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# Development of a Fuzzy Risk Model for Criticality Analysis of a 25 MW Dual-Fuel Power Plant in Bangladesh

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**ABSTRACT**

In every sector, maintenance is one of the most crucial tasks, especially in large-scale production, where identifying essential equipment is significant for prioritizing maintenance activities. The current study discusses the criticality analysis of all the major components of a power plant by using traditional RBM method and fuzzy RBM method. For this purpose, a case study has been performed on a 25 MW dual-fuel power plant in Bangladesh. Both models have been originated by taking into account factors like operational impact, operational flexibility, maintenance costs, safety, and environmental considerations. By analyzing both models, here identified 3 critical assets, 5 semi-critical assets, and 46 non-critical assets. As most of the assets have been found in non-critical condition in both approaches, the plant can be considered in a non-critical state. This model is also applicable to other industries by varying the related factors.

Keywords: Criticality Analysis, FIS, Fuzzy Risk Model, Risk-Based Maintenance (RBM)



## 1. Introduction

For a developing nation like Bangladesh, power is a highly limited resource. Here, ensuring an uninterrupted power supply is so difficult. These are always the result of equipment failure in the power plant. Resource availability for maintenance is well recognized to be limited. It ought to be applied as efficiently as possible. Equipment must be prioritized according to importance in order to be used to its full potential [1]. Generally, a power plant, consisting of a boiler, turbine, generator, power network, and loads, is a complex multivariable controlled plant. The sustainability of the electricity industry depends on cutting-edge technology and procedures for preserving unit performance, operation, flexibility, and availability [2]. The rate of injuries and incidents of illness at work is decreased when human aspects are precisely taken into consideration which enhances health and safety. Additionally, it offers significant advantages by lowering the price of such incidents and raising productivity. An Electrical Industry Safety Risk Index (EISRI) for the power distribution industry, using a fuzzy analytic hierarchy process (FAHP) to assess risks across personal, environmental, and organizational components. EISRI proved comparable to traditional methods like FMEA, suggesting its suitability for industry-specific risk management [3]. A refined FMECA methodology is developed through the integration of Type-I fuzzy inference systems, effectively capturing expert risk perceptions within cyber-power grids. The application of fuzzy sets and a sophisticated 125-rule fuzzy model overcomes the limitations of traditional FMECA, significantly enhancing the accuracy of failure mode prioritization for robust reliability analysis [4]. The Fuzzy Analytic Hierarchy Process (AHP)-VIKOR framework, a Multicriteria Decision-Making method, is utilized to prioritize and rank risks specific to the nuclear power sector. This approach focuses on identifying an optimal sequence of risks to mitigate potential failures while minimizing recovery time and associated costs [5]. A fuzzy logic–based safety risk assessment system is developed for power production, utilizing fuzzy membership functions and reasoning to evaluate uncertain risk factors. It enables real-time monitoring and early warning, achieving high accuracy in risk identification and prediction to support effective safety management [6]. Condition monitoring is used to assess the criticality of such a unit or set of machines through the Failure Mode, Effect, and Criticality Analysis (FMECA) process. The key equipment in a super thermal power plant was identified using a practical approach, and condition monitoring of this equipment was carried out [7]. A case study is performed in a 25 MW Dual Fuel base power plant in Bangladesh to check the proposed model. The aim of this paper is to establish a comprehensive framework for predicting various industrial hazards in scenarios where relevant data is limited. It further involves the creation of a fuzzy criticality assessment model, which is evaluated alongside the traditional risk-based maintenance (RBM) model. By comparing the two approaches, the study seeks to provide management and regulatory bodies with more precise tools for decision- making concerning critical assets.

## 2. Methodology

### 2.1 Framework of the Working Process

Initially, data were gathered from a 25 MW Dual Fuel Power Plant. A fuzzy RBM model was then developed to assess the criticality of assets. Following this, the fuzzy RBM model was compared with the traditional RBM model to prioritize assets according to their criticality levels. These

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operations were carried out to guide necessary actions for mitigating risks within the industry. A general framework for the study is shown in Fig. 1.

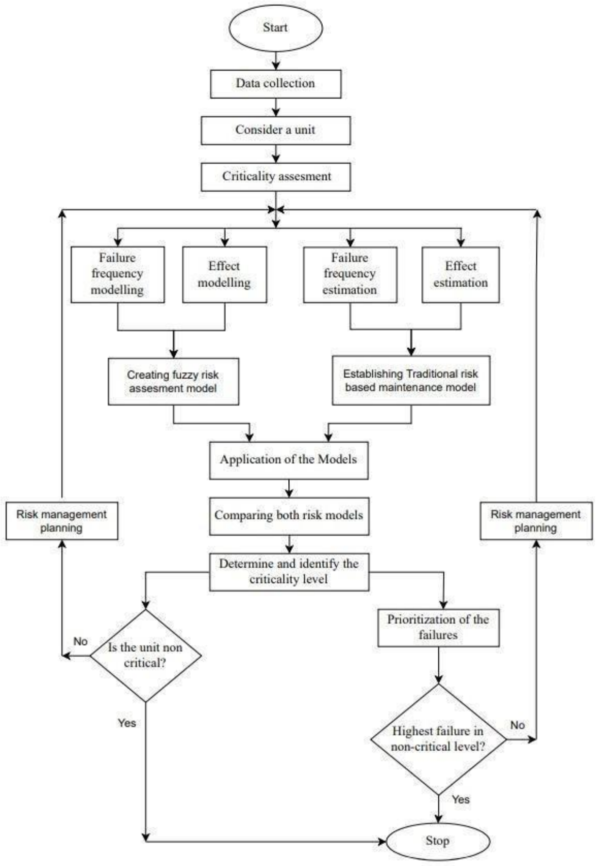


**Fig. 1** A framework for the fuzzy criticality assessment

2.2 The RBM Model

Risk-based maintenance (RBM) is a systematic approach to maintenance that prioritizes assets based on their risk. It is a proactive approach to maintenance that aims to prevent failures before they occur. This approach gives maintenance planners and decision-makers a tool to lower the likelihood of failure and its effects. It directs resources for maintenance toward equipment whose failure would have the greatest impact. It is a way for figuring out how to use maintenance resources most effectively [8]. In order to minimize the danger of a failure, this is done to optimize the maintenance effort across a facility. The resulting maintenance plan increases equipment dependability while lowering overall maintenance costs. For this study, different types of data were collected including: operational impact (OI), operational flexibility (OF), maintenance cost (MC), impact on safety and environment factor (ISE). The assessment of criticality for each asset was determined from the product of the failure frequency (FF) and effect Of failure (E). Mathematically,

$$CV = FF \times E = FF \times \{(OI \times OF) + MC + ISE\} \qquad (1)$$

The various factors related to RBM are modeled based on input from a Delphi team comprising experts in maintenance, process, operations, health, safety, and one academician. Each failure's operational impact on the facility is assessed using a five-point scale, from immediate plant shutdown to no significant effect on operations, with ratings between 1 and 10. Asset operational flexibility is evaluated on a scale of 1 to 4. Maintenance costs are categorized into three levels (high, medium, and low) represented by values of 1, 1.5, and 2, respectively. Safety and environmental impacts are ranked using six tiers, ranging from 0 (very low impact) to 8 (extremely high impact). By applying the highest values from this model to equations 1 and 2, the maximum risk score is 200. Experts assigned three risk levels to assets, similar to those defined by Márquez for process industries [9]. Assets with a risk score above 100 up to the maximum are considered critical, while those with scores below 40 are non-critical. Assets with risk values between 40 and 100 are classified as semi-critical.

2.3 The FRBM Model

Fuzzy logic is a form of multi-valued logic where variables can take on truth values ranging between 0 and 1, enabling it to capture varying degrees of truth rather than relying on the binary true or false system. This approach is especially beneficial for handling partial truths. In contrast to conventional Boolean logic, a fuzzy inference system (FIS) relies on fuzzy membership functions and rule-based reasoning to derive conclusions. In fuzzy theory, a fuzzy set A, within the universe X, is defined by function,

$\mu A(x): X \rightarrow [0, 1]$

Where,

$\mu A(x) = 1$, if x is entirely in A;

$\mu A(x) = 0$, if x is not remain in A;

$0 < \mu A(x) < 1$, if x is partly in A.

In this research, the Mamdani fuzzy inference system is applied to develop the FIS. A fuzzy inference system is a type of artificial intelligence (AI) that employs fuzzy logic to aid in decision-making. It consists of four main components: fuzzification, the knowledge base, the inference system itself, and defuzzification. Fig. 2 illustrates the structure of a typical fuzzy inference system through a visual diagram.

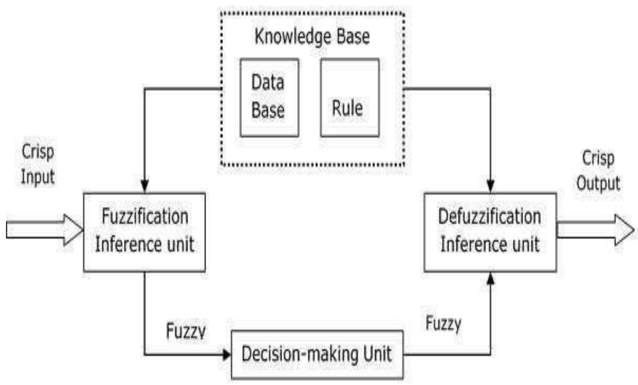


**Fig. 2** Fuzzy inference system [10]

## 3. Fuzzy Modeling Algorithm

In fuzzy modeling, input and output variables are expressed as linguistic variables. The process of fuzzification converts these variables into fuzzy sets by mapping crisp values accordingly. Various approaches exist for building a fuzzy inference system (FIS). In this study, MATLAB's fuzzy logic toolbox is selected due to its adaptability and intuitive interface, which allows for the determination of fuzzy risk values. Several functions, such as triangular, Gaussian, trapezoidal, and sigmoid, can be employed to transform input and output variables into fuzzy sets. For this research, a combination of triangular and trapezoidal membership functions is utilized to represent all inputs and outputs. For instance, the input variable "frequency" (F) is mapped to the linguistic terms excellent, good, average, and poor, within a numerical range of 0 to 4, as illustrated in Fig. 3(a). Another input variable, "effect" (E), uses terms such as very low, low, medium, high, and very high, with values ranging from 0 to 60, and is similarly modeled with triangular and trapezoidal functions, shown in Fig. 3(b). The output variable, "criticality level" (CL), is defined by the categories Non-Critical (NC), Semi- Critical (SC), and Critical (C), with the membership functions modeled using both triangular and trapezoidal functions, as displayed in

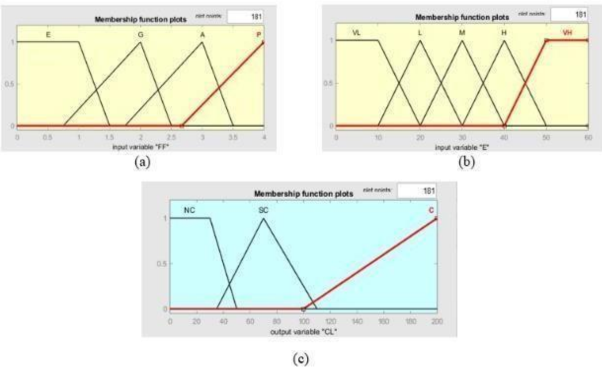


**Fig. 3** (a) Input variable (FF); (b) Input variable (E); (c) Output variable (CL)

Fig. 3(c). After defining the membership functions for the variables, the next phase involves creating FIS rules. In this study, the Mamdani fuzzy inference system is employed, where rules are structured using IF-THEN statements. An example rule is: "If FF is E and E is VH, then CL is SC," where the linguistic terms E, VH, and SC represent fuzzy sets. The 'IF' part defines the conditions, while the 'THEN' part describes the outcomes, connected by logical operators like AND/OR. Fig. 4 provides an overview of the FIS used for risk assessment.

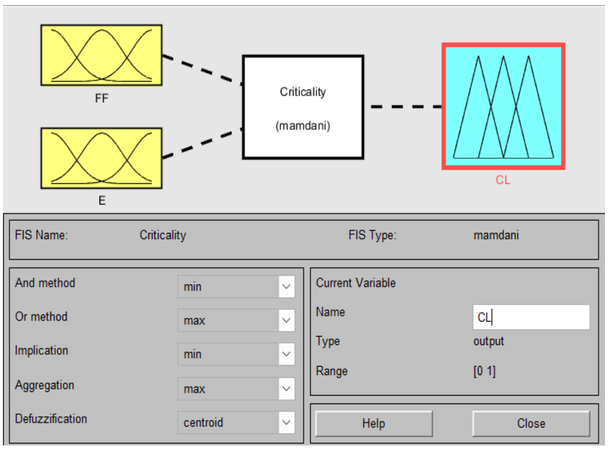


**Fig. 4** FIS for risk modeling (Mamdani)

The mapping of the failure frequency, results and final critical value is performed by the use of fuzzy 'if-then' rules. The total number of rules can be obtained by the product of the input parameters membership functions number which is expressed as,

$$N=m\times n \tag{2}$$

Where,

N = number of fuzzy if-then rules;

m = number of membership function of frequency of failure (FF);

n = number of membership function of Effects (E);

By using the Eq. (2), a total of twenty 'if-then' fuzzy rules are formed based on expert's knowledge which is shown in Fig. 5, a complete set of rules created using MATLAB's fuzzy logic toolbox. A sample rule base of this proposed fuzzy risk model is presented in Fig. 6.

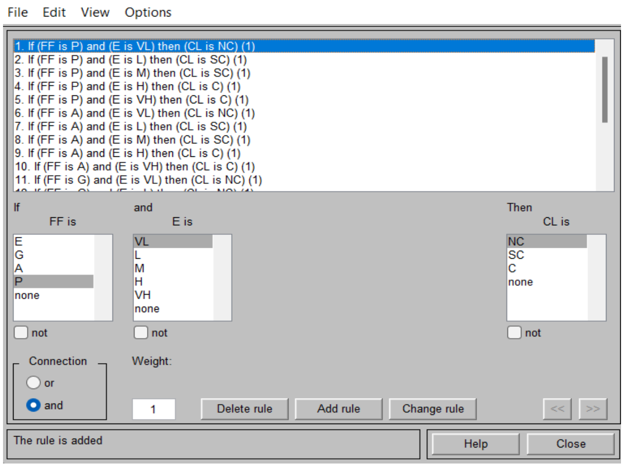


**Fig. 5** Fuzzy rule editor of MATLAB

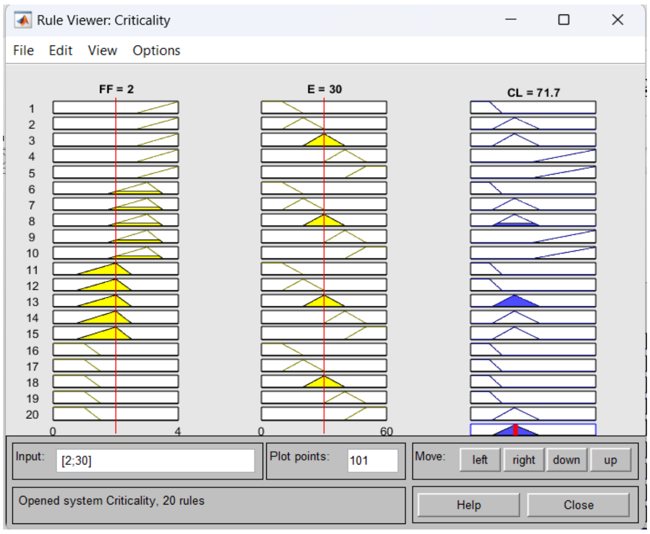


**Fig. 6** Fuzzy Rule View

## 4. Case Study and Results

A real-world case study was conducted to validate the fuzzy RBM model. The inventory assets of a 25 MW Dual Fuel Power Plant were analyzed to evaluate the asset risk model and prioritize the plant's assets accordingly. The power plant has 54 inventory assets which are involved in the production operation of power and electricity. The result of each of the asset present in power plant is calculated using equation 1 from the other related factors such as operational impact (OI), operational flexibility (OF), maintenance cost (MC) and safety and environment impact (ISE). The fuzzy model provides the fuzzy critical value for the assets which are also incorporated in Table 1 to compare with the RBM critical quality. Table 1 represents the traditional RBM critical value and Fuzzy RBM critical value for the 30 regular components of power plant. Here, rest of the 24 equipments were found in non-critical condition in both traditional RBM and Fuzzy RBM model approaches. Fig. 7. shows the graphical representation of the RBM value and fuzzy critical value. The comparison shows that the calculated failure critical value of the 46 assets are non-critical and failure critical value for the 8 assets are in breakdown position, the risk is minimal and mostly acceptable. Whereas, the risk is moderate and should be considered to take actions to mitigate the risk of the failure of the semi critical assets. Engine Booster Module, Instrument Air Compressor Unit and Starting Air Compressor unit have different criticality level; they are non-critical in traditional RBM model and semi critical in the fuzzy model. This is due to the extremely high value in ISE and operational Impact (0I). Moreover, Exhaust Gas Boiler (UNEX H (TYPE 1A)), HFO/LFO Feeder Pump (ACG, MOTOR: 7A*, 7B*, 14BG*) and HFO Separator Unit are in semi- critical level in traditional RBM, but fuzzy risk value suggested them to critical level due to their high-risk consequence value. It means that fuzzy RBM is more sensitive than the traditional RBM.

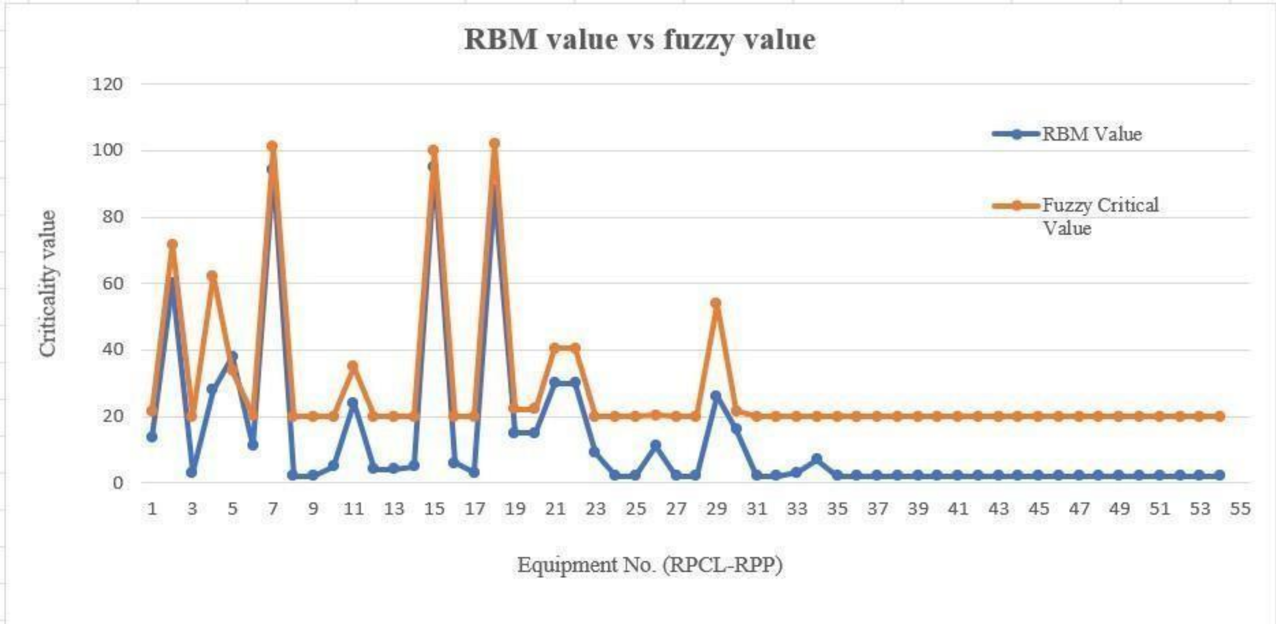


**Fig. 7** Graphical representation of the RBM value and fuzzy critical value

**Table 1** Comparison of fuzzy critical and RBM critical value for a 25 MW Dual Fuel Power Plant

| Sl No. | Name of the equipment | Critical value CV=FF×E | Criticality level | Fuzzy Critical value | Fuzzy Critical level |
|---|---|---|---|---|---|
| 1 | Alternator (AMG 1120 MP08 DSE) | 13.5 | NC | 21.4 | NC |
| 2 | Engine (W20V32) | 60 | SC | 71.7 | SC |
| 3 | Engine Auxiliary Module | 3 | NC | 19.9 | NC |
| 4 | Engine Booster Module | 28 | NC | 62.2 | SC |
| 5 | Engine Exhaust Gas Module | 38 | NC | 33.6 | NC |
| 6 | Auxiliary Boiler | 11 | NC | 20.3 | NC |
| 7 | Exhaust Gas Boiler (UNEX H (TYPE 1A)) | 94 | SC | 101 | C |
| 8 | Lube Oil Unloading Pump | 2 | NC | 19.9 | NC |
| 9 | Used Lube Oil Unloading Pump (DELTA PUMP: DHG-299 LP) | 2 | NC | 19.9 | NC |
| 10 | LO Separator Unit | 5 | NC | 19.9 | NC |
| 11 | LO (Mobile) Transfer Pump Unit (ACE 038) | 24 | NC | 34.9 | NC |
| 12 | LO (Mobile) Transfer Pump Unit (ACE 038) | 4 | NC | 19.9 | NC |

| Sl No. | Name of the equipment | Critical value CV=FF×E | Criticality level | Fuzzy Critical value | Fuzzy Critical level |
|---|---|---|---|---|---|
| 13 | LFO Transfer Pump (ACG 052 N7 NVBP) | 4 | NC | 19.9 | NC |
| 14 | HFO Transfer Pump (ACG 052 N7 NTBP) | 5 | NC | 19.9 | NC |
| 15 | HFO/LFO Feeder Pump(ACG, MOTOR: 7A*, 7B*, 14BG*) | 95 | SC | 100 | C |
| 16 | HFO Unloading Pump (D2SH- 105/058) | 6 | NC | 19.9 | NC |
| 17 | LFO Unloading Pump (D2SH- 88/052) | 3 | NC | 19.9 | NC |
| 18 | HFO Separator Unit | 88 | SC | 102 | C |
| 19 | Water Treatment Unit | 15 | NC | 22.1 | NC |
| 20 | Fire Pump | 15 | NC | 22.1 | NC |
| 21 | Instrument Air Compressor Unit | 30 | NC | 40.5 | SC |
| 22 | Starting Air Compressor Unit | 30 | NC | 40.5 | SC |
| 23 | Compressor dryer | 9 | NC | 19.9 | NC |
| 24 | Foam Tank | 2 | NC | 19.9 | NC |
| 25 | Auxiliary Boiler LFO Tank | 2 | NC | 19.9 | NC |
| 26 | Aux. Boiler Feed Water Tank | 11 | NC | 20.3 | NC |
| 27 | Boiler Washing Unit | 2 | NC | 19.9 | NC |
| 28 | Deep Tubewell Pump | 2 | NC | 19.9 | NC |
| 29 | Power Transformer | 26 | NC | 53.9 | SC |
| 30 | Auxiliary Transformer | 16 | NC | 21.6 | NC |

## 5. Fuzzy Criticality Surface

A criticality surface serves as an effective tool for qualitative criticality assessments, helping to categorize criticality levels and guide to control measures. The Surface Viewer, a graphical interface, allows users to visualize the output surface of a Fuzzy Inference System (FIS) based on one or two input variables. The fuzzy criticality surface offers more precise and reliable outcomes compared to traditional criticality matrices. It has been observed that the fuzzy approach is particularly well-suited for practical applications, as it more effectively addresses uncertainties than conventional methods.

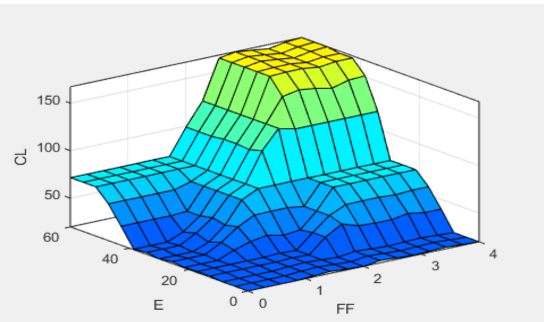


**Fig. 8** Fuzzy Criticality Surface

## 6. Conclusion

Asset failure is widely acknowledged as a leading cause of significant industrial accidents. So, for mitigating failure of assets effective risk modeling and asset prioritization crucial for ensuring both safety and operational efficiency in industries. This study presents a novel risk modeling approach for a power plant using a fuzzy RBM framework. Compared to the traditional RBM method, the proposed model exhibited greater accuracy in managing input uncertainties. The analysis identified 3 critical assets, 5 semi-critical assets, and 46 non-critical assets, indicating that the plant is overall in a non-critical state. Furthermore, the flexibility of the fuzzy RBM model extends its applicability beyond power plants, making it suitable for any industry where managing risks in industrial processes is essential.

## 7. Acknowledgement

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## 8. References

[1] Singh, R. Kumar, and Makarand S. Kulkarni. "Criticality analysis of power-plant equipments using the Analytic Hierarchy Process." International Journal of Industrial Engineering & Technology 3, no. 4 (2013): 1-14.

[2] Sai, T. K., and K. A. Reddy. "Neural Network Applications in a Power Station." International Journal of Soft Computing and Engineering (IJSCE)
4, no. 6 (2015): 112-120

[3] Sadeghi-Yarandi, Mohsen, Salman Torabi-Gudarzi, Nasrin Asadi, Hamedeh Golmohammadpour, Vahid Ahmadi-Moshiran, Mostafa Taheri, Aysa Ghasemi-Koozekonan, Ahmad Soltanzadeh, and Bahare Alimohammadi. "Development of a novel Electrical Industry Safety Risk Index (EISRI) in the electricity power distribution industry based on fuzzy analytic hierarchy process (FAHP)." Heliyon 9, no. 2 (2023).

[4] Zúñiga, Andrés A., João FP Fernandes, and Paulo JC Branco. "Fuzzy-Based failure modes, effects, and criticality analysis applied to Cyber-Power grids." Energies 16, no. 8 (2023): 3346.

[5] Das, Anwesa, Vinay Kumar, and Subrata Dutta. "A fuzzy-based AHP-VIKOR framework for risk analysis of safety-critical systems: A case study of nuclear power plant." Annals of Nuclear Energy 209 (2024): 110841.

[6] Li, Lumin, Gang Liang, Junqiang Jia, Maihebubai Xiaokaiti, and Jian Yang. "Construction of Power Production Safety Risk Assessment System Based on Fuzzy Logic Algorithm." In 2024 4th International Conference on Mobile Networks and Wireless Communications (ICMNWC), pp. 1-6. IEEE, 2024.

[7] Mohanty, J. K., P. R. Dash, and P. K. Pradhan. "FMECA analysis and condition monitoring of critical equipments in super thermal power plant." International Journal of System Assurance Engineering and Management 11, no. 3 (2020): 583-599.

[8] Selvik, Jon T., and Terje Aven. "A framework for reliability and risk centered maintenance." Reliability engineering & system safety 96, no. 2 (2011): 324-331.

[9] A. C. Márquez, The maintenance management framework: models and methods for complex systems maintenance. Springer Science & Business Media, 2007.

[10] Jamshidi, Ali, Abdolreza Yazdani-Chamzini, Siamak Haji Yakhchali, and Sohrab Khaleghi. "Developing a new fuzzy inference system for pipeline risk assessment." Journal of loss prevention in the process industries 26, no. 1 (2013): 197-208.