HUMAN PERFORMANCE OBSERVATION AND DATA COLLECTION IN DIGITAL MAIN CONTROL ROOMS OF NUCLEAR POWER PLANTS: A CASE STUDY IN CHINA

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The lacking of human performance data in human reliability analysis (HRA) is lamented since the born of HRA. It is even worse for conducting HRA in digital main control rooms (MCRs) in nuclear power plants (NPPs). In order to make HRA being more objective and realistic, several sources, such as simulator observation, human factors experiments, operating events, are used to collect and extract human performance data. We focused on full-scope simulator observation. This case study showed how we collected human performance data from two full-scope simulators in China. Three types of human performance data, operator errors, operation time, and mental workload, were recorded. Operator errors were classified according to the cognitive framework of macrocognitive function failures in NUREG-2114. Operation time was analyzed using the time-line analysis. Mental workload was measured by the NASA-Task Load Index measure. Failure of understanding and sensemaking and failure of teamwork were found to be the two predominant macrocognition failures in our case. These initial efforts help us build the preliminary operator performance database for HRA specific to digital main control rooms. Collecting and accumulating more data is our ongoing work.

I. INTRODUCTION

The safety and integrity of complex, large-scale systems, for example, nuclear power plants (NPPs), aircraft, and process plants, is highly dependent on human performance. In the human performance literature, it is widely accepted that poor human performance is a major cause of incidents and accidents (Reason, 1990, IAEA, 2013b). Convergent evidence shows that the contribution of human error to incidents and accidents in safety-critical systems is approximately 30%-90% (Griffith and Mahadevan, 2011). More than 50% of operating events were implicated with operator errors from 1991 to 2011 in Chinese nuclear power plants (NPPs) (Wang and Li, 2012). One lesson learned from the Fukushima accident is that it is a man-made disaster and that human and organizational factors are critically important to nuclear safety (IAEA, 2013a).

In probabilistic risk assessment (PRA) or probabilistic safety analysis (PSA), we should consider the contribution of human and organizational elements to system reliability. Human reliability analysis is a structured approach used to identify potential human failure events and to systematically estimate the probability of those events using data, models, or expert judgment (ASME, 2013). Following the first well-documented HRA method, the Technique for Human Error Rate Prediction (THERP) (Swain and Guttmann, 1983), more than 50 HRA techniques and tools have been developed (Bell and Holroyd, 2009).

However, the lacking of human performance data in HRA is lamented since the born of HRA (Liu and Li, 2014, Hallbert and Kolaczkowski, 2007, Boring et al., 2012, Preischl and Hellmich, 2013). Collecting and accumulating operator performance data for HRA, operator error prevention program, and human factor review program are paid close attention during these years. Several reports (Hallbert et al., 2014, KAERI, 2013, Chang et al., 2014) have been published to provide guidelines to collect data in simulators for HRA. However, the current work cannot effectively support and improve HRA.

Digitalization is a trend in main control rooms (MCRs) of NPPs (Liu and Li, 2016a, Liu and Li, 2016b). Digital MCRs extensively use digital human-system interfaces, integrated information systems, soft controls, computer-based procedures, etc. However, most of HRA methods commonly used today do not properly account for the effects of digital techniques on operator performance (Porthin et al., 2015) and no current HRA method provides guidance on how to treat human reliability considerations for digital techniques (Boring, 2014). That is, the current HRA methods may be not appropriate for digital MCRs. If so, the explanation of HRA outcomes from digital MCRs should be cautioned.

One solution is to collect and update human performance models and data for digital MCRs (Liu et al., 2016a). This paper will demonstrate our initial efforts in collecting operator performance data from digital full-scope simulator training activities for HRA. The next is broken down as follows. Section II introduces the methodological issues, including participants and human performance metrics (operator error, operation time, and mental workload). Section III presents and discusses our results. Section IV concludes our study.

II. METHODOLOGY

II.A. Participants

Operators as participants came from two digital full-scope simulators (named Simulators A and B). In these simulators, the crews were trained to follow emergency operating procedures (EOPs) and mitigate the simulated accident emergencies. We observed the crews actions during their training and EOP validation and verification for 6 times.

II.B. Human Performance Metrics

Human performance data recorded and observed in our case were classified into three types, human error, operation time, and mental workload. These human performance data are not only required in HRA, but also required in human factors engineering review programs. As NUREG-0711 (O'Hara et al., 2012) stresses that, a hierarchal set of performance measures including measures of plant performance, personnel task performance, situation awareness, cognitive workload, and anthropometric/physiological factors, should be considered in integrated system validation activities.

II.B.1. Human Error

It is difficult to observe and collect operator errors in full-scope simulators or real plants. Thus, there are limited databases of operator errors. Several existing databases, for example, CORE-DATA (Kirwan et al., 1997) and NUCLARR (Gertman et al., 1988), are not updated. Their data may be not appropriate for HRA in digital MCR.

We used the model of macrocognition failures in NUREG-2114 (Whaley et al., 2016) to classify and organize the observed operator errors in digital simulators. The NUREG-2114 model describes five macrocognitive functions: (1) detecting and noticing, (2) understanding and sensemaking, (3) decision making, (4) action implementation, and (5) team coordination. The NUREG-2114 model suggests a generic cognitive framework of macrocognitive functions failures to describe its proximate causes (i.e., error type), failure mechanisms leading to proximate causes, and performance influencing factors (PIFs), as shown in Fig. 1.

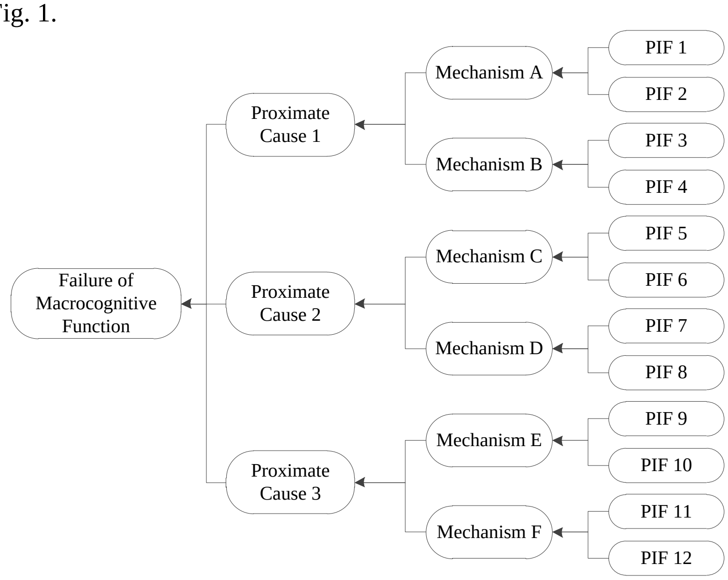

Fig. 1. NUREG-2114 Cognitive Framework of Macrocognitive Function Failures (Whaley et al., 2016)

A macrocognitive function can fail in many ways due to failure of its various cognitive mechanisms. Proximate causes are the outcomes of failure of cognitive mechanisms. Cognitive mechanisms are the processes by which macrocognitive functions work. PIFs are the individual, organizational, and environmental factors that contribute to human performance in a work environment. Take the failure of detecting and noticing as example. It has three proximate causes, i.e., cue/information not perceived, cue/information not attended to, and cue/information misperceived; for the proximate cause of cue/information not perceived, it has five failure mechanisms, i.e., cue content - cue salience is low and not detected, vigilance in monitoring - unable to maintain vigilance, attention - inattentional blindness, expectation - mismatch between expected and actual cue, and working memory capacity overload. For these failure mechanisms, there have dozens of PIFs to trigger them. This model of macrocognitive functions is expected to describe the logic relationship between failures of macrocognitive functions, proximate causes, failure mechanisms, and PIFs (Whaley et al., 2016). This model is supposed to firm the cognitive basis of HRA.

In our observation, it was challenging to identify the cognitive mechanisms and PIFs. We focused on which macrocognitive function failed and its proximate cause when an operator error occurred. TABLE I summarizes the five macrocognition failures and their proximate causes from NUREG-2114. The Scenario Authoring, Characterization, and Debriefing Application (SACADA) database (Chang et al., 2014) also collects crew performance results in terms of macrocognitive functions and specific performance problems (i.e., proximate causes; for example, 'not detecting a key alarm' and 'late in detecting a key alarm' are two specific performance problems of the detecting macrocognitive function). The framework of macrocognitive failures in NUREG-2114 has been used to identify human errors in petrochemical plants (Liu et al., 2016b).

TABLE I. Macrocognition Failures and Their Proximate Causes (summarized from Whaley et al., 2016)

Macrocognition Failure	Proximate Cause	Description
Failure of detecting and noticing	Cue/information not perceived	The cue or information may simply be missed, not seen, or not heard, in which case it is not perceived
	Cue/information not attended to	The cues or information may be sensed and perceived but not attended to
	Cue/information misperceived	The cues or information may be sensed but misperceived. The sensed information is tagged with the incorrect meaning.
Failure of understanding and sensemaking	Incorrect data	The data the person is comparing with a frame is incomplete, incorrect, or otherwise insufficient to understand the situation
	Incorrect integration of data, frames, or data with a frame	Not properly integrate pieces of information together, does not correctly match data with a frame, or does not appropriately integrate multiple frames, such as when a person does not properly merge a frame for a system (i.e., a system model) with the frame for the ongoing event (i.e., a situation model).
	Incorrect frame	The frame used to understand the situation is incorrect, incomplete, or otherwise insufficient to properly interpret the data.
Failure of decision making	Incorrect goals or priorities set	The operator is working toward an inappropriate goal, or has goals improperly prioritized.
	Incorrect internal pattern matching	The operator has mapped the situation to an inappropriate mental model.
	Incorrect mental simulation or evaluation of options	The operator has engaged in incorrect projection of a possible course of action, or has unrealistically evaluated the options
Failure of action implementation	Error of omission	The operator neglects to implement the chosen action
	Error of commission	The operator executes the chosen action incorrectly
Failure of teamwork	Failure of team communication	Key information is not properly shared or distributed among the crew members, and as a result, the entire team does not share a mental model
	Error in leadership/supervision	Supervisory or team management problems, such as the leader not facilitating group discussion, or failing to identify and correct an operator error

II.B.2. Operation Time

Except operator errors, it is worthy to record other performance indicators (e.g., operation time, mental workload, situation awareness). For example, the OPERA database (Park and Jung, 2007) mainly stores operators' operation time data in emergency operating procedures (EOPs). In total of 112 simulation records have been collected from six accident scenarios, loss of coolant accident (LOCA), steam generator tube rupture (SGTR), loss of all feed water (LOAF), excessive steam demand event (ESDE), loss of off-site power (LOOP), and station blackout (SBO) (Jung et al., 2007). Available time or time pressure is an important PIF in HRA. Operators' operation time is necessary to determine available time. Developing the database of operation time can be used to update and modify the existing PSA/HRA outcomes. Actually, the major significance of the OPERA database is that it provides essential inputs to an HRA and improve the technical adequacy of HRA (Jung et al., 2007).

The operators followed EOPs in a step-by-step manner. We recorded operators' respondent time in each procedural step. Before the observation, we prepared a standard sheet containing the procedural steps. Experimenters needed to record operators' operation time (start time or end time) and error type for each step. If allowed, we can use a video-recording technique to record operator behavior and crew activities, and the computerized displays they used. It would be beneficial to post-interview and accurate recordings. Operation time also can be extracted from simulator log file (Chang et al., 2014). At present, two independent experimenters with the background of human reliability analysis and human factors recorded time information of EOP steps and operator errors.

Time-line analysis (Jung et al., 2007) can be conducted if time data of EOP steps are recorded. It is a graphic technique and helps us capture the operation time distribution of EOP steps in accident simulations.

II.B.3. Mental Workload

Mental workload is an important PIF contributing to operator errors. It is also an important performance measure (O'Hara et al., 2012, Reinerman-Jones et al., 2015). For workload measurements, NUREG/CR-7190 summarizes subjective, performance, and physiological metrics that may be used in the context of main control rooms of NPPs (Reinerman-Jones et al., 2015). Subjective metrics include self-report questionnaires, interviews and third-party observation and report. Performance metrics uses primary and secondary task performance to indicate mental workload. Decrements of task performance indicate a change in workload (Wickens et al., 2013). Physiological metrics monitor bodily responses (e.g., heart and brain activities).

In our case, we considered operators' mental workload in following EOPs. We adopted the NASA-Task Load Index (NASA-TLX) (Hart and Staveland, 1988). It is a self-report metric of subjective mental workload that has been validated in numerous studies and applied in various performance settings. It measures six dimensions of perceived workload, mental demand, physical demand, temporal demand, performance, frustration, and effort. In our application, 1 denotes low demand and 10 denotes high demand. After accident scenarios, operators were invited to fill the NASA-TLX questionnaire.

III. RESULTS AND DISCUSSION

III.A. Human Error

TABLE II and TABLE III illustrate several operator errors in Simulator A and Simulator B. Their macrocognition failures and corresponding proximate causes were identified.

TABLE II. Selected Operator Errors in Simulator A

Error	Description	Macrocognition Failure	Proximate Cause
1	During SGTR event with SG#2 tube rupture, the crew failed to identify the condition of SG#1 and assumed that SG#1 also ruptured.	Failure of understanding and sensemaking	Uncertain
2	Failure of control room supervisor (CRS) to arrange operators to monitor one continuous step	Failure of teamwork	Failure of team coordination
3	Operator failed to monitor the actuation signals of the fourth stage ADS valves during execution of ES-1.3 (ADS Stage 1-3 Actuation Response) procedure	Failure of action implementation	Error of omission

TABLE III. Selected Operator Errors in Simulator B

Error	Description	Macrocognition Failure	Proximate Cause
1	Following loss of main feedwater with ATWS (anticipated transient without scram) occurred afterwards, operator followed Step 19 (Check for reactivity insertion from uncontrolled RCS cooldown) in FR-S.1 and failed to perform the RNO (response not obtained) steps due to his wrong judgment of relevant parameters (RCS temperature or SG pressure)	Failure of understanding and sensemaking	Uncertain
2	Following loss of main feedwater and startup feedwater, operator failed to follow the RNO (response not obtained) column of Step 8.a in ES-0.1 (Reactor Trip Response) and continued to perform Step 8.b.	Failure of action implementation	Errors of commission
3	Following a station blackout, when the RNO column of Step 4 in E-0 (reactor trip or safeguards actuation) was performed, operator failed to follow RNO 4c “go to ES-0.1” and continued to perform Step 5.	Failure of understanding and sensemaking	Uncertain

A total of 23 operator error events were observed in our observation. Fig. 1 depicts their macrocognitive function failures. Failure of understanding and sensemaking in the observed operator error events was predominant that 52% of (12 out of 23) operator error events were related to this macrocognition failure. Failure of teamwork was also a significant macrocognitive failure and it was associated with 30% of (7 out of 23) operator error events.

It was difficult to identify the proximate causes related to failure of understanding and sensemaking. This macrocognition failure has three proximate causes, (1) incorrect data, (2) incorrect integration of data, frames, or data with a frame, (3) incorrect frame. Without immediate interviewing the involved operators, it is impossible to determine its proximate causes. The main reasons are that the proximate causes (i.e., outcomes of failed cognitive mechanisms) are not observable and the difficulty in understanding and distinguishing the differences of the three proximate causes (Liu et al., 2016b). The cognitive framework of macrocognitive function failures in NUREG-2114 (Whaley et al., 2016) lay foundation for the latest NRC-sponsed HRA method, Integrated Decision-Tree Human Event Analysis System (IDHEAS) (Xing et al., in press). One interesting fact, however, is that the IDHEAS method considers proximate causes of other macrocognition failures in the name of crew failure modes (e.g., ‘critical data dismissed/discounted’ and ‘miscommunication’), and ignores the internal crew failures modes in the macrocognitive function of understand and sensemaking. The developers of the IDHEAS method may realize the difficulty for identifying and determining the proximate causes (or crew failure modes) related to the macrocognitive function of understand and sensemaking.

For the seven failures of teamwork, the proximate cause for all of them was failure of team coordination. In addition, four of them was because of ‘source error of omission’ (e.g., reactor operator forget to report to control room supervisor) and three of them was because of ‘source error of commission’ (e.g., control room supervisor gave wrong command).

The proximate cause for the failure of detecting and noticing was ‘cues and information not perceived’. The involved operators ignored critical alarms.

The proximate causes for the three failures of action implementation were ‘error of omission’ (n = 2) and ‘error of commission’ (n = 1). One involved operator ignored to perform required steps, failed to monitor critical signals, and performed unexpected actions.

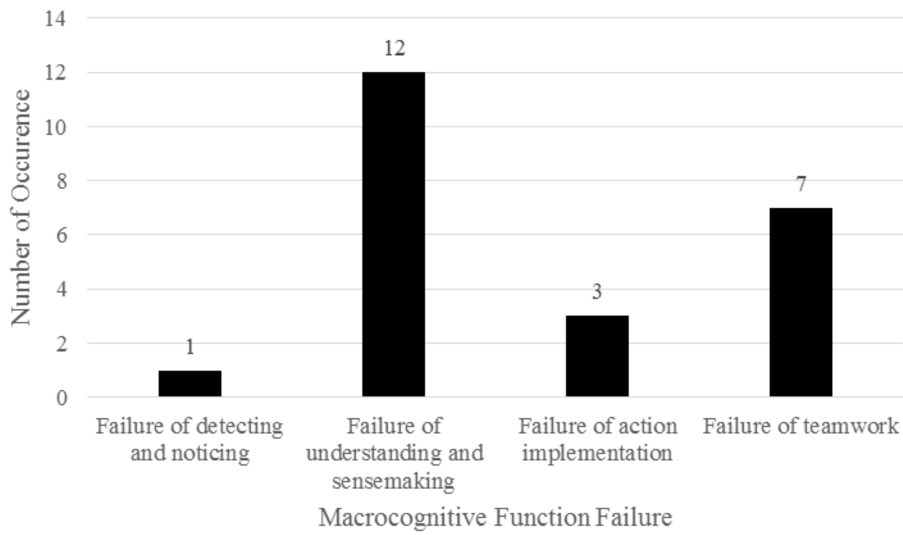

Fig. 1. Distribution of Macrocognitive Function Failures

III.B. Operation time

The operation time data for the EOP steps were averaged and stored in our database. The time data may be used to update time-related PIF information or time-reliability curve based HRA. Time-line analysis in our case was illustrated in Fig. 2.

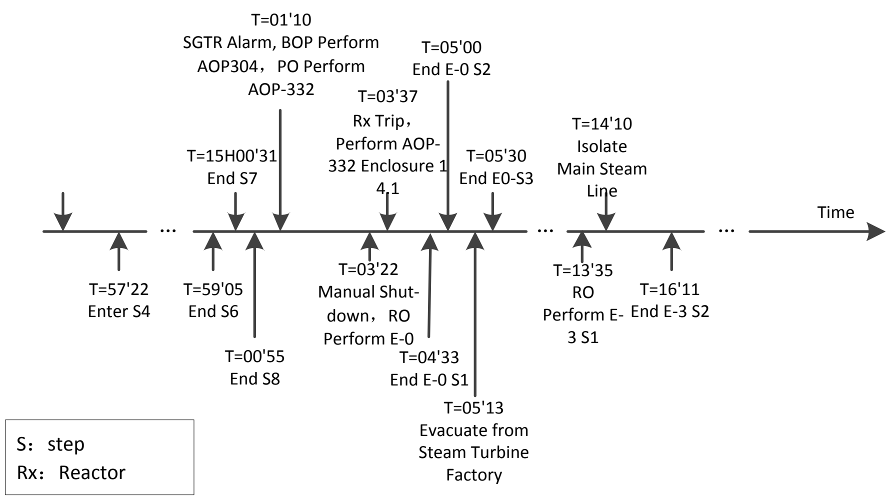

Fig. 2. Demonstration of Time-Line Analysis

III.C. Mental Workload

Mental workload was measured through the NASA-TLX questionnaire (Hart and Staveland, 1988). At present, seven operators self-reported their mental workload, as shown in TABLE IV. Because of the limited number of operators participating in reporting their workload, we could not make quantitative comparisons between different types of operators and between different accident scenarios. We only made qualitative arguments at present. TABLE IV indicates that the surveyed operators reported relatively high workload on the dimensions of performance (Mean = 7.1) and effort (Mean = 7.7). Two CRS operators reported relatively high workload (Overall Workload = 33 and 35, respectively).

TABLE IV. Operator Mental Workload

Num	Operator Type	Mental Demand	Physical Demand	Temporal Demand	Performance	Effort	Frustration	Overall Workload
1	CRS	4	3	4	7	8	7	33
2	RO	4	2	3	9	8	2	28
3	STA	5	1	4	4	7	2	23
4	PO	5	4	4	9	8	8	38
5	BOP	5	3	7	8	6	3	32
6	CRS	9	1	7	8	8	2	35
7	Unclear	4	4	6	5	9	1	29
Mean		5.1	2.6	5.0	7.1	7.7	3.6	31.1

Note: CRS, control room supervisor; RO, reactor operator; BOP, balance of plant; STA, shift technical assistant; PO, peer operator.

IV. CONCLUSIONS

Collecting and accumulating operator performance data for HRA, operator error prevention program, and human factor review program are paid close attention during these years. We visited and observed two full-scope digital simulators, collected human performance data in terms of operator error, operation time, and workload. The initial effort helps us build human performance database for HRA.

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