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Original Article

Extended cognitive reliability and error analysis method for advanced control rooms of nuclear power plants

Xiaodan Zhang *, Shengyuan Yan, Xin Liu

College of Mechanical and Electrical Engineering, Harbin Engineering University, Harbin, 150001, China

A R T I C L E I N F O

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A B S T R A C T

This study proposes a modified extended cognitive reliability and error analysis method (CREAM) for achieving a more accurate human error probability (HEP) in advanced control rooms. The traditional approach lacks failure data and does not consider the common performance condition (CPC) weights in different cognitive functions. The modified extended CREAM decomposes tasks using a method that combines structured information analysis (SIA) and the extended CREAM. The modified extended CREAM performs the weight analysis of CPCs in different cognitive functions, and the weights include cognitive, correlative, and important weights. We used the extended CREAM to obtain the cognitive weight. We determined the correlative weights of the CPCs for different cognitive functions using the triangular fuzzy decision-making trial and evaluation laboratory (TF-DEMATEL), and evaluated the importance weight of CPCs based on the interval 2-tuple linguistic approach and ensured the value of the importance weight using the entropy method in the different cognitive functions. Finally, we obtained the comprehensive weights of the different cognitive functions and calculated the HEPs. The accuracy and sensitivity of the modified extended CREAM were compared with those of the basic CREAM. The results demonstrate that the modified extended CREAM calculates the HEP more effectively in advanced control rooms.

1. Introduction

In recent years, there has been increased interest in human reliability analysis (HRA). With the development of technology, advanced control rooms have modern digital human–system interfaces (HSIs) that change the tasks of operators in nuclear power plants [1–4]. Thus, HRA can play an essential role in addressing safety issues in advanced control rooms.

There are numerous methods for performing HRA, including the Technique for Human Error Rate Prediction (THERP) [5,6], CREAM [7,8], success likelihood index methodology (SLIM) [9,10,11] and standardized plant analysis risk-human reliability analysis (SPAR-H) [12–15]. The CREAM method can analyze context and cognitive functions, and can be applied in many fields. Yang combined fuzzy logic and a Bayesian network to modify CREAM in marine engineering [16]. Chen improved the CREAM approach and converted it into deep-sea sampling mission [17]. Ung applied fault tree analysis to a fuzzy CREAM and proved that the Number of Simultaneous Goals is the major reason for oil tanker collisions [18]. Scholars have used various methods to modify CREAM. Wang combined the analytic hierarchy process (AHP) with fuzzy extended CREAM to improve the accuracy of the results [19]. Liu uses the interval 2-tuple and cluster analysis to assess dependence in the HRA [20]. Zhou proposed a new approach that consists of a Bayesian network and fuzzy CREAM, and concluded that the method is consistent with CREAM [21]. Ahn constructed a new framework that uses the fuzzy multiple attributive group decision-making method, Bayesian networks and evident reasoning to modify CREAM, and solve human errors[22]. The past decade has witnessed the rapid development of weight analysis using CREAM by utilizing a hesitant fuzzy matrix (HFM) with CREAM to handle the expert's scores and ensure that the HFM-CREAM is correct [23]. Yao constructed the logic between common performance conditions (CPCs) and contextual control mode (COCOM) to modify CREAM [24]. Recently, the importance and relationship between CPC weights has been regarded as significant factors contributing to CREAM. Tai used a rule-based method to address the CPC weights and proved that the modified CREAM is reasonable [25]. TIM calculated HEP combined CPC weights and analysis sensitivity using the modified CREAM [26]. Kim et al. adopted a profiling technique to quantify the weightings of performance-shaping factors when performing HRA during low-power and shutdown (LPSD) operations [27]. CPCs have some correlation in CREAM, which can be determined using interval type-2 fuzzy sets and

* Corresponding author.
E-mail address: xiaodan@hrbeu.edu.cn (X. Zhang).

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Table 1
A generic cognitive-activity-by-cognitive-demand matrix [7].

Activity type	COCOM function			
	Observation	Interpretation	Planning	Execution
Co-ordinate			✓	✓
Communicate				✓
Compare		✓		
Diagnose		✓	✓	
Evaluate		✓	✓	
Execute				✓
Identify		✓		
Maintain			✓	✓
Monitor	✓	✓		
Observe	✓			
Plan			✓	
Record		✓		✓
Regulate	✓			✓
Scan	✓			
Verify	✓	✓		

Table 2
Nominal values and uncertainty bound for cognitive function failure[7].

Cognitive function	Generic failure type	Lower bound	Basic value	Upper bound
Observation	O1	3.0E-4	1.0E-3	3.0E-3
	O2	2.0E-2	7.0E-2	1.7E-2
	O3	2.0E-2	7.0E-2	1.7E-2
Interpretation	I1	9.0E-2	2.0E-1	6.0E-1
	I2	1.0E−3	1.0E−2	1.0E−1
	I3	1.0E−3	1.0E−2	1.0E−1
Planning	P1	1.0E−3	1.0E−2	1.0 E−1
	P2	1.0E−3	1.0E−2	1.0E−1
Execution	E1	1.0E−3	3.0E−3	9.0E−3
	E2	1.0E−3	3.0E−3	9.0E−3
	E3	5.0E−5	5.0E−4	5.0E−3
	E4	1.0E−3	3.0E−3	9.0E−3
	E5	2.5E−2	3.0E−2	4.0E−2

the analytic network process (ANP) [28]. A fuzzy ANP was used to ensure the weights of the CPCs in an urban railway [29]. Considering the relationship between CPCs and their weights, Zhang provided a modified fuzzy CREAM [30]. Sun used the triangular fuzzy decision-making trial and evaluation laboratory (DEMATEL) and fuzzy AHP methods to improve the weights and verify their accuracy [31]. The DEMATEL-based analytic network process (DANP) is needed for CREAM to handle the correlations among CPCs [32]. However, research on the importance of CPCs in different cognitive functions is currently lacking.

This study develops a modified and extended CREAM having the following features. First, we combine structure information analysis and extended CREAM to decompose tasks into different cognitive functions. Second, we incorporate the TF-DEMATEL to calculate the correlative weight of CPCs for different cognitive functions. Finally, we use the interval 2-tuple linguistic evaluation and entropy methods to obtain the important weights of CPCs for different cognitive functions. The remainder of this paper is organized as follows. Section 2 introduces the modified extended CREAM and gives a description of the extended CREAM, the interval type-2 fuzzy linguistic. Section 3 presents a case study that demonstrates the applicability of the modified extended CREAM. Finally, Section 4 discusses the rationality and data sensitivity of the approach based on the modified extended CREAM.

2. The modified extended CREAM approach

CREAM can be divided into two categories: basic CREAM and extended CREAM [7]. The extended CREAM decomposes the tasks in detail and provides to more accurate solutions. The extended CREAM has nine CPCs. We obtain cognitive activity through the extended CREAM, which identifies cognitive failure modes. Some cognitive failure modes correspond to cognitive activities using extended CREAM. The post-decomposition obtains get the cognitive function probability (CFP_0) and the weight of the CPCs, which is used to calculate the HEP. The modified extended CREAM approach comprises three main components: task decomposition, correlative weight analysis, and importance weight analysis. Task decomposition involves breaking tasks down into specific subtasks based on different cognitive functions.

2.1. Structured information analysis

One method for analyzing tasks is a structured approach that involves scenario analysis, goal-means analysis, and cognitive function analysis using the extended CREAM [33]. Scenario analysis focuses on the specific situations in which an event occurs, whereas goal analysis determines the objective of the event. Finally, cognitive function analysis identifies task cognitive functions using extended CREAM. Cognitive functions include observation, interpretation, planning, and execution. The relationship between cognitive activity and function is listed in Table 1.

In this phase, we analyze events using structural information analysis. We begin by decomposing the tasks using hierarchical task analysis (HTA) [34]. Next, we establish an event sequence called a cognitive activity sequence table. Finally, we identify cognitive behaviors and functions and then determined the failure probability. In the modified extended CREAM, there are 13 different failure modes, along with the nominal values and uncertainty bounds for cognitive function failure. These values are listed in Table 2. After obtaining the values, the weights of the CPCs are ensured. The weight of CPCs can be divided into the cognitive weight, the correlative weight and the important weight.

2.2. Ensuring the weight of CPCs

2.2.1. The cognitive weight of CPCs

Analyzing cognitive function is essential to accurately assess weight. By utilizing structured information analysis (SIA), we can determine the cognitive weight of the CPCs. Table 3 displays the cognitive weights of the CPCs.

After obtaining the cognitive weights of CPCs, we analyze the correlative and important weights of CPCs in different cognitive functions.

2.2.2. The correlative weight of CPCs

The correlative weight of CPCs describes the correlation between CPCs, which has been studied by Hollnagel et al. Considering that the correlative weight between CPCs in different cognitive functions is crucial, the DEMATEL method is an effective method to deal with the relationship between CPCs [35–37]. In this section, we use the TF-DEMATEL method to calculate the relationship between the CPCs, and the Converting Fuzzy Data into Crisp Scores (CFCS) defuzzification method to handle the fuzzy values. The steps are as follows.

Step 1. Constructing the fuzzy linguistic scale. When the experts evaluated the relationship among the CPCs, we set five levels of the fuzzy linguistic scale to evaluate CPCs. It has the triangular fuzzy number and linguistic terms. The linguistic terms are shown, including “very high influence (VH)”, “high influence (H)”, “low influence (L)”, “very low influence (VL)”, and “no influence (N)” in Table 4. The initial impact matrix $X = (x_{ij})_{n\times n}$, where $x_{ij} = (i_{ij}, m_{ij}, r_{ij})$ represents the correlative weight between CPCs.

Step 2. Defuzzification and obtaining the standardized impact matrix Y. Using the CFCS method to calculate the initial impact matrix X, the triangular fuzzy numbers are defuzzification to obtain the direct

Table 3
Weight factors for CPCs [7].

CPC name	Level	COCOM function			
		Observation	Interpretation	Planning	Execution
Adequacy of organization	Very efficient	1.0	1.0	0.8	0.8
	Efficient	1.0	1.0	1.0	1.0
	Inefficient	1.0	1.0	1.2	1.2
	Deficient	1.0	1.0	2.0	2.0
Working conditions	Advantageous	0.8	0.8	1.0	0.8
	Compatible	1.0	1.0	1.0	1.0
	Incompatible	2.0	2.0	1.0	2.0
Adequacy of MMI Procedures/plans	Supportive	0.5	1.0	1.0	0.5
	Adequate	1.0	1.0	1.0	1.0
	Tolerable	1.0	1.0	1.0	1.0
	Inappropriate	5.0	1.0	1.0	5.0
Availability of procedures/plans	Appropriate	0.8	1.0	0.5	0.8
	Acceptable	1.0	1.0	1.0	1.0
	Inappropriate	2.0	1.0	5.0	2.0
Number of simultaneous goals	Fewer than capacity	1.0	1.0	1.0	1.0
	Matching current capacity	1.0	1.0	1.0	1.0
	More than capacity	2.0	2.0	5.0	2.0
Available time	Adequate	0.5	0.5	0.5	0.5
	Temporarily inadequate	1.0	1.0	1.0	1.0
	Continuously inadequate	5.0	5.0	5.0	5.0
Time of day	Day-time (adjusted)	1.0	1.0	1.0	1.0
	Night-time (unadjusted)	1.2	1.2	1.2	1.2
Adequacy of training and preparation	Adequate, high experience	0.8	0.5	0.5	0.8
	Adequate, low experience	1.0	1.0	1.0	1.0
	Inadequate	2.0	5.0	5.0	2.0
Crew collaboration quality	Very efficient	0.5	0.5	0.5	0.5
	Efficient	1.0	1.0	1.0	1.0
	Inefficient	1.0	1.0	1.0	1.0
	Deficient	2.0	2.0	2.0	5.0

Table 4
The fuzzy linguistic scales.

Linguistic terms	Triangular fuzzy number
very high influence (VH)	(0.75 1.00 1.00)
high influence (H)	(0.50 0.75 1.00)
low influence (L)	(0.25 0.50 0.75)
very low influence (VL)	(0.00 0.25 0.50)
no influence (N)	(0.00 0.00 0.25)

impact matrix X', and the standardized impact matrix Y is converted using Eq. (1).

$$Y = \frac{X'}{\max_{i \le n} \sum_{j=1}^{n} X'_{ij}} = [y_{ij}]_{n \times n'} \ (0 \le y_{ij} \le 1) \tag{1}$$

Step 3. Ensuring the total-relation matrix Z. The total-relation matrix Z is given by Eq. (2), where E is the identity matrix.

$$Z = Y(E - Y)^{-1} \tag{2}$$

Step 4. Obtaining the correlative weight ω_i of CPCs. Before obtaining the correlative weight, we need to calculate the values of "Influence" and "Relation". The sum of rows, *H,* is denoted by Eq. (3) and the sum of columns, *F,* is denoted by Eq. (4).

$$H = \sum_{j=1}^{n} Z_{ij} \tag{3}$$

$$F = \sum_{i=1}^{n} Z_{ij} \tag{4}$$

The "Influence" is *(H–F)* and the "Relation" is $(H + F)$. When we get the "Influence" and "Relation", we obtain the correlative weight of CPCs ω_i as:

$$w_i = \sum_{k=1}^{m} \left[\left(H_j^k + F_i^k \right) / \left(\sum_{i=1}^{n} H_j^k + F_i^k \right) \right] \tag{5}$$

2.2.3. The important weight of CPCs

Various CPCs affect human performance differently, and their weight is crucial to the modified extended CREAM of different cognitive functions. We consider the calculation of important weights to be a multi-attribute decision-making problem. The interval 2-tuple linguistic approach is used in multi-attribute decision analysis [38]. The 2-tuple linguistic approach is introduced below[39]:

Assuming that there is $S = \{s_0, s_1, \ldots, s_g\}$, and each is referred to as a language term. S satisfies the following three conditions:

1. $i \le j$, then $s_i \le s_j$.
2. Neg $(s_i) = s_j, j = g - i$.
3. When $i \ge j$, the maximum value is s_i and the minimum value is s_j.

Definition 1. Assuming that $\mathrm{s} = \{\mathrm{s}_0, \mathrm{s}_1, \ldots, \mathrm{s}_g\}$, $\beta \in [0, g]$. And Δ is 2-tuple linguistic:

$$\Delta : [0, g] \rightarrow \mathrm{s} \times [-0.5, 0.5) \tag{6}$$

Then,

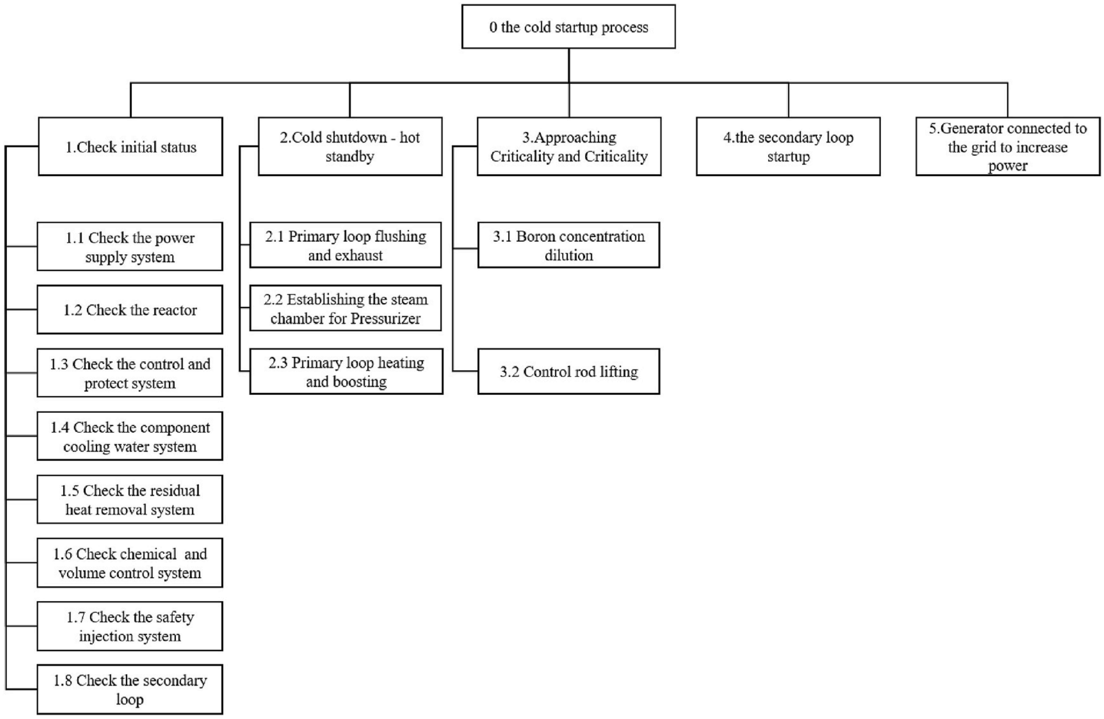

Fig. 1. The process of cold startup in nuclear power plant.

$$\Delta(\beta) = (s_i, a_i) \tag{7}$$

and

$$s_i, i = \mathrm{round}(\beta), a = \beta - i, a_i \in [-0.5, 0.5) \tag{8}$$

Where round () is an integer function, and a is a symbol transfer function.

The Δ has inverse function Δ^{-1}, which is defined as follows:

$$\Delta^{-1} : s \times [-0.5, 0.5) \in [0, g] \tag{9}$$

$$\Delta^{-1}(s_i, a_i) = i + a_i = \beta \tag{10}$$

Definition 2. There are language term sets in the interval 2-tuple linguistic approach, which are defined by Eq. (11).

$$[(s_k, a_1), (s_l, a_2)]\left(s_k, s_l \in s, a_1, a_2 \in \left[-\frac{1}{2g}, \frac{1}{2g}\right\}, (s_k, a_1) \le (s_l, a_2)\right) \tag{11}$$

The interval value $\Delta[\beta_1, \beta_2](\beta_1, \beta_2 \in [0,1], \beta_1 \le \beta_2)$ is calculated by the following formula :

$$\Delta^{-1}[(s_k, a_1), (s_l, a_2)] = \left(\frac{k}{g} + a_1, \frac{l}{g} + a_2\right) = [\beta_1, \beta_2] \tag{12}$$

The interval 2-tuple linguistic approach converts to the interval value $[\beta_1 \ , \ \beta_2]$ as follows:

$$\Delta[\beta_1, \beta_2] = [(s_k, a_1), (s_l, a_2)] \text{ with } \begin{cases} s_k, k = \mathrm{round}(\beta_1, g) \\ s_l, l = \mathrm{round}(\beta_2, g) \\ a_1 = \beta_1 - \frac{k}{g}, a_1 \in \left[-\frac{1}{2g}, \frac{1}{2g}\right\} \\ a_2 = \beta_2 - \frac{l}{g}, a_2 \in \left[-\frac{1}{2g}, \frac{1}{2g}\right\} \end{cases} \tag{13}$$

Definition 3. The function S(A) is defined as

$$S(A) = \frac{k+1}{(2g)} + \frac{a_1 + a_2}{2} \tag{14}$$

Definition 4. [40]: The interval 2-tuple weighted average is calculated as follows: $A = [(s_k, a_k), (s_l, a_l)]$ is a set of interval 2-tuple and the weight is such that

$$\mathrm{ITWA}\ (s_k, a_k) = \Delta\left[\sum_{i=1}^{n} w_i \Delta^{-1}(s_i, a_i), \sum_{i=1}^{n} w_i \Delta^{-1}(s_i', a_i')\right] \tag{15}$$

where $w = \{w_0, w_1, ..., w_n\}$, $w_i \in [0,1]$ and $\sum_{i=1}^{n} w_i = 1$.

Let $E_i(i = 1, 2, ..., n)$ represents the experts, $\lambda_k(k = 1, 2, ..., l, \sum_{i=1}^{n} \lambda_k = 1)$ is the important weight of the experts, and $\dot{\omega}_i\left(i = 1, 2, ..., l, \sum_{i=1}^{n} \dot{\omega}_i = 1\right)$ is the important weight of the CPCs. For different cognitive functions, it sets the matrix $D^k = (d_{ij}^k)_{m\times n}$ to denote the linguistic evaluation matrix of the importance matrix of CPCs by the expert E_k under the decision attribute C_j.

Step 1. The language comparison matrix D^k is converted into the interval 2-tuple comparison matrix R^k:

$$R^k = \left\{\left(S_{ij}^k, 0\right), \left(a_{ij}^k, 0\right)\right\} \tag{16}$$

Where $S_{ij}^k, a_{ij}^k \in S, S = \{S_i | i = 0, 1, 2, ..., g\}, S_{ij}^k < a_{ij}^k$.

Step 2. The weights of the experts are then calculated. Group decisions are a process of discussion among many experts whose opinions tend to be consistent. Therefore, the weights of experts can be determined based on the differences between individual and group decisions. If the difference between individual and group decision-making is small, then its weight is large, and vice versa. The expert weights of the CPCs are calculated using Eq. (17):

Table 5
The cognitive activities of the cold startup.

Step	Tasks step or activity	Subtask	Cognitive activity
1.1.1	Check the power supply system	Check the integrity of standby power supply and the voltage of important load is normal.	Evaluate
1.2.1	Check the reactor	Check that it is in a subcritical state, with a boron concentration of 2000 ppm and a shutdown depth of no less than 5000p/cm.	Evaluate Verify
1.3.1	Check the control and protect system	Check and prepare for startup, and other protection, control, and detection instrumentation systems of the reactor are also put into operation.	Identify
1.4.1	Check the component cooling water system	Check one for operation and one for backup, which can supply cooling water	Evaluate
1.5.1	Check the residual heat removal system	Check that the system is in operation and control the temperature of the primary loop between 38- 60 °C.	Evaluate Verify
1.6.1	Check chemical and volume control system	Check if it is in an available state and control the boron concentration in the coolant.	Evaluate
1.7.1	Check the safety injection system	In a bootable state.	Evaluate
1.8.1	Check the secondary loop	All devices are shutdown.	Evaluate
2.1.1	Filling water from the RCV system	During the filling of the water, the desalinated water from the makeup system is injected into the primary loop for dilution operation, so that the shutdown depth of the reactor is not less than 1000 pcm at the end of the water filling. When filling water, operator need to adjust the flow rate of the residual heat removal system, and jumping the temperature to 50–70 °C.	Execute Verify
2.1.2	Heating up the primary loop	Start the heaters of the three main pumps and the pressurizer to heat the primary loop Water heating. The heating rate is controlled at 28°C/h by the residual heat removal system. Purify the primary Water purification with the demineralize of the chemical and volume system, and monitor the primary loop water quality.	Execute Monitor
2.1.3	Adding Hydrazine to coolant to remove dissolved oxygen	When heating the temperature from 90°C/h to 120°C/h, LiOH is added to control the pH value, and adding Hydrazine to coolant to remove dissolved oxygen.	Execute Verify
2.2.1	Establishing the steam chamber for pressurizer	Reduce the charging capacity, increase the discharge capacity, and use manual control to maintain the pressurizer water level. The pressure is maintained by RCA at a constant value between 2.5 and 3.0MPa.	Execute Verify
2.2.2	Isolated the residual heat removal system	The shutdown process of the residual heat removal system mainly includes operations such as cooling, depressurization, and pressure monitoring. The purpose of pressure monitoring is to ensure that the system inlet isolating valve is not leaking.	Execute Verify
2.3.1	When the pressure of the primary loop reaches 8.5 MPa, the temperature rises to 284 °C	When heating up, pay attention to the heating rate and ensure that the temperature difference between the loops does not exceed the limit. When the system reaches normal operating pressure and temperature, cut off the backup heater power supply to the pressurizer. The pressure control is switched from manual to automatic control and enters the hot shutdown condition.	Execute Verify
3.1.1	Diluting boron concentration	Dilute the boron concentration in the coolant to a predetermined value corresponding to a critical condition.	Execute Verify
3.1.2	Lifting the control rod	Lift the rod to the given position. Dilute to the given rod position. Lifting the rod to reach the critical point	Execute
4.1.1	The secondary loop startup	The steam warms up the main steam pipe through the bypass valve of the isolating valve, such as at low speed. The reactor power rises to about 5% of the rated power, and the turbine accelerates at the specified speed until the rated speed is reached.	Execute Regulate
5.1.1	Generators combine with the grid, and generate electricity	Increasing the reactor power to 15% of rated power manually.	Execute Verify
5.1.2		Normal startup and load increase of steam turbine generator unit.	Execute monitor

$$\lambda_k = \frac{\sum_{j=1}^{n} d(s_{ij})}{\sum_{i=1}^{m}\sum_{j=1}^{n} d(s_{ij})} \tag{17}$$

Step 3. According to Definition 2 in Section 2.2, it converts the interval 2-tuple matrix into the interval numbers.

Step 4. The interval 2-tuple comparison matrix R is normalized to obtain matrix B, for which the elements are calculated as

$$b_{ij} = \frac{(r_{max} - r_{ij})}{r_{max}} r_{max} - r_{min} \tag{18}$$

where r_{min}, r_{max} represent the maximum and minimum values in different CPCs, respectively.

Step 5. According to the definition of entropy, there are the experts E_i and the C_i in the CPCs. We multiply the weight of each expert by the expert's judgment results to determine the entropy value of the CPCs using Eq. (19).

$$H_i = -\frac{\sum_{j=1}^{m} \lambda_{ij} f_{ij} \ln f_{ij}}{\ln m} \tag{19}$$

Table 6
Nominal CFPs for part of the tasks.

Task step or activity	Cognitive activity	Error mode	Nominal CFP
1.1.1	Evaluate	I1	0.200
1.2.1	Evaluate	I2	0.010
1.2.1	Verify	O2	0.070
1.3.1	Identify	I1	0.200
1.4.1	Evaluate	I1	0.200
1.5.1	Evaluate	I2	0.010
1.5.1	Verify	O2	0.070
1.6.1	Evaluate	I2	0.010
1.7.1	Evaluate	I2	0.010
1.8.1	Evaluate	I2	0.010
2.1.1	Execute	E2	0.003
2.1.1	Verify	O2	0.070
2.1.2	Execute	E4	0.003
2.1.2	Monitor	O3	0.07
2.1.3	Execute	E2	0.003
2.1.3	Verify	O2	0.07
2.2.1	Execute	E1	0.003
2.2.1	Verify	O2	0.070
2.2.2	Execute	E4	0.003
2.2.2	Verify	O2	0.070
2.3.1	Execute	E2	0.003
2.3.1	Verify	O3	0.070
3.1.1	Execute	E1	0.003
3.1.1	Verify	O3	0.070
3.1.2	Execute	E4	0.003
4.1.1	Execute	E4	0.003
4.1.1	Regulate	E1	0.003
5.1.1	Execute	E1	0.003
5.1.1	Verify	O3	0.070
5.1.2	Execute	E4	0.003
5.1.2	Monitor	O3	0.070

where $f_{ij} = -\frac{b_{ij}}{\sum b_{ij}}$, with $i = 1, 2, \ldots, n$ and $j = 1, 2, \ldots, m, 0 \le H_i \le 1$. When f_{ij} is 0, H_i is the entropy value of CPCs.

Step 6. Computing the important weight of CPCs using the entropy value, and the important weight of the C_i is defined as:

$$\dot{\omega}_i = \frac{1 - H_i}{n - \sum_{i=1}^{n} H_i} \tag{20}$$

where $\dot{\omega}_i$ is the important weight of the C_i of CPCs. We obtain the important weight value of CPCs to solve the complex and fuzzy scenes using the entropy method.

2.2.4. The comprehensive weight of CPCs

In order to obtain more accurate weights of CPCs, the weights of CPCs are linearly combined using the combination weighting method, and adjustment parameters ρ_1 and ρ_2 are introduced. The comprehensive weight, W, is given by Eq. (21).

$$W = w_i^{\cdot\cdot}(\rho_1 w_i + \rho_2 \dot{\omega}_i) \tag{21}$$

where $W = (w_1, w_2, \ldots, w_n)$, $w_i^{\cdot\cdot}$ is the cognitive weight, ω_i is the correlative weights, $\dot{\omega}_i$ is the important weights, and the values of ρ_1 and ρ_2 are 0.5.

2.3. Calculating the HEP

According to the cognitive weight, correlative weight and important weight of CPCs in different cognitive activities, we calculate the weight of CPCs to obtain the "comprehensive weight", and the CFP_{adjust} is computed as

$$CFP_{adjust} = CFP_{nominal} \times \text{comprehensive weight}. \tag{22}$$

After obtaining the CFP_{adjust}, the HEP value for this event can be obtained as

$$P = 1 - \prod_{i=1}^{n} (1 - CFP_i) \tag{23}$$

Table 7
The level and cognitive weight of CPCs.

CPC name	Level	COCOM function			
		Observation	Interpretation	Planning	Execution
Adequacy of organization	Inefficient	1.0	1.0	1.2	1.2
Working conditions	Compatible	1.0	1.0	1.0	1.0
Adequacy of MMI	Tolerable	1.0	1.0	1.0	1.0
Availability of procedures/plans	Inappropriate	2.0	1.0	5.0	2.0
Number of simultaneous goals	Matching current capacity	1.0	1.0	1.0	1.0
Available time	Adequate	0.5	0.5	0.5	0.5
Time of day	Day-time (adjusted)	1.0	1.0	1.0	1.0
Adequacy of training and preparation	Inadequate	2.0	5.0	5.0	2.0
Crew collaboration quality	Efficient	1.0	1.0	1.0	1.0

Table 8
The initial impact matrix of CPCs in observation.

CPC	CPC_1	CPC_2	CPC_3	CPC_4	CPC_5	CPC_6	CPC_7	CPC_8	CPC_9
CPC_1	N	H	H	H	M	H	M	VH	H
CPC_2	VH	N	M	L	H	H	H	M	M
CPC_3	M	VH	N	H	H	VH	L	VH	M
CPC_4	H	M	H	N	VH	H	M	VH	VH
CPC_5	M	M	M	H	N	VH	M	M	H
CPC_6	H	H	VH	VH	H	N	L	H	H
CPC_7	L	M	L	L	L	M	N	L	H
CPC_8	H	H	H	VH	H	VH	M	N	L
CPC_9	H	L	M	M	H	H	M	M	N

Table 9
The initial impact matrix of CPCs in interpreting.

CPC	CPC_1	CPC_2	CPC_3	CPC_4	CPC_5	CPC_6	CPC_7	CPC_8	CPC_9
CPC_1	VL	H	M	H	M	H	M	H	H
CPC_2	VH	VL	M	M	H	VH	H	M	L
CPC_3	M	H	VL	H	H	VH	M	VH	M
CPC_4	H	M	H	VL	VH	H	L	VH	VH
CPC_5	M	M	M	H	VL	VH	M	VH	M
CPC_6	VH	VH	VH	VH	VH	VL	H	H	H
CPC_7	H	M	H	L	L	M	VL	M	H
CPC_8	H	H	H	VH	H	H	H	VL	L
CPC_9	VH	H	M	M	H	H	H	M	VL

Table 10
The initial impact matrix of CPCs in planning.

CPC	CPC_1	CPC_2	CPC_3	CPC_4	CPC_5	CPC_6	CPC_7	CPC_8	CPC_9
CPC_1	VL	H	M	H	L	H	L	H	M
CPC_2	VH	VL	M	L	M	H	M	L	L
CPC_3	L	M	VL	M	M	VH	L	H	L
CPC_4	M	L	M	VL	H	H	L	VH	H
CPC_5	L	L	M	M	VL	H	L	H	M
CPC_6	M	H	H	H	H	VL	L	M	H
CPC_7	L	M	L	L	L	L	VL	L	M
CPC_8	M	M	M	H	M	H	M	VL	L
CPC_9	H	L	L	L	M	M	M	M	VL

Table 11
The initial impact matrix of CPCs in execution.

CPC	CPC_1	CPC_2	CPC_3	CPC_4	CPC_5	CPC_6	CPC_7	CPC_8	CPC_9
CPC_1	VL	H	M	H	L	M	M	H	H
CPC_2	VH	VL	M	L	H	H	H	L	M
CPC_3	L	H	VL	H	H	VH	L	VH	M
CPC_4	H	L	H	VL	VH	H	L	H	VH
CPC_5	L	M	M	H	VL	H	L	VH	M
CPC_6	H	H	H	VH	H	VL	H	H	H
CPC_7	M	M	M	L	L	H	VL	L	H
CPC_8	H	H	H	VH	H	H	M	VL	L
CPC_9	VH	M	L	M	H	H	H	VL	VL

Table 12
The correlative weight of CPCs in the different cognitive function.

	Observation	Interpreting	Planning	Execution
CPC_1	0.1151	0.1135	0.1144	0.1119
CPC_2	0.1088	0.1093	0.1089	0.1094
CPC_3	0.1131	0.1113	0.1105	0.1111
CPC_4	0.1161	0.1122	0.1146	0.1149
CPC_5	0.1125	0.1105	0.1106	0.1107
CPC_6	0.1218	0.1225	0.1278	0.1252
CPC_7	0.0894	0.1005	0.0901	0.0989
CPC_8	0.1149	0.1138	0.1169	0.1108
CPC_9	0.1083	0.1064	0.1062	0.1071

3. Case study

3.1. Structured information analysis

SIA is used to decompose the cold startup process in a nuclear power plant. This process primarily involves filling, exhausting, and boosting loops. SIA has three components: scenario analysis, goals–means analysis, and cognitive function analysis.

The scenario analysis is the cold startup in nuclear power plant, where the pressurized reactor has been inactive for a prolonged period, causing the temperature to drop below 60 °C. Goals–means analysis uses HTA to decompose tasks, as illustrated in Fig. 1.

Table 5 displays the tasks involved in the cold startup process. According to Table 1, cognitive function analysis uses the cognitive function determined by CREAM to identify the corresponding cognitive activities and functions, as displayed in Table 5.

According to the tasks after SIA, we identified the error mode and nominal CFP by considering the operators during task execution. According to Table 2, the error modes and the nominal CFPs are listed in Table 6.

After analyzing the structural information and nominal CFPs, we computed the weights of the CPCs of different cognitive functions, as described in the next section.

3.2. Calculating the weight of CPCs

3.2.1. Calculating cognitive function weight of CPCs

After taking the SIA, the cognitive function is assessed by means of a cognitive function analysis. According to Table 3, the levels and cognitive weights of CPCs are listed in Table 7.

3.2.2. Calculating the correlative weight of CPCs

To establish a group for evaluating the relationship between CPCs and construct the initial impact matrix X, five experts were selected. Table 4 displays the linguistic terms. The initial impact matrices X of the CPCs are listed in Tables 8–12 for different cognitive functions. Finally, the TF-DEMATEL method was used to calculate the correlative weights of the CPCs.

Once we completed the defuzzification process, we obtained the total-relation matrix Z for the different cognitive functions. We

Table 13
The initial matrix to evaluate the important weight of CPC_s.

CPC	Cognitive function	E1	E2	E3	E4	E5
CPC_1	Observation	VP-P	P-M	VP-MP	MP	VP-P
	Interpretation	VP-M	VP	VP-P	VP-P	P
	Planning	M	MP-M	VP	P-M	P-MG
	Execution	M	MG-G	M-G	MP-MG	MG
CPC_2	Observation	M	MP	MG	MP-MG	G
	Interpretation	M	MG	P	MG	MP-MG
	Planning	VP	P	VP-P	P-MP	MP
	Execution	M	MG	M-MG	M-G	MP-MG
CPC_3	Observation	VG	G-VG	MG-VG	MG-G	G
	Interpretation	P-M	P	VP-P	VP-MP	VP
	Planning	VP-P	VP-MP	P	MP	P-MP
	Execution	VG	G	MG-VG	G-VG	G
CPC_4	Observation	M	P-MP	P	MP	MG
	Interpretation	VP	P	MP	VP-MP	P-MP
	Planning	VG	MG-G	M-G	G-VG	G
	Execution	M	MG	MP-MG	M	MP-MG
CPC_5	Observation	M	P-M	P-MP	MP	P
	Interpretation	M	VP	P	MP	VP-MP
	Planning	VG	M-G	MG	G-VG	M
	Execution	M	MG	M-G	MG-VG	G
CPC_6	Observation	VG	MG-VG	G-VG	G	VG
	Interpretation	VG	M-G	MG-VG	MG-G	G-VG
	Planning	VG	MG	G	M-G	MG
	Execution	VG	MG-G	G-VG	MG-VG	MG-G
CPC_7	Observation	VP-MP	VP-P	VP-MP	P-MP	P
	Interpretation	VP-P	VP-MP	P	VP-P	MP
	Planning	VP-P	P	VP	VP-P	VP-MP
	Execution	VP-MP	P	MP	VP	P-MP
CPC_8	Observation	VG	MG-G	M-G	M-VG	G-VG
	Interpretation	VG	G	G-VG	M-G	M
	Planning	VG	MG	MG-VG	G-VG	G
	Execution	M	M-G	M-MG	G	MG
CPC_9	Observation	VG	MG	G-VG	MG-VG	VG
	Interpretation	VG	MG-VG	G-VG	VG	G
	Planning	VG	G	M-G	MG	G-VG
	Execution	VG	MG-VG	MG-G	G	MG-VG

calculated the values of "Influence" and "Relation" for different cognitive functions. Finally, the entropy weight was used to obtain the correlative weights of the CPCs. The results are presented in Table 12.

In Table 12, we present the values and trends of the CPCs for different cognitive functions. CPC6 was the most important CPC, and the CPCs showed similar trends for different cognitive functions. After obtaining the correlative weights of the CPCs, we calculated their important weights.

Clearly that CPC6 holds the highest significance among all the CPCs, and the CPCs show a consistent trend across different cognitive functions. Once the correlative weights of the CPCs are determined using the entropy weight, it is important to calculate their important weights.

3.2.3. *Calculating the important weight of CPCs*

The expert group uses the interval 2-tuple linguistic to evaluate the CPCs of the cold startup tasks in different cognitive functions. Setting $D^k = (d_{ij}^k)_{m\times n}$ is the linguistic evaluation matrix of CPC_s under the decision attribute C_i given by expert E_j for task A_k.

The CPCs evaluation with the 2-tuple linguistic set is defined as $S = \left\{ \begin{array}{lll} s_0: \text{very poor(VP)} & & s_2: \text{medium poor(MP)} \\ s_3: \text{medium(M)} & s_1: \text{poor(P)} & s_4: \text{medium good(MG)} \\ s_5: \text{good(G)} & & s_6: \text{very good(VG)} \end{array} \right\}$,the group uses the interval 2-tuple linguistic to evaluated the important weights of CPCs, and the initial matrix of CPCs in different cognitive functions, and then it is shown in Table 13

After getting the initial matrix to evaluate the important weight of

Table 14
The interval 2-tuple matrix to evaluate the objective weight of CPC_s.

CPC	Cognitive function	E1	E2	E3	E4	E5
CPC_1	Observation	$[(s_0, 0), (s_0,0)]$	$[(s_1, 0), (s_1,0)]$	$[(s_0, 0), (s_2,0)]$	$[(s_2, 0), (s_2,0)]$	$[(s_0, 0), (s_1,0)]$
	Interpretation	$[(s_0, 0), (s_0,0)]$	$[(s_0, 0), (s_0,0)]$	$[(s_0, 0), (s_1,0)]$	$[(s_0, 0), (s_1,0)]$	$[(s_1, 0), (s_1,0)]$
	Planning	$[(s_3, 0), (s_3,0)]$	$[(s_2, 0), (s_3,0)]$	$[(s_0, 0), (s_0,0)]$	$[(s_1, 0), (s_3,0)]$	$[(s_1, 0), (s_4,0)]$
	Execution	$[(s_3, 0), (s_3,0)]$	$[(s_4, 0), (s_5,0)]$	$[(s_3, 0), (s_5,0)]$	$[(s_2, 0), (s_4,0)]$	$[(s_4, 0), (s_4,0)]$
CPC_2	Observation	$[(s_3, 0), (s_3,0)]$	$[(s_2, 0), (s_2,0)]$	$[(s_4, 0), (s_4,0)]$	$[(s_4, 0), (s_4,0)]$	$[(s_5, 0), (s_5,0)]$
	Interpretation	$[(s_3, 0), (s_3,0)]$	$[(s_4, 0), (s_4,0)]$	$[(s_1, 0), (s_1,0)]$	$[(s_4, 0), (s_4,0)]$	$[(s_4, 0), (s_4,0)]$
	Planning	$[(s_0, 0), (s_0,0)]$	$[(s_1, 0), (s_1,0)]$	$[(s_0, 0), (s_1,0)]$	$[(s_1, 0), (s_2,0)]$	$[(s_2, 0), (s_2,0)]$
	Execution	$[(s_3, 0), (s_3,0)]$	$[(s_4, 0), (s_4,0)]$	$[(s_3, 0), (s_4,0)]$	$[(s_3, 0), (s_5,0)]$	$[(s_2, 0), (s_4,0)]$
CPC_3	Observation	$[(s_6, 0), (s_6,0)]$	$[(s_5, 0), (s_6,0)]$	$[(s_4, 0), (s_6,0)]$	$[(s_4, 0), (s_5,0)]$	$[(s_5, 0), (s_5,0)]$
	Interpretation	$[(s_0, 0), (s_0,0)]$	$[(s_1, 0), (s_1,0)]$	$[(s_0, 0), (s_1,0)]$	$[(s_0, 0), (s_2,0)]$	$[(s_0, 0), (s_0,0)]$
	Planning	$[(s_0, 0), (s_0,0)]$	$[(s_0, 0), (s_0,0)]$	$[(s_1, 0), (s_1,0)]$	$[(s_2, 0), (s_2,0)]$	$[(s_1, 0), (s_2,0)]$
	Execution	$[(s_6, 0), (s_6,0)]$	$[(s_5, 0), (s_5,0)]$	$[(s_4, 0), (s_6,0)]$	$[(s_5, 0), (s_6,0)]$	$[(s_5, 0), (s_5,0)]$
CPC_4	Observation	$[(s_3, 0), (s_3,0)]$	$[(s_1, 0), (s_2,0)]$	$[(s_1, 0), (s_1,0)]$	$[(s_2, 0), (s_2,0)]$	$[(s_4, 0), (s_4,0)]$
	Interpretation	$[(s_0, 0), (s_0,0)]$	$[(s_1, 0), (s_1,0)]$	$[(s_2, 0), (s_2,0)]$	$[(s_0, 0), (s_2,0)]$	$[(s_1, 0), (s_2,0)]$
	Planning	$[(s_6, 0), (s_6,0)]$	$[(s_4, 0), (s_5,0)]$	$[(s_3, 0), (s_5,0)]$	$[(s_5, 0), (s_6,0)]$	$[(s_5, 0), (s_5,0)]$
	Execution	$[(s_3, 0), (s_3,0)]$	$[(s_4, 0), (s_4,0)]$	$[(s_2, 0), (s_4,0)]$	$[(s_3, 0), (s_3,0)]$	$[(s_2, 0), (s_4,0)]$
CPC_5	Observation	$[(s_3, 0), (s_3,0)]$	$[(s_1, 0), (s_3,0)]$	$[(s_1, 0), (s_2,0)]$	$[(s_2, 0), (s_2,0)]$	$[(s_1, 0), (s_1,0)]$
	Interpretation	$[(s_3, 0), (s_3,0)]$	$[(s_0, 0), (s_0,0)]$	$[(s_1, 0), (s_1,0)]$	$[(s_2, 0), (s_2,0)]$	$[(s_0, 0), (s_2,0)]$
	Planning	$[(s_6, 0), (s_6,0)]$	$[(s_3, 0), (s_5,0)]$	$[(s_4, 0), (s_4,0)]$	$[(s_5, 0), (s_6,0)]$	$[(s_3, 0), (s_3,0)]$
	Execution	$[(s_3, 0), (s_3,0)]$	$[(s_4, 0), (s_4,0)]$	$[(s_3, 0), (s_5,0)]$	$[(s_4, 0), (s_6,0)]$	$[(s_5, 0), (s_5,0)]$
CPC_6	Observation	$[(s_6, 0), (s_6,0)]$	$[(s_4, 0), (s_6,0)]$	$[(s_5, 0), (s_6,0)]$	$[(s_5, 0), (s_5,0)]$	$[(s_6, 0), (s_6,0)]$
	Interpretation	$[(s_6, 0), (s_6,0)]$	$[(s_3, 0), (s_5,0)]$	$[(s_4, 0), (s_6,0)]$	$[(s_4, 0), (s_5,0)]$	$[(s_5, 0), (s_6,0)]$
	Planning	$[(s_6, 0), (s_6,0)]$	$[(s_4, 0), (s_4,0)]$	$[(s_5, 0), (s_5,0)]$	$[(s_3, 0), (s_5,0)]$	$[(s_4, 0), (s_4,0)]$
	Execution	$[(s_6, 0), (s_6,0)]$	$[(s_4, 0), (s_5,0)]$	$[(s_5, 0), (s_6,0)]$	$[(s_4, 0), (s_6,0)]$	$[(s_4, 0), (s_5,0)]$
CPC_7	Observation	$[(s_0, 0), (s_0,0)]$	$[(s_0, 0), (s_1,0)]$	$[(s_0, 0), (s_2,0)]$	$[(s_1, 0), (s_2,0)]$	$[(s_1, 0), (s_1,0)]$
	Interpretation	$[(s_0, 0), (s_0,0)]$	$[(s_0, 0), (s_2,0)]$	$[(s_1, 0), (s_1,0)]$	$[(s_0, 0), (s_1,0)]$	$[(s_2, 0), (s_2,0)]$
	Planning	$[(s_0, 0), (s_0,0)]$	$[(s_1, 0), (s_1,0)]$	$[(s_0, 0), (s_0,0)]$	$[(s_0, 0), (s_1,0)]$	$[(s_0, 0), (s_2,0)]$
	Execution	$[(s_0, 0), (s_0,0)]$	$[(s_1, 0), (s_1,0)]$	$[(s_2, 0), (s_2,0)]$	$[(s_0, 0), (s_0,0)]$	$[(s_1, 0), (s_2,0)]$
CPC_8	Observation	$[(s_6, 0), (s_6,0)]$	$[(s_4, 0), (s_5,0)]$	$[(s_3, 0), (s_5,0)]$	$[(s_0, 0), (s_3,0)]$	$[(s_5, 0), (s_6,0)]$
	Interpretation	$[(s_6, 0), (s_6,0)]$	$[(s_5, 0), (s_5,0)]$	$[(s_5, 0), (s_6,0)]$	$[(s_3, 0), (s_5,0)]$	$[(s_3, 0), (s_3,0)]$
	Planning	$[(s_6, 0), (s_6,0)]$	$[(s_4, 0), (s_4,0)]$	$[(s_4, 0), (s_6,0)]$	$[(s_5, 0), (s_6,0)]$	$[(s_5, 0), (s_5,0)]$
	Execution	$[(s_3, 0), (s_3,0)]$	$[(s_3, 0), (s_5,0)]$	$[(s_3, 0), (s_4,0)]$	$[(s_5, 0), (s_5,0)]$	$[(s_4, 0), (s_4,0)]$
CPC_9	Observation	$[(s_6, 0), (s_6,0)]$	$[(s_4, 0), (s_4,0)]$	$[(s_5, 0), (s_6,0)]$	$[(s_4, 0), (s_6,0)]$	$[(s_6, 0), (s_6,0)]$
	Interpretation	$[(s_6, 0), (s_6,0)]$	$[(s_4, 0), (s_6,0)]$	$[(s_5, 0), (s_6,0)]$	$[(s_6, 0), (s_6,0)]$	$[(s_5, 0), (s_5,0)]$

(continued on next page)

Table 14 (*continued*)

CPC	Cognitive function	E1	E2	E3	E4	E5
	Planning	[(s_6, 0), (s_6,0)]	[(s_5, 0), (s_5,0)]	[(s_3, 0), (s_5,0)]	[(s_4, 0), (s_4,0)]	[(s_5, 0), (s_6,0)]
	Execution	[(s_6, 0), (s_6,0)]	[(s_4, 0), (s_6,0)]	[(s_4, 0), (s_5,0)]	[(s_5, 0), (s_5,0)]	[(s_4, 0), (s_6,0)]

Table 15
The weight of experts in different cognitive functions.

	E_1	E_2	E_3	E_4	E_5
Observation	0.03	0.17	0.31	0.24	0.25
Interpreting	0.04	0.23	0.38	0.15	0.2
planning	0.03	0.26	0.12	0.26	0.33
execution	0.04	0.13	0.34	0.17	0.32

Table 16
The important weight of CPCs.

CPC	Observation	Interpreting	planning	execution
CPC_1	0.1251	0.0999	0.1104	0.1187
CPC_2	0.1185	0.1068	0.1311	0.1068
CPC_3	0.1029	0.0965	0.1227	0.1065
CPC_4	0.1208	0.1334	0.1073	0.1062
CPC_5	0.0997	0.0962	0.1038	0.1136
CPC_6	0.1057	0.1112	0.0999	0.1092
CPC_7	0.1162	0.1274	0.1109	0.1246
CPC_8	0.103	0.1191	0.1049	0.1087
CPC_9	0.1081	0.1095	0.109	0.1057

Table 17
The comprehensive weight of CPCs.

	Observation	Interpreting	planning	execution
CPC_1	0.1104	0.0716	0.0739	0.1217
CPC_2	0.0989	0.0737	0.0696	0.0892
CPC_3	0.0892	0.0678	0.0661	0.0903
CPC_4	0.2151	0.0945	0.2996	0.1863
CPC_5	0.0860	0.0671	0.0559	0.0960
CPC_6	0.0494	0.043	0.0311	0.0522
CPC_7	0.0797	0.0808	0.0487	0.0941
CPC_8	0.1815	0.4279	0.2989	0.1839
CPC_9	0.0898	0.0736	0.0562	0.0863

CPC_s, we convert it to the interval 2-tuple matrix to evaluate the important weight of CPC_s, and it is shown in Table 14.

We use Definition 1 in section 2.2 to convert the initial matrix to the interval 2-tuple matrix. According to Definition2 in section 2.2, we calculate the expert weights of CPCs in different cognitive functions. The results are shown in Table 15.

We normalize the interval 2-tuple comparison matrix, and then calculate the important weight of CPC_s using entropy weight method. The results are shown in Table 16.

After getting the important weight, we calculate the comprehensive weight of CPCs.

3.2.4. Calculating the comprehensive weight of CPCs

To obtain more accurate CPCs weights in the modified CREAM, it is important to calculate the cognitive weight, the correlative weight and the important weight of the CPCs. Once we have determined the important weight of the experts and CPCs in different cognitive functions, we can obtain the important weight of CPCs by Eq. (20). The final comprehensive weight of CPCs can then be obtained using Eq. (21), and this information is presented in Table 17.

Table 18
The adjusted CFPs of the cold startup process.

Task elements	Error modes	Nominal CFPs	Comprehensive weights	Adjusted CFPs
1.1.1	I1	0.200	0.051991747	0.010398349
1.2.1	I2	0.010	0.025551328	0.000255513
1.2.1	O2	0.070	0.025551328	0.001788593
1.3.1	I1	0.200	0.025551328	0.005110266
1.4.1	I1	0.200	0.131640000	0.026328000
1.5.1	I2	0.010	0.131640000	0.001316400
1.5.1	O2	0.070	0.025551328	0.001788593
1.6.1	I2	0.010	0.025551328	0.000255513
1.7.1	I2	0.010	0.131640000	0.001316400
1.8.1	I2	0.010	0.131640000	0.001316400
2.1.1	E2	0.003	0.025551328	0.000076654
2.1.1	O2	0.070	0.025551328	0.001788593
2.1.2	E4	0.003	0.131640000	0.000394920
2.1.2	O3	0.070	0.025551328	0.001788593
2.1.3	E2	0.003	0.131640000	0.000394920
2.1.3	O2	0.070	0.025551328	0.001788593
2.2.1	E1	0.003	0.131640000	0.000394920
2.2.1	O2	0.070	0.025551328	0.001788593
2.2.2	E4	0.003	0.131640000	0.000394920
2.2.2	O2	0.070	0.025551328	0.001788593
2.3.1	E2	0.003	0.025551328	0.000076654
2.3.1	O3	0.070	0.025551328	0.001788593
3.1.1	E1	0.003	0.131640000	0.000394920
3.1.1	O3	0.070	0.025551328	0.001788593
3.1.2	E4	0.003	0.131640000	0.000394920
4.1.1	E4	0.003	0.131640000	0.000394920
4.1.1	E1	0.003	0.131640000	0.000394920
5.1.1	E1	0.003	0.131640000	0.000394920
5.1.1	O3	0.070	0.025551328	0.001788593
5.1.2	E4	0.003	0.131640000	0.000394920
5.1.2	O3	0.070	0.025551328	0.001788593

Table 19
The HEP of different methods.

Methods	The basic CREAM	The modified extended CREAM
HEP	[0.001 , 0.1]	0.06809

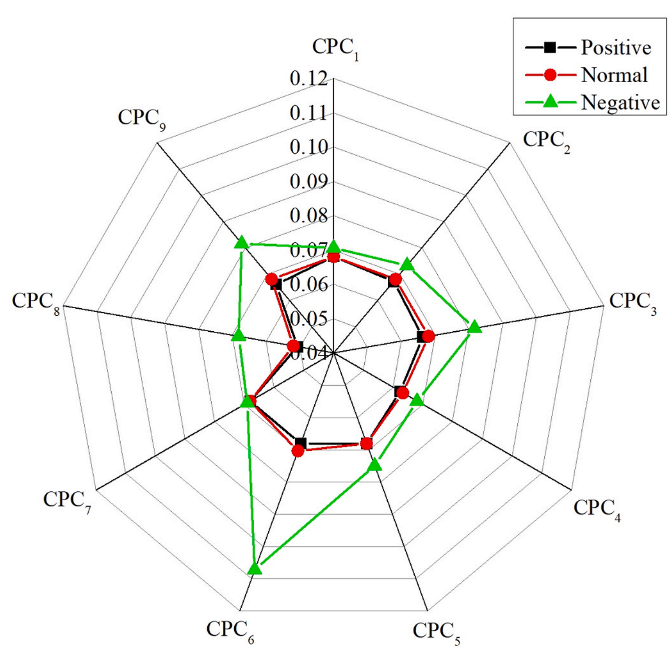

Fig. 2. The value of CPCs in different state.

3.3. Calculating the HEP

This section presents the error mode, nominal CFPs, and comprehensive weights. The adjusted CFPs were obtained using Eq. (22), and the results are presented in Table 18. Furthermore, the HEP after the adjustment was 0.06809.

4. Model verification

There are two axioms for verifying the correctness and sensitivity of the modified extended CREAM [16]. Correctness analysis was performed by calculating the HEP with the basic CREAM and comparing the HEP between the basic CREAM and modified extended CREAM. In the sensitivity analysis, we changed the state of the CPCs slightly, which had a significant impact on the HEP. Positive changes decrease the HEP, whereas negative changes increase it.

4.1. Correctness analysis

The basic CREAM is used to calculate the probability of human error, which ranged from 0.001 to 0.1. The result is 0.06809 by the modified extended CREAM, and then it is in the range by the basic CREAM. Ultimately, the modified extended CREAM was found to be accurate and within the range of the basic CREAM in Table 19.

4.2. Sensitivity analysis

After completing the correctness analysis, it is important to continue the sensitivity analysis using the modified extended CREAM to predict HEP more accurate, which can then be verified using an axiom in HRA. The axiom states that CPCs have an impact on HEP. In this study, we obtained the comprehensive weights of the CPCs, as displayed in Table 17. When we changed any one of the CPCs to positive or negative, the HEP was calculated using the modified extended CREAM. The results are shown in Fig. 2, and demonstrate the different states of HEP.

Based on the analysis of the modified extended CREAM, it appears that the HEP is affected by positive and negative changes in the CPCs. Fig. 2 shows the sensitivity analysis, revealing that the human error rate increases with negative changes, but reduces under positive changes. These findings align with the axioms, confirming the validity of the improved method.

5. Conclusion

This study presented a modified extended CREAM to calculate HEP more accurately. In the modified extended CREAM, we used structure information analysis to handle the tasks, and the correlative and important weights of the CPCs were calculated for different cognitive functions. The comprehensive weights of the CPCs included cognitive, correlative, and important weights. Thus, we decomposed the tasks using structure information analysis, extended the CREAM, and obtained the cognitive weight of the CPCs. We used TF-DEMATEL to handle the correlative weights of the CPCs, and the interval 2-tuple linguistic approach and entropy method were used to compute the important weights of the CPCs. We used the modified extended CREAM to calculate the HEP of the cold startup, obtaining an HEP value of 0.06809. Finally, correctness and sensitivity analyses were performed to verify the modified CREAM. The HEP ranged from 0.001 to 0.1 when the basic CREAM was used, and the results were consistent with those obtained using the modified extended CREAM. The sensitivity analysis showed that the HEP changed with the CPCs in different states. The modified extended CREAM considers the cognitive functions important to HRA and was demonstrated to be an effective method for calculating the HEP of an advanced control room.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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