of the use of data provides the conceptual approach of the overall framework to support HEP predictions. The discussion of data repository specifies the types of data to be collected. The discussion of data source compares pros and cons of various data sources. Section 3 discusses the perceived technical challenges in applying the framework and the prospective solutions to the challenges. Section 4 discusses aspects of collecting and exchanging simulator data in the framework. Section 5 discusses the HERA current status and outlook for supporting HRA applications. Section 6 is the conclusion.

1 Data Framework Overview

A data framework consists of three key elements (i.e., data sources, data repository, and use of data) and has been developed in the NRC to support data-based HEP predictions in HRA. The framework assumes that the human failure events (HFEs) for HEP predictions have been identified and the contextual information of the HFEs can be specified.

Figure 1 shows the framework. Block 1 of Figure 1 shows a PRA event tree that contains HFEs of interest. The HFEs in PRA are typically defined at plant functional level, which in some situations contain too much uncertainty for predicting their HEPs. The HRA analysts may represent the HFE by a set of sub-HFEs (Block 2) so that the contextual situation of each sub-HFE can be specified more precisely to reduce uncertainty. In order to prevent terminology confusion, this paper uses performance profile (PP) to indicate all possible forces that would affect HEP value in HRA applications. If two different tasks to be performed have the same performance profiles, we expect that the HEPs of these two tasks will be in close vicinity.

Blocks 3, 4, and 5 are the three key elements: data sources, data repository, and use of data , respectively. Block 3 indicates two types of data to be collected. The first type of data is from detailed analysis of each individual event. This includes identification of all human response opportunities within the event, specifying the PPs of these response opportunities, and evaluations of the human responses to these response opportunities. The second type of data is task performance statistics (i.e., the failure probability of completing certain tasks). The data could be obtained by reviewing the operational logs (most likely the equipment maintenance activities) to obtain the number of times that the tasks have been performed and the number of times that the tasks were not successfully completed. Other industries' data also can be included. For all these data, the analysts need to specify their PPs in order to be used in the data framework.

Once the data is collected, the data are deposited in a data repository (Block 4). In the data repository, each data point has its PP that was characterized by a set of factors. The state of PP of every data point (i.e., human response to a response opportunity or performing a certain task) in the database is specified. Because data collection is a retrospective event analysis activity, the opportunities of human responses within an event scenario can be identified. The successes or failures of the human responses to these opportunities can be determined, and the PPs of the response opportunities can be specified. Consistent with the types of data collected in Block 3, two types of data are stored in the data repository to support the data framework. The first type data is the detailed analysis of human responses to each response opportunity. The prospective data repository is the NRC's HERA system which represents each response opportunity as a subevent. The second type of data is the HEP of completing a task. Currently HERA does not collect this type of data. The analysts would mainly rely on the PPs to identify the data points in the database to be used for HEP predictions.

Block 5 uses PP similarity as the venue for the use of data. The PPs are represented by a set of factors conveniently take advantage of computer power. In Block 5, data (in Block 4) with the same or similar PPs to the HFE/sub-HFE of interest (in Block 2) are identified. This process is called similarity assessment. An HEP is calculated based on the Block 4.1 data. Bayesian methods would be needed if the data of Block 4.1 are incomplete. After obtaining the HEP from Block 4.1 data, the Bayesian update would be used to generate final HEP estimate of the HFE/sub-HFE shown in Block 2 by data inputs from Blocks 4.1 and 4.2. Repeat the process for all sub-HFEs of Block 2 and the HEP of the HFE in Block 1 can be obtained.

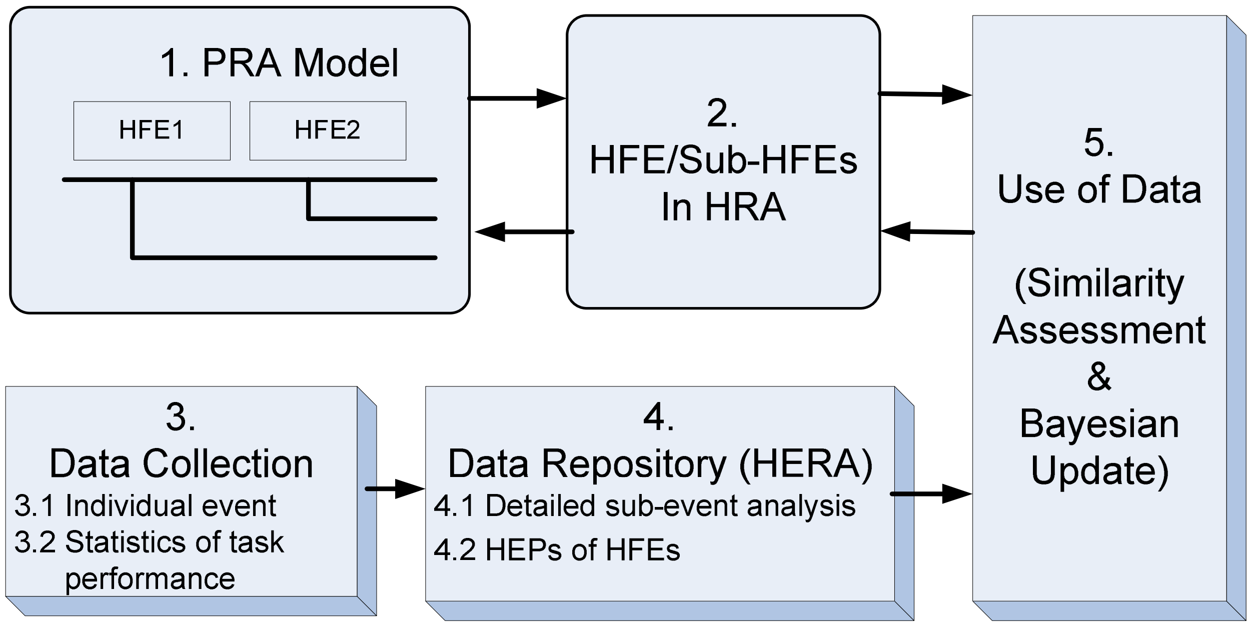

Figure 1 A data framework for data-based human error probabilities predictions

2 Key Elements

This section discusses the three key elements of the data framework in a reversed sequence. Section 2.1 discusses the use of data. The idea of using response opportunities as the basic analysis units for calculating HEPs are discussed. This lays out the theoretical foundation of the framework. Data repository (section 2.2) discusses the types of data collected in current HERA and perceived information that may be added later. Section 2.3 discusses various data sources that HERA has been used or intended to use, and the pros and cons of these options.

2.1 Use of Data

As mentioned earlier, two types of data will be used for HEP predictions: analyses of human responses to human response opportunities and HEPs of performing certain tasks. A HEP will first be calculated from the first type of data. Then the HEP will combine with the HEPs from the second type of data using the Bayesian update to calculate final HEP. This section discusses the process.

HEP is the probability of human failed to respond to a response opportunity given the success criteria specified to the response opportunity. Thus, HEP can be simply represented by Eq. 1:

$$\mathbf{HEP} = \frac{\#\,\mathbf{Failures}}{\#\mathbf{Response\ Opportunities}} = \frac{\#\mathbf{Failures}}{\#\mathbf{Failures} + \#\mathbf{Successes}} \qquad (\mathbf{Eq.1})$$

Human performance is sensitive to the contextual situation in which the human activities were performed. The contextual situation is characterized by PPs. Therefore, Eq.1 can be modified to Eq.2. for a PP-specific HFE.

$$\mathbf{HEP(HFE|PPi)} = \frac{\mathbf{\#Failures\ (PPi)}}{\mathbf{\#Failures\ (PPi) + \#Successes\ (PPi)}} \qquad \mathbf{(Eq.2)}$$

The numbers of failures and successes in eq.2 are expected to be obtained from HERA human subevents (Block 4.1 in Figure 1). Currently, HERA represents an event's timeline as a list of important chronological subevents. The subevent types include human subevents (including successes and failures), plant subevents (e.g., components unavailable), and external subevents (e.g., extreme weather). For the purpose of HEP quantification, only human subevents are used in Eq. 2. In the situations in which the numbers of failures and successes are inadequate for calculating an HEP due to incomplete data, Bayesian methods may be used to combine other information to calculate the HEP.

If there are HEPs in Block 4.2 having the same PPs as the HFE of analysis, the Bayesian update can be applied to calculate the final HEP of the HFE with inputs from the HEP obtained from Blocks 4.1 and 4.2.

2.2 Data Repository

HERA is the prospective data repository to support the data framework discussed in this paper. HERA provides the basic infrastructure to support the framework but modifications and enhances are needed for HERA to support the framework in a practical manner. Currently, the HERA system is undergoing a significant revision to improve its taxonomy and tool in order to more effectively and efficiently support to the framework. Some capabilities discussed in this paper do not exist in the current HERA. These are considered for future HERA improvements.

A HERA data taxonomy has been developed [2] and a world wide web based database software has been implemented [3]. The data taxonomy specifies the types of information to be collected. The HERA software is to streamline the data collection and analysis process. Currently, the types of information collected in HERA from detail event analysis include:

- General information
  Event type, (i.e., pre, is an, or post initiating event), plant type (i.e., PWR or BWR), date/time of the events, operation mode, power level, types of workers involved, affected plant function, and system and components are in this class.
- Event description
  Narrative event description and event timeline are used to describe an event. The event narrative highlights the dynamics during the events. The event timeline divides an event into a chronological set of subevents for explicit event sequence.
- Human performance summary
  This provides a short summary of the key human failures and the causes and impacts on the plant operation.
- Index of success or failure of a human subevent
  HERA represents each human response opportunity within events as a subevent. Based on the context of the situations, the human performance within a subevent will be

either judged as a failure (e.g., human induced a system fault) or a success (e.g., human recovers a system fault).

- Human activity types
  Four methods of specifying human activity types are used including: (1) the standard nuclear operation work types (e.g., balance of plant operation in control room, testing a system or components, and calibrating equipment); (2) common nuclear plant operations (e.g., change electrical lineup or instrumentation configuration, restore component/system back to service after maintenance); (3) generic human cognitive process (i.e., perception, interpretation, planning, and execution); and (4) cognitive complexity (i.e., skill, rule, or knowledge based responses).
- Human error types
  In addition to failures of the types of human activity discussed in the previous bullet, two commonly accepted error taxonomies are included. These are error of commission vs. error of omission and the classification of slip, lapse, mistake, circumvention and sabotage.
- Performance shaping factors
  HERA divides the performance shaping factors (PSFs) into two classes depending on whether the PSFs having positive or negative effects on human performance in a subevent. A three-level hierarchical structure containing about 250 PSFs are in the current HERA. The top level contains 11 PSF classes.

Some of the above data can be used to characterize PPs such as human activity types, human error types, and PSFs. Recently, an ongoing study indicates that error mechanism may also be a good option to be added into the list. Once the error mechanism approach has been fully developed, the information is expected to be collected in HERA.

As mentioned earlier, currently both the HERA data taxonomy and tool are undergoing significant revision. Key focuses of the revision are to better support data-based HEP predictions and ease of use of HERA methodology and tool. After the revision, HERA is expected to be a handy, useful tool to support the data framework.

2.3 Data Sources

The potential data sources include event reports, event investigations, simulation observations, and event statistics. Event reports are products of event investigations that include licensee's corrective action event reports, and the events met the event reporting criteria [4] such as licensee event reports, and NRC's inspection reports, special inspection reports, and augment inspection reports. Using event reports as a data source, the HERA event coders can only rely on the information within the reports to reconstruct the event sequence and perform analysis. Because the HERA event coders would not be able to interview the individuals who were involved in the events and the reports typically do not provide information in sufficient detail to identify human response opportunities and the PPs, obtaining information from event reports is less cost effective. In the past, event reports were the main data source for HERA. In the future, HERA may shift toward more cost effective data sources (e.g., event investigations and simulator exercises).

Event investigations are used when the HERA event coder is a member of an event investigation team. The coder is able to obtain the operating procedures and interview the individuals who involved in an event. Simulation observations refer to when the HERA event coder is an observer of simulator exercises. Therefore, not only are the procedures and interview available, the HERA coder is also a witness of the event. Information obtained from event investigations and simulation observations have high fidelity and require less effort to code into HERA. This is mainly because the event timeline can be quickly constructed in these cases. Event investigations and simulation observations would be more cost effective data sources for HERA than event reports.

Event statistics are based on credible counts of numbers of response opportunities and successes and failures of human responses to the response opportunities. Systematic simulator exercises (e.g., the international HRA empirical study [5]) could obtain HEPs of operating crews in performing certain tasks. The data also could be from industries other than nuclear industries such as hospitals' treatment to their patients and commercial aircraft operations. Use of data from the industries other than nuclear industry requires understanding the task details, the contextual information of performing the task, and the system fault tolerance to human errors.

3 Technical Challenges

Three key technical challenges are identified in implementing the data framework described in section 2:

- Challenge 1: Define the unit of measurement for Eq. 2
- Challenge 2: Specify the PP
- Challenge 3: Inform HEP quantifications with incomplete data

Challenge 1 is about that the HERA human subevents (i.e., data point in the Block 4 of Figure 1) and the HFE/sub-HFE (in Block 2) need to be identified with the same basis so the numbers of successes and failures are valid to be used in equations 1 and 2. Challenge 2 is about identifying the human success subevents and failure subevents in the database that can be used to calculate the HEP of the HFE/sub-HFE of interest. This relies on the PP similarities between data and applications. Challenge 3 recognizes that HERA data are unlikely to be perfect (e.g., not having all human successes and failures in real events) so Eq. 2 alone cannot be used to calculate HEPs. Other forms of data (e.g., event statistics from simulator exercises and available generic HEP values) need to be incorporated within a Bayesian framework to calculate HEPs.

In addressing Challenge 1, a workshop was held in October 2009 by the NRC to develop guidance on developing a set of rules for HERA subevent parsing. The same set of rules is expected to be applied to PRA HFEs (Block 1 of Figure 1) and represented by a set of HFEs/sub-HFEs in HRA (Block 2 of Figure 1). The workshop participants' expertise includes HRA, PRA, cognitive engineering, and nuclear plant operation. The workshop follow-up activities would provide a draft set of detailed rules for review.

Regarding Challenge 2, a review of HRA methods' approaches to PP similarity found that human activity types, error mechanisms, and performance shaping factors (PSFs) are common elements used to characterize PPs. On human activities types, SPAR-H [6] and CBDT [7] classify human activities into two types: diagnosis and action. CREAM [8] classifies human activities into 15 types including coordinate, communicate, compare, diagnose, evaluate, execute, identify, maintain, monitor, observe, plan, record, regulate, scan, and verify. Other methods use combinations of action type and partial contextual situations to classify activity types. For example, "perform rule-based actions when written procedures are available" is used in THERP [9], and "carry out simple single manual action with feedback and, therefore, not necessarily with procedure" is used in NARA [10]. On error mechanisms, CBDT identifies 8 error mechanisms for diagnosis activity such as "the required data are physically not available to the control room operators" and "the relevant step in the procedure is skipped." On PSFs, almost all HRA methods explicitly or implicitly provide a set of PSFs to be considered that would affect HEP values. The above examples suggest that substantial work has been done in characterizing PP in HRA. A key criterion for choosing a PP characterization method for HERA is that the method needs to be practical for data collection. Some considerations on practicality include:

- clear and orthogonal definitions of the factors to characterize PP
- the factors that characterize PP can be identified with ease and their states can be objectively, easily assessed by event investigators
- the factors that characterize PP should include the influence of earlier subevents within the same event on the current subevent. In other words, the dependency effects between different subevents should be included in the PP of the current subevent.

Regarding Challenge 3, incomplete data include insufficient data and incomplete data. Insufficient data indicates that there is no sufficient data relevant to the HFE of analysis to make statistically significant prediction on the HFE's HEP. Incomplete data indicates that some human successes or human failures were not identified because the detailed information not available. Systematic simulator exercises (e.g., the international HRA empirical study) to obtain statistic human performance information can be evidence to be integrated into the Bayesian framework. Other HEPs available may also be used in the Bayesian framework if the detailed information is available for HFE parsing and PP characterization.

4 Simulator Data Collection and Exchange

Simulator data collection should be discussed as part of the overall data collection program for HRA. For different HRA needs, the level of information detail and the types of information to be collected may be different. Therefore, the discussion of simulator data collection and exchange also cannot be separated for its intentional purposes. For example, a key purpose of the international HRA empirical study is to compare HRA methods' predictions against simulation results. Therefore, a set of HFEs defined in PRA are the analysis units in the empirical study. In the international empirical study, the human performance analysis and HEP results are based on the analysis units. Performing data analysis at the HFE of PRA is appropriate for the purpose of comparing methods' predictions against simulation results; however, PRA HFEs may not be the optimal analysis units for a wider use of the simulator data for HRA. The first technical challenge discussed in Section 3 addresses this issue. It is expected that the optimal level of analysis units should have segmentations equal to or finer than the PRA HFEs.

For the convenience of use and exchange of simulator data, a central data repository platform would be an essential tool to facilitate the efforts. Currently, HERA has the basic infrastructure to support the effort. The HERA database can be accessed through the internet (the accessibility must be granted by the NRC). The HERA database is segregated into a number of sub-databases to control accessibility and protect proprietary information. Currently HERA is undergoing significant enhancements. Once the enhancements are complete, the HERA is expected to be a handy, useful tool to support the exchange of simulator data and the development of a larger scope HRA data program.

5 Prospective HERA Enhancements

As mentioned earlier, a world wide web based HERA database software has been implemented. Currently, ongoing HERA enhancements focus on usability and implementation of the data framework. The specific revisions were developed based on lessons learned from past HERA operation experience.

Improving HERA software usability is the first step to increase the acceptability of using HERA. An intelligently designed graphical user interface would guide the event coders to identify the desired information with ease instead of going through a long check list. This would significantly benefit PSF identification in HERA. Currently, HERA contains about 250 PSFs in various levels of detail. Prospective changes to the PSFs include: (a) consolidating the positive and negative PSFs into a set of PSFs with neutral language; (b) removing non-PSF items. Currently some HERA PSFs are behaviors rather than PSFs. An example is "adhesion to procedures less than adequate;" (c) identifying the likely causal chains and hierarchical structures among the PSFs; (d) defining PSFs in an orthogonal and intuitive manner; and (e) providing reference points for specifying PSFs' states. Currently, HERA's PSFs only have two states: present and not present. A multiple-state scale would improve the usefulness of HERA data for HRA. Other items on improving usability are to remove unnecessary information to reduce the workload of event coding.

On establishing a clear and practical path for the use of HERA data for HEP predictions, the previous approach is to provide data for HRA methods to calibrate their parameters. The current approach is to use HERA data in a Bayesian framework to support HEP predictions. In other words, the HERA data will be directly used to support HEP predictions instead of through HRA methods. Under the current approach, overcoming technical challenges 1 and 2 stated in section 3 is a key to success.

Trending of human performance is of interest to the human performance discipline rather than to HRA; however, human performance is a stakeholder of human events. Adding function to perform trending analysis in HERA data would gain the support from human performance stakeholders. That, in turn, could support HERA event coding to speed up the use of HERA data.

6 Conclusion

The collection and exchange of simulator data should be discussed within a data framework that incorporates data from all sources (simulator data and others). This paper discusses a framework for data-based HEP prediction. This would reduce the use of expert judgment in HEP predictions which would, in turn, enhance the reliability and accuracy of the HEP predictions. The framework also provides a transparent method on the use of data for HEP estimates. HERA is under revision to enhance its data taxonomy and tool to support the framework. In the future, HERA will be a useful and handy tool to support not only the exchange of simulator data but also data from other sources and formats.

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