Journal of Loss Prevention in the Process Industries 56 (2018) 524–530

Contents lists available at ScienceDirect

Journal of Loss Prevention in the Process Industries

journal homepage: www.elsevier.com/locate/jlp

Simulator based performance metrics to estimate reliability of control room operators

Mohd Umair Iqbal[a], Rajagopalan Srinivasan[b,*]

[a] Indian Institute of Technology Gandhinagar, Palaj, Gandhinagar 382355, India
[b] Indian Institute of Technology Madras, Chennai 600036, India

ARTICLE INFO

Keywords:
Human error
Control room operator
Human performance
Risk assessment

ABSTRACT

Chemical processes rely on several layers of protection to prevent accidents. One of the most important layers of protection is human operators. Human errors are a key contributor in a majority of accidents today. Estimation of human failure probabilities is a challenge due to the numerous drivers of human error, and still heavily dependent on expert judgment. In this paper, we propose a strategy to estimate the reliability of control room operators by measuring their control performance on a process simulator. The performance of the operator is translated to two metrics – margin-of-failure and available-time to respond to process events – which can be calculated using process operations data that can be generated from training simulator based studies. These metrics offer a qualitative estimate of operators' reliability. We conducted a set of experiments involving 128 students of differing capabilities from two different institutions and tasked to control a simulated ethanol production plant. Our results demonstrate that differences in the performance of expert vs. novice student operators can be clearly distinguished using the metrics.

1. Introduction

The chemical industry commonly deals with large quantities of hazardous materials at extreme conditions, thus taking on severe hazards which have to be appropriately managed. To manage these hazards and prevent accidents, it is important to identify and assess risks (Kalantarnia et al., 2009). Risk assessment deals with key aspects of accidents like accident prediction, consequences analysis, and development of strategies for emergency preparedness and minimization of damage (Khan and Abbasi, 1998). In spite of improvements in automation and technology, accident rates have not been decreasing (Drogaris, 1993). Accidents occur due to various causation factors such as pump failure, sensor freezing, valve failure, errors of omission and commission by humans etc. Of the various causation factors, human errors are considered to be a key contributor today.

The work of process operators during the normal operation of the plant is primarily supervisory in nature and mainly involves maintaining various process variables within pre-specified limits. When variables cross the safe limits, operators have to take actions to bring the plant back to normal before untoward outcomes result. Thus, human operators form an important layer of protection against accidents in a process plant. Occasionally, the operator is unable to control the process during an abnormal situation. Such failures typically occur due to human failure (e.g. wrong diagnosis, incorrect action). The risk associated with a plant is dependent on the performance of human operators; it is therefore important to determine the likelihood of human failure.

Human failure may arise due to improper training, lack of experience, lack of skills, high stress levels, fatigue, sleep deprivation, etc. Unlike failure rates of equipment and instruments, human failure rates depend on hard to quantify factors such as interpersonal conditions in an organization and specific plant. These failure rates can hence vary widely. A number of methods have been proposed in literature to estimate human failure rates, however all of them suffer from various shortcomings. In this paper, we focus on the reliability of control room operators and propose a new method that has a potential to estimate control room operator failure probability using plant operations data. The rest of this paper is organized as follows: in Section 2, we review the existing literature for estimating human reliability and identify their strengths and shortcomings. In Section 3, we propose a simulation and process data-based approach to estimate human performance. We demonstrate the approach in Section 4 using a case study and report results from experiments involving human participants who play the role of control room operators.

* Corresponding author.
E-mail address: raj@iitm.ac.in (R. Srinivasan).

http://dx.doi.org/10.1016/j.jlp.2017.10.011
Received 8 May 2017; Received in revised form 27 September 2017; Accepted 19 October 2017
Available online 20 October 2017

2. Literature review

Human error is a mismatch between the demands from a process and the human capabilities to meet these demands (Embrey et al., 1994). Human errors are one of the main contributing factors to catastrophic accidents in various industries today (Gupta, 2002; Kim and Bishu, 1996). Over 70% of the accidents in the process industry occur because of human errors (Leveson, 2004). With advancement in technology, human errors tend to be proportionally more common than technological failures; increasing process sophistication and complexity results in greater challenges to the human operators (Chu et al., 1994). Hence, it becomes imperative to study human errors to reduce the number of accidents. However, limited research has been done in understanding human errors. This is partly attributed to the lack of data related to human performance (Moura et al., 2014; Grabowski et al., 2009; IAEA, 1990) – no publicly accessible data banks of human reliability exist. Further, there are intrinsic and practical difficulties in obtaining generalizable human performance related data, key among them being proprietary and sensitivity issues (Massaiu, 2014). This leaves human reliability to the subjective judgments of experts (Park and Lee, 2008) making it prone to error and inconsistency (Massaiu, 2014).

Human reliability statistics addresses issues like the number of personnel failing to perform given tasks, factors affecting their performance, and likelihood of failure. Among these, studies of human failure probabilities are more common and mostly based on task-level success and failures (Hollnagel, 1996; Fleming et al., 1975). For example, human failure assessment has been carried out for human errors during maintenance operations of pumps (Noroozi et al., 2013, 2014) and hydrogen refueling stations (Castiglia and Giardina, 2013). Broadly speaking, human failure analysis techniques can be classified into three categories: derived-data based techniques like Technique for Human Error Rate Prediction (THERP) and Human Error Assessment and Reduction Technique (HEART), analytical techniques involving predominantly expert judgments like Success Likelihood Index Method (SLIM), and simulator-based. However, the boundaries between these techniques often blur and we find techniques which try to incorporate various principles from each of the categories to suit a situation. Generally speaking, the application of expert judgment is common to every technique.

The first structured method can be traced to Swain (1963) which was later developed into Technique for Human Error Rate Prediction - THERP (Swain and Guttmann, 1983). THERP is one of the best known first generation human reliability analysis methods (Reason, 1990; Hollnagel, 1996; Kirwan, 1997). The technique involves defining system failure, listing the human operations, predicting individual error rates, determining the effects of human errors on the system, and then recommending necessary changes to reduce failure rates (Swain, 1963). One of the main features of THERP is the use of Performance Shaping Factors (PSFs), which describe the general conditions that may influence the performance of the tasks and consequently the probabilities (Hollnagel, 1996). Individual error rates are predicted by experts based on data available in literature as well as on their judgment. Another technique called Human Error Assessment and Reduction Technique (HEART) was later developed to analyze personnel tasks at a higher level compared to THERP, and also allow application to a range of industries (Williams, 1986). Deacon et al. (2013) developed a framework for human error analysis of offshore evacuations to identify and analyze human error risk for critical steps in the escape, evacuation and rescue process. The framework employed HEART along with other techniques like hazard and operability (HAZOP), risk matrix, etc. Several other human reliability techniques, preferred by practitioners were developed later like Justification of Human Error Data Information (Kirwan and James, 1989). The reason behind the popularity of these methods among practitioners is that their output is in the form of event trees or a probability value which can easily be used in probabilistic risk assessments (Moura et al., 2014). The above first generation methods suffer from many limitations. They fail to comprehensively address errors of commission as distinct from errors of omission. Lack of a strong theoretical and structural basis also makes them prone to significant variations in end results when conducted by different analysts. The limited experimental data used by some methodologies is not sufficient to statistically support quantification. Finally, the techniques mainly focused on the task performed by the operators but not the context in which the tasks are performed. Human cognition is an area where, to date, scientific understanding is primitive at best. It is evident that there are numerous determinants to human decision making performance in general, and particularly in the context of human error. The problem is further compounded by the limited availability of data. To our knowledge, there is no strong theoretical basis to date which provides specifically for a deterministic understanding of human cognitive errors. Empirical approaches therefore become interesting, for instance the generation and analysis of human performance data through simulator based experiments that has been customized to the actual system of interest (such as a chemical plant) and carried out by the actual human users of the actual system (i.e., plant operators), as proposed in this work.

The intrinsic complexity in collection of human reliability data led to the development of methods which involved extensive use of expert judgment (Moura et al., 2014; Grabowski et al., 2009). One such widely used method is SLIM – Success Likelihood Index Method (Embrey et al., 1984), which involves a decision-analytic approach to weigh Performance shaping factors based on expert judgment. SLIM has been used in offshore oil and gas industry because of the lack of availability of human error data bases in that sector. For example, DiMattia et al. (2005) used it to determine error probabilities for offshore musters. It has also been modified by incorporating the Analytic Hierarchy Process (AHP) to address inconsistencies associated with expert judgments e.g. AHP-SLIM (Park and Lee, 2008). Khan et al. (2006) proposed a technique called Human Error Probability Index (HEPI), based on SLIM, to assess human failure probabilities in offshore platform musters. It should be noted that expert judgment still remains critical in these methods due to inadequacy of empirical human error data.

Considering the difficulty in obtaining human reliability data, methods were devised which could empirically generate the required data so that the error mechanisms could be better understood. When simulations are feasible, human failure probability was calculated on the basis of number of successes and failures involved in performing a particular task. However, quantification of such data, so that it could be used in probabilistic risk assessments, proved challenging when complex tasks are involved (Massaiu, 2014). It would require a lot of people and sessions to deal with such complex tasks to generate the data that could be considered statistically reliable. Further, considering the complexity in the task, it is difficult to ensure that the conditions (i.e., context) around the human operators remain same in all such sessions so that results from different sessions can be reliably combined (Moray, 1990). Therefore, newer methods involve simulator experiments combined with extensive study of cognitive, psychological and emotional aspects. Chang and Mosleh (2007) have demonstrated the application of information, decision, and action in crew context (IDAC) model for human reliability analysis. IDAC involves modeling the behavior of operators through a cognitive model. However, such methods are, to our knowledge, still in their infancy and limited to academic exercises. Simulator-based studies to understand human performance and errors have not received much attention in the chemical process community; however, it has been the subject of many studies in other high-risk domains such as nuclear power plants. Zhang et al. (2007) demonstrated the use of simulator studies in nuclear power plants, to determine Human Cognitive Reliability model. They highlight that simulator studies offer the only way by which human operator responses can be systematically inquired, especially during accident scenarios. Human error probabilities (HEPs) are typically quantified by beginning with a nominal or base HEP (i.e., generic human error rates) and then modified by PSF coefficient values, which are often treated as multipliers to obtain the case-specific HEP (Boring, 2009). Therefore, identifying and quantifying the effect of PSFs is a critical step in HRA studies. Monferini et al. (2013) devised a methodology to relate Human and Organizational Factors (HOFs) to the response time of operators in safety critical operations. The main outcome of their study was the design of virtual experiments that examined correlations between response time and Common Performance Conditions (CPCs) variations. Forester et al. (2014) highlight the strengths and limitations of various human reliability assessment methodologies and demonstrate the potential of simulator studies. Musharraf et al. (2014) demonstrate a simulation-based virtual experimental technique way to collect human performance data during offshore emergency evacuation. Their work seeks to address the scarcity of data corresponding to emergencies in offshore industries. There is a similar need to develop a methodology to understand human error during abnormal situations in chemical process industries, which are characterized by a diverse set of emergency scenarios, and where the human operator is often the last layer of protection. The data obtained can be utilized to estimate human performance at least qualitatively.

In summary, various techniques exist to assess human failure probabilities. However, most of them are challenged by the lack of availability of human failure data. Organizational and Safety culture also plays an important role. Humans may operate differently in different industrial settings. They may even operate and behave differently in similar settings but in different plants because organizational culture plays an important role in how an individual behaves and acts. The deviation in human behavior in terms of diagnosis, decision making and action varies because of differences in training, organizational safety culture, design, etc. This makes it unrealistic to analyze human failure over a broad spectrum of conditions using a single database. Another consequence of the variety of methods for estimating human error probabilities is that different human reliability analysis methodologies often lead to significantly different end results for the same task. This has been best brought out by the studies done at the Halden Human-Machine Laboratory as reported by Forester et al. (2014). Thus, it becomes imperative to analyze the impact of human actions on the plant behavior in response to disturbances, failures and untoward situations using plant specific data. The interaction between the plant behavior and human performance is best studied empirically. This motivates a methodology to gauge human performance, and consequently human reliability, based on easily available, empirical plant-specific data. In this paper, we propose such a methodology to measure human performance experimentally as detailed next.

3. Proposed metrics and methodology

A chemical process plant involves a number of unit operations with many control loops that ensure that important variables are maintained at pre-specified values by rejecting disturbances. The role of control room operator in a modern-day process is primarily one of supervising the process during normal conditions. The role of the operator can, however, suddenly become safety critical when something goes wrong in the process such as equipment or instrument failure. When such abnormal conditions occur that are beyond the realm of the automatic control system, the operator has to quickly detect that there is in fact an abnormality that has occurred, accurately decipher from the available measurements the root cause of the abnormality, and take corrective actions to return the process to a safe condition. The control room operator's ability in situation assessment and recovery is a direct measure of his/her reliability. In our proposed methodology, we seek to quantify this ability of the operator.

We propose two metrics as direct measures of the operator's reliability – margin-to-failure and available-time. The margin-to-failure measures how close the process has been to an unsafe state after an incident has occurred and the operator has intervened by taking some action(s) to ensure safety. This is reflected by the time profile of the variables safety critical process variables (e.g. temperature, pressure, level, etc) during the course of a safety incident. Safety limits for important variables are usually predetermined during the process design stage and various alarms and shutdown logic may be configured to reflect them. The margin-to-failure of each variable can be calculated by comparing its extremum value during the course of the incident to its safe limit. As an illustration, consider a process where temperature is a safety critical variable. During normal operation a low-level regulatory (such as PID) controller may manipulate a variable (such as coolant flow rate) to ensure that the temperature remains in a safe range. A failure such as a stuck control valve may lead to an increase in temperature – the operator may typically become aware of the issue when the high temperature alarm goes off. The operator would take some time to assess the situation, determine its root cause and then take recovery action. For instance, when the control valve fails stuck, the operator may operate an alternate bypass valve manually in order to reduce the temperature and bring it within the safe limits. The difference between the shutdown limit and the maximum temperature that occurred in the reactor during this episode is the margin-to-failure as illustrated in Fig. 2. It is neither controlled nor a response but an outcome arising from the operator's actions. The margin-to-failure of the whole plant can be conservatively defined to be the minimum value of the margin-to-failure of all the safety critical variables pertinent to that event. The process operations can be used to determine the margin-to-failure.

Similarly, the available-time is the difference between the maximum allowable time for the incident before automatic shutdown is triggered and the operator's response time defined as the duration from occurrence of the first alarm to the clearance of the disturbance characterized by all variables returning to their normal limits (see Fig. 2). In other words, available-time is the maximum further duration the operator could have utilized to stabilize the process without any safety impact. This can also be calculated from process data for each event.

For example, consider a tank containing hazardous chemicals. We need to ensure that the tank does not overflow or there is no excessive pressure inside the tank, so that there is no spillage and consequent possibility of exposure to toxic chemicals, fire or explosion, etc. To prevent these, the tank is equipped with a pressure relief valve. Also the input flow to the tank is controlled to ensure safe limits of level in the tank. The tank is provided with high level alarm, so in case of unexpected high-level (e.g. due to some failure in the level control-loop), the operator can close a manual valve on the feed line. Human error reflects itself as the operator failing to close the manual valve when required – this would manifest itself in the form of liquid level in the tank approaching overflow limits (higher than the level alarm limit). Also, the speed of the operator's response to stabilize the process and bring the level below alarm limit is an indication of the operator's reliability.

The reliability of the operator based on the above metrics can be estimated in one of two ways: (1) by mining the historical operations data especially during plant incidents, and (2) by conducting experiments using the operating training simulator (OTS) that is widely deployed in many chemical plants. We focus on the latter in this paper since the availability of the historical operations data from emergencies are limited at best. The necessary experiments can evaluate actual plant personnel by requiring them to control the plant during a variety of different scenarios. These different situations may be designed by studying the various accident scenarios identified in the HAZOP analysis of the plant. The evolution of the process variables with time is recorded during the experiments. The recorded data is finally analyzed to measure operators performance and reliability. We demonstrate this approach of accessing control room operator's performance in the next section using a case study involving an ethanol production plant.

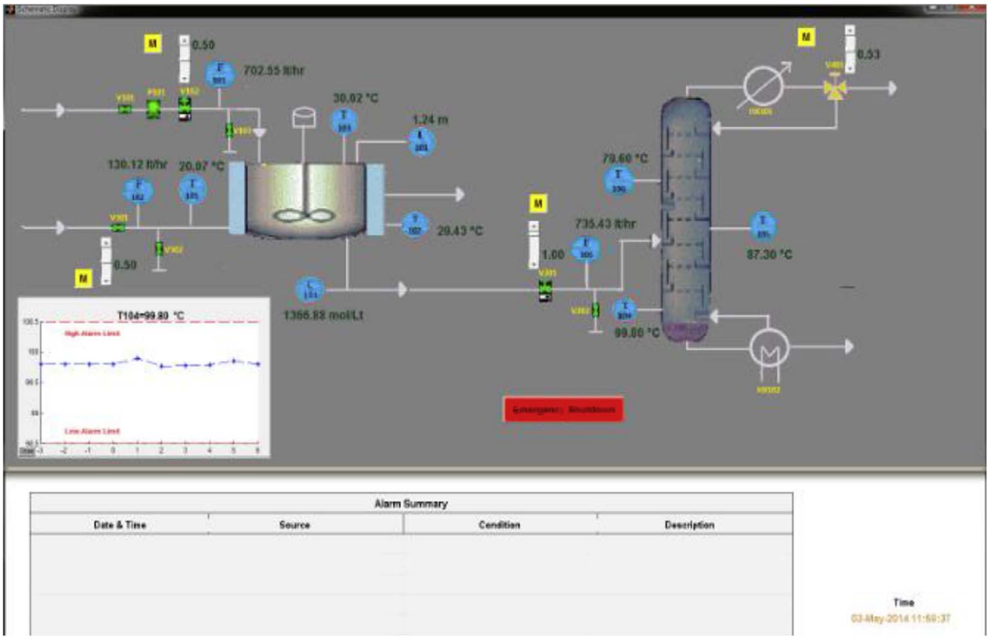

Fig. 1. Modeled ethanol plant interface.

4. Case study: ethanol production process

In the ethanol production plant, feed of ethene and water enters a Continuous Stirred Tank Reactor (CSTR) in which an exothermic reaction takes place resulting in the formation of ethanol. To control the temperature within the CSTR, a coolant (water) is circulated in the jacket of the CSTR. The reaction contents are distilled in a distillation column, where ethanol of required purity is obtained as the top product while the unreacted raw materials form the bottoms. The process is controlled to ensure safe operation despite various disturbances. An operator supervises the control of the process using a distributed control system (DCS). The interface of the ethanol production plant's DCS is shown in the Fig. 1. The flow rates in various streams are controlled by valves, and the values of various process variables (like temperature, flow rate, etc.) are displayed in the human-machine interface (HMI). The interested reader is directed to Sharma et al. (2016) for a detailed description of the HMI used in the experiment. In this process, various abnormalities can occur. For example, suppose the reactor temperature starts increasing due to reasons initially unknown to the operator (e.g. sensor has failed, or a control valve has got stuck). Unless the operator is able to respond quickly, the temperature may cross acceptable limits, and lead to an uncontrollable runaway reaction with adverse consequences (reactor damaged, loss of reactor containment, potential for fire and explosion). Thus there is a need to maintain various process variables within acceptable safe limits (e.g. alarm limits). Further, a measure of the operator's reliability is the response time and extent of deviation of critical process variables from their safe limits. Such data can be obtained from historical process data. In other words, by analyzing process operations data during various abnormal conditions, it is possible to evaluate the reliability of process operators.

We conducted human subject based experiments to study the variation in reliability according to operators' experience level. Our study included a total of 128 participants who played the role of plant operator for the simulated ethanol production plant. These participants were graduate and undergraduate students at Indian Institute of Technology Gandhinagar and National Institute of Technology Srinagar. The participants were drawn from two different groups – one set of 76 participants, hereby called novice operators, had no prior experience in control of the ethanol process nor of any other simulator based process control experiments. The other set of 52 participants, called expert operators, had previously operated the simulated process, although they may not have handled the same disturbance considered in these experiments. Before the start of the experiment, both sets of participants were given the same training on how to operate the plant. The training involved studying an instruction manual and a video demonstration of using the HMI to interact with the process. During the experiment, the operator is tasked to monitor the process and respond to any disturbance if any process variable deviates outside its alarm limits. Further, the operator is required to return the process within its safe operating bounds within a stipulated amount of time (5 min). The operators are notified of alarms in the HMI by the change in color of the tag from grey to red. A list of variables in alarm status is also displayed in the HMI's alarm panel.

Next, we describe a typical failure scenario that has to be handled by the operator. The reactor temperature is maintained by a feedback control loop that controls the coolant flow rate to the CSTR. In our case study, the temperature sensor can suddenly get stuck (i.e. value reported by the sensor does not change) at some instant of time. The erroneous input to the controller due to the freezing of the temperature sensor would lead to poor temperature control and a consequent rise or fall in the CSTR temperature given the exothermic nature of the reaction. When an alarm is triggered, the operator has to quickly take necessary decisions so as to bring the temperature and other variables (which are affected by the disturbance) within acceptable limits; else there would be an automatic shutdown (also considered as a human failure). If the operator is unable to troubleshoot the root cause of the disturbance(s) he also has the choice to trigger an emergency shutdown of the process. This is also considered a failure on the part of the operator.

The reliability of the plant operators to control the process can be studied by considering the margin-to-failure and the available-time. The margin-to-failure measures how close a safety critical variable (e.g. temperature of CSTR) approaches the shutdown limit during the course of the episode. The process data generated experimentally can be used to determine the margin-to-failure. Similarly, the available-time is the difference between the maximum allowable time for the incident before automatic shutdown is triggered (in our case 5 min) and the operator's response time defined as the duration from occurrence of the first alarm to the clearance of the disturbance (characterized by all variables returning to their normal limits). This can also be calculated from process data for each episode as illustrated in Fig. 2 above. Next, we report our conclusions from our experimental study.

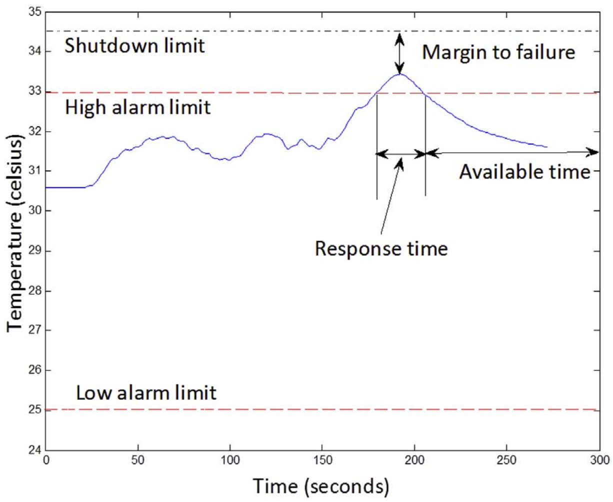

Fig. 2. Process variable trend during a typical experiment.

4.1. Results

Following the procedure discussed above, for analysis we considered the CSTR temperature and distillation column temperature and pressures to be safety critical process variables. Since the temperature and pressure of the distillation column didn't show much variation in the disturbances studied here, and their range stayed within safe limits in all cases, in the following we only consider CSTR temperature for assessing human performance. From the operations data for each operator, the response times of the operator and the deviation in the temperature of the CSTR were determined. Out of the 76 novice participants that performed the experiment, only 32 (about 42%) were able to bring the plant to normal after the incident. Similarly, among the 52 expert participants, 28 (about 54%) were able to successfully tackle the disturbance. The relatively low success rate reflects the overall difficulty of the task. Further, the higher proportion of success of the expert operators highlights their higher expertise. Next, the available-time and margin-to-failure were analyzed for those novice and expert operators who were successful in completing the task.

Fig. 3 shows a plot of the available-time against margin-to-failure for the novice operators. The normalized difference between the shutdown limit for the CSTR temperature, and the maximum temperature attained during the process of operating the plant is used to calculate the margin-to-failure. In a similar fashion, the available time is normalized to a scale of 100 based on the difference between actual response time and the maximum allowable time. The axes are scaled so that the results can be compared while determining the human performance based on different key variables for different tasks or processes, as required. This helps in generalization. From the figure, it can be observed that as the available-time is higher, the margin-to-failure is also more. Consider for example, a data point in the bottom right of the plot. The available time is around 81 s (on a scale of [0100] seconds) and the margin-to-failure is 0.74 (on a scale of [0 1]). This shows that the operator corresponding to whom these values are obtained has not allowed the temperature to deviate too much and at the same time he has also been successful in controlling the plant within a short period of time. The variability in the response times in Fig. 3 also points to have high variability in response times (i.e. human performance). This means that variability in the underlying distribution from which human failure probabilities are sampled is high. This needs to be reflected when such human failure probabilities are incorporated into risk analysis and would indicate a higher risk for the plant (Iqbal and Srinivasan, 2016).

We carried out the same analysis with the operations data from the expert operators. The resulting curve is shown in Fig. 4. The trend for the expert operators is also similar to that for the novice operators. However, a comparison of the two classes of operators as shown in Fig. 5, reveals the following. The trend line for expert operators has shifted in an anti-clockwise direction, i.e., the margin-to-failure for expert operators has improved which indicates that these operators tend to control the plant better and do not allow safety critical variables to get close to the failure limits. . Whenever a process variable, crosses its safety limits, the process is exposed to a safety hazard, which has the potential to result in an unplanned shutdown or accident. Kleindorfer et al. (2012) have attempted to determine the magnitude of such loss, in monetary terms, by introducing a new concept of potential safety loss (PSL); the longer the variables stay outside the acceptable limits more is the potential of the plant to experience a loss due to safety issues. Further, the spread in margin-to-failure in the case of expert operators is noticeably lower than that of the novice operators – 0.60 units for experts and 0.71 units for novices. This shows less variability in the performance of the expert operators, and consequently less risk. Thus,

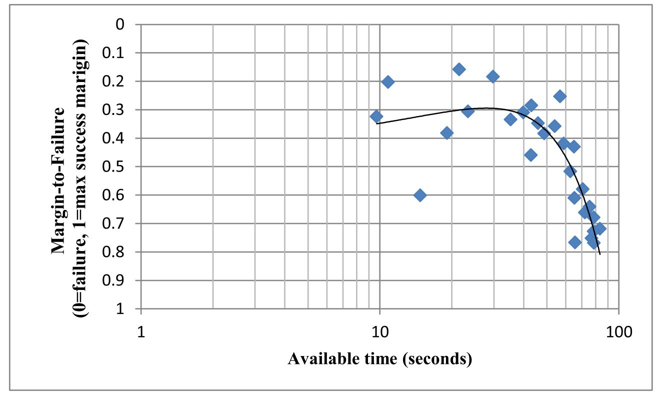

Fig. 4. Available time vs. margin-to-failure curve for experienced operators.

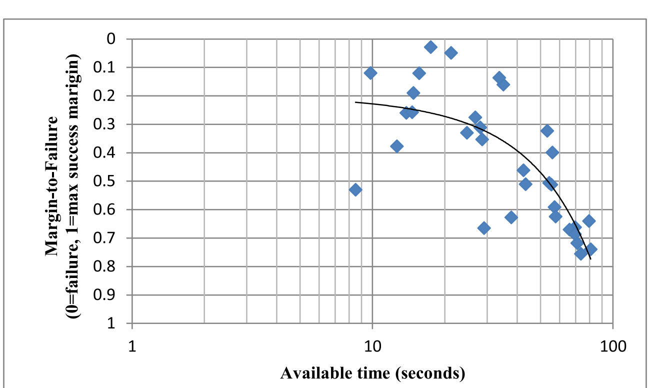

Fig. 3. Available time vs margin-to-failure curve for novice operators.

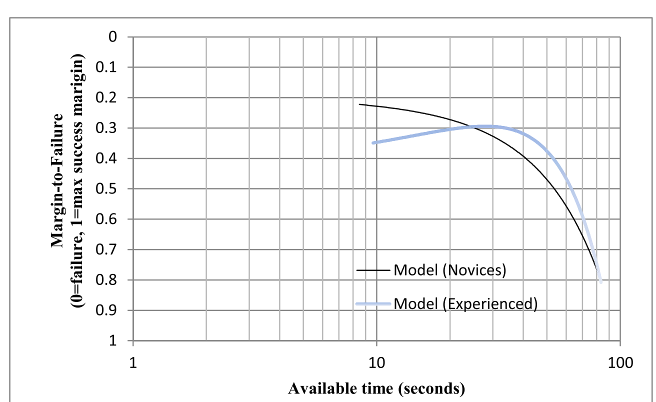

Fig. 5. Comparison of model curves for novice and experienced operators.

this analysis quantifies the benefit that experience offers in performance improvement. The gulf between the performances of experienced and novice operators is believed to become more distant and visible during the complex and more difficult tasks that are encountered in an industrial setting.

The advantage of the proposed methodology is that we can study the performance of human operators on plant specific basis from the plant's operating data. This ensures better validation of human failure probabilities associated with that plant, as well as devising a better and targeted strategy to improve human performance. Human reliability analysis methods and the subsequent probabilistic safety assessments are challenged by plant-specific organizational factors (Mohaghegh and Mosleh, 2009) and the interdependencies between organizational issue creates and safety barriers are not reflected well. The proposed approach for measurement of plant-specific human performance provides an (indirect) approach to incorporate organizational, factors like training, awareness, etc in the reliability estimates. Operator actions, and hence performance, need to be understood in a contextual manner i.e. in relation to the people attempting (together), in a particular environment, to make sense of the system and the environment, and act on the basis of available (incomplete) information while relying on social conventions, cognitive heuristics and affordances provided by the environment (Reiman and Rollenhagen, 2011).

The proposed methodology and the metrics also have an important application in the context of near-misses. Near misses have been defined as departures from and subsequent returns to normal operating range for process variables (Pariyani et al., 2012). Near-misses are less obvious compared to accidents since they are often not 'visible' and have little or no immediate impact on business, process, or individuals (Kleindorfer et al., 2012). In our approach, near-misses are characterized by successful tasks but with a low margin-to-failure. By quantifying performance using the proposed metrics, we thus provide a measure of near-misses. These near-miss measures are therefore beneficial and offer a way to predict the occurrence of unsafe conditions during regular operations, which are often a precursor to catastrophes (Kleindorfer et al., 2012).

5. Conclusions and discussion

Chemical process industries routinely handle hazardous materials having inherent risk associated with them. Abnormalities may lead to incidents of varying consequence – from near-misses to catastrophic accidents. A number of Layers of Protection are used to minimize these. Humans form an important element of such protective systems; however, the failure probability associated with human operators is not fully known. Due to the belief that human error is inevitable and unpredictable, and that advances in automation will make human action unnecessary, the domain of human error has received limited attention. However, human error accounts for over 70% of accidents in the chemical industry. A proper understanding of human errors, especially failure probabilities is therefore imperative.

In this paper we propose metrics and a strategy for estimating failure probabilities experimentally for control room operators. The strategy is based on the time taken by operators to bring a plant to a normal state, in response to an abnormal event. The inability of the human operator to bring the plant within normal limits is considered to be a measure of their reliability. We propose two metrics – margin-to-failure and available time to quantify this. Such a granular measurement of human performance is important because it enables us to look into human failure beyond the binary notions of success and failure – thus accounting for higher order cognitive skills and diagnosis ability which are increasingly critical in today's automated plants. The magnitude of variance in the metrics also reflects the extent of risk, i.e., lower the variance in performance, the higher the operator's reliability when a particular disturbance occurs. Through such metrics, we focus more on quantitatively analyzing the overall performance of an operator as different from an investigation of the step-by-step actions/inactions over the course of the task. By measuring these, we can gauge the operator's skill and effectiveness of training. Analyzing the performance data opens up opportunities to mine for focused training. Thus, the risk to the plant because of variability in human performance can be brought down by appropriate steps like guided training, awareness, etc. This will be the focus of our future work. Further, the proposed methodology has been demonstrated for a specific scenario; however, it can be directly applied to various other scenarios, even in an industrial setting, in a similar manner.

References

Boring, R., 2009. Human reliability analysis in cognitive engineering. In: Frontiers of Engineering: Reports on Leading-edge Engineering from the 2008 Symposium. National Academy of Engineering, Washington, DC, pp. 103–110.

Castiglia, F., Giardina, M., 2013. Analysis of operator human errors in hydrogen refuelling stations: comparison between human rate assessment techniques. Int. J. hydrogen energy 38 (2), 1166–1176.

Chang, Y.H.J., Mosleh, A., 2007. Cognitive modeling and dynamic probabilistic simulation of operating crew response to complex system accidents. Part 2: IDAC performance influencing factors model. Reliab. Eng. Syst. Saf. 92 (8), 997–1013.

OctoberChu, R., Bullemer, P., Harp, S., Ramanathan, P., Spoor, D., 1994. Qualitative user aiding for alarm management (QUALM): an integrated demonstration of emerging technologies for aiding process control operators. In: Systems, Man, and Cybernetics, 1994. Humans, Information and Technology., 1994 IEEE International Conference on, vol. 1. IEEE, pp. 735–740.

Deacon, T., Amyotte, P.R., Khan, F.I., MacKinnon, S., 2013. A framework for human error analysis of offshore evacuations. Saf. Sci. 51 (1), 319–327.

DiMattia, D.G., Khan, F.I., Amyotte, P.R., 2005. Determination of human error probabilities for offshore platform musters. J. loss Prev. process Industries 18 (4), 488–501.

Drogaris, G., 1993. Learning from major accidents involving dangerous substances. Saf. Sci. 16 (2), 89–113.

Embrey, D.E., Humphreys, P., Rosa, E.A., Kirwan, B., Rea, K.S., 1984. An Approach to Assessing Human Error Probabilities Using Structured Expert Judgement (NUREG/CR-3518). US Nuclear Regulatory Commission, Washington, DC.

Embrey, D.E., Kontogiannis, T., Green, M., 1994. Guidelines for Preventing Human Error in Process Safety. Center for Chemical Process Safety, American Institute of Chemical Engineers, New York.

Fleming, K.N., Raabe, P.H., Hannaman, G.W., Houghton, W.J., Pfremmer, R.D., Dombek, F.S., 1975. HTGR Accident Initiation and Progression Analysis Status Report. Volume II. AIPA Risk Assessment Methodology. General Atomic Co.

Forester, J., Dang, V.N., Bye, A., Lois, E., Massaiu, S., Bromberg, H., Braarud, P.Ø., Boring, R., Männistö, I., Liao, H., Julius, J., Parry, G., Nelson, P., 2014. The International HRA Empirical Study Lessons Learned from Comparing HRA Methods Predictions to HAMMLAB Simulator Data. NUREG-2127. US Nuclear Regulatory Commission, Washington DC, USA.

Grabowski, M., You, Z., Zhou, Z., Song, H., Steward, M., Steward, B., 2009. Human and organizational error data challenges in complex, large-scale systems. Saf. Sci. 47 (8), 1185–1194.

Gupta, J.P., 2002. The Bhopal gas tragedy: could it have happened in a developed country? J. Loss Prev. Process Industries 15 (1), 1–4.

Hollnagel, E., 1996. Reliability analysis and operator modelling. Reliab. Eng. Syst. Saf. 52 (3), 327–337.

International Atomic Energy Agency, 1990. Human Error Classification and Data Collection. Report of a Technical Committee Meeting Organised by the IAEA. Vienna, 20–24 February 1989. INIS Clearinghouse, Vienna.

Iqbal M.U., & Srinivasan R. (2016). A novel experimental strategy for validating human failure probabilities in risk assessment. Proceedings of the 26th European Symposium on Computer Aided Process Engineering – ESCAPE 26.

Kalantarnia, M., Khan, F., Hawboldt, K., 2009. Dynamic risk assessment using failure assessment and Bayesian theory. J. Loss Prev. Process Industries 22 (5), 600–606.

Khan, F.I., Abbasi, S.A., 1998. Techniques and methodologies for risk analysis in chemical process industries. J. Loss Prev. Process Industries 11 (4), 261–277.

Khan, F.I., Amyotte, P.R., DiMattia, D.G., 2006. HEPI: a new tool for human error probability calculation for offshore operation. Saf. Sci. 44 (4), 313–334.

Kim, B., Bishu, R.R., 1996. On assessing operator response time in human reliability analysis (HRA) using a possibilistic fuzzy regression model. Reliab. Eng. Syst. Saf. 52 (1), 27–34.

Kirwan, B., 1997. Validation of human reliability assessment techniques: part 1—validation issues. Saf. Sci. 27 (1), 25–41.

Kirwan, B., James, N.J., 1989. Development of a Human Reliability Assessment System for the Management of Human Error in Complex Systems. Reliability'89, Brighton, June 14–16. 5A/2/1–5A/2/11.

Kleindorfer, P., Oktem, U.G., Pariyani, A., Seider, W.D., 2012. Assessment of catastrophe risk and potential losses in industry. Comput. Chem. Eng. 47, 85–96.

Leveson, N., 2004. A new accident model for engineering safer systems. Saf. Sci. 42 (4), 237–270.

Massaiu, S. (2014). Extracting Human Reliability Information from data collected at different simulators: A feasibility test on real data. Probabilistic Safety Assessment and Management Conference (PSAM 12), Honolulu, Hawaii.

Mohaghegh, Z., Mosleh, A., 2009. Incorporating organizational factors into probabilistic risk assessment of complex socio-technical systems: principles and theoretical foundations. Saf. Sci. 47 (8), 1139–1158.
Monferini, A., Konstandinidou, M., Nivolianitou, Z., et al., 2013. A compound methodology to assess the impact of human and organizational factors impact on the risk level of hazardous industrial plants. Reliab. Eng. Syst. Saf. 119, 280–289.
Moray, N., 1990. Dougherty's dilemma and the one-sidedness of human reliability analysis (HRA). Reliab. Eng. Syst. Saf. 29 (3), 337–344.
Moura, R., Beer, M., Pattelli, E., Lewis, J., Knoll, F., 2014, September. Human error analysis: review of past accidents and implications for improving robustness of system design. In: Proceedings of the 24th European Safety and Reliability Conference, pp. 14–18.
Musharraf, M., Bradbury-Squires, D., Khan, F., Veitch, B., MacKinnon, S., Imtiaz, S., 2014. A virtual experimental technique for data collection for a Bayesian network approach to human reliability analysis. Reliab. Eng. Syst. Saf. 132, 1–8.
Noroozi, A., Khakzad, N., Khan, F., MacKinnon, S., Abbassi, R., 2013. The role of human error in risk analysis: application to pre-and post-maintenance procedures of process facilities. Reliab. Eng. Syst. Saf. 119, 251–258.
Noroozi, A., Khan, F., MacKinnon, S., Amyotte, P., Deacon, T., 2014. Determination of human error probabilities in maintenance procedures of a pump. Process Saf. Environ. Prot. 92 (2), 131–141.
Pariyani, A., Seider, W.D., Oktem, U.G., Soroush, M., 2012. Dynamic risk analysis using alarm databases to improve process safety and product quality: Part I—data compaction. AIChE J. 58 (3), 812–825.
Park, K.S., Lee, J., 2008. A new method for estimating human error probabilities: AHP–SLIM. Reliab. Eng. Syst. Saf. 93 (4), 578–587.
Reason, J., 1990. Human Error. Cambridge University Press, Cambridge.
Reiman, T., Rollenhagen, C., 2011. Human and organizational biases affecting the management of safety. Reliab. Eng. Syst. Saf. 96 (10), 1263–1274.
Sharma, C., Bhavsar, P., Srinivasan, B., Srinivasan, R., 2016. Eye gaze movement studies of control room operators: a novel approach to improve process safety. Comput. Chem. Eng. 85, 43–57.
Swain, A.D., 1963. Method for Performing a Human-factors Reliability Analysis (No. SCR–685). Sandia Labs, Albuquerque, N. Mex. (USA).
Swain, A.D., Guttmann, H.E., 1983. Handbook of Human-reliability Analysis with Emphasis on Nuclear Power Plant Applications. Final report (No. NUREG/CR-1278; SAND-80–0200). Sandia National Labs, Albuquerque, NM (USA).
AprilWilliams, J.C., 1986. HEART–a proposed method for assessing and reducing human error. In: 9th Advances in Reliability Technology Symposium. University of Bradford.
Zhang, L., He, X., Dai, L.-C., Huang, X.R., 2007. The simulator experimental study on the operator reliability of Qinshan nuclear power plant. Reliab. Eng. Syst. Saf. 92, 252–259.