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A Human Reliability Analysis Method for Offshore Operation

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Abstract

In order to increase the accuracy of human reliability analysis for offshore operation, a quantitative analysis model is proposed based on cognitive reliability and error analysis method (CREAM) in this paper. Firstly, the common performance conditions (CPC) of CREAM are classified systematically according to the characteristics of offshore environment. Secondly, the relationship between CPC score and control modes is determined by using the BP neural network to improve the veracity of CREAM. Thirdly, the neural network model of the human reliability for offshore operation is proposed. Fourthly, the human error probability is calculated according to the revised formula. Finally, a case study is demonstrated to validate the feasibility of this method.

Keywords: Human reliability analysis, cream, offshore operation, neural network..

1. Introduction

There is very high risk for an offshore platform because it is difficult for people to escape and deploy rescue resources during an emergency (see Deacon et al. [6]). Huge casualties and property losses are always the consequence of offshore fire. The proportion of marine accident induced by human error is increasing recently (see Chai et al. [5]). Human error has become a main cause of the accidents. Therefore, there is an urgent need to establish a quantitative method of human reliability analysis for offshore production to provide theoretical support for reducing the probability of human error.

The first generation HRA methods have been strongly influenced by the viewpoint of probabilistic safety assessment and have identified man as a mechanical component, thus losing all aspects of dynamic interaction with the working environment, both as a physical environment and as a social environment (see Tucci et al. [20], Kumar et al. [15] and Islam et al. [11]). As a representative second-generation human reliability analysis method, CREAM has a capacity to do binary function-retrospections and predictions (see Hollnagel et al. [10]). In order to promote the accuracy of quantitative prediction of human error probability (HEP), many researchers have proposed a series of improved methods. For example, HE Xu-hong et al [8] proposed to combine the basic method and the extension method to realize the continuous calculation of error probability; Konstandinidou et al [14] introduced a fuzzy classification system for human reliability analysis in order to calculate the probability of erroneous actions; Man et al [17] used Bayesian network to determine the cognitive control mode; Felice et al [7] propose a hybrid model for human error probability analysis based on CREAM and Systematic Human Error Reduction and Prediction Approach Method; Zhou et al [27] apply fuzzy logic technique based on the triangle and trapezoidal membership functions to model the uncertainty and ambiguity of the CPCs as well as the control modes in CREAM; Ung [21] propose a new fuzzy CREAM methodology to resolve the problems of lack of considering input weights and the loss of useful information due to the application of min-max fuzzy inference method; Akyuz [1] presents a risk-based methodology utilizing quantified CREAM method to predict the probability of human error for designated tasks.

The relationship between CPC and control modes in above references are all based on the method developed by Hollnagel [10]. However, CREAM method was originated from the nuclear industry. It couldnt be used in flexible work practice because of the different contexts when it is applied to offshore platform. Moreover, Hollnagel [10] determined the correspondence rules of the relationship between CPC score and control modes without presenting its theoretical basis, so this article will generalize the CPC suitable for offshore operation by systematically analyzing the affecting factors. In order to improve the veracity of CREAM, the relationship between the CPC score and control modes is determined by the BP neural network. Eventually, a quantitative analysis method of human reliability for offshore operation is researched.

2. Human Reliability Analysis Model for Offshore Platform

In this section, a human reliability analysis model is proposed as Figure 1.

2.1. CREAM (cognitive reliability and error analysis method)

One of the most recognized methods of human reliability analysis is CREAM. It attempts to examine the environmental context in which humans operate and evaluate actions within the framework of a psychological model (see Kirwan et al. [13]). CREAM was originally developed for nuclear power plant applications (see Kirwan et al. [13], Jung et al. [12], Lee et al. [16] and Tang et al. [19]) and was adopted by the National Aeronautics and Space Administration (NASA) in the early 1990s to predict human error (see Kirwan et al. [18]). Nowadays, the method has been applied in other industries. Yang et al. [26] proposed a modified CREAM to facilitate human reliability quantification in marine engineering sector by incorporating fuzzy evidential reasoning and Bayesian inference logic; the outcomes can provide safety engineers with a transparent tool to realize the instant estimation of human reliability performance for a specific task. Akyuz and Celik [3] adopted CREAM basic and extended versions to assess human reliability along with the cargo loading process on-board LPG tanker ships, which can improve maritime safety at sea and reduction of human injury and loss of life on-board LPG

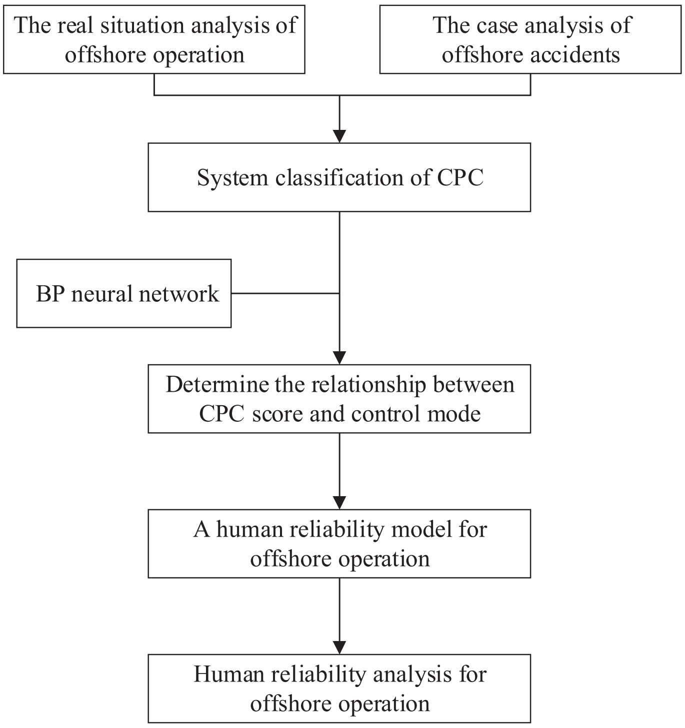

Figure 1: Flowchart of human reliability analysis model.

ship. Meanwhile, Akyuz [2] presented a risk-based methodology utilizing quantified CREAM method to predict human error probability (HEP) for gas inerting process onboard crude oil tankers. Xi et al. [25] proposed a modified CREAM model based on an Evidential Reasoning (ER) approach and a Decision Making Trial and Evaluation Laboratory (DEMATEL) technique to quantify human error probability in maritime domain.

CREAM divides the error events into observational errors (phenotypes) and non-observational ones. Phenotypes, which are known as error modes, are the errors that have the external manifestations. Errors, which cannot be observed, are the errors that do not have the external appearance and they occur during the human thinking process. CREAM considers that the phenotypes are the consequence of non-observational errors by certain transformation of cause to effect, while the latter is considered as the ultimate causes which lead to the human errors. The CREAM method defines nine Correction Factors CFPs: 1) adequacy of organization; 2)working conditions; 3) adequacy of MMI and operational support; 4) availability of procedures/plans; 5) number of simultaneous goals; 6) available time; 7) time of day; 8)adequacy of training and 9) preparation and crew collation quality. There are several levels of each factor to reflect its effect to human performance. In order to reflect the scenario effects on human cognitive behaviors, the CREAM method defines four cognitive control modes, which are scrambled, opportunistic, tactical and strategic [7].

The procedure to assess the error probability is to add to the nine CPC levels that contribute positively (Σ improved) and those who contribute negatively (Σ reduced), getting a pair of values that are inserted in figure 2 to locate one of the four categories of control mode: 1)Scrambled: unpredictable situation, operator does not have control; 2) Opportunistic: limiting actions, lack of knowledge and staff competence; 3) Tactical: planned actions, operator knows the rules and procedures of the system; and 4) Strategic: Operator has a long time to plan its work (see Felice et al. [7]).

2.2. System classification of CPC

In accordance with the real situation of offshore operation (see Vinnem et al. [23]) and the case analysis of offshore accidents, the CPC was classified systematically into eight types that cover the entire context of offshore operations essentially, as follows: the status of operation staff, the condition of equipment, the circumstance, safety climate, rules and regulations, operation plan, education and training, task characteristics and support system (see He et al. [9]).

Based on the above descriptions, values are assigned to the corresponding evaluation level and performance effect (see Wu et al. [24]) as shown in Table 1.

2.3. BP neural network model based on Matlab

BP neural network, the basic structure of which is composed by nonlinear units, could approximate any function in theory. Therefore, it is of strong nonlinearity mapping capacity for BP neural network. Besides, it is very flexible to set the number of middle layers, the number of process units for each layer and the learning coefficient of the whole network (see Wang et al. [23]).

A neural network is a mathematical algorithm model that processes distributed parallel information using a physical device to simulate the structure and function of a biological neural network; it is composed of multiple inputs and single output neurons connected according to certain topological structures; further, it studies through sample training, changes the weight value and threshold value of the internal connection such that the error between the output value and target value is minimal, and obtains a nonlinear mapping that can describe the relationship between the input and output of a system [6]. A neural network has massive parallel ability, distributed storage and processing power, powerful self-organization, self-adaptive and self-learning abilities, as well as fault tolerant and generalization ability without prior knowledge. It is suitable for processing problems that have inaccurate and fuzzy information while considering many factors and conditions. In this paper, the relationship between CPC score and control modes is researched using BP neural network.

The main idea of BP neural network is to modify weights between nodes in an iteration through error back propagation so as to reduce in the next iteration the error between output of neural network and the expected output until error goal is met or iteration number is reached

Table 1: CPC and effect.

CPC name	Level /Descriptors	Expected effect on Performance reliability	CPC name	Level /Descriptors	Expected effect on Performance reliability
The status of operation staff	Advantageous Compatible Incompatible	Improved Not significant Reduced	Operation plan	Appropriate Acceptable Inappropriate	Improved Not significant Reduced
The condition of equipment	Supportive Adequate Tolerable Inappropriate	Improved Not significant Not significant Reduced	Education and training	Advantageous Compatible Incompatible	Improved Not significant Reduced
The circumstance	Advantageous Compatible Incompatible	Improved Not significant Reduced	Task characteristics	Appropriate Acceptable Inappropriate	Improved Not significant Reduced
Safety climate and rules and regulations	Very efficient Efficient Inefficient Deficient	Improved Not significant Not significant Reduced	Support system	Very efficient Efficient Inefficient Deficient	Improved Not significant Not significant Reduced

In this paper, the relationship between CPC score and control modes is researched using BP neural network.

2.3.1. Generation and processing of sample data

The CREAM basic method presented by Hollnagel [10], includes nine kinds of CPC factors and four kinds of control modes. It builds a relationship between CPC score and control modes. The relationship is widely accepted and very authentic. Therefore, this article generates sample data based on the relationships and builds the new relationship to suit for offshore platform.

CPC's Performance expectations include "Improved", "Not significant" and "Reduced". The corresponding value are assigned according to the following rules: 'Improved' = "1", "Not significant"= "0", "Reduced" = "-1". According to the relationship between CPC score and control modes, the CPC score and the corresponding control mode are defined, and the value are assigned according to the following rules to generate 52 sets of sample data: strategic = "1", tactical= "2", opportunistic= "3" and scrambled = "4". The sets of sample data are shown in Table 2. The SOI is the sum of Improved, the SOR is the sum of Reduced and M is control modes' value.

2.3.2. Build the BP neural network model

The established BP neural network is shown in Figure 2, including four layers: input layer, double hidden layers and output layer. $\{X_1, X_2\}$ are the input data of BP neural

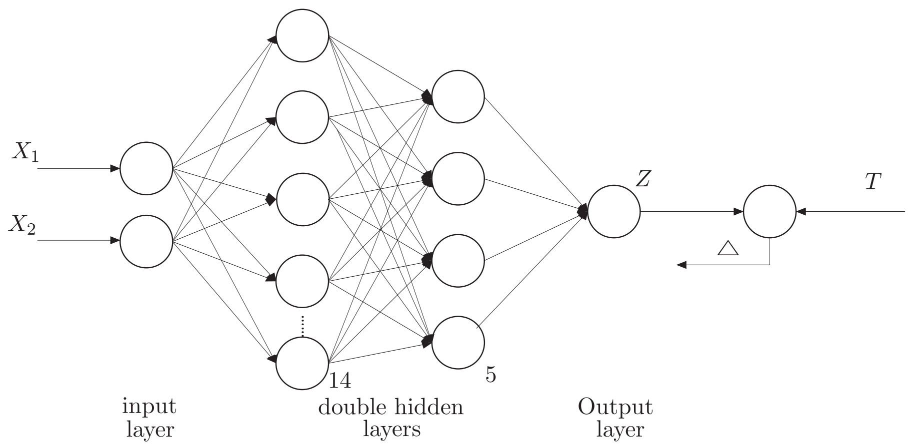

Figure 2: BP network structure of the relation between CPC and control modes.

network. X_1 and X_2 respectively represent the vertical and horizontal coordinates of feature points of the relationship between CPC score and control modes. Z is the output data of BP neural network and preserves the control mode. T stands for the actual control mode. After repeated simulations, it is concluded that the mean error of the network is the minimum when the respective number of nodes in the hidden layers are 14, 5.

There are 52 sets of sample data. The numbers of training data and testing data for BP neural network are 42 and 10, respectively. Thereafter, the parameters are set as follows. The input and output samples are normalized by "mapminmax" function. The activation function of hidden layers is "tansig" and the transfer function of output layer is "purelin". The training function is "trainlm" (see Marseguerra et al. [18]). The minimum error is 0.001 and the initial weights are given by the system. The momentum factor is set to 0.9. The neural network model is trained using the software Matlab to meet the error requirement. The final EAV result is 0.0029726. The training results are shown in Figure 3 and Figure 4.

After anti-normalization, the training results are rounded to integer values. The prediction results are compared with the data sets in Table 2. The comparison shows that the proposed neural network model fits perfectly with the sample data. It can be seen that the proposed neural network can be used to build the relationship between control mode and CPC for offshore platform.

The test data set is listed in Table 2. After normalization, data sets are put into the trained neural network. The diagram for determining the relation between control mode and CPC of offshore platform is built, as shown in Figure 5.

2.4. Quantitative prediction of human error

The corresponding relation between reliability impact index and control mode is shown in Table 3 (see Tucci et al. [20]).

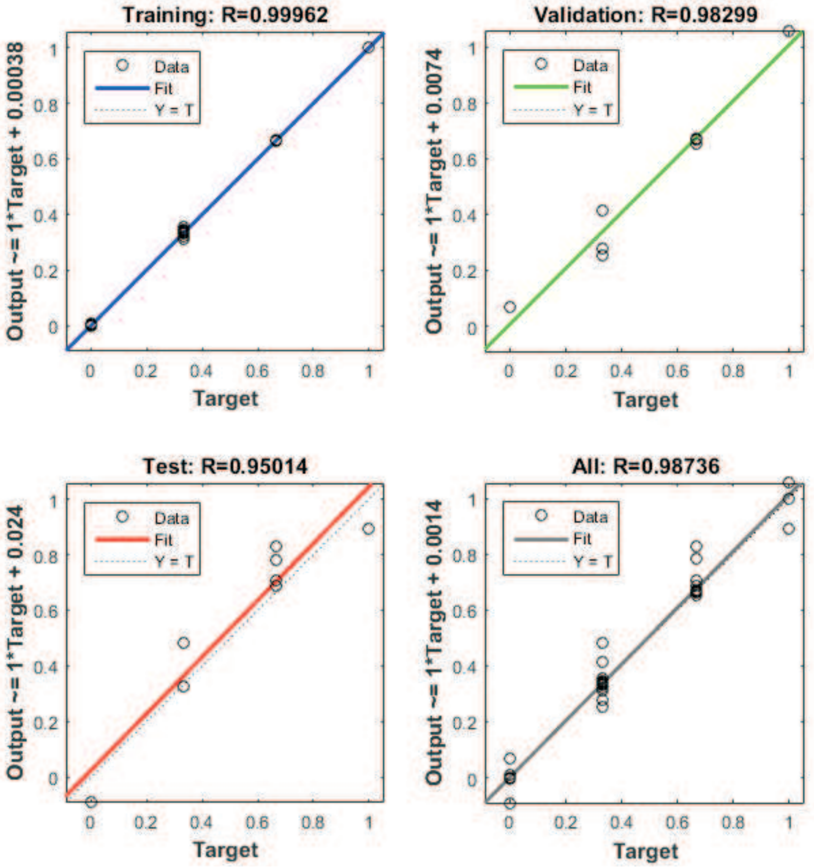

Figure 3: Regression result.

Normally the human reliability increase with the improvement of the task context. So there is an approximate correspondence between human error probability (HEP) and task context. Based on this assumption, the natural logarithm model can be used to fit the relationship between HEP and reliability impact index R (see Tucci et al. [20]).

$$\ln(P_{HEP})/P_{HEP,0}) = kR \tag{2.1}$$

where, k is a constant, which can be deduced by the following equations:

$$\ln(P_{\mathrm{HEP,max}}/P_{\mathrm{HEP,0}}) = kR_{\min} \tag{2.2}$$

$$\ln(P_{\mathrm{HEP,max}}/P_{\mathrm{HEP,0}}) = kR_{\max} \tag{2.3}$$

$$k = \ln(P_{\mathrm{HEP,max}}/P_{\mathrm{HEP,min}})/(R_{\min} - R_{\max}) \tag{2.4}$$

$$P_{\mathrm{HEP,0}} = P_{\mathrm{HEP,max}}/e^{kR_{\min}}. \tag{2.5}$$

Seen from the corresponding human error probability in Table3, $P_{\mathrm{HEP,max}} = 1$; $P_{\mathrm{HEP,min}} = 0.00005$; $R_{\min} = -8$, $R_{\max} = 8$, which are substituted into equation (2.4) and equation (2.5), it can be calculated that $k \approx -0.619$, $P_{\mathrm{HEP,0}} \approx 0.00707$.

Table 2: The sets of sample data.

N	1	2	3	4	5	6	7	8	9	10	11
SOI	0	0	0	0	0	0	0	0	0	0	1
SOR	0	1	2	3	4	5	6	7	8	9	0
M	2	2	2	3	3	3	4	4	4	4	2
N	12	13	14	15	16	17	18	19	20	21	22
SOI	1	1	1	1	1	1	1	1	2	2	2
SOR	1	2	3	4	5	6	7	8	0	1	2
M	2	2	3	3	3	3	3	3	2	2	2
N	23	24	25	26	27	28	29	30	31	32	33
SOI	2	2	2	2	2	3	3	3	3	3	3
SOR	3	4	5	6	7	0	1	2	3	4	5
M	2	3	3	3	3	2	2	2	2	2	3
N	34	35	36	37	38	39	40	41	42	43	44
SOI	3	4	4	4	4	4	4	5	5	5	5
SOR	6	0	1	2	3	4	5	0	1	2	3
M	3	1	2	2	2	2	2	1	1	2	2
N	45	46	47	48	49	50	51	52			
SOI	5	6	6	6	6	7	7	7			
SOR	4	0	1	2	3	0	1	2			
M	2	1	1	1	2	1	1	1			

Table 3: R and control mode.

Reliability impact index R	Control mode	Human error probability
$4 \leq R \leq 8$	Strategic	$(5 * 10^{-5},\ 10^{-2})$
$0 \leq R < 4$	Tactical	$(10^{-3}, 10^{-1})$
$-4 \leq R < 0$	Opportunistic	$(10^{-2}, 0.5)$
$-8 \leq R < -4$	Scrambled	$(10^{-1}, 1)$

The human error probability formula is revised using the proposed method in this paper:

$$P_{\text{HEP}} = 0.007071e^{-0.6190R} \tag{2.6}$$

$$R = \sum_{i=1}^{7} 8\omega_i C_{cpc,i} \tag{2.7}$$

where: R is the reliability influence index; ω_i, $1 \leq i \leq 7$ are the weight values of CPC; $C_{cpc,i}$, $1 \leq i \leq 7$ are the scores of performance expectancy of CPC; H_{HEP} is the human error probability.

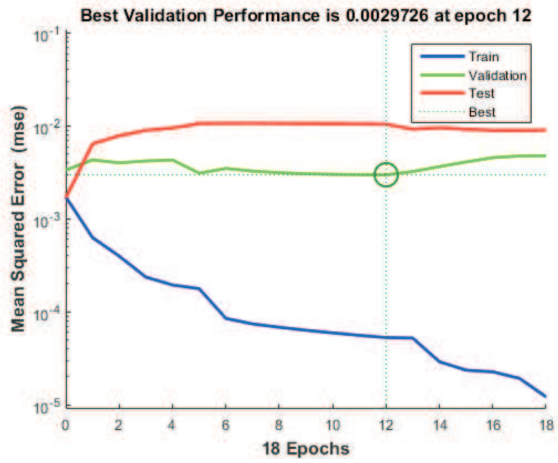

FIgure 4. Training sample error.

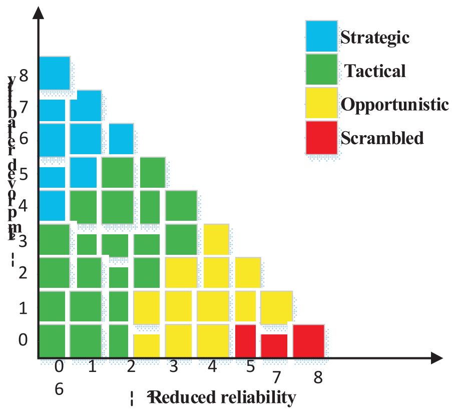

Figure 5. Relation between control modes and cpc of offshore platform.

3. Case Study

In order to verify the feasibility of the proposed method, Piper Alpha accident is analyzed in this section. In 1988, explosion and oil-and-gas fire killed 167 people in Piper Alpha platform. Quantitative analysis of human reliability are carried out according to accident investigation reports and CPC evaluation standards.

According to the context description of the accident investigation report, it can be seen that the control system, communication system and fire fighting system are all destroyed although the alarm system work as soon as possible; The rescue operations through helicopters and ships were also blocked by the fire; Emergency commanders made wrong decisions, resulting in the reduction of the available safe evacuation time; Because the accident happened at night, dense smoke aggravated panic among personnel. The management teams consist of young people, whose business knowledge and management experience are not enough; Safety and skill training results are not measured and assessed and there is insufficient training for full-time staff in emergency response events. The license certification system is not well implemented.

Based on the above task environments, five experts from ocean engineering area are invited to evaluate the levels of all kinds of CPC. The corresponding results are shown in Table 4.

Entrust with the same weight to each of CPC, namely $\omega_i = 1/8$.

According to the Equations (6) and (7), it can be got that $R = -4$ and $P_{\text{HEP}} = 0.007071e^{-0.6190R} = 0.0841$.

Table 4: Evaluation of CPC.

CPC name	Level /descriptors	Effect on performance reliability
The status of operation staff	Compatible	Not significant
equipment condition	Inappropriate	Reduced
The circumstance	Incompatible	Reduced
Safety climate	Deficient	Reduced
Operation plan	Inappropriate	Reduced
Education and training	Compatible	Not significant
Task characteristics	Acceptable	Not significant
Support system	Inefficient	Not significant

By querying the Table 3, the corresponding error probability interval is (10-2,0.5). The type of control mode is opportunistic. The accident context had a greater influence on the staff behavior.

4. Conclusions

By integrating CREAM with the BP neural network, the correspondence relations between control mode and CPC are simulated. Furthermore, Compared with original CREAM Method, the aforementioned method has some unique and significant characteristics as follows:

(1) CPC, which is systematically classified according to the characteristics of offshore environment, can be used to characterize the operation context of offshore platform. This enhances the universality of CREAM, which can be applied to offshore operation.

(2) The corresponding relationship between control mode and CPC is established using BP neural network. The new model makes the foundation for human reliability analysis of this field and improves the accuracy of analysis.

(3) The feasibility of the method is verified by a case study. The human error probability under specific situation can be quantitatively calculated. The proposed method is revised to be applicable to offshore platform field.

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