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Hybrid Fuzzy Analytic Hierarchy Process-Bayesian Network Framework for Human Reliability Analysis in Smart Grid Systems

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Abstract
The human factor plays a decisive role in the safe and reliable functioning of modern smart grids, where increasing automation and system complexity impose greater cognitive load on operators. This paper presents a hybrid approach that combines the Fuzzy Analytic Hierarchy Process (FAHP) and Bayesian Network (BN) to assess the probability of human error under uncertain conditions. Triangular fuzzy numbers are used to express expert judgments and are processed through FAHP to obtain the relative significance of key performance shaping factors (PSFs). The normalized weight of each subfactor is calculated and converted into fuzzy possibility scores (FPSs), which are further transformed into fuzzy failure probabilities (FFPs). These probabilities are incorporated into a BN model built in GeNIe to evaluate the effects of individual and grouped factors on human reliability. The model indicates a high level of operator reliability while highlighting the need for improvement in critical situations. The findings suggest that training and knowledge sharing programs, alarm design and management, cognitive load, and shift management are among the most influential subfactors. A case study from the smart grid power distribution sector was conducted to demonstrate the applicability of the proposed framework. Expert opinions from experienced power system engineers and grid operators were collected using purposive sampling to evaluate human reliability factors. The hybrid framework provides a clear understanding of how different conditions affect operator reliability and supports utilities in improving training, communication processes, and control room design. The proposed FAHP BN framework offers a systematic and flexible method for analyzing human reliability in the smart grid environment and serves as a practical tool for identifying critical factors and guiding actions that enhance the safety and reliability of smart grid operations.

Keywords- Human reliability, Fuzzy set theory, Fuzzy AHP, Bayesian network, Smart grid.

Abbreviations

FAHP: Fuzzy Analytic Hierarchy Process
BN: Bayesian Network
BBN: Bayesian Belief Network
HRA: Human Reliability Analysis
TOPSIS: Technique for Order Preference by Similarity to Ideal Solution
SPAR-H: Standardized Plant Analysis Risk Human Reliability Analysis
HEART: Human Error Assessment and Reduction Technique
MCDM: Multi Criteria Decision Making
DG: Distributed Generation
RES: Renewable Energy Systems
HEP: Human Error Probability
FFP: Fuzzy Failure Probability
SHRA: Systematic Human Reliability Analysis
THERP: Technique for Human Error Rate Prediction
FTOPSIS: Fuzzy Technique for Order Preference by Similarity to Ideal Solution
DEMATEL-ANP: Decision Making Trial and Evaluation Laboratory - Analytical Network Process
HAZOP: Hazard and Operability
FPS: Fuzzy Possibility Scores
IFS: Intuitionistic Fuzzy Set
IVIFS: Interval-Valued Intuitionistic Fuzzy Set

CPS: Cyber Physical System
FMEA: Failure Modes and Effects Analysis
SAIFI: System Average Interruption Frequency Index
SAIDI: System Average Interruption Duration Index
PSF: Performance Shaping Factor
DEMATEL-ISM: Decision Making Trial and Evaluation Laboratory- Interpretive Structural Model
PFS: Pythagorean Fuzzy Set
q-ROFS: q-Rung Orthopair Fuzzy Set
RAW: Risk Achievement Worth
RRW: Risk Reduction Worth
HuREX: Human Reliability Data Extraction
SACADA: Scenario Authoring, Characterization, and Debriefing Application

1. Introduction

Modern smart grids integrate advanced technologies, such as distributed generation, renewable energy sources, intelligent sensors, communication networks, and automated control systems. These developments improve the flexibility and efficiency of power system operations; however, they also increase system complexity. Despite the high level of automation, human operators continue to play a critical role in system monitoring, decision-making, and responding to unexpected events. Therefore, human error remains an important factor that can influence the overall safety and reliability of smart grid operations.

Human Reliability Analysis (HRA) is used to examine the likelihood of human error and the influences that impact the performance of an operator. Traditional HRA methods, such as the Technique for Human Error Rate Prediction (THERP) (Swain,1964; Ramezani et al., 2020), "Standardized Plant Analysis Risk Human Reliability Analysis" (SPAR-H) (Gertman et al., 2005; Elidolu et al., 2023) and "Human Error Assessment and Reduction Technique" (HEART) (Aydin, 2023; Bowo et al., 2025) can be used, but they are not easy to implement in smart grids. This is explained by the fact that smart grids involve complex interactions between people, machines, and automated systems, and in most instances, there is no history of human errors. In addition, the experts will be able to offer personal or unverified opinions on how different factors affect the performance of the operators. To solve these problems, researchers have started to use advanced methods such as Bayesian Networks (BNs) and fuzzy multi-criteria decision-making (MCDM) methods. Bayesian Networks are applied in modeling the cause-and-effect relationship of human, technical and environmental factors and can be updated in case new information is available. The Fuzzy Analytic Hierarchy Process (FAHP) helps convert uncertain or linguistic expert judgments into meaningful numerical weights. These two methods may be combined to provide a stronger and more realistic approach to human reliability analysis in smart grid systems. Fuzzy AHP helps in deciding and prioritizing the factors that affect the performance of operators, and Bayesian Networks use the factors to calculate the probability of human error in different situations. This combination approach can contribute to improved decision-making in training, procedure development, control room design, and risk management.

The suggested FAHP Bayesian Network model is significant as it allows the systematic assessment of human reliability in the conditions of uncertainty and facilitates risk-based decision-making in smart grid system. The methodology, though illustrated with a case of a distribution-level smart grid, is general and can be used in other safety-critical, information-intensive systems where human performance is a major factor in determining the overall reliability.

2. Literature Review

The shift towards smart grid infrastructure in traditional power grids has significantly altered the manner in which reliability is evaluated. A smart grid is a combination of distributed generation (DG), renewable energy systems (RES), complex communication systems, intelligent sensing, and adaptive control systems. Such additions introduce more complexity, variability, and interdependence into the system, and more advanced techniques for reliability modelling are required. The past researches largely compared the traditional grid features with the new smart grids and identified the need of improved communication, automation, and bi-directional power flow control in order to make the intermittency of the renewable energy sources possible. Using the example of Ourahou et al. (2020), the authors explained that the inclusion of renewable sources will increase energy security and reduce emissions, but it will also lead to operational problems that will require more efficient grid control and reliability evaluation systems. With the increased penetration of renewable energy, the methods of reliability assessment have changed to reflect the stochastic characteristics of solar and wind energy. Akhtar et al. (2021) established that the combination of DG and RES and intelligent control strategies can affect the overall system reliability, and the results of the case studies indicated that renewable sources could enhance the grid performance under the condition of proper management. Similar studies have been conducted to enhance fault detection and the reliability of protection. Alonso et al. (2020) created a smart sensor that can adjust protection settings in real time and coordinate with other grid devices, and demonstrated excellent performance compared to conventional relays in the IEEE 34-bus system. Also, hierarchical and multi-state modelling methods have been proposed to model the various operating modes of smart grids. Zheng et al. (2021) suggested a hierarchical reliability model based on layered fault trees and continuous-time Markov chains to measure system availability and weak components. Moreover, the smart grid is now considered more as a cyber-physical system (CPS), where failure can spread through communication and power layers. Amani and Jalili (2021) discussed smart grids in the complex network framework and highlighted the necessity of resilience-oriented modelling to reduce cascading failures. Similarly, Jha et al. (2021) investigated the communication technologies required to ensure effective smart grid CPS operation, and the main protocols were mapped to the applications. High-level sensing and monitoring solutions also lead to the improvement of reliability. Rao and Sushama (2023) assessed an Internet of Things (IoT) based smart sensing system to monitor real-time voltage and current data to assist in the analysis of reliability and power quality. Recent surveys of smart grid technologies, including the study conducted by Muqeet et al. (2023), emphasize the role of communication, automation, and protection systems in improving grid performance. In the recent development, Tiwari et al. (2025) presented intuitionistic fuzzy reliability assessment of a smart grid system under the Weibull distribution and UGF technique.

The risk-based approach and data-driven approach have also been used to analyze reliability issues in distribution networks. To determine the critical failures at power and cyber layers, Zúñiga et al. (2020) used Failure Modes and Effects Analysis (FMEA), and suggested preventive maintenance measures to mitigate the risks. The use of machine learning applications is on the rise, and Bashir et al. (2021) prove that decision tree models are highly accurate in predicting the stability of smart grids. Wider research indicates that smart grids increase the efficiency and sustainability of industries. Khan et al. (2025) discussed the concept of smart grid and Industry 5.0 integration, which is associated with better resource management and minimized environmental impact. According to field research, including Gabriel et al. (2025), distributed energy resources, demand-side response, and automated restoration are effective in enhancing the reliability of the distribution network. Smart grid advantages are also confirmed by localized studies. Sinishaw et al. (2021) optimized the location of switching devices and reconfiguring the network in an Ethiopian distribution system and demonstrated significant increases in such reliability indices as “System Average Interruption Frequency Index (SAIFI)” and “System Average Interruption Duration Index (SAIDI)”. In general, efficiency, reliability, sustainability, and security enhancements are recurrently mentioned in the research on smart grids by Butt et al. (2021).

Human Reliability Analysis (HRA) has become an important field alongside physical reliability issues because of the greater contact between operators, automation, and cyber-physical elements. The smart grid environment involves making decisions quickly in the face of uncertainty; thus, human performance is a critical factor that defines the reliability of operations. Classical HRA methods include THERP, HEART and SPAR-H, which are popular, but they cannot reflect uncertainties in expert judgment, dependency in model Performance Shaping Factors (PSFs), and dynamically update probabilities. These shortcomings have prompted researchers to use Bayesian Networks (BNs) as an advanced probabilistic method in contemporary HRA applications. Research on safety-critical systems has demonstrated that BNs are effective in learning causal relationships between PSFs and allow evidence-based revision of human error probabilities (Dindar et al., 2020; Liu et al., 2022).

Recent studies have also promoted dynamic and integrated HRA methods. Liu et al. (2025) suggested a DEMATEL-ISM (Decision Making Trial and Evaluation Laboratory- Interpretive Structural Model) and dynamic modelling method to reflect the behaviour of PSFs over time to give more realistic estimates of human error. Guglielmi et al. (2022) proposed a hybrid SPAR-H and HEART approach, which focuses on human factors as safety barriers, and proved its efficiency with the help of an industrial case study. Si and Niu (2024) enhanced SPAR-H evaluation in the domain of crane operation by connecting text-mined operator errors to the PSF weighting of DEMATEL-ANP (Decision Making Trial and Evaluation Laboratory - Analytical Network Process). The effects of the quality of supervision, work environment, and operator competency on the probability of human errors have been highlighted in accident-based studies, including that of Rahmati et al. (2025). Bayesian methods are still being developed, and Zhao (2022) suggested weighted ensemble modelling to compare HRA methodologies based on actual performance information. Fuzzy logic and Bayesian reasoning hybrid methods have also been created. To illustrate, Yan et al. (2022) transformed qualitative PSFs into fuzzy numbers and fuzzy rules with BN reasoning to assess the performance of operators in nuclear power plants. In a similar manner, Garg et al. (2023) applied the evidence of simulators to revise the Human Error Probability (HEP) values in case of advanced nuclear reactor conditions, and proved the strength of BN inference. In other works, Jo and Lee (2022) proposed a Bayesian Belief Network (BBN) based human reliability analysis model for start-up and shutdown operations in a nuclear power plant system. Hossein et al. (2024) combined FAHP and BN for Human Reliability analysis (HRA) and identified the human error affecting factors. Pant et al. (2024) applied the Analytical Hierarchy Process (AHP), a multi-criteria decision-making method, to identify the best weight management practice in a smart healthcare system.

Along with BN developments, multi-criteria decision-making (MCDM) techniques, particularly fuzzy AHP and hybrid fuzzy AHP-TOPSIS, have been extensively applied to rank human, organizational, and technical aspects in the face of uncertainty. These techniques facilitate systematic expert opinions and vagueness in linguistic tests. As an example, Kukreja (2023) used fuzzy AHP-TOPSIS to determine the main issues in industrial reinforcement learning problems, whereas Demircan and Yetilmezsoy (2023) applied a hybrid method to assess smart waste management strategies. Rajabpour et al. (2022) and Gupta et al. (2025) used FAHP based models to rank sustainability and risk factors in organizational and environmental studies. The use of fuzzy AHP in manufacturing also proved to be valuable in enhancing human performance, as Velmurugan et al. (2022) demonstrate. Abdullah et al. (2023) applied FAHP-FTOPSIS to determine the key obstacles and suggest efficient measures to make operations greener in the context of sustainability.

Recent studies have indicated innovations in human reliability, risk evaluation, and decision-making techniques in both industrial and social domains. Bona et al. (2021) came up with the SHRA methodology to calculate the likelihood of human error in the event of an industrial emergency whereas Mashio and Ito (2021) suggested a comprehensive human error management model to design nuclear power plants. Rawat et al. (2022) carried out a review of the general use of AHP in the process of making sustainable development decisions. Alqahtani and Noman (2024) have selected and ranked factors that affect the manual assembly error through fuzzy Delphi and fuzzy AHP and Mandali et al. (2025) have combined machine learning, Bayesian networks, and MCDM with Hazard and Operability (HAZOP) data to perform a useful process-risk assessment. Katiyar et al. (2025) utilized the application of the fuzzy AHP and scenario planning to assist in the recovery efforts of the hospitality and tourism industry after the COVID.

The current research on smart grid reliability is primarily focused on technical and cyber-physical, whereas human reliability is under-researched. Conventional HRA techniques like THERP, SPAR-H and HEART are not easily applicable to smart grids because of uncertainty in expert judgments, absence of error data and complex interactions among the influencing factors. Despite the fact that Bayesian Networks and fuzzy AHP have been used independently in various fields, there is limited literature that combines the two techniques in the analysis of human reliability in smart grid systems. This study suggests a hybrid Fuzzy AHP Bayesian Network model of HRA in smart grid operations. The innovation is in the connection of fuzzy AHP based factor prioritization to Bayesian probabilistic reasoning. The fuzzy weights of the sub factors are converted to fuzzy possibility scores (FPS) and fuzzy failure probabilities (FFP) and these are the inputs to the Bayesian Network. The framework takes into account human, technical, environmental, and organizational factors and determines the key contributors based on the Fussel-Vesely importance measure. Together, these methodological integration, probabilistic transformation, and smart-grid-focused application distinguish the proposed approach from existing FAHP, BN, and hybrid FAHP BN based human reliability studies.

The primary aim of the research is to determine human reliability in smart grids under uncertainty. The key contributions are:

- Determination of key factors and sub factors that influence human reliability in smart grid operations.
- The use of fuzzy AHP to measure uncertain expert judgments.
- Combination of fuzzy AHP outcomes with a Bayesian Network to determine the probability of human error.
- Determination of the most powerful sub factors that lead to human error.

The rest of the paper is structured in the following way. Section 3 outlines the proposed hybrid FAHP BN methodology. Section 4 outlines the smart grid system as the case study. Section 5 addresses the findings and their implications to human reliability analysis. Lastly, Section 6 is the conclusion of the study.

3. Research Methodology

This study develops a hybrid model that integrates the Fuzzy Analytic Hierarchy Process (FAHP) and Bayesian Network (BN) to predict the probability of human error in a smart grid system. The use of FAHP based expert elicitation was due to the fact that it gives a systematic approach to dealing with uncertainty and vagueness in expert judgments with the help of triangular fuzzy numbers. In addition, FAHP can be easily combined with the Bayesian Network framework, which allows the conversion of fuzzy priority weights into probabilistic inputs to evaluate human errors. This section provides a theoretical background on the methods and their integration.

3.1 Assessment of the Probability Associated with Key Factors Contributing to Human Error

In human reliability research, the significance of each performance shaping factor (PSF) is usually established by expert's experience, knowledge of the domain, or available quantitative data concerning the system. However, in smart grid systems, quantitative information on human errors and the factors affecting them is often incomplete. Consequently, expert judgment emerges as an important source of information to assess PSFs that affect operator performance. Despite the usefulness of expert assessments as a source of qualitative information, they are associated with uncertainty, subjectivity, and inconsistency. To address these uncertainties, several analytical techniques have been proposed in the literature. Among them, fuzzy set theory is widely recognized as one of the most effective approaches. Fuzzy theory enables linguistic and uncertain judgments to be represented mathematically by replacing crisp numerical values with fuzzy numbers. Unlike classical crisp sets, a fuzzy set allows elements to hold partial membership values within the interval of 0 to 1, making it particularly suitable for modelling expert opinions that cannot be expressed with precision. Various types of fuzzy numbers exist for decision-making applications, with triangular fuzzy numbers and trapezoidal fuzzy numbers being the most commonly used (Kumar and Yelam, 2025a; Kumar and Yelam, 2025b). Triangular fuzzy numbers were selected because they provide a simple, transparent, and computationally efficient way to represent expert uncertainty and integrate smoothly with the FAHP BN framework. Although advanced fuzzy models such as Intuitionistic fuzzy set (IFS), Interval-Valued Intuitionistic Fuzzy Set (IVIFS), Pythagorean Fuzzy Set (PFS), q-Rung Orthopair Fuzzy Set (q-ROFS) can capture uncertainty in greater detail, they require higher computational complexity and more demanding expert elicitation. Therefore, triangular fuzzy numbers were considered appropriate for developing a practical and interpretable human reliability assessment model.

A Triangular fuzzy number is expressed as (l, m, u) and its membership function is defined by (Kumar and Yelam, 2025a)

$$\mu_{\tilde{A}}(x) = \begin{cases} \left(\frac{x-l}{m-l}\right) ; & l \leq x \leq m \\ \left(\frac{n-x}{n-m}\right) ; & m \leq x \leq n \\ 0 ; & \text{otherwise} \end{cases} \tag{1}$$

In this form, l denotes the minimum possible value, m represents the central value, and u indicates the maximum possible value assigned by the expert. A typical triangular membership function is illustrated in **Figure 1**.

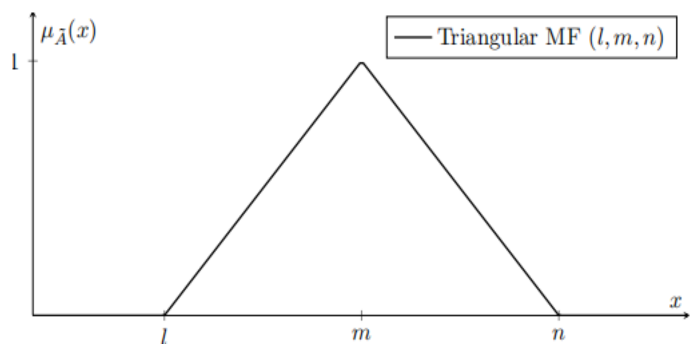

Figure 1. A membership function of TFN.

The identification of the main PSFs and their sub-factors was carried out based on a past literature review. To determine the importance of the main PSFs, the five-point fuzzy scale presented in **Table 1** is applied, and the fuzzy sets employed for expressing preferences among sub-factors in pairwise comparison matrices are detailed in **Table 2**. In **Table 2**, crisp numbers are expressed as triangular fuzzy numbers. In order to assess the probability of human error in smart grid operations by applying the Fuzzy AHP method, structured questionnaires were created to gather expert opinions on each PSF. **Table 3** presents the full list of PSFs and their sub-factors used in this study. After designing the questionnaires, the survey was sent to the experts who had a significant experience in the field of smart grid operation, protection, communication systems, maintenance, and operations management. The panel of experts consist of operational, technical, maintenance, management, and methodological experts, as summarized in **Table 4**. Their evaluations contributed to the development of the pairwise comparison matrices required for the Fuzzy AHP analysis. To guarantee the reliability and validity of the experts' ratings, the ratio of consistency of each pairwise comparison matrix was computed. According to Saaty (2004), a consistency ratio of less than 0.1 is acceptable. It was ensured that the expert responses met the acceptable consistency levels required in the Fuzzy AHP based analysis.

Table 1. Five-point rating scale used to assign weights to the main factors (Chou and Cheng, 2012).

Importance	Preferred value	Corresponding fuzzy set
Very low	1	(0,0,0.25)
Low	2	(0,0.25,50)
Medium	3	(0.25,0.50,0.75)
High	4	(0.55,0.75,1)
Very high	5	(0.75,1,1)

Table 2. Fuzzy preference set applied for sub-factor comparisons in the pairwise comparison matrix (Chou and Cheng, 2012).

Linguistic terms	Preferred value	Corresponding fuzzy set
Equal importance	1	(1,1,1)
Weakly more important	2	(1,2,3)
Moderate importance	3	(2,3,4)
Moderate plus importance	4	(3,4,5)
Strong importance	5	(4,5,6)
Strong plus importance	6	(5,6,7)
Very strong importance	7	(6,7,8)
Very very strong importance	8	(7,8,9)
Extreme importance	9	(8,9,9)

3.2 Experts' Consensus in Aggregated Fuzzy Failure Possibility (AFFP) Format

The expert's consensus method was chosen due to the fact that there is not much reliable data on human errors in smart grid operations, and structured expert judgment is required to develop the model. This approach allows the evaluation to be consistent in the presence of uncertainty and allows it to be effectively integrated with the FAHP Bayesian Network framework. One widely used and conceptually straightforward approach is the linear opinion pool, which combines individual expert assessments through weighted averaging method (Bolger and Houlding, 2017). In the weighted averaging method, after collecting the completed questionnaires, the fuzzy sets provided in **Table 1** and **Table 2** are applied to convert the experts' qualitative responses into numerical form.

Suppose the total number of experts participating in the survey is represented by 'Z'.

The fuzzy number assigned by expert 'z'for the influence of each main factor at the first level of the hierarchy is written as
$\tilde{s}_{iz} = (a_{iz}, b_{iz}, c_{iz})$

The combined or consensus judgment of all experts for factor 'k' is then obtained using the following expression (Hossein et al., 2024).

$$\tilde{S}_k = (a_k, b_k, c_k) = \left(\min_z\{a_{kz}\}, \frac{\sum_{z=1}^{Z} b_{kz}}{Z}, \max_z\{c_{kz}\}\right), (z = 1,2, \dots, Z) \quad (2)$$

Here, a_k, c_k, and b_k represent the lower limit, upper limit, and midpoint of the fuzzy number corresponding to factor k. The fuzzy number derived from the collective opinions of the experts represents the fuzzy score assigned to each factor influencing the probability of human error. To obtain the final score for every factor, a weighted average of these scores is computed using the formula given below (Hossein et al., 2024).

$$S_j = \sum_{i=1}^{n} s_i w_i \ , \sum_{i=1}^{n} w_i = 1 \tag{3}$$

Here, S_j denotes the final score of the j^{th} influencing factor at the second level of hierarchy. The term n refers to the total number of second-level factors associated with the i^{th} first-level factor, while W_i represents the corresponding weight assigned to the i^{th} second-level factor. These weights reflect how strongly each second-level factor contributes to the related factor in the first level. Several methods are available for estimating such weights; this research utilizes the Analytical Hierarchy Process (AHP) within a fuzzy framework to identify the weights of the sub-factors found in the second level of the hierarchy.

3.3 Fuzzy Analytical Hierarchy Process (FAHP)

The Analytical Hierarchy Process (AHP) is a recognized approach for multi-criteria decision-making (MCDM) that aids in assessing the relative significance of different criteria, especially in situations where uncertainty is present. Developed by Saaty (2004), AHP relies on pairwise comparisons among criteria. Despite its popularity, the method faces limitations, particularly due to the potential imbalance in the comparison scale and the inherent uncertainty in human judgments. To address these issues, researchers introduced the fuzzy AHP (FAHP), which incorporates fuzzy logic into the pairwise comparison process (Balusa and Gorai, 2018). Several FAHP formulations have been reported in the literature, including Van Laarhoven and Pedrycz (1983) fuzzy priority method, Buckley's (1985) geometric mean method, Chang (1996) extent analysis method, Mikhailov (2000) fuzzy preference programming method, Mikhailov (2003) fuzzy prioritization method and the logarithmic least squares FAHP approach (Wang et al., 2006), which provide alternative procedures for deriving fuzzy priority weights. Among the available FAHP techniques, in this study extent analysis method proposed by Chang (1996) is used. In this study, Chang's extent analysis was selected because it offers a computationally simple, widely accepted, and practically interpretable procedure for handling pairwise comparison data expressed through triangular fuzzy numbers. In this approach, the criteria or alternatives are first expressed through linguistic terms, after which the extent analysis procedure is carried out. The general steps of the fuzzy AHP extent analysis method as proposed by Chang (1996) are outlined below.

3.3.1 Formation of the Fuzzy Pairwise Comparison Matrix

The fuzzy pairwise comparison matrix, denoted as $\tilde{F}$, is prepared by combining and processing the fuzzy values obtained from the experts' judgments. The resulting fuzzy pairwise comparison matrix is shown below (Chang, 1996).

$$\tilde{F} = \begin{bmatrix} 1 & \tilde{a}_{12} \cdots & \tilde{a}_{1n} \\ \tilde{a}_{21} & 1 \ddots & \tilde{a}_{2n} \\ \tilde{a}_{n1} & \tilde{a}_{n2} \cdots & 1 \end{bmatrix} \tag{4}$$

The matrix is composed of fuzzy numbers, where each element satisfies the reciprocal property $\tilde{a}_{ij} = \frac{1}{\tilde{a}_{ji}}$.

In this study, a '5'point fuzzy scale is adopted to form the fuzzy pairwise comparison matrix. The fuzzy values and their corresponding membership functions for each linguistic term are listed in **Table 2**.

3.3.2 Computation of Fuzzy Synthetic Extent Values

After the formation of the fuzzy pairwise comparison matrices, the fuzzy synthetic extent values (S_i) represented as triangular fuzzy numbers, are computed using Equation (5) (Chang, 1996).

$$S_i = \sum_{j=1}^{m} M_{gi}^{j} \left[\sum_{i=1}^{n}\sum_{j=1}^{m} M_{gi}^{j}\right]^{-1} \tag{5}$$

$$\sum_{j=1}^{m} M_{gi}^{j} = \left(\sum_{j=1}^{m} l_j , \sum_{j=1}^{m} m_j , \sum_{j=1}^{m} u_j\right) \tag{6}$$

$$\sum_{i=1}^{n}\sum_{j=1}^{m} M_{gi}^{j} = \left(\sum_{i=1}^{n} l_i , \sum_{i=1}^{n} m_i , \sum_{i=1}^{n} u_i\right) \tag{7}$$

$$\left[\sum_{i=1}^{n}\sum_{j=1}^{m} M_{gi}^{j}\right]^{-1} = \left(\frac{1}{\sum_{i=1}^{n} u_i}, \frac{1}{\sum_{i=1}^{n} m_i}, \frac{1}{\sum_{i=1}^{n} l_i}\right) \tag{8}$$

where, l_i first component, m_i second component and u_i third component of fuzzy number.

3.3.3 Estimating the Degree of Possibility

Once the values of S_i are obtained, the next step is to calculate the relative degree of possibility for each S_i If $M_1 = (l_1, m_1, u_1)$ and $M_2 = (l_2, m_2, u_2)$ be two triangular fuzzy numbers, the possibility degree from M_1 to M_2 denoted as $V(M_2 \geq M_1)$ is calculated from Equation (9) (Chang, 1996). This value is shown in **Figure 2**.

$$V(M_2 \geq M_1) = \begin{cases} 1 & if\ m_2 \geq m_1 \\ 0 & if\ l_1 \geq u_2 \\ \dfrac{(l_1-u_2)}{(m_2-u_2)-(m_1-l_1)}, & \text{otherwise} \end{cases} \tag{9}$$

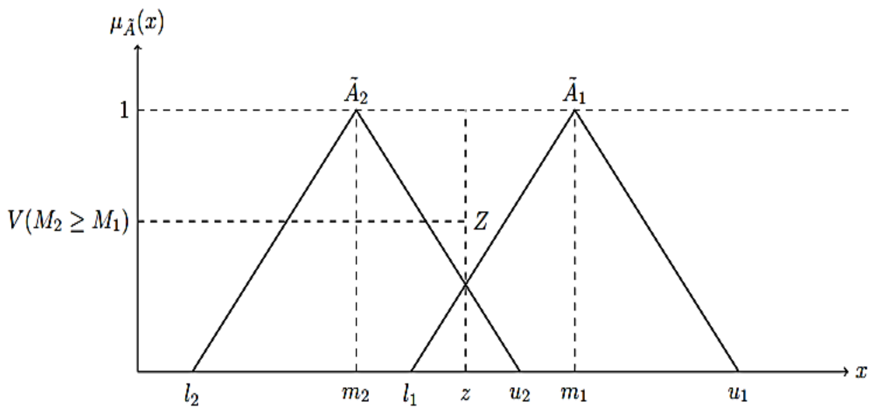

Figure 2. The degree of possibility $V(M_2 \geq M_1)$.

3.3.4 Estimating the Weight of Each Sub-Factor

The weight of each sub-factor is calculated from the fuzzy pairwise comparison matrix using the following equation.

$$d'(A_i) = Min\ V\ (S_i \geq S_k), k = 1,2, \ldots, n, k \neq i \tag{10}$$

Then, the weight vector is given by

$$W' = \left(d'(A_1), d'(A_2), \ldots, d'(A_n)\right)^T \tag{11}$$

3.3.5 Estimating the Final Normalized Weight of the Sub-Factor

The sub-factor weight vector obtained from the previous steps are normalized and get the final weight for each sub-factor.

$$W = \left(d(A_1), d(A_2), \dots, d(A_n)\right)^T \tag{12}$$

3.3.6 Converting Fuzzy Scores to the Fuzzy Probability Values

To estimate the likelihood that each factor contributes to human error, the fuzzy scores are transformed into fuzzy possibility scores (FPSs). These FPSs indicate the level of possibility associated with the root nodes and are calculated using the following equation.

$$FPS = \left(\frac{1-u}{1+(u-m)}\right) + 1 - \left(\frac{1-l}{1+(m-l)}\right) \tag{13}$$

Here, $l, m,$ and u represent the lower, middle, and upper values of a triangular fuzzy number, respectively. Because Bayesian networks operate on probabilistic information, the possibility measures must be transformed into fuzzy probability values. This conversion is carried out using the formulation proposed by Onisawa (1988).

$$FFP = \begin{cases} \frac{1}{10^k} & , FPS \neq 0 \\ 0, & FPS = 0 \end{cases} \tag{14}$$

where, $k = \left[\left(\frac{1}{FPS}\right) - 1\right]^{\frac{1}{3}} \times 2.301.$

Here, FFP represents the fuzzy failure probability for each factor, while FPS represents the fuzzy possibility scores.

3.4 Bayesian Networks

A Bayesian Network (BN) is a graphical framework used to represent and analyze probability distributions. Originating from the ideas of Thomas Bayes, BNs have gained considerable importance in recent years as an effective tool for modelling joint probability distributions through conditional probability principles (Studený and Haws, 2014). In a BN, nodes represent different variables, and the directed links between them illustrate cause-and-effect relationships in a clear visual form. Each variable is associated with one or more probability distributions that describe its possible states.

Bayesian Networks are particularly useful in evaluating risks and uncertainties because they capture probabilistic dependencies among variables and allow systematic reasoning under uncertainty (Cussens et al., 2017). The joint probability distribution for set of variables $X = \{X_1, X_2, \dots, X_n\}$ in the network can be obtained using the following equation (Jensen and Nielsen, 2007).

$$P(X) = \prod_{i=1}^{n} [(P(X_i | P_a(X_i))] \tag{15}$$

where, $P_a(X_i)$ is the parent set of X_i variables in the network.

In a Bayesian Network, new evidence is used to revise the probabilities of earlier events. Based on Bayes' theorem, the updated or posterior probability distribution of a variable can be obtained as shown in Equation (16).

$$P(X_i | E) = \frac{P(X_i, E)}{P(E)} = \frac{P(E | X_i) P(X_i)}{\sum P(X_i | E) P(X_i)} \tag{16}$$

In this context, $P(X_i|E)$) represents the posterior or updated probability of X_i after considering the evidence E. The term $P(X_i)$ refers to the prior probability of event X_i, while $P(E|X_i)$ indicates the likelihood of observing the evidence E when X_i occurs. The quantity $P(E)$ denotes the overall probability of the evidence, and the expression $\sum P(X_i|E)P(X_i)$ reflects the joint probability distribution associated with the evidence.

Using this framework, the system reliability can be determined through Equation (17) by incorporating the corresponding probability of error (Sahu and Palei, 2022).

$$R = 1 - P(X) \tag{17}$$

Here, R represents the reliability of the system, while $P(X)$ denotes the probability of human error of the system.

3.5 Determining the Importance Degree of Factors Affecting Human Error

In complex systems, every component does not contribute equally to overall performance. Similarly, the factors that influence human error vary in their impact on the likelihood of failures. Understanding which factors carry greater significance is essential for effectively managing, monitoring, and minimizing human error. In this study, the Fussell–Vesely method was used by Hossein et al. (2024) to determine the importance of each contributing factor. The Fussel-Vesely measure of importance was used since it directly measures the contribution of each factor to the overall system failure probability, which is in line with the aim of prioritizing dominant performance shaping factors influencing human error. The FV index is more interpretable in practical risk-reduction and decision-making in smart grid operations than the Birnbaum, Risk Achievement Worth (RAW) and Risk Reduction Worth (RRW) measures. The importance value for a factor in the Fussell–Vesely framework, denoted as $FVI(X_i)$, is computed using Equation (18) (Van der Borst and Schoonakker, 2001).

$$FVI(X_i) = \frac{P(X_i)}{P(X)} \tag{18}$$

where, $P(X_i)$ represents probability of human error of i^{th} component of the system and $P(X)$ denotes the probability of human error of the system.

3.6 Overall Workflow of the Proposed Hybrid FAHP BN Framework

This subsection elaborates the general procedure of the proposed Fuzzy Analytic Hierarchy Process-Bayesian Network (FAHP-BN) model in a step-by-step understandable way. The purpose of the framework is to approximate the probability of human errors in the smart grid operations through fuzzy expert judgment and probabilistic modeling.

To begin with, the literature review and expert opinion are used to identify the important performance shaping factors (PSFs) that influence the operator performance in smart grid control systems. These are human, technical, organizational and environmental factors. The experts then give pairwise comparisons in terms of linguistic terms which are given as triangular fuzzy numbers to indicate uncertainty. Then, the relative importance (weights) of PSFs and their sub-factors is calculated by FAHP method. These fuzzy weights are then transformed to fuzzy possibility scores and ultimately transformed to fuzzy failure probabilities. This step establishes a distinct connection between the outputs of FAHP and the input of Bayesian Network.

Then a Bayesian Network model is created to demonstrate the interrelationship between PSFs and their impact on human error. With the help of Bayesian inference, the total probability of human error and the corresponding probabilities in various conditions are determined. Lastly, the importance analysis using the Fussel-Vesely measure is conducted to identify the most significant aspects that lead to human error. The outcomes are useful in the risk-informed decision-making, operator training, and safe operation of smart grids. Generally, the suggested workflow offers a clear and practical path of transitioning between expert knowledge and probabilistic human reliability estimation in smart grid systems. **Figure 3** gives a summary of the methodological framework.

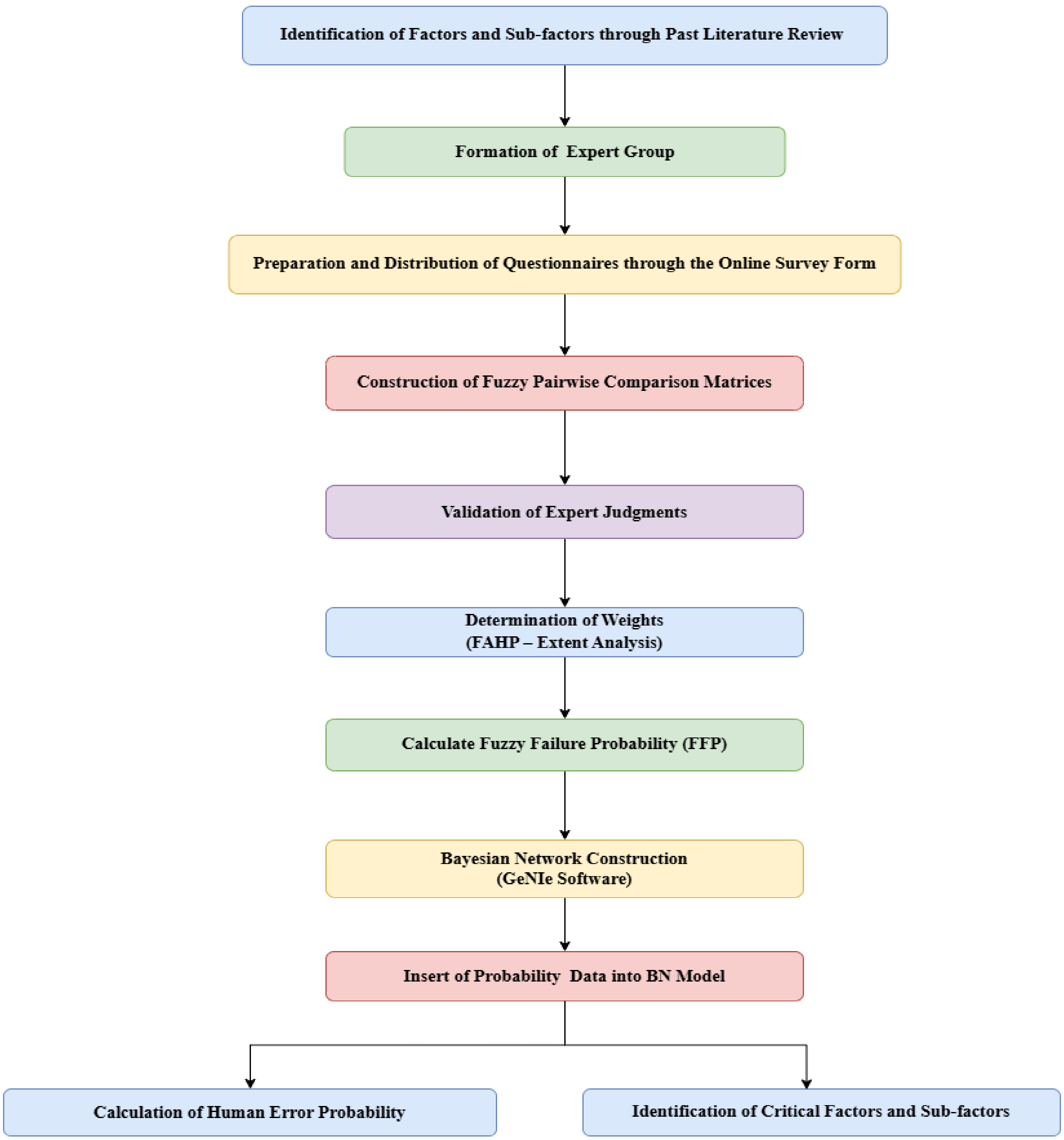

Figure 3. Flow chart of methodology.

4. Case Study

To demonstrate the applicability of the proposed Hybrid FAHP-BN framework, a case study was conducted in the smart grid power distribution industry. The study focuses on the human reliability of operators involved in the monitoring, control, and maintenance of smart grid systems. The statistical population of this study consists of professionals working in smart grid operations, including power system engineers, grid operators, maintenance engineers, and safety experts who have experience in smart grid management and operation. These experts possess practical knowledge about operational procedures, system monitoring, and potential human errors in smart grid environments. A total of 12 experts participated in the study. The participants were selected based on their professional experience, technical expertise in power systems, and familiarity with smart grid operations. Their experience ranged from 5 to 15 years in the energy and power distribution sector. The purposive sampling method was used to select the participants. This sampling approach is commonly used in reliability and risk assessment studies where expert knowledge is required to evaluate complex systems. The selected experts provided pairwise comparisons for the FAHP analysis and contributed to the estimation of conditional probabilities in the Bayesian Network through structured questionnaires and expert elicitation. The collected expert judgments were used to determine the relative importance of performance shaping factors (PSFs) using the FAHP extent analysis method. These weights were then incorporated into the Bayesian Network model to analyze the relationships between human factors and system reliability in the smart grid system. The proposed hybrid framework enables the identification of critical human factors influencing system performance and supports decision-makers in improving operational safety and reliability within smart grid infrastructures.

4.1 Identification of Factors and Sub-Factors Influencing Human Reliability

To understand the factors that lead to human errors in smart grid operations, information was collected from two sources, previous research and discussions with experts who work directly with grid operation, protection systems, communication networks, and field maintenance. Based on the experts and field observations discussions, four major categories of factors were identified that influence human performance in the operation of smart grids: human factors, technical factors, environmental factors, and organizational factors. These factors and sub-factors have been listed in **Table 3**.

Table 3. Factors affecting HRA in smart grid system.

Factor	Factor notation	Sub-factors	Sub-factors notation
Human Factors	F_1	Cognitive Load	F_1S_1
		Fatigue and Stress	F_1S_2
		Training and Experience	F_1S_3
		Situational Awareness	F_1S_4
		Human-Machine Interaction	F_1S_5
Technical Factors	F_2	System Automation Level	F_2S_1
		Communication Infrastructure	F_2S_2
		System Complexity	F_2S_3
		Alarm Design and Management	F_2S_4
Environmental Factors	F_3	Weather	F_3S_1
		Lighting	F_3S_2
		Noise	F_3S_3
		Cyber-Physical Threats	F_3S_4
Organizational Factors	F_4	Management Policies	F_4S_1
		Safety Culture	F_4S_2
		Communication and Coordination	F_4S_3
		Shift Management	F_4S_4
		Training and Knowledge Sharing Programs	F_4S_5

In the first stage, questionnaires were prepared to gather expert opinions and to score each performance shaping factor (PSF). The questionnaires were based on a two-level structure main PSF categories and their sub-factors The survey was conducted using SurveyMonkey online survey platform (SurveyMonkey Inc., n.d.). The research involved twelve professionals. These specialists work in different spheres of the smart grid, including control room work, system protection, communication engineering, cybersecurity, field maintenance, and human factors. The expert panel structure is given in **Table 4**. They were chosen because they have a working experience in operations such as fault diagnosis, switching, and power restoration in real smart grid environments.

Table 4. Expert panel composition.

Category	Role
Operational Experts	Senior Control Room Operator
	Protection and Automation Engineer
	Distribution System Operator
Technical Experts	Power System Engineer
	Communication/Network Engineer
	Cybersecurity Engineer
Maintenance & Field Experts	Substation Maintenance Engineer
	Line Maintenance Technician
Management Experts	Operations / Control Center Manager
	Safety & Reliability Manager
Methodological Experts	Human Factors Specialist
	Academic researcher (HRA / FAHP)

4.2 Determination of Weight of Sub-Factors Using Extent Analysis FAHP

The Fuzzy Analytic Hierarchy Process (FAHP) was applied to determine the importance of each factor. The experts used simple linguistic words to express their judgments, such as low importance and high importance. These expressions were then translated into fuzzy numbers with the scales in **Tables 1** and **2**. The comparison matrices for all factors are presented in **Tables 5, 6, 7,** and **8**, respectively.

Table 5. Fuzzy pair-wise comparison matrix of human factor.

Human factor	F_1S_1	F_1S_2	F_1S_3	F_1S_4	F_1S_5
F_1S_1	(1,1,1)	(0.33,0.5,1)	(0.25,0.33,0.5)	(0.33,0.5,1)	(0.5,1,2)
F_1S_2	(1,2,3)	(1,1,1)	(0.5,1,2)	(0.5,1,2)	(1,2,3)
F_1S_3	(2,3,4)	(0.5,1,2)	(1,1,1)	(1,2,3)	(1,2,3)
F_1S_4	(1,2,3)	(0.5,1,2)	(0.33,0.5,1)	(1,1,1)	(1,2,3)
F_1S_1	(0.5,1,2)	(0.33,0.5,1)	(0.33,0.5,1)	(0.33,0.5,1)	(1,1,1)

Table 6. Fuzzy pair-wise comparison matrix of technical factor.

Technical factor	F_2S_1	F_2S_2	F_2S_3	F_2S_4
F_2S_1	(1,1,1)	(1,2,3)	(0.5,1,2)	(1,2,3)
F_2S_2	(0.33,0.5,1)	(1,1,1)	(0.5,1,2)	(1,2,3)
F_2S_3	(0.5,1,2)	(0.5,1,2)	(1,1,1)	(1,2,3)
F_2S_4	(0.33,0.5,1)	(0.33,0.5,1)	(0.33,0.5,1)	(1,1,1)

Table 7. Fuzzy pair-wise comparison matrix of environmental factor.

Environmental factor	F_3S_1	F_3S_2	F_3S_3	F_3S_4
F_3S_1	(1,1,1)	(1,2,3)	(1,2,3)	(0.5,1,2)
F_3S_2	(0.33,0.5,1)	(1,1,1)	(0.5,1,2)	(1,2,3)
F_3S_3	(0.33,0.5,1)	(0.5,1,2)	(1,1,1)	(1,2,3)
F_3S_4	(0.5,1,2)	(0.33,0.5,1)	(0.33,0.5,1)	(1,1,1)

Table 8. Fuzzy pair-wise comparison matrix of organizational factor.

Organizational factor	F_4S_1	F_4S_2	F_4S_3	F_4S_4	F_4S_5
F_4S_1	(1,1,1)	(0.5,1,2)	(0.33,0.5,1)	(1,2,3)	(0.5,1,2)
F_4S_2	(0.5,1,2)	(1,1,1)	(0.5,1,2)	(0.5,1,2)	(1,2,3)
F_4S_3	(1,2,3)	(0.5,1,2)	(1,1,1)	(0.5,1,2)	(1,2,3)
F_4S_4	(0.33,0.5,1)	(0.5,1,2)	(0.5,1,2)	(1,1,1)	(1,2,3)
F_4S_5	(0.5,1,2)	(0.33,0.5,1)	(0.33,0.5,1)	(0.33,0.5,1)	(1,1,1)

In order to make sure that the expert comparisons were reliable, the consistency ratio (CR) was computed on each comparison matrix and provided in **Table 9**. According to Saaty (2004), a consistency ratio of less than 0.1 is acceptable. This requirement was satisfied by all the comparison matrices in this study, implying that the expert judgments were coherent and reliable. These comparison matrices were used for further calculations. The weights of all subfactors were computed using the FAHP extent analysis method described in section 3.3, and the results are presented in **Table 10**. These weights were then normalized by dividing each sub-factor weight by the sum of the corresponding sub-factor weights to obtain the final normalized weight for each sub-factor. The resulting normalized weights are listed in **Table 11**.

Table 9. Consistency ratio for the pairwise comparison matrix.

Factor	Consistency ratio (CR)
Human Factors (F_1)	0.012
Technical Factors (F_2)	0.023
Environmental Factors (F_3)	0.093
Organizational Factors (F_4)	0.05

Table 10. Weights for the individual sub-factors.

Sub-factor	Weight (W')	Sub-factor	Weight (W')	Sub-factor	Weight (W')
F_1S_1	0.4833	F_2S_2	0.8555	F_3S_4	0.6552
F_1S_2	0.8762	F_2S_3	0.9128	F_4S_1	0.8922
F_1S_3	1.0000	F_2S_4	0.5401	F_4S_2	0.9337
F_1S_4	0.8338	F_3S_1	1.0000	F_4S_3	1.0000
F_1S_5	0.5262	F_3S_2	0.8555	F_4S_4	0.8922
F_2S_1	1.0000	F_3S_3	0.8555	F_4S_5	0.6808

Table 11. Normalized weights for the individual sub-factors.

Sub-factor	Weight (W)	Sub-factor	Weight (W)	Sub-factor	Weight (W)
F_1S_1	0.1299	F_2S_2	0.2586	F_3S_4	0.1946
F_1S_2	0.2356	F_2S_3	0.2759	F_4S_1	0.2028
F_1S_3	0.2689	F_2S_4	0.1633	F_4S_2	0.2122
F_1S_4	0.2242	F_3S_1	0.2971	F_4S_3	0.2273
F_1S_5	0.1415	F_3S_2	0.2541	F_4S_4	0.2028
F_2S_1	0.3023	F_3S_3	0.2541	F_4S_5	0.1548

4.3 Conversion of Sub-Factor Weights into Fuzzy Failure Probabilities

As the Bayesian Network (BN) model needs probability values, the next step to transform the expert's consensus scores and normalized fuzzy weights from **Table 11** into fuzzy probability values of each sub-factor. Using the normalized weights presented in **Table 11** and Equations (2) and (3) from Section 3.2, the experts' scores are converted into fuzzy scores. Subsequently, Equation (13) is applied to transform the fuzzy scores into fuzzy possibility scores (FPS), which are presented in **Table 12**. Then, Equation (14) is used to convert the FPS values into fuzzy failure probability (FFP) values. The resulting FFP values are reported in **Table 13** and are used as input probabilities for constructing the Bayesian Network, which is employed to estimate the probability of human error during smart grid operations.

To clarify the computational procedure, the step-by-step calculation of FPS and FFP is illustrated for the representative sub-factor cognitive load **(**F_1S_1**)**.

Assume the aggregated expert judgment for sub-factor cognitive load **(**F_1S_1**)** is the triangular fuzzy number: $\tilde{A}_{F_1S_1} = (0.25,0.667,1.25)$

Suppose the normalized FAHP weight of this sub-factor from **Table 11** is $\widetilde{W}_{F_1S_1} = 0.1299$.

The final fuzzy score becomes:
$\tilde{S}_{F_1S_1} = (\tilde{A}_{F_1S_1}).(\widetilde{W'}_{F_1S_1}) = 0.1299.(0.25,0.667,1.25) = (0.032,0.087,0.162)$.

Using the Equation (13) fuzzy possibility score (FPS) for subfactor cognitive load (F_1S_1) is
$FPS = \left(\frac{1-u}{1+(u-m)}\right) + 1 - \left(\frac{1-l}{1+(m-l)}\right) = \left(\frac{1-0.162}{1+(0.162-0.087)}\right) + 1 - \left(\frac{1-0.032}{1+(0.087-0.032)}\right) = 0.8607.$

Using Equation (14) FPS converted to FFP
$FFP = \begin{cases} \frac{1}{10^k} & ,FPS \neq 0 \\ 0\,, & FPS = 0 \end{cases}.$

where, $k = \left[\left(\frac{1}{FPS}\right) - 1\right]^{\frac{1}{3}} \times 2.301$, and
FFP =0.0557.

Similarly, the FPS and FFP values for each sub-factor were calculated.

Table 12. Fuzzy possibility scores (FPS) for the sub-factors.

Sub-factor	FPS	Sub-factor	FPS	Sub-factor	FPS
F_1S_1	0.8607	F_2S_2	0.7778	F_3S_4	0.8399
F_1S_2	0.7633	F_2S_3	0.7716	F_4S_1	0.8335
F_1S_3	0.7838	F_2S_4	0.8846	F_4S_2	0.8203
F_1S_4	0.8172	F_3S_1	0.7832	F_4S_3	0.8275
F_1S_5	0.8495	F_3S_2	0.8260	F_4S_4	0.8586
F_2S_1	0.7964	F_3S_3	0.7962	F_4S_5	0.8953

Table 13. Fuzzy failure probabilities (FFP) for the sub-factors.

Sub-factor	FFP	Sub-factor	FFP	Sub-factor	FFP
F_1S_1	0.0557	F_2S_2	0.0305	F_3S_4	0.0474
F_1S_2	0.0277	F_2S_3	0.0293	F_4S_1	0.0452
F_1S_3	0.0318	F_2S_4	0.0681	F_4S_2	0.0410
F_1S_4	0.0401	F_3S_1	0.0316	F_4S_3	0.0432
F_1S_5	0.0510	F_3S_2	0.0427	F_4S_4	0.0548
F_2S_1	0.035	F_3S_3	0.0346	F_4S_5	0.0749

4.4 Bayesian Network Modelling for Estimation of Human Error Probability

After calculating the Fuzzy Failure Probability of sub-factors using the Fuzzy AHP method, a Bayesian Network (BN) model was developed to calculate the probability of human error in smart grid operations. The BN was created using GeNIe 5.0 (Bayes Fusion LLC, 2024) to capture the relationships among the identified factors and understand how they jointly influence human error, as shown in **Figure 4**. In the BN structure, all sub-factors were treated as input nodes, the four main categories human, technical, environmental, and organizational factors were considered as intermediate nodes, and the final node (F) represented the overall human error probability. The probabilities of the subfactors were assigned based on the fuzzy failure probabilities obtained from the Fuzzy AHP extent analysis in **Table 13**. The estimated error probabilities for each main factor, total human error, and human reliability are presented in **Table 14**. Using this model, the probability of human error under normal operating conditions was found to be 8.89%, which indicates a human reliability level of 91.11%. Although this reflects a good level of reliability, even small errors during fault isolation or restoration tasks can cause service delays or safety concerns. Therefore, it is important to identify the factors that contribute most to the overall error probability.

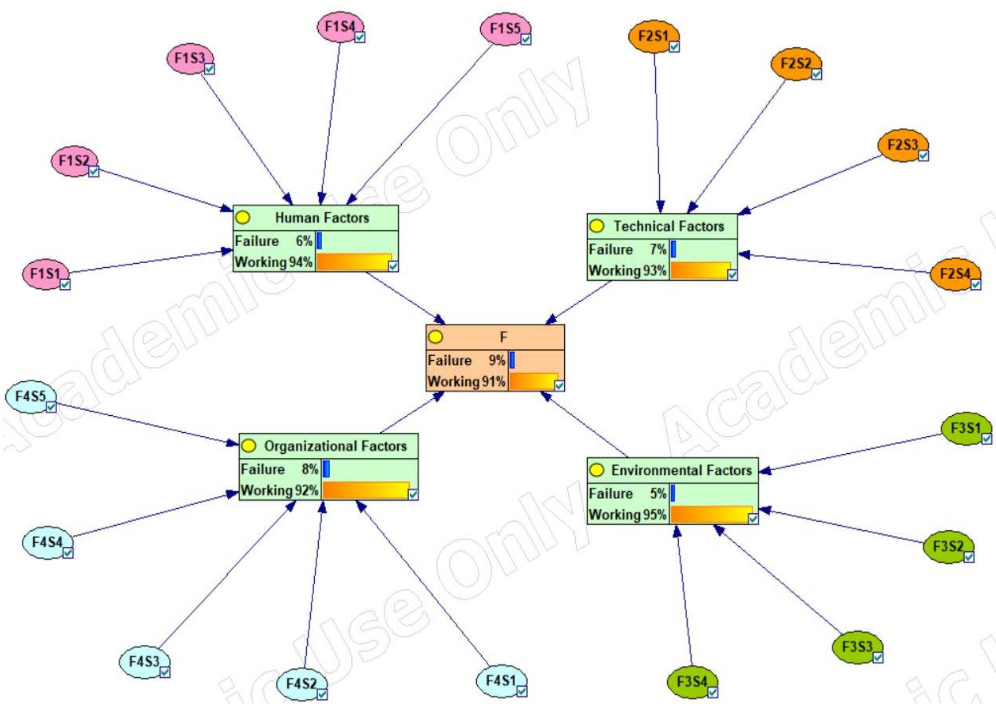

Figure 4. Bayesian network representation of the factors influencing human error occurrence.

Table 14. Probabilities of human error for the primary factors and overall error.

Factor	Human error probability
Human Factors (F_1)	0.0634
Technical Factors (F_2)	0.0740
Environmental Factors (F_3)	0.0501
Organizational Factors (F_4)	0.0783
Total Human error	0.0889
Human Reliability	0.9111

4.5 Assessment of Factor Importance in Human Error Analysis

This section identifies and analyzes the factors that affect human error in smart grid operations. As mentioned above, these factors do not affect human error in the same way, and certain factors are more important for the reliability of the operator than others. Thus, it is necessary to determine the most significant factors from a human reliability perspective. In this analysis, the Fussel-Vesely technique, as outlined in Section 3.5, was used to measure the significance of each factor influencing human error. **Tables 15** and **16** show the results of the importance analysis of the main factors and sub-factors, respectively, and are graphically illustrated in **Figures 5** and **6**.

Table 15. Importance levels of the main factors.

Factor	Importance measure	Rank
Human Factors (F_1)	0.7136	3
Technical Factors (F_2)	0.8319	2
Environmental Factors (F_3)	0.5639	4
Organizational Factors (F_4)	0.8809	1

Table 16. Importance levels of the sub-factors.

Sub-factor	Notation	Importance measure	Rank
Cognitive Load	F_1S_1	0.6269	3
Fatigue and Stress	F_1S_2	0.3116	18
Training and Experience	F_1S_3	0.3574	14
Situational Awareness	F_1S_4	0.4512	11
Human-Machine Interaction	F_1S_5	0.5736	5
System Automation Level	F_2S_1	0.3896	12
Communication Infrastructure	F_2S_2	0.3433	16
System Complexity	F_2S_3	0.3293	17
Alarm Design and Management	F_2S_4	0.7658	2
Weather	F_3S_1	0.3559	15
Lighting	F_3S_2	0.4807	9
Noise	F_3S_3	0.3891	13
Cyber-Physical Threats	F_3S_4	0.5329	6
Management Policies	F_4S_1	0.5083	7
Safety Culture	F_4S_2	0.4611	10
Communication and Coordination	F_4S_3	0.4860	8
Shift Management	F_4S_4	0.6164	4
Training and Knowledge Sharing Programs	F_4S_5	0.8427	1

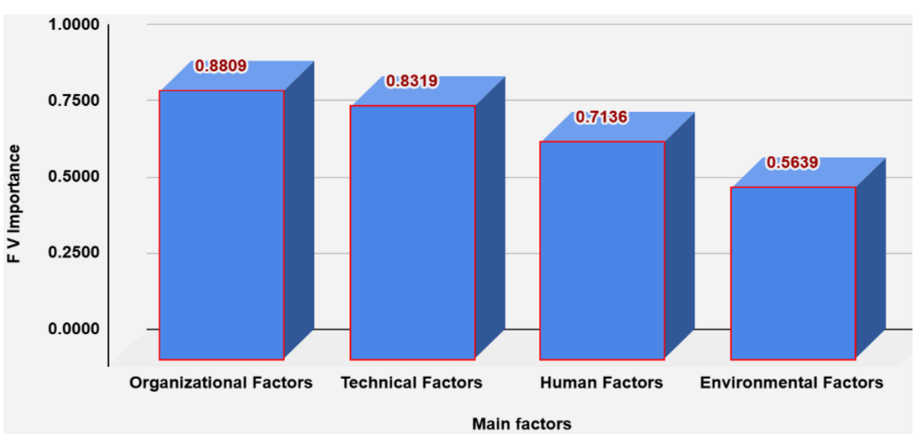

Figure 5. Importance of main factors of smart grid system.

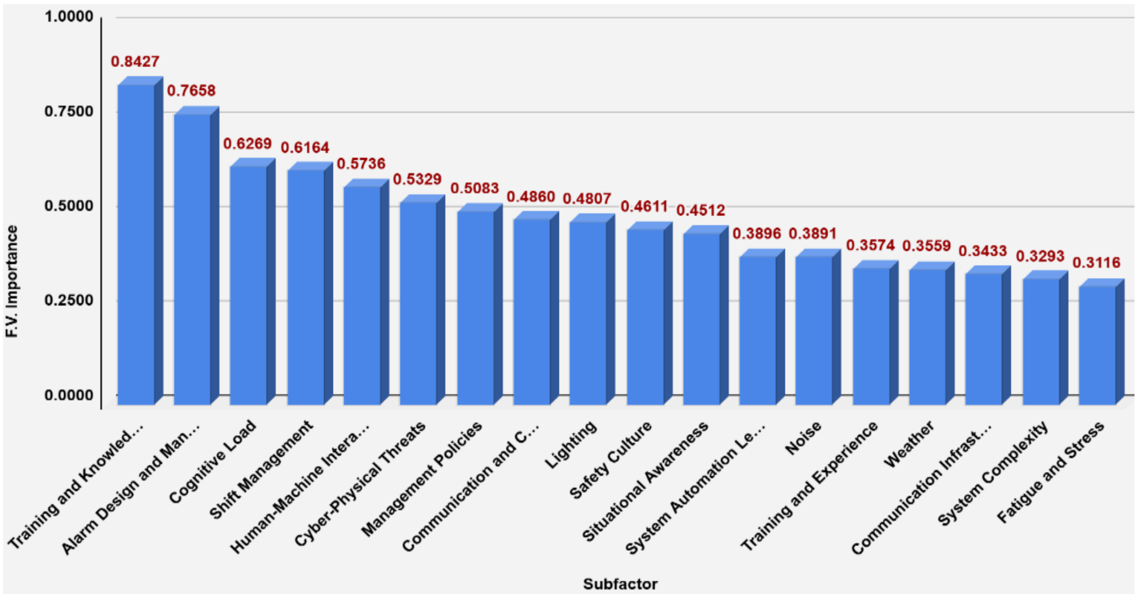

Figure 6. Importance of sub-factors of smart grid system.

5. Result and Discussion

This section provides the findings of the proposed hybrid Fuzzy AHP-Bayesian Network model and explains the implications of the findings on human reliability in smart grid operations. **Table 14** summarizes the probability analysis of human error. Organizational factors have the greatest human error probability, followed by technical and human factors. The lowest error probability in the considered case was observed for environmental factors. The total probability of human error in the selected working operation was estimated to be 0.0889, which indicates that the reliability of the operators is usually high. Nevertheless, even the slightest chance of failure is important in smart grid conditions, where any wrong choice may cause a chain reaction of failures, risks, or even service disruptions.

The relative impact of the key factors shown in **Table 15** is further explained by importance analysis. Organizational factors ranked first, with an importance measure of 0.8809. Technical factors ranked second, with an importance measure of 0.8319. Human factors take the third place and environmental factors take the fourth place implying a relatively less significant influence in this case study.

Table 16, the sub-factor importance analysis, gives a better idea of the main causes of human error in smart grid operations. Training and knowledge sharing programs is the most influential sub-factor, which means that continuous learning and proper sharing of operational knowledge is very important in minimizing human error. Alarm Design and Management is second and it emphasizes that improperly designed or too many alarms may overload operators and cause wrong or delayed decisions. Cognitive load is also of high importance implying that operators with high mental load are more likely to make errors when performing complex operational tasks. The sub-factors of shift management and human-machine interaction seem to be among the moderately influential ones, and the importance of appropriate work scheduling and effective communication with the system interfaces in keeping the operators alert and performance-oriented. Cyber-physical threats and management policies are sub-factors with a moderate contribution, as they have an indirect but significant impact on operational reliability. The middle range also includes communication and coordination, lighting, safety culture and situational awareness, which means that they do not play the leading role, but they still influence the overall human performance. Sub-factors that are ranked lower are system automation level, noise, training and experience, weather, communication infrastructure, system complexity, and fatigue and stress. These sub-factors are not as important in this case study, but they cannot be overlooked. Their role in human error can become even more important under other operating conditions, system configurations, or stress scenarios.

In practical terms, these findings point out a number of important implications. To begin with, it is possible to enhance the clarity and usability of automated systems to minimize the number of operators who are confused and need to work manually. Second, competence and confidence of operators can be improved through the reinforcement of training programs and effective knowledge sharing. Third, organizational practices, including safety culture and shift schedules, can be paid attention to in order to decrease fatigue-related errors. Lastly, reliability can be improved by training operators on how to operate in unfavorable weather conditions and having a well-developed communication system.

Comprehensively, the joint outcomes prove that the human error in the smart grid operations is conditioned by a complex of technical, human, organizational, and environmental factors. The suggested hybrid framework suggests a systematic and feasible instrument of detecting the key areas of weaknesses and justifying specific interventions.

5.1 Validation of Results

The results obtained were confirmed by consistency checking of expert judgments in the FAHP process and probabilistic coherence checking in the Bayesian Network structure. The critical factors and importance rankings were also compared with the results reported in the related literature on human reliability and smart grid, and there was a reasonable agreement. There was no possibility of direct validation with actual operational human error data because of data constraints, which is admitted to be a limitation of the study. The work in the future will involve simulator-based experiments and the collection of empirical data to enhance the accuracy and reliability of the model.

5.2 Practical Implications

The results of this research are valuable practical information on how to enhance human reliability in complex systems. The suggested FAHP-Bayesian Network model allows identifying and prioritising the key performance-shaping factors (PSFs) that have a significant impact on human error and system reliability. In managerial terms, the outcomes can assist the decision-makers in prioritizing safety measures, enhancing the operator training programs, and distributing the maintenance and safety resources more efficiently. Moreover, the causal relationships that are modelled in the Bayesian Network give a more insightful view of how various human, operational and environmental factors interact in the system. This knowledge can assist organizations to enhance operational processes, system design and safety management techniques to minimize the chances of human errors and improve the overall system reliability.

6. Conclusion

The paper introduced a hybrid Fuzzy Analytic Hierarchy Process and Bayesian Network model to determine the human reliability in smart grid operation. The suggested method was effective in managing uncertainty in expert estimates and the causal relationships between human, technical, environmental, and organizational factors. The framework was able to give a realistic estimate of human error probability by combining fuzzy prioritization with probabilistic reasoning. The findings discovered that the Probability of human error in the smart grid task was low, which means that there was a high degree of reliability of the operator. However, the analysis also showed that organizational and technical factors are dominant in determining the performance of operators. The study shows that better training and knowledge sharing, improved alarm design, reduced cognitive load, and healthier shift schedules can lower the risk of human error. These steps are important to ensure safe and reliable smart grid operation, where even small mistakes can cause serious problems.

The proposed hybrid FAHP Bayesian Network system provides a process and practical method of assessing the human reliability in smart grid setups. It assists in making informed decisions in the design of control-rooms, operational plans and workforce management by determining the conditions that affect the performance of operators. The ability of the framework to scale to various smart grid configurations and scenarios of operation increases its applicability to real-life application. The study is therefore very useful in advising both researchers and industry practitioners aiming at enhancing the safety, reliability and resilience of smart grid systems.

6.1 Limitations and Future Work

Although these contributions are made, this study has some limitations. Expert judgments were collected using the SurveyMonkey online tool, which may introduce subjectivity into the assessment. Structured expert elicitation techniques, including the Delphi technique, can be used in future research to enhance the strength of expert responses. Moreover, the probabilities of human errors were not confirmed with actual operational or experimental data. This limitation can be overcome in future work by employing simulator-based studies to produce realistic human error data in various smart grid conditions. SACADA ("Scenario Authoring, Characterization, and Debriefing Application") and HuREX ("Human Reliability Data Extraction") are data collection tools that can be used to facilitate validation and enhance model accuracy.

Future work can improve the proposed FAHP–Bayesian Network model by using advanced fuzzy sets such as intuitionistic fuzzy sets (IFS), Interval-Valued Intuitionistic Fuzzy Sets (IVIFS), Pythagorean Fuzzy Sets (PFS), q-Rung Orthopair Fuzzy Sets (q-ROFS) to better represent uncertainty in expert opinions. These methods may provide more accurate human reliability results in complex smart grid systems.

Conflicts of 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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The author(s) declare that no assistance is taken from generative AI to write this article.

References

Abdullah, A., Saraswat, S., & Talib, F. (2023). Barriers and strategies for sustainable manufacturing implementation in SMEs: a hybrid fuzzy AHP-TOPSIS framework. *Sustainable Manufacturing and Service Economics*, *2*, 100012. https://doi.org/10.1016/j.smse.2023.100012

Akhtar, I., Kirmani, S., & Jameel, M. (2021). Reliability assessment of power system considering the impact of renewable energy sources integration into grid with advanced intelligent strategies. *IEEE Access*, *9*, 32485-32497. https://doi.org/10.1109/ACCESS.2021.3060892

Alonso, M., Amaris, H., Alcala, D., & Florez, R.D.M. (2020). Smart sensors for smart grid reliability. *Sensors*, *20*(8), 2187. https://doi.org/10.3390/s20082187

Alqahtani, F.M., & Noman, M.A. (2024). An integrated fuzzy Delphi and fuzzy AHP model for evaluating factors affecting human errors in manual assembly processes. *Systems, 12*(11), 479. https://doi.org/10.3390/systems12110479

Amani, A.M., & Jalili, M. (2021). Power grids as complex networks: resilience and reliability analysis. *IEEE Access*, *9*, 119010-119031. https://doi.org/10.1109/ACCESS.2021.3107492

Aydin, M. (2023). An analysis of human error and reliability in the operation of fixed CO2 systems on cargo ships using HEART Dempster-Shafer evidence theory approach. *Ocean Engineering*, *286*(Part 2), 115686. https://doi.org/10.1016/j.oceaneng.2023.115686

Balusa, B.C., & Gorai, A.K. (2018). Design of a multi-criteria decision-making model using fuzzy-AHP for selection of appropriate underground metal mining method. *International Journal of Mining and Mineral Engineering*, *9*(4), 259-301. https://doi.org/10.1504/IJMME.2018.097425

Bashir, A.K., Khan, S., Prabadevi, B., Deepa, N., Alnumay, W.S., Gadekallu, T.R., & Maddikunta, P.K.R. (2021). Comparative analysis of machine learning algorithms for prediction of smart grid stability. *International Transactions on Electrical Energy Systems*, *31*(9), e12706. https://doi.org/10.1002/2050-7038.12706

Bayes Fusion, LLC. (2024, October 10). *GeNIe 5.0*. https://www.bayesfusion.com/2024/10/10/genie-5-0/

Bolger, D., & Houlding, B. (2017). Deriving the probability of a linear opinion pooling method being superior to a set of alternatives. *Reliability Engineering & System Safety*, *158,* 41-49. https://doi.org/10.1016/j.ress.2016.10.008

Bona, G.D., Falcone, D., Forcina, A., & Silvestri, L. (2021). Systematic human reliability analysis (SHRA): a new approach to evaluate human error probability (HEP) in a nuclear plant. *International Journal of Mathematical, Engineering and Management Sciences, 6*(1), 345-362. https://doi.org/10.33889/IJMEMS.2021.6.1.022

Bowo, L.P., Ispandiari, A.R., Wibowo, D.A., Irawati, N., & Furusho, M. (2025). Maritime accident analysis and reduction technique for analysing maritime collision accidents. *Australian Journal of Maritime & Ocean Affairs*, *17*(3), 468-495. https://doi.org/10.1080/18366503.2024.2350792

Buckley, J.J. (1985). Fuzzy hierarchical analysis. *Fuzzy Sets and Systems*, *17*(3), 233-247. https://doi.org/10.1016/0165-0114(85)90090-9

Butt, O.M., Zulqarnain, M., & Butt, T.M. (2021). Recent advancement in smart grid technology: future prospects in the electrical power network. *Ain Shams Engineering Journal*, *12*(1), 687-695. https://doi.org/10.1016/j.asej.2020.05.004

Chang, D.-Y. (1996). Applications of the extent analysis method on fuzzy AHP. *European Journal of Operational Research*, *95*(3), 649-655. https://doi.org/10.1016/0377-2217(95)00300-2

Chou, W.-C., & Cheng, Y.-P. (2012). A hybrid fuzzy MCDM approach for evaluating website quality of professional accounting firms. *Expert Systems with Applications*, *39*(3), 2783-2793. https://doi.org/10.1016/j.eswa.2011.08.138

Cussens, J., Järvisalo, M., Korhonen, J.H., & Bartlett, M. (2017). Bayesian network structure learning with integer programming: polytopes, facets and complexity. *Journal of Artificial Intelligence Research*, *58*(2017), 185-229. https://doi.org/10.1613/jair.5203

Demircan, B.G., & Yetilmezsoy, K. (2023). A hybrid fuzzy AHP-TOPSIS approach for implementation of smart sustainable waste management strategies. *Sustainability*, *15*(8), 6526. https://doi.org/10.3390/su15086526

Dindar, S., Kaewunruen, S., & An, M. (2020). Bayesian network-based human error reliability assessment of derailments. *Reliability Engineering & System Safety*, *197*, 106825. https://doi.org/10.1016/j.ress.2020.106825

Elidolu, G., Ahn, S.I., Sezer, S.I., Kurt, R.E., Akyuz, E., & Gardoni, P. (2023). Applying evidential reasoning extended SPAR-H modelling to analyse human reliability on crude oil tanker cargo operation. *Safety Science*, *164*, 106169. https://doi.org/10.1016/j.ssci.2023.106169

Gabriel, L.M.N., Adebisi, J.A., Ndjuluwa, L.N.P., & Chembe, D.K. (2025). Investigation of smart grid technologies deployment for energy reliability enhancement in electricity distribution networks. *Franklin Open*, *10*, 100227. https://doi.org/10.1016/j.fraope.2025.100227

Garg, V., Vinod, G., Prasad, M., Chattopadhyay, J., Smith, C., & Kant, V. (2023). Human reliability analysis studies from simulator experiments using Bayesian inference. *Reliability Engineering & System Safety*, *229*, 108846. https://doi.org/10.1016/j.ress.2022.108846

Gertman, D., Blackman, H., Marble, J., Byers, J., & Smith, C. (2005). The SPAR-H human reliability analysis method. *US Nuclear Regulatory Commission*, *230*(4), 35.

Guglielmi, D., Paolucci, A., Cozzani, V., Mariani, M.G., Pietrantoni, L., & Fraboni, F. (2022). Integrating human barriers in human reliability analysis: a new model for the energy sector. *International Journal of Environmental Research and Public Health*, *19*(5), 2797. https://doi.org/10.3390/ijerph19052797

Gupta, I., Raeisi, S.T., Correa, S., & Wicaksono, H. (2025). Evaluating risk factors in automotive supply chains: a hybrid fuzzy AHP-TOPSIS approach with extended PESTLE framework. *Journal of Open Innovation: Technology, Market, and Complexity*, *11*(1), 100489. https://doi.org/10.1016/j.joitmc.2025.100489

Hossein, A.R.Z., Sayadi, A.R., Rahimdel, M.J., & Moradi, M.R. (2024). Human reliability analysis in maintenance and repair operations of mining trucks: a Bayesian network approach. *Heliyon*, *10*(15), e34765. https://doi.org/10.1016/j.heliyon.2024.e34765

Jensen, F.V., & Nielsen, T.D. (2007). *Bayesian networks and decision graphs: February 8, 2007*. Springer, New York. https://doi.org/10.1007/978-0-387-68282-2

Jha, A.V., Appasani, B., Ghazali, A.N., Pattanayak, P., Gurjar, D.S., Kabalci, E., & Mohanta, D.K. (2021). Smart grid cyber-physical systems: communication technologies, standards and challenges. *Wireless Networks*, *27*(4), 2595-2613. https://doi.org/10.1007/s11276-021-02579-1

Jo, W., & Lee, S.J. (2022). Bayesian belief network-based human reliability analysis methodology for start-up and shutdown operations in nuclear power plants. *Annals of Nuclear Energy*, *179*, 109403. https://doi.org/10.1016/j.anucene.2022.109403

Katiyar, R., Kumar, D., Mahapatra, D., & Badola, S. (2025). Strategic and policy responses to COVID-19 recovery in hospitality and tourism industry: evidence from emerging economy. *International Journal of Mathematical, Engineering and Management Sciences, 10*(2), 441-463. https://doi.org/10.33889/IJMEMS.2025.10.2.022

Khan, S., Mazhar, T., Shahzad, T., Khan, M.A., Rehman, A.U., & Hamam, H. (2025). Integration of smart grid with industry 5.0: applications, challenges and solutions. *Measurement: Energy*, *5*, 100031. https://doi.org/10.1016/j.meaene.2024.100031

Kukreja, V. (2023). Hybrid fuzzy AHP–TOPSIS approach to prioritizing solutions for inverse reinforcement learning. *Complex & Intelligent Systems*, *9*(1), 493-513. https://doi.org/10.1007/s40747-022-00807-5

Kumar, A., & Yelam, P. (2025a). Modeling availability of a multistate geothermal power plants through fuzzy universal generating function. *Discover Applied Sciences*, *7*(6), 573. https://doi.org/10.1007/s42452-025-07166-z

Kumar, A., & Yelam, P. (2025b). Estimating reliability and ranking of wind turbine plant under fuzzy environment through generalized trapezoidal fuzzy numbers (GTFNs). *International Journal of Mathematical, Engineering and Management Sciences*, *10*(5), 1563-1584. https://doi.org/10.33889/IJMEMS.2025.10.5.074

Liu, J., Zou, Y., Wang, W., Zio, E., Yuan, C., Wang, T., & Jiang, J. (2022). A Bayesian belief network framework for nuclear power plant human reliability analysis accounting for dependencies among performance shaping factors. *Reliability Engineering & System Safety*, *228*, 108766. https://doi.org/10.1016/j.ress.2022.108766

Liu, X., Yan, S., Zhang, X., & Ahmed, W. (2025). Dynamic human reliability analysis method for nuclear power plant main control room based on SPAR-H and SD. *Nuclear Engineering and Technology*, *57*(3), 103253. https://doi.org/10.1016/j.net.2024.10.015

Mandali, H., Keighobadi, E., Ebrahimi, H., Hanifi, S.M., Ayat, S.M., & Ghashghaei, M. (2025). Machine learning and bayesian network based on fuzzy AHP framework for risk assessment in process units. *Scientific Reports, 15*(1), 39083. https://doi.org/10.1038/s41598-025-25690-1

Mashio, K., & Ito, K. (2021). Application of integrated human error management in human factors engineering process to nuclear power plant design. *International Journal of Mathematical, Engineering and Management Sciences, 6*(4), 1186-1198. https://doi.org/10.33889/IJMEMS.2021.6.4.071

Mikhailov, L. (2000). A fuzzy programming method for deriving priorities in the analytic hierarchy process. *Journal of the Operational Research Society*, *51*(3), 341-349. https://doi.org/10.1057/palgrave.jors.2600899

Mikhailov, L. (2003). Deriving priorities from fuzzy pairwise comparison judgements. *Fuzzy Sets and Systems*, *134*(3), 365-385. https://doi.org/10.1016/S0165-0114(02)00383-4

Muqeet, H.A., Liaqat, R., Jamil, M., & Khan, A.A. (2023). A state-of-the-art review of smart energy systems and their management in a smart grid environment. *Energies*, *16*(1), 472. https://doi.org/10.3390/en16010472

Onisawa, T. (1988). An approach to human reliability in man-machine systems using error possibility. *Fuzzy Sets and Systems*, *27*(2), 87-103. https://doi.org/10.1016/0165-0114(88)90140-6

Ourahou, M., Ayrir, W., Hassouni, B.E., & Haddi, A. (2020). Review on smart grid control and reliability in presence of renewable energies: challenges and prospects. *Mathematics and Computers in Simulation*, *167*, 19-31. https://doi.org/10.1016/j.matcom.2018.11.009

Pant, S., Garg, P., Kumar, A., Ram, M., Kumar, A., Sharma, H.K., & Klochkov, Y. (2024). AHP-based multi-criteria decision-making approach for monitoring health management practices in smart healthcare system. *International Journal of System Assurance Engineering and Management*, *15*(4), 1444-1455. https://doi.org/10.1007/s13198-023-01904-5

Rahmati, M., Ghalenoei, M., Ghasemi, F., Faridan, M., & Omidvari, M. (2025). Human reliability assessment and accident prevention: a bayesian network approach to identify and mitigate human error. *Safety in Extreme Environments*, *7*(2), 8. https://doi.org/10.1007/s42797-025-00122-5

Rajabpour, E., Fathi, M.R., & Torabi, M. (2022). Analysis of factors affecting the implementation of green human resource management using a hybrid fuzzy AHP and type-2 fuzzy DEMATEL approach. *Environmental Science and Pollution Research*, *29*(32), 48720-48735. https://doi.org/10.1007/s11356-022-19137-7

Ramezani, A., Nazari, T., Rabiee, A., Hadad, K., & Faridafshin, M. (2020). Human error probability quantification for NPP post-accident analysis using cognitive-based THERP method. *Progress in Nuclear Energy*, *123*, 103281. https://doi.org/10.1016/j.pnucene.2020.103281

Rao, S.P.C., & Sushama, M. (2023). An IoT-based sensor technology for improving reliability and power quality in smart grid systems. *International Journal of Electrical and Electronic Engineering & Telecommunications*, *12*(4), 264-271. https://doi.org/10.18178/ijeetc.12.4.264-271

Rawat, S.S. Pant, S., Kumar, A., Ram, M., Sharma, H.K. & Kumar, A. (2022). A state-of-the-art survey on analytical hierarchy process applications in sustainable development. *International Journal of Mathematical, Engineering and Management Sciences, 7*(6), 883-917. https://doi.org/10.33889/IJMEMS.2022.7.6.056

Saaty, T.L. (2004). Decision making the analytic hierarchy and network processes (AHP/ANP). *Journal of Systems Science and Systems Engineering*, *13*(1), 1-35. https://doi.org/10.1007/s11518-006-0151-5

Sahu, A.R., & Palei, S.K. (2022). Fault analysis of dragline subsystem using Bayesian network model. *Reliability Engineering & System Safety*, *225*, 108579. https://doi.org/10.1016/j.ress.2022.108579

Si, W., & Niu, L. (2024). Enhancing human reliability prediction in smart tower crane interfaces: a refined approach using simplified plant analysis risk–human reliability assessment and the decision-making trial and evaluation laboratory–analytic network process. *Buildings*, *14*(4), 1083. https://doi.org/10.3390/buildings14041083

Sinishaw, G.Y., Bantyirga, B., & Abebe, K. (2021). Analysis of smart grid technology application for power distribution system reliability enhancement: a case study on Bahir Dar power distribution. *Scientific African*, *12*, e00840. https://doi.org/10.1016/j.sciaf.2021.e00840

Studený, M., & Haws, D. (2014). Learning Bayesian network structure: towards the essential graph by integer linear programming tools. *International Journal of Approximate Reasoning, 55*(4), 1043-1071. https://doi.org/10.1016/j.ijar.2013.09.016

SurveyMonkey Inc. (n.d.) *SurveyMonkey*. https://www.surveymonkey.com

Swain, A.D. (1964). *THERP: a technique for human error rate prediction*. Sandia Corporation.

Tiwari, V., Kumar, A., & Ram, M. (2025). Fuzzy reliability assessment of smart grid system with intuitionistic fuzzy sets. In: Kumar, R., Verma, A.K., Verma, O.P., Rajpurohit, J. (eds) *Soft Computing: Theories and Applications*. Springer Nature, Singapore, pp. 507-516. https://doi.org/10.1007/978-981-96-5955-5_43

Van der Borst, M., & Schoonakker, H. (2001). An overview of PSA importance measures. *Reliability Engineering & System Safety*, *72*(3), 241-245. https://doi.org/10.1016/S0951-8320(01)00007-2

Van Laarhoven, P.J.M., & Pedrycz, W. (1983). A fuzzy extension of Saaty's priority theory. *Fuzzy Sets and Systems*, *11*(1-3), 229-241. https://doi.org/10.1016/S0165-0114(83)80082-7

Velmurugan, K., Saravanasankar, S., Venkumar, P., Sudhakarapandian, R., & Di Bona, G. (2022). Hybrid fuzzy AHP-TOPSIS framework on human error factor analysis: Implications to developing optimal maintenance management system in the SMEs. *Sustainable Futures*, *4*, 100087. https://doi.org/10.1016/j.sftr.2022.100087

Wang, Y.-M., Elhag, T.M.S., & Hua, Z. (2006). A modified fuzzy logarithmic least squares method for fuzzy analytic hierarchy process. *Fuzzy Sets and Systems*, *157*(23), 3055-3071. https://doi.org/10.1016/j.fss.2006.08.010

Yan, S., Yao, K., Li, F., Wei, Y., & Tran, C.C. (2022). Application of a Bayesian network to quantify human reliability in nuclear power plants based on the SPAR-H method. *International Journal of Occupational Safety and Ergonomics*, *28*(4), 2588-2598. https://doi.org/10.1080/10803548.2022.2026074

Zhao, Y. (2022). A Bayesian approach to comparing human reliability analysis methods using human performance data. *Reliability Engineering & System Safety*, *219*, 108213. https://doi.org/10.1016/j.ress.2021.108213

Zheng, J., Okamura, H., Pang, T., & Dohi, T. (2021). Availability importance measures of components in smart electric power grid systems. *Reliability Engineering & System Safety*, *205*, 107164. https://doi.org/10.1016/j.ress.2020.107164

Zúñiga, A.A., Baleia, A., Fernandes, J., & Branco, P.J.D.C. (2020). Classical failure modes and effects analysis in the context of smart grid cyber-physical systems. *Energies*, *13*(5), 1215. https://doi.org/10.3390/en13051215