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A weighted CREAM model for maritime human reliability analysis

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ABSTRACT

Human error can be regarded as a significant factor contributing to marine accidents. Crew onboard vessels often perform duties in circumstances where technological, environmental and social factors emerge which may contribute to the occurrence of human failures. Fuzzy Cognitive Reliability and Error Analysis Methods (CREAM) is one of the most recognized HRA methods capable of tackling such difficulties. However, shortcomings are still disclosed and weaken the applicability of such an approach. These include the lack of considering input weights, the dubitation of the logicality of adopting rule base approaches to evaluate the relations between inputs and output and the loss of useful information due to the application of min–max fuzzy inference method. A new fuzzy CREAM methodology capable of resolving the aforementioned difficulties is proposed based on a rule base approach. The framework is validated using two axioms and demonstrated by virtue of an oil tanker example. The results are consistent with the principles evolved from the axioms since the outcomes are sensitive to the minor alterations of input data and weights. It is concluded that the weighted CREAM model is able to produce reliable human performance failure results and the strengths will not be compromised even if applied in circumstances where membership function shapes of fuzzy sets are various from traditional studies.

1. Introduction

Since the advent of the notable shipping accidents of Amoco Cadiz and Derbyshire and offshore tragedies of Alexander L. Kielland and Piper Alpha, tremendous efforts have been devoted to the improvement of ship construction and system reliability. Despite the shipping modernization, marine accidents still occur nowadays. Over decades, a variety of studies have suggested that human errors are the major cause of shipping accidents (Ćorović and Djurović, 2013; Rudan et al., 2013; Baniela and Ríos, 2013). Human reliability analysis (HRA) has been proven useful for the mitigation of human errors and this is particularly true for the nuclear industry. However, the availability of human failure statistics in the maritime domain is either scarce or inexistent and thus causes challenges for the implementation of an effective and quantitative HRA method (Yang et al., 2013, 2010; Martins and Maturana, 2010; Ren et al., 2008). The duties performed by crew onboard ships reveal a nature of highly contextual dependency where technological, environmental and social factors often emerge and constitute a complex working condition in an interactive way (Yang et al., 2013). The second generation methods consider the context as the most crucial factor affecting the human performance failure and capable of overcoming the difficulties encountered by the shipping industry. Cognitive Reliability and Error Analysis Methods (CREAM) is one of the most recognized methods of the second generation for addressing such contextual influence. It enables qualitative opinions from experts to be converted into quantitative human failure analysis results. However, the CREAM approach often provides an approximation analysis generating interval results due to the lack of sufficient failure data. Accordingly, a number of CREAM studies incorporating fuzzy logic have been proposed. Although such models are capable of producing crisp outcomes, shortcomings are still exposed for practical applications. In this paper, a new fuzzy CREAM methodology is developed. Different from traditional studies, the strengths of the model will include the consideration of the weight of each Common Performance Conditions (CPCs), refinement of the logicality between the CPC and Contextual Control Mode (COCOM) and the deliberations of useful information from each input. The methodology proposed will be validated and demonstrated by virtue of an oil tanker study discharging crude oil.

2. Human reliability analysis

Human reliability can be defined as the probability of a person who correctly performs an action required by the system in the

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required time and does not perform any extraneous activity that could degrade the system (Swain and Guttman, 1983; Swain, 1987). Any methods by which the human reliability is evaluated can be designated as HRA. It typically includes the phases of the identification of human action, modeling of important actions and assessment of probabilities of human action. The objective of HRA is to evaluate the operator contribution to system reliability by predicting human error rates and evaluating the degradation to human machine systems likely to be caused by human errors in association with equipment functioning, operational procedures and practices, and human characteristics which influence the system behavior (Swain and Guttman, 1983). HRA has been well-accepted and integrated into the risk assessment process in a variety of industries. It identifies the errors and weaknesses in the system by examining the systems of work including those who work in the system (Lyons et al., 2004). Many methods have been developed based on expert judgement, statistical data and simulation proofs (Konstandinidou et al., 2006). In general, HRA methods can be divided into two generations. The first generation of the HRA approaches is developed based on the idea that because of inherent deficiencies, humans naturally fail to perform tasks just like mechanical, electrical or structural components do (Marsguerra et al., 2007). Such methods include Technique for Human Error Rate Prediction (THERP), response time-based Operator Action Tree (OAT), Human Cognitive Reliability (HCR) analysis, expert judgement-based Tecnica Empirica Stima Errori Operatori (TESEO), Human Error Assessment and Reduction Technique (HEART) and Success Likelihood Index Methodology (SLIM) (Kim and Bishu, 2006). The first generation approaches assign human error probabilities (HEP) to operators considering the task characteristics as the most influential factors whereas the environmental conditions under which the tasks are performed are treated as corrective elements. However, extensive studies of human performance in accidents reveal that the importance of the contextual conditions in which the task is performed is greater than the characteristics of the task itself (Marseguerra et al., 2006). Furthermore, the first generation methods cause limitations due to the lack of a well-defined classification system, an explicit model and an accurate representation of dynamic system interactions. In addition, poor representation of Performance Shaping Factors (PSF) on human performance is often criticized (Konstandinidou et al., 2006). This leads to the development of the second generation methods which consider the context as the most crucial factor affecting the human performance failure and model the relationship between the context and the HEP associated. The second generation approaches also consider the issues such as the probabilistic approach of human behavior to risk analysis, cognitive model complexity, integration of PSF and model validation. Typical HRA approaches of the second generation include CREAM, A Technique for Human Error Analysis (ATHEANA), the COGnitive evENT tree system (COGENT), Human Interaction Time-LINE (HITLINE) and Connectionism Assessment of Human Reliability (CAHR).

2.1. CREAM

One of the most recognized methods of the second generation is CREAM. It attempts to examine the environmental context in which humans operate and evaluate actions within the framework of a psychological model (Kirwan, 1998). The method allows for the retrospective analysis of historical events as well as a prospective analysis of high risk systems or processes. It is based on a cognitive model to explain human behaviors. The CREAM methodology starts with the construction of an event sequence in a specific situation. This is followed by the description of actions and cognitive activities for performance segments to determine the relevant cognitive functions. Finally, the identification of the likely error modes is conducted (Hollnagel, 1998). The scheme is capable of identifying tasks that require human cognition and depend on cognitive reliability and determining the conditions where cognitive reliability may be reduced constituting a source of risk. It is also able to provide consequence analysis of human performance on system safety by virtue of probabilistic results (Hollnagel, 1998). In CREAM, the competence and control of operators are combined to form COCOM that is depicted in terms of the degree of control that operators have over the situation. Thus, COCOM can be regarded as an outcome of the controlled use of competence adapted to the requirements of the situation (Hollnagel, 1998). The objective of COCOM is to specify how people are able to maintain control of a situation rather than to explain the masked mental mechanisms of operator performance (Konstandinidou et al., 2006). COCOM is defined by four characteristic control modes, namely, Scrambled, Opportunistic, Tactical and Strategic according to the human cognition and action context. Such control modes are determined by a set of nine CPCs. These are adequacy of organization, working conditions, adequacy of man–machine interface and operational support, availability of procedures and plans, 'number of simultaneous goals, available time, time of day, adequacy of training and experience and crew collaboration quality, respectively'. Such CPCs are characterized using a set of pre-defined linguistic descriptors to provide a concise description of how human performance is affected by the context.

2.2. Fuzzy CREAM

Due to the fact that human errors of misdiagnosis during unanticipated events are considered as the major causes of tragic accidents, subjectivity becomes a crucial issue in HRA. In addition, the complexity of system deteriorates the ability of human operators in providing precise and significant statements about system behaviors. On the other hand, lack of sufficient failure data jeopardizes the applicability of CREAM and this is particular true for the maritime domain. Accordingly, a number of HRA studies incorporating subjectivity data based on fuzzy logic have been proposed (Onisawa, 1996; Kim and Bishu, 2006; Marseguerra et al., 2007; Konstandinidou et al., 2006; Ung and Shen, 2011). Some of the aforementioned studies have been constructed to evaluate HEP considering CPCs under the CREAM framework.

2.3. Critical review of fuzzy CREAM

Although the traditional approaches are capable of transferring qualitative opinions into quantitative yet probabilistic results, some practical problems are exposed. These include the negligence of different effects caused by input weights, the ignorance of the logicality of using rule base to evaluate the relations between CPCs and control modes and loss of useful information due to the application of min–max inference method (Konstandinidou et al., 2006; Yang et al., 2013; Ung, 2013). While a modified CREAM using Bayesian reasoning recently proposed is capable of avoiding the loss of useful information during the inference operations and allowing for CPC dependencies, the other aforementioned critics remain unsolved. Thus, it is necessary to develop a model that addresses such practical problems in particular the lack of considering the weight of parameters and the logicality of adopting rule base to model the relations between CPCs and control modes.

3. Methodology

3.1. Establishment of the membership functions for the linguistic terms to be adopted for CPCs

On this stage, the number of the input variables i.e. the CPCs is first determined. Secondly, the number of the linguistic terms