Computer Modeling in
Engineering & Sciences

Tech Science Press

DOI: 10.32604/cmes.2023.030957

ARTICLE

Assessment of Dependent Performance Shaping Factors in SPAR-H Based on Pearson Correlation Coefficient

Xiaoyan Su[1,*], Shuwen Shang[1], Zhihui Xu[2], Hong Qian[1] and Xiaolei Pan[1]

[1]School of Automation Engineering, Shanghai University of Electric Power, Shanghai 200090, China

[2]State Key Laboratory of Nuclear Power Safety Monitoring Technology and Equipment, Shenzhen, 518172, China

*Corresponding Author: Xiaoyan Su. Email: suxiaoyan@shiep.edu.cn

Received: 06 March 2023 Accepted: 20 June 2023 Published: 17 November 2023

ABSTRACT

With the improvement of equipment reliability, human factors have become the most uncertain part in the system. The standardized Plant Analysis of Risk-Human Reliability Analysis (SPAR-H) method is a reliable method in the field of human reliability analysis (HRA) to evaluate human reliability and assess risk in large complex systems. However, the classical SPAR-H method does not consider the dependencies among performance shaping factors (PSFs), which may cause overestimation or underestimation of the risk of the actual situation. To address this issue, this paper proposes a new method to deal with the dependencies among PSFs in SPAR-H based on the Pearson correlation coefficient. First, the dependence between every two PSFs is measured by the Pearson correlation coefficient. Second, the weights of the PSFs are obtained by considering the total dependence degree. Finally, PSFs' multipliers are modified based on the weights of corresponding PSFs, and then used in the calculating of human error probability (HEP). A case study is used to illustrate the procedure and effectiveness of the proposed method.

KEYWORDS

Reliability evaluation; human reliability analysis; SPAR-H; performance shaping factors; dependence; pearson correlation analysis

1 Introduction

Reliability assessment is the process of evaluating the reliability of a system, product, or process to ensure that it performs its intended function consistently and without failure. It involves identifying potential sources of failure, estimating the likelihood and consequences of failure, and developing strategies to mitigate or manage the risks associated with failure. Reliability assessment can be applied to various areas, such as engineering design [1–3], information security [4–6], power industry [7–9], and social science [10–12].

The foundation of risk and reliability evaluation is the modeling of uncertain information. How to handle uncertainty has attracted much attention. Many methods have been proposed, such as evidence theory [13–15], fuzzy sets, and random permutation set [16], which are applied in various fields, like pattern classification [17,18], decision making [19,20] and information fusion [21]. Among these, probabilistic safety assessment (PSA) is a specific type of reliability assessment method that is focused on evaluating the safety and risk associated with complex systems, such as nuclear power plants, space agencies, or other high-risk industrial facilities.

Human reliability analysis (HRA) has become an important part of PSA [22], and plays an important role in avoiding human error and improving system reliability. Human error is an important factor to be considered in the design and risk assessment of large complex systems [23]. HRA has gained widespread attention. To quantify the impact of human error on the system and reduce human error probability (HEP), various methods have been proposed [24–26].

One method is the Standardized Plant Analysis Risk-Human Reliability Analysis (SPAR-H), introduced by Gertman et al. in 2005 [27] to solve the problem of risk assessment and human performance evaluation in nuclear power plants. SPAR-H provides a specific method to evaluate HEP. It categorizes human error events into two categories: diagnosis and action, based on professionals' sorting and mechanism analysis of event reports.

Since HEP varies greatly in different situations, such as task complexity and operator pressure levels, SPAR-H suggests eight performance shaping factors (PSFs) that influencing human performance to be considered in the evaluation of HEP. The eight PSFs are available time, stress/stressors, complexity, experience/training, procedures, Ergonomics/Human-System Interface (HSI), fitness for duty, and work process. By evaluating the levels of these PSFs, the basic HEP is modified. The final HEP is the sum of the diagnosis and action error probabilities. As the SPAR-H method is effective and easy to understand and calculate [28], it has been widely used in various fields such as the petroleum industry [29,30], nuclear power plant risk analysis [31–33], chemical industry [34], occupational risk [35] and maritime accidents [36,37].

However, the classical SPAR-H method does not take into account the dependence among PSFs when calculating HEP. This kind of dependence is universal in practical engineering, and failing to consider it can significantly affect the results. For instance, the current task is highly complex, which is bound to impose a heavy psychological burden on the operator and increases the multiplier factor of "stress/stressors". As a result, the HEP repeatedly calculates the negative effect, causing the calculated result to be higher than the actual situation. Moreover, if there are multiple groups of dependence or deep dependence degrees, the excessively repeated calculation can lead to a significant difference between the final HEP result and the actual situation. Therefore, analyzing and addressing dependence problems is crucial for enhancing the rationality and accuracy of SPAR-H results.

In recent years, more and more researches have been conducted to deal with the dependencies among PSFs in HRA [38–41]. For the SPAR-H method, there has been also increasing attention given to identifying and quantifying dependence among PSFs. Laumann et al. [42] identified limitations in the definitions of SPAR-H PSFs and levels, and thus proposed new definitions to increase the resolution and nuance of the PSFs. Liu et al. [43] investigated the dependence between every two PSFs and its corresponding psychological mechanism that triggers human errors, and improved the design of PSF multipliers in SPAR-H. However, the PSF multiplier design needs to rely on expert opinions, which are subjective. Liu et al. [44] studied the highly complex dependencies among PSFs in both qualitative and quantitative ways, providing valuable insights for future dynamic HRA research. Nevertheless, due to the lack of available data and the complexity involved in quantifying HEPs based on PSFs, the modeling curves may be imprecise. Xu et al. [45] used the DEMATEL method to identify the dependence among PSFs, and proved that it effectively reduced the repeated calculation of the related part of PSFs through additional cases, and the result was more reasonable. However, DEMATEL's input data is generated by expert opinions, which is subjective to some extent. Liu et al. [46] extracted and integrated data from 219 nuclear power plant operation event reports, and used Grey theory-based data mining-Apriori algorithm, Exploratory factor analysis, and Pearson correlation analysis to analyze the dependence among eight PSFs, and obtained relatively consistent conclusions. Among these methods, Pearson correlation analysis, as a mathematical model to measure the linear dependence between two variables, can clearly represent the dependence between two PSFs in numerical form, which provides strong data support for the analysis of dependence among PSFs. However, no subsequent processing of the dependence in calculating HEP was provided in Liu et al.'s method.

In this paper, we propose a new method to deal with the dependencies among PSFs in SPAR-H based on the Pearson correlation coefficient. Firstly, we calculate the relative weight of each PSF by determining its comprehensive independence degree using the Pearson correlation coefficient based on Liu et al.'s method [46]. Secondly, the PSF multipliers are modified by discounting them based on the relative weights of corresponding PSFs. Finally, the classical SPAR-H formula is used to obtain the final HEP. The proposed method can effectively handle the dependencies among PSFs, reduce the repeated calculation of related parts during the process of SPAR-H, and generate more reasonable results.

This paper is organized as follows: Section 2 introduces the basic theoretical knowledge of SPAR-H and Pearson correlation analysis. Section 3 illustrates the procedure of the proposed approach. Section 4 presents a basic case study and an additional cases to prove the method's effectiveness. Finally, Section 5 summarizes the paper.

2 Preliminaries

2.1 SPAR-H [27]

The SPAR-H method presents several advantages, including high reliability and easy-to-use [47]. Specifically, SPAR-H offers a systematic approach for evaluating HEP as follows.

Human failure events are sorted out and analyzed under low power and shutdown conditions in nuclear power plant. Different multipliers are assigned to each PSF according to the influence of different PSF levels on the HEP, as is shown in Table 1 (source from Table 1 of [45]). When the PSF multiplier shows P (failure) = 1.0, it indicates that the PSF at this time poses a severe threat to the security of the system, and it will undoubtedly lead to system failure with a human error probability of 1. During the diagnosis and action sections, the analysts determine the levels for each PSF by evaluating event reports based on Table 1. If the evaluation opinion of PSF is at the nominal level, the corresponding PSF multiplier is 1. When the evaluation opinion of PSF is negative, i.e., the current PSF has an adverse impact on the system, the multiplier of PSF is greater than 1, and the more negative the impact, the greater the multiplier. On the contrary, when the evaluation opinion of PSF is at the positive level, the PSF multiplier is less than 1, and the greater the positive impact, the smaller the PSF multiplier.

Table 1: Values of 8 PSFs under low power and shutdown condition

SPAR-H PSFs	Diagnosis		Action	
	SPAR-H PSF levels	SPAR-H multipliers	SPAR-H PSF levels	SPAR-H multipliers
Available time	Inadequate time	P (failure) = 1.0	Inadequate time	P (failure) = 1.0
	Barely adequate time (≈2/3 × nominal)	10	Time available ≈ the time required	10
	Nominal time	1	Nominal time	1
	Extra time (≤2 × nominal)	0.1	Time available ≥5 × the time required	0.1
	Expansive time (>2 × nominal)	0.1 to 0.01	Time available is ≥50 × the time required	0.01
Stress /stressors	Extreme	5	Extreme	5
	High	2	High	2
	Nominal	1	Nominal	1
Complexity	Highly complex	5	Highly complex	5
	Moderately complex	2	Moderately complex	2
	Nominal	1	Nominal	1
	Obvious diagnosis	0.1		
Experience /training	Low	10	Low	3
	Nominal	1	Nominal	1
	High	0.5	High	0.5
Procedure	Not available	50	Not available	50
	Incomplete	20	Incomplete	20
	Available, but poor	5	Available, but poor	5
	Nominal	1	Nominal	1
	Diagnostic/symptom oriented	0.5		
Ergonomics /HMI	Missing/misleading	50	Missing/misleading	50
	Poor	10	Poor	10
	Nominal	1	Nominal	1
	Good	0.5	Good	0.5
Fitness for duty	Unfit	P (failure) = 1.0	Unfit	P (failure) = 1.0
	Degraded fitness	5	Degraded fitness	5
	Nominal	1	Nominal	1
Work process	Poor	2	Poor	5
	Nominal	1	Nominal	1
	Good	0.8	Good	0.5

After receiving evaluation opinions from the analysts during the diagnosis and action sections on the eight PSFs, the HEP is calculated using the following equation:

$$HEP = NHEP \cdot \prod_{i=1}^{8} f_i \tag{1}$$

where NHEP (nominal HEP) is the basic error probability of each event. NHEP = 0.01 for diagnosis and NHEP = 0.001 for action. f_i is the multiplier of the ith PSF.

When there are too many negative levels (more than or equal to 3), the HEP needs to be modified as follows:

$$HEP = \frac{NHEP \times \prod_{i=1}^{8} f_i}{NHEP(\prod_{i=1}^{8} f_i - 1) + 1} \tag{2}$$

Through the calculation of Eqs.(1) or (2), the HEP_D for the diagnosis part and the HEP_A for the action part can be obtained. Subsequently, the final HEP^* for the system is calculated as Eq. (3).

$$HEP^* = HEP_D + HEP_A \tag{3}$$

2.2 Pearson Correlation Analysis [48]

Pearson correlation coefficient is a mathematical model based on statistical measures of the linear dependence between two sample variables X and Y of the same length and n sample size. Its correlation coefficient consists of the covariance and standard deviation of the estimated sample:

$$r(X, Y) = \frac{Cov(X, Y)}{\sigma_X \cdot \sigma_Y} = \frac{\sum_{j=1}^{n} (x_j - \overline{x})(y_j - \overline{y})}{\sqrt{\sum_{j=1}^{n} (x_j - \overline{x})^2}\sqrt{\sum_{j=1}^{n} (y_j - \overline{y})^2}} \tag{4}$$

where, x_j and y_j are the jth variable data of variables X and Y. $\overline{x}$ and $\overline{y}$ take the sample mean of variables X and Y. The correlation coefficient $r(X, Y)$, which can be described by r_{XY}, is in the range [−1,1]. When $r_{XY} = 0$, variables X and Y are not correlated, namely, they are independent of each other. When $r_{XY} < 0$, the two variables are positively correlated, that is, when one variable changes, the other changes in the same trend. When $r_{XY} > 0$, the two variables are negatively correlated, that is, when one variable changes, the other changes in the opposite trend. And the two trends increased with the increase of dependence degree $|r_{XY}|$.

3 The Proposed Approach

In this study, a flow chart for dependence processing in the SPAR-H method is presented as shown in Fig. 1. The detailed steps are as follows:

Step 1. Determine experts involved in the evaluation

It is essential that we enlist the help of individuals with the necessary skills and knowledge to conduct the evaluation. These experts must possess a deep understanding of nuclear power plants and their operations, as well as an extensive background in conducting evaluations. Their expertise will contribute to the assessment process, ensuring a comprehensive and accurate evaluation of nuclear power plants.

Step 2. Determine the PSF levels and multipliers based on event reports

The assessment involved experts who utilized their expertise and experience to analyze the event reports, and based on their analysis, determined the PSF levels and multipliers as outlined in Table 1.

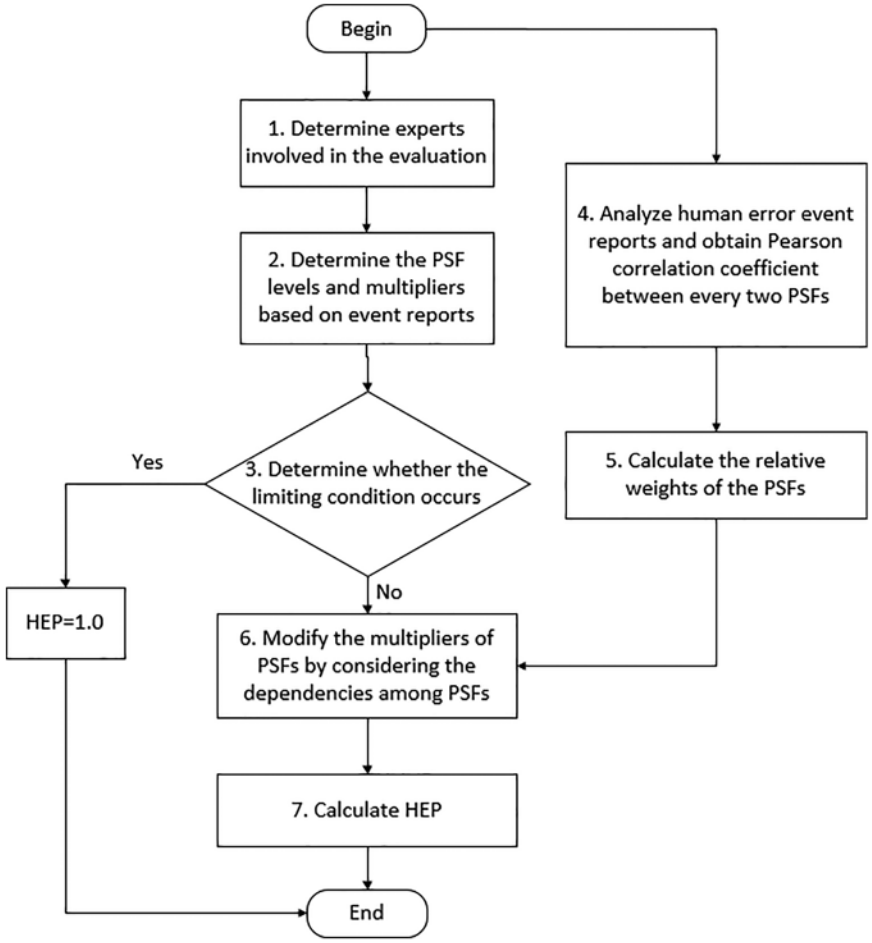

Figure 1: Flow chart of the proposed method

Step 3. Determine whether the limiting condition occurs

Table 1 reveals that if the level of PSF "available time" is categorized as "inadequate" or the level of PSF "fitness for duty" is classified as "unfit", then the HEP score is directly assigned a value of 1, and the process comes to an end. However, if neither of these limiting conditions is met, the process continues with the subsequent steps.

Step 4. Analyze human error event reports and obtain Pearson correlation coefficient between every two PSFs

The method of handling event reports in [46] can be adopted in this step to obtain the Pearson correlation coefficient between every two PSFs. Firstly, we need to sift through all the published event reports, analyze and summarize the direct and root causes of each event, and then isolate the reports where the failure source is attributed to human error. Once we have a refined sample data set, we can calculate the Pearson correlation coefficient between every pair of PSFs using Eq. (4). More details can be found in [46].

Step 5. Calculate the relative weights of the PSFs

Suppose that the set composed of the 8 PSFs is $\theta = \{PSF_i\}$, where PSF$_i$ is the ith PSF, and define dependence degree D_{ij} and independence degree N_{ij} among PSFs, as shown in Eqs. (5) and (6).

$$D_{ij} = \left|r_{ij}\right| \tag{5}$$

$$N_{ij} = 1 - D_{ij} \tag{6}$$

where D_{ij} is the dependence degree between PSF$_i$ and PSF$_j$, and r_{ij} is the Pearson correlation coefficient between PSF$_i$ and PSF$_j$. N_{ij} represents the independence degree between PSF$_i$ and PSF$_j$.

The total independence degree T_i between PSF$_i$ and all other PSFs is defined as Eq. (7).

$$T_i = \sum_{j=1}^{8} N_{ij} \tag{7}$$

$$w_i = T_i / \max_i T_i \tag{8}$$

The total independence degree T_i represents the degree that PSF_i is uncorrelated with other PSFs, which shows the independent influence of PSF_i on the HEP. Thus, the multiplier of PSF_i under a certain circumstance (level) should play more important role in the fusion of multipliers of different PSFs. In this paper, larger weight is assigned to the PSF with more independent influence on HEP. In the extreme situation that all PSFs are independent, the weights are all equal to 1, which downward to the situation assumed in classic SPAR-H method. As shown in Eq. (8), T_i is normalized, and w_i, as the relative weight of PSF$_i$, discounts the corresponding multiplier in subsequent processing.

Step 6. Modify the multipliers of PSFs by considering the dependencies among PSFs

Assuming that a certain PSF$_i$ is suggested a negative evaluation (i.e., $f_i < 1$), its negative impact on the results will be repeatedly calculated if it is dependent on other PSFs. Therefore, under the dependence situation, the evaluation should be modified to weaken the negative impact of the repeated part, which will be closer to the nominal evaluation ($f_i = 1$). In other words, the range of the modified PSF$_i$ multiplier f_i^* should be $1 > f_i^* > f_i$. Similarly, if a certain PSF$_i$ is given a positive evaluation (i.e., $0 > f_i > 1$) and is dependent on other PSFs, the positive impact of this PSF$_i$ on the results will be repeatedly calculated. Thus, under the dependence situation, the evaluation should be modified to weaken the positive impact of the repeated part, which will be closer to the nominal evaluation ($f = 1$). That is, the range of the modified PSF$_i$ multiplier f_i^* is $f_i > f_i^* > 1$. If $f_i = 1$, using Eqs. (1) or (2) in the SPAR-H method does not affect the results, and there is no need to discount the nominal evaluation. In order to meet the above requirements, the discount-modified equation in [45] is adopted as follows:

$$f_i^* = w_i \cdot f_i + (1 - w_i) \times 1 \tag{9}$$

where f_i is the multiplier of the PSF$_i$ suggested by experts according to Table 1, f_i^* is the result of f_i after discount modification, and w_i is the relative weight of the PSF$_i$. When the relative weight w_i is smaller, indicating that the PSF$_i$ contains less independent information, the discounted multiplier f_i^* becomes closer to the nominal evaluation ($f = 1$). When the relative weight $w_i = 0$, meaning that the PSF$_i$ is completely dependent on other PSFs and does not contain independent information, $f_i^* = 1$. This scenario does not affect HEP, and Eq. (9) is in line with the hypothesis.

Step 7. Calculate HEP

The modified PSF multiplier f_i^* is used to replace the original multiplier f_i in Eqs. (1) or (2) to calculate HEP. The final HEP is the sum of two parts, as shown in Eq. (3).

4 Case Study

In this section, the HRA worksheet of the event “Failure to Recover RHR” in “Loss of Inventory with RCS Pressurized” for low power and shut down (LP/SD) [27] is used to demonstrate the procedures of the proposed method.

The event “Failure to Recover RHR” in “Loss of Inventory with RCS Pressurized” refers to a scenario in a nuclear power plant where the Reactor Coolant System (RCS) loses coolant inventory and becomes pressurized. In this scenario, the High-Pressure Safety Injection (HPSI) and Low-Pressure Safety Injection (LPSI) systems are activated to recover the RCS inventory and restore system pressure. However, in the event of a “Failure to Recover RHR,” the plant’s emergency response systems are unable to recover the RCS inventory or restore system pressure to normal levels. This can lead to a potential loss of coolant accident (LOCA) and a breach of the fuel cladding, which can release radioactive materials into the surrounding environment. The consequences of a “Failure to Recover RHR” event can be severe and may include damage to the reactor core, release of radioactive material, and potential harm to personnel and the environment. Therefore, it is critical that nuclear power plant operators have robust emergency response procedures and systems in place to prevent and mitigate such events.

4.1 Application Process of the Proposed Method

Step 1. Determine experts involved in the evaluation

The experts have been chosen for their professional experience and knowledge in the field of HRA, particularly in nuclear power plants. Note that the study does not involve any concrete implementation of this step, the data source is based on the opinions of experts from [27], which is sufficient for demonstrating the use of the proposed method.

Step 2. Determine the PSF levels and multipliers based on event reports

According to Appendix D, page 156, in [27], the PSF levels and multipliers of the “Recovery RHR” event report for diagnosis and action part are shown in Table 2.

Table 2: Diagnosis and action multipliers

PSF_i	PSFs	PSF levels	Multiplier for diagnosis (f_i^D)	PSF levels	Multiplier for action (f_i^A)
1	Available time	Nominal time	1	Nominal time	1
2	Stress/stressors	High	2	Nominal	1
3	Complexity	Nominal	1	Nominal	1
4	Experience/training	High	0.5	High	0.5
5	Procedure	Diagnostic/symptom oriented	0.5	Available, but poor	5
6	Ergonomics/HSI	Poor	10	Good	0.5
7	Fitness for duty	Nominal	1	Nominal	1
8	Work Process	Nominal	1	Nominal	1

Step 3. Determine whether the limiting condition occurs

No limiting conditions occur in this case.

Step 4. Analyze human error event reports and obtain Pearson correlation coefficient between every two PSFs

Liu [46] counted 219 event reports at China's nuclear power plants from 2007 to 2017, out of which 89 reports were related to human errors. Based on these reports, correlation coefficients between every pair of PSFs can be obtained. In this paper, we use the correlation coefficient table shown in Table 3 (source from [46]) as the data source for calculating the relative weights.

Table 3: Results of pearson correlation analysis of 8 PSFs

PSFs	Available time	Stress /stressors	Complexity	Experience /training	Procedure	Ergonomics /HSI	Fitness for duty	Work process
Available time	1	0.374	0.232	−0.200	0.081	−0.136	0.333	−0.251
Stress/stressors	0.374	1	0.681	−0.159	−0.091	−0.168	0.564	−0.130
Complexity	0.232	0.681	1	−0.167	−0.204	−0.247	0.384	−0.191
Experience/training	−0.200	−0.159	−0.167	1	−0.162	−0.176	−0.140	0.433
Procedure	0.081	–0.091	–0.204	–0.162	1	0.312	0.056	–0.321
Ergonomics/HSI	−0.136	−0.168	−0.247	−0.176	0.312	1	−0.095	−0.320
Fitness for duty	0.333	0.564	0.384	−0.140	0.056	−0.095	1	−0.176
Work process	−0.251	−0.130	−0.191	0.433	−0.321	−0.320	−0.176	1

Step 5. Calculate the relative weights of the PSFs

Based on Table 3, the dependence degree D_{ij} and independence degree N_{ij} of PSFs are calculated according to Eqs. (5) and (6), and then the total independence degree T_i and relative weight w_i of eight PSFs can be obtained based on Eqs. (7) and (8), as shown in Table 4.

Table 4: The relative weights of PSFs

PSF_i	PSFs	Total independence degree (T_i)	Weight (w_i)
1	Available time	5.3930	0.9342
2	Stress/stressors	4.8330	0.8372
3	Complexity	4.8940	0.8477
4	Experience/training	5.5630	0.9636
5	Procedure	5.7730	1.0000
6	Ergonomics/HSI	5.5460	0.9607
7	Fitness for duty	5.2520	0.9098
8	Work process	5.1780	0.8969

Step 6. Modify the multipliers of PSFs by considering the dependencies among PSFs

Based on Eq. (9), the modified multipliers of PSFs can be obtained as shown in Table 5.

Table 5: Modified multipliers for diagnosis and action portion

PSF_i	Weight (w_i)	Multiplier for diagnosis (f_i^D)	Modified multiplier for diagnosis (f_i^{D*})	Multiplier for action (f_i^A)	Modified multiplier for action (f_i^{A*})
1	0.9342	1	1	1	1
2	0.8372	2	1.8621	1	1
3	0.8477	1	1	1	1
4	0.9636	0.5	0.5	0.5	0.5
5	1	0.5	0.5504	5	4.5968
6	0.9607	10	9.3028	0.5	0.5387
7	0.9098	1	1	1	1
8	0.8969	1	1	1	1

Step 7. Calculate HEP

According to Eq. (1), the HEP for the diagnostic part is 0.04592, the HEP for the action part is 0.00135, and the final HEP is 0.04726, while the final HEP calculated in [27] is 0.05125. The reason for the difference is that the proposed method considers the dependence among PSFs and modifies the PSF multipliers.

4.2 Discussion

The PSFs weights calculated by the proposed method are compared with those calculated by Xu et al. [45]. Table 6 shows the weight ranking of PSFs for the two methods and the difference in ranking. As can be seen from Table 6, the ranking of PSFs by the two methods is consistent in general, the top three PSFs of the two methods are similar, and two PSFs "Complexity" and "Fitness for duty" have the same ranking. In addition, the HEP calculated by Xu is 0.04891, and the HEP calculated by the method in this paper is 0.04726, which is very close. There are also some different results derived from these two methods. For example, the variance of weight calculated by the two methods is different. Xu's is 0.0119, while this paper's is 0.0029. Based on the above data analysis, some possible explanations are as follows.

The two methods differ in variance for the following reasons. For the elements in DEMATEL's input matrix in Xu's method [45], the influence of X on Y is different from that of Y on X, that is, DEMATEL is directional when expressing the dependence of alternative schemes, while Pearson correlation analysis, as a statistical method, has the same correlation coefficient no matter the influence of X on Y or the influence of Y on X. That is, the relevance of alternatives is expressed without regard to directivity.

The ranking of PSFs of the two methods is consistent in general, but some local differences exist. The reasons for the difference can be concluded as follows. One possible explanation for this discrepancy is that the data sources are different. Xu's method [45] relied on expert opinions as input data for the DEMATEL analysis. Specifically, he constructed a comparison scale using discontinuous integers ranging from 0 to 9 and mapped different numbers to corresponding semantic labels. As a result, distinct boundaries existed among different dependencies. In contrast, the method presented in this paper employs statistical methods. Firstly, human error event reports of nuclear power plants are counted, and the results of Pearson correlation analysis are used as data sources. The dependence between every two PSFs can be expressed by any number between 0 and 1, thereby blurring the boundary between different dependence levels. The second possible explanation is that Pearson correlation analysis is a way to measure the linear dependence between two variables, while the actual dependence among PSFs is not necessarily linear. This suggests that relying solely on Pearson correlation analysis may not capture the true nature of the dependence among PSFs.

Table 6: Comparison of the results of the two methods

PSF_i	PSFs	Xu's method		Proposed method		Rank difference
		Weight (w_i)	Rank	Weight (w_i)	Rank	
1	Available time	0.7176	6	0.9342	4	2
2	Stress/stressors	0.8621	4	0.8372	8	−4
3	Complexity	0.7153	7	0.8477	7	0
4	Experience/training	1.0000	1	0.9636	2	−1
5	Procedure	0.8992	3	1.0000	1	2
6	Ergonomics/HSI	0.9225	2	0.9607	3	−1
7	Fitness for duty	0.7422	5	0.9098	5	0
8	Work process	0.6902	8	0.8969	6	2

In dealing with the dependence among PSFs, DEMATEL is a qualitative analysis method which requires evaluations from domain experts, and Pearson correlation analysis is a quantitative analysis method which is preferred when enough event reports (data) is available. The appropriate method should be chosen according to the specific situation.

5 Conclusion

In this paper, statistical methods were used to conduct a quantitative analysis of the dependence among PSFs. The Pearson correlation analysis is used to model the dependence among PSFs, and Pearson correlation coefficient between two PSFs is used as input data instead of expert opinions, thus eliminating subjectivity. Considering the relative weight of PSFs and using the discount equation to discount the original multipliers of PSFs of classical SPAR-H, the calculation results are more reasonable. The results of the proposed method are generally consistent with Xu's method, which shows the effectiveness of the proposed method. Considering the limitations of the Pearson correlation analysis, further study of more appropriate statistical methods should be investigated in the future.

Acknowledgement: The author greatly appreciates the editor's encouragement and the anonymous reviewers' suggestions to improve our paper.

Funding Statement: The work is partially supported by Shanghai Rising-Star Program (Grant No. 21QA1403400), Shanghai Sailing Program (Grant No. 20YF1414800), Shanghai Key Laboratory of Power Station Automation Technology (Grant No. 13DZ2273800).

Author Contributions: The authors confirm contribution to the paper as follows: study conception and design: Xiaoyan Su; data collection: Shuwen Shang; analysis and interpretation of results: Xiaoyan

Su, Hong Qian; draft manuscript preparation: Shuwen Shang, Xiaolei Pan. All authors reviewed the results and approved the final version of the manuscript.

Availability of Data and Materials: The data used in this study are from [27,45,46], and the data cited are all stated in the paper. There is no unavailable data cannot be released in this paper.

Conflicts of Interest: The authors declare that they have no conflicts of interest to report regarding the present study.

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