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Criticality Analysis of Steel Industry Using Fuzzy Model

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Abstract

The steel sector plays a crucial role in the global economy, producing essential raw materials for a wide range of businesses. With increased competitiveness and market complexity, steel manufacturers confront different issues that might impair their overall performance and sustainability. To handle these difficulties successfully, it is necessary to identify and prioritize critical aspects that substantially impact the steel industry's performance. This paper gives a complete criticality analysis of the steel industry using a fuzzy model, which facilitates the management of uncertainties and imprecise data typically seen in real-world decision-making processes. The research adopts a multi-criteria decision-making framework, integrating fuzzy logic and expert knowledge to examine the essential aspects determining the industry's performance and success.

Keywords: Criticality Analysis, Fuzzy Model, Steel Industry, RBM model, Multi-Criteria Decision Making, Uncertainty, Decision Support, Sensitivity Analysis.

1. Introduction

The steel industry is a crucial sector of the global economy, playing a vital role in various industries such as construction, automotive, and manufacturing. Over the past decade, the steel industry has experienced significant shifts in terms of concentration and production patterns. According to Gonzalez and Kaminski, the iron and steel industry is complex and intrinsically linked with the world economy. This intricate relationship is evidenced by the fact that steel consumption serves as a key indicator of national development, attracting the continuous interest of global manufacturing giants [1]. The demand for steel products stems from a diverse range of industries, including automotive, construction, and manufacturing sectors. The iron and steel industry supplies raw materials such as tubes, plates, and sheets to other important manufacturing enterprises, such as the automobile, aircraft, and beverage industries. According to Gonzalez and Kaminski, the entire production process of iron and steel can be divided into three sections: ironmaking, steelmaking-continuous casting, and steel rolling. Ironmaking involves converting iron ore, scrap, and other input factors into iron, which serves as the primary raw material for steel production. The second phase, steelmaking-continuous casting, involves the conversion of iron into steel through a series of chemical reactions. During this phase, impurities are removed and specific alloying elements are added to achieve the desired properties of the steel. Furthermore, the steel rolling process involves shaping the steel into various forms such as sheets, plates, and bars [2]. The steel industry plays a crucial role in the economic development of Bangladesh. Steel is a versatile material that has multiple uses in various industries, such as construction, manufacturing, and transportation. steel in Asia, indicating the country's increasing demand for this essential material [3]. According to sources, the steel industry in Bangladesh is primarily concentrated in Chittagong city, where there is a thriving market for steel due to the rapid expansion of various steel-based projects, shipbuilding, and the real estate sector. This sector shows great potential for further growth and development in the coming years. The steel industry in Bangladesh is an important contributor to the country's long-term economic prosperity and social development [4]. One of the key factors driving the expansion of the steel industry in Bangladesh is the increasing demand for steel in various sectors such as construction, infrastructure development, and manufacturing. Furthermore, it is important to note that a significant portion of the steel consumed in Bangladesh originates from the shipbreaking yards. The flow analysis of steel from shipbreaking yards conducted by Sujauddin and co-authors highlighted the reuse of various items from ships in the industrial sectors of Bangladesh. The ship-recycling industry in Bangladesh has been a major source of raw materials for the steel and iron industry [5]. Artificial Intelligence (AI) is the emulation of human cognitive functions through machines, especially computer systems. A field of computer science, AI strives to construct intelligent systems capable of learning from experience, adapting to new inputs, and performing human-like activities. It has become essential to the technological industry. AI techniques, including fuzzy logic and neuro-

fuzzy systems,are extensively utilized in sectors like control engineering demonstrating their adaptability and industrial importance.[6]

2. Criticality Assessment

Criticality evaluation may involve either quantitative or qualitative. Quantitative criticality assessment needs a lot of data for both the evaluation of failure frequency possibilities and the results it produces. Different types of methods like fault tree or decision tree are usually used to find the probability of a certain sequence of events. On the other hand, qualitative criticality judgments are less thorough. The results are usually presented as a simple risk matrix. A risk matrix is made of two axis- one axis represents failure frequency, and another axis represents its outcomes or effects. By concerning a chance and consequence of the risk matrix, a criticality level can be found. However, the criticality values are always subjective, choosing the criticality levels of the assets based on these values are always debatable [7]. RBM method is a method for forming a group communication process so that the process will be effective in allowing a group of individuals to deal with the complex problems [8].

3. Development of Fuzzy Control System

Traditional probability models based on classic set theory struggle to effectively communicate risks. The lack of precise and relevant data, as well as the uncertainty surrounding the relationship between cause and effect, pose challenges in accurately determining specific risk levels using these models alone [9].

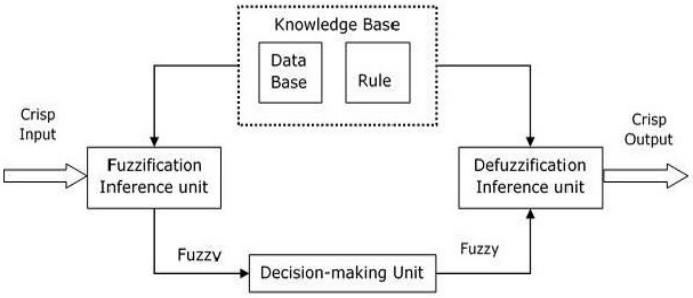


Fig. 1. Fuzzy inference system [9]

The following steps were followed in developing the fuzzy RBM model:

Step 1. Identification of Fuzzy inference system: There are almost 118 applications which can be used for developing fuzzy model. MATLAB, Fortran/ Fortran 77, C/C++/Turbo C, Lingo, GAMS are some of the popular development tools. Among them, MATLAB and C/C++/Turbo C are used mostly because of their user-friendly interface [10].

Step 2. Identification of input and output parameters: To develop the fuzzy modeling, all relevant input and output parameters were specified. The purpose of the model is given by the input-output relationships.

Step 3. Determination of input and output variables: In fuzzy modeling, the input-output variables are defined as linguistic variables where linguistic values are in words or synthetic languages. The fuzzification process decomposes the input [failure frequency (FF) and effect (E)] and output variables [criticality level (CL)] and maps the crisp values into fuzzy sets.

Step 4: Ascertaining the roles of membership: A curve that indicates how each point in the input space is transferred to a membership value between 0 and 1 is called a membership function (MF). This function indicates the extent to which an input fits within a set. These functions transfer non-fuzzy input data to fuzzy linguistic concepts and vice versa in the fuzzification and defuzzification stages of a fuzzy logic system [11]. Due to their simplicity, fuzzy number members that are trapezoidal (ZFN) or triangular (TFN) are typically employed to represent linguistic variables. Fuzzy membership functions in this work were implemented using the TFN and ZFN combination [12].

Step 5: Formulating fuzzy inference rules: A set of fuzzy rules that characterize the input-output connections are included in the rule base unit. These rules are written as conditional statements with an if-then structure. For instance: C is Z if A is X and/or B is Y. where the fuzzy sets represent the linguistic variables X, Y, and Z. The fuzzy rule's "If" denotes the antecedents, and its "Then" denotes the consequence, both of which are related by "And / Or" operators [13].

Step 6: Defuzzification: The centroid approach was used in this investigation to achieve defuzzification. The weighted average of each criticality output is the system's ultimate output.

Step 7. Evaluation of the fuzzy model: After developing the fuzzy model, the criticality risk values were obtained. The values were evaluated by the traditional RBM method to validate the model.

3.1 RBM-Based Asset Criticality Assessment

The criticality assessment for each asset is calculated by multiplying the failure frequency factor (FF) with the effects of the failure (E), expressed as follows:

$$CV = FF \times E \quad (4.1)$$

In this equation, *CV* denotes the critical value, *FF* represents the failure frequency factor, which indicates the number of failures occurring within a specific time period (a year), *E* stands for the effects of the failure measured. The effects of failure (E) are further defined as:

$$E = (OI \times OF) + MC + ISE \quad (4.2)$$

Here, *OI* represents the Operational Impact factor, *OF* signifies the Operational Flexibility factor, *MC* indicates This methodology offers a detailed approach for assessing the criticality of assets within a system by factoring in failure frequency and the combined effects of operational impact, flexibility, maintenance costs, as well as safety and environmental considerations. The scaling and classification of failure frequency factors range from Very Low to Very High, utilizing fuzzy linguistic terms to describe each level. These terms enable a more refined analysis, accommodating uncertainty and variability. For example, "Occasional" equipment breakdowns signify that failures happen intermittently but are not frequent. In a similar manner, the classification and scaling of the Operational Impact factor assess various elements such as energy efficiency or emissions, with levels ranging from Very Low to Very High. For instance, "Above Average" energy efficiency implies a better-than-average performance but highlights areas for improvement. The Operational Flexibility factor is also categorized based on specific criteria, such as Production Adjustability or Equipment Adaptability, with flexibility ratings spanning from Low to High. Fuzzy linguistic terms are used to evaluate flexibility; for example, "Moderately Flexible" equipment suggests adaptability to different processes, though there may be limitations. The Maintenance Cost factor is assessed in a comparable way, with scales provided to gauge maintenance expenses, tailored to the specific context of an organization. Asset failures can substantially impact both the safety of the industry and the surrounding environment. To mitigate these risks, industries must ensure safe working environments and maintain proper environmental conditions. For the Safety and Environmental Impact factor, six scales were assigned, ranging from 0 to 8. When the highest values are applied to all factors in equation 4.2, the maximum critical value for an asset reaches 530. Experts have established three ranges to determine an asset's criticality within process industries. This classification system enables industries to prioritize their assets effectively based on criticality levels.

Max CV = 10× [(10 × 4) + 5 +8] = 530

Classification of asset criticality based on specific critical value (CL) thresholds. Assets are categorized as "Critical" when their critical value exceeds 160, while those with a critical value between 145 and 160 are considered "Semi-Critical." Assets with a critical value below 145 are classified as "non-critical." This system helps prioritize assets according to their importance and potential impact.

3.2 Fuzzy Modeling for Critical Value

A framework for categorizing system inputs and outputs using linguistic variables and corresponding numerical ranges. Inputs include two key variables: Failure Frequency (FF) and Effect (E). Failure Frequency is divided into four linguistic values: "Rare" (R) with a numerical range of [0 2 4], "Occasional" (O) with a range of [1 4 5], "Frequent" (F) with a range of [3 6 7], and "Persistent" (P) with a range of [5 8 10]. Effect (E) is classified into five linguistic values: "Very Low" (VL) with a range of [0 10 20], "Low" (L) with a range of [5 20 30], "Medium" (M) with a range of [15 30 40], "High" (H) with a range of [25 40 50], and "Very High" (VH) with a range of [35 50 53]. The output variable is the Criticality Level (CL), which is divided into three linguistic terms: "Non-Critical" (NC) with a numerical range of [0 50 100], "Semi-Critical" (SC) with a range of [35 110 212], and "Critical" (C) with a range of [110 212 530]. These classifications help in assessing system performance based on failure frequency and the associated effect. Different fuzzy risk outputs are produced by the various fuzzy membership functions. Type of the membership function and all the fuzzy numbers are determined according to the traditional RBM factor.

For the Failure Frequency (FF) input variable:

$$FF(i_1) = \begin{cases} i_1, 1 \le i_1 \le 4 \\ 0, \ otherwise \end{cases} \quad (4.3)$$

For the Effect (E) input variable:

$$E(i_2) = \begin{cases} i_2, 10 \le i_2 \le 50 \\ 0, \ otherwise \end{cases} \quad (4.4)$$

For the Criticality Level (CL) output variable:

$$CL(o_1) = \begin{cases} o_1, 30 \le o_1 \le 530 \\ 0, \ otherwise \end{cases} \quad (4.5)$$

Here, i_1 and i_2 represent the input variable of failure frequency (FF) and effect (E) respectively and o_1 represents the output variable fuzzy criticality level (CL) [14].

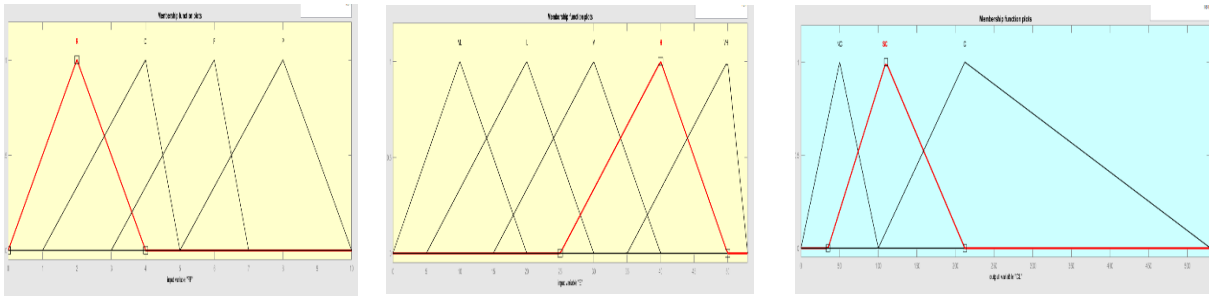


Fig. 2. Membership function for input and output variable Failure Frequency (FF), Effect (E) and Criticality Level (CL)

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,

$$N = m \times n \quad (4.4)$$

Where, N = number of fuzzy if-then rules; m = number of membership function of failure frequency (FF); n = number of membership function of effect (E).

Table 1. Fuzzy Rules

Input Variable	Very Low	Low	Medium	High	Very High
Persistent	Non-Critical	Semi Critical	Semi Critical	Critical	Critical
Occasional	Non-Critical	Semi Critical	Semi Critical	Critical	Critical
Frequent	Non-Critical	Non-Critical	Semi Critical	Semi Critical	Semi Critical
Rare	Non-Critical	Non-Critical	Non-Critical	Non-Critical	Semi Critical

4. Criticality Level of the Assets

The fuzzy RBM model can be applied to the real field application to check the criticality level as well as to measure the worth of the model. Refineries account for half of plant failures, chemical plants for 32%, and gas processing plants for 5%, according to King and Hirst [13]. Thus, the three units of BSRM (Melting-2) plant were taken into consideration in this study to define the level of the asset criticality. The Steel Melting Shop (SMS), the Continuous Casting Machine (CCM) and the Air Pollution Control (APC) unit were taken into consideration to determine asset criticality. The critical value for each asset of all three unit is measured using RBM model and then compared with the proposed fuzzy model.

4.1 Steel Melting Shop (SMS)

The Steel Melting Shop (SMS) has 10 assets which are involved in the production operation of billet. The Steel Melting Shop (SMS) relies on a range of assets to facilitate the production of billet. These assets include equipment like Transfer Trolleys, Vibratory Feeders, Coreless Induction Feeders, Pneumatic Lining Vibrators, and Ladle Refining Furnaces. Additionally, the operation of the SMS involves the use of various cranes, including those numbered from 1 to 9. All of these resources is essential to the manufacturing process and enhances the Steel Melting Shop's overall efficacy and efficiency.Whether it's the transportation of materials, the feeding of raw materials into the melting process, or the refinement of molten metal in ladles. Figure 3 shows the result of each of the asset present in SMS shop is calculated using equation 4.2 from the other related factors such as operational impact (OI), operational flexibility (OF), maintenance cost (MC) and safety and environment impact (ISE). Waste Transfer Trolley has the highest effect due to its high operational impact and high impact on safety and environment on any failure. On the other hand, Crane 9, Ladle Refining Furnace have the minimum result.

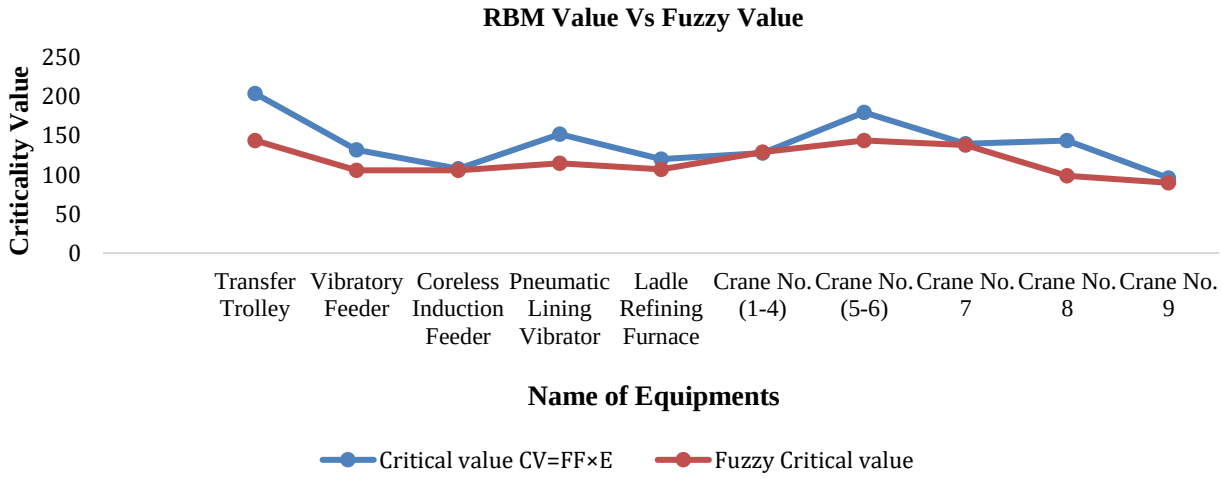


Fig. 3. Graphical representation of the RBM value and fuzzy critical value

4.2 Continuous Casting Machine (CCM)

The Continuous Casting Machine (CCM) has 10 assets which are involved in the process operation of billet production. These are Ladle turret, Tundish, Mould tube inside the Mould Jacket, Mould Oscillator, Dummy Bar, Withdrawal Straightener, Pre-cutter roller table, Automatic Gas cutter, Discharge roller table, and Turn Over cooling bed. Figure 4 shows the result of each of the asset present in CCM is calculated using equation 4.2 from the other related factors such as operational impact (OI), operational flexibility (OF), maintenance cost (MC) and safety and environment impact (ISE). Mold tube and Discharge roller table both have the highest result due to its low operational impact and high impact on safety and environment on any failure. On the other hand, Dummy bar has the minimum result.

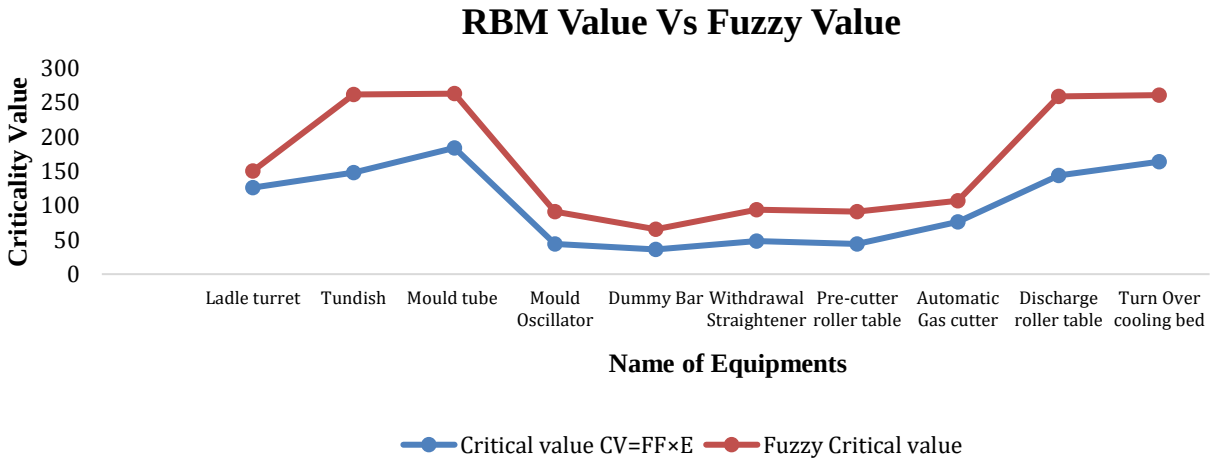


Fig. 4. Graphical representation of the RBM value and fuzzy critical value

4.3 Air Pollution Control (APC) Unit

Air Pollution Control Unit has 11 assets which are involved in the process of water treatment process operation. These are Suction Hood, Furnace Draft Control Damper, LRF Draft control Damper, Spark Arrestor, Emergency Damper, Induced Draft Fan, Electric Motor, Common Bag House, Rotary Air Lock Valve, Flow Conveyor, Dust Bag. Figure 5 shows the result of each of the asset present in APC unit is calculated using equation 4.2 from the other related factors such as operational impact (OI), operational flexibility (OF), maintenance cost (MC) and safety and environment impact (ISE). Common Bag House and Spark Arrestor has the highest result due to its low operational impact and high impact on safety and environment on any failure.

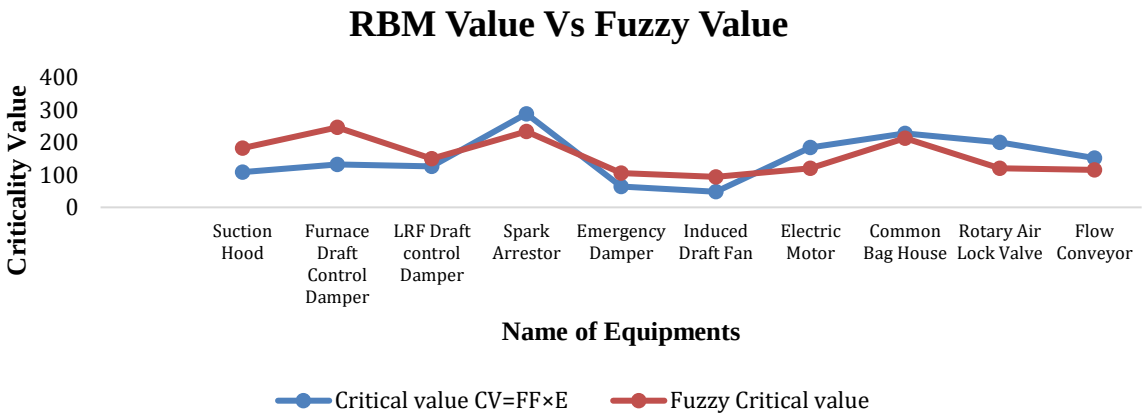


Fig. 5. Graphical representation of RBM value and fuzzy critical value

5. Conclusion

This research introduces a criticality assessment framework for melting plant of steel industry's operations by integrating both traditional risk-based maintenance (RBM) methods and a fuzzy RBM approach. The model's accuracy hinges on precise data collection from operational processes, supported by a robust safety culture and continuous tracking of failure frequencies and associated consequences. To assess asset criticality, a Mamdani fuzzy inference system (FIS) was employed, leveraging expert insights to classify assets based on their criticality. The approach was validated through a case study conducted at a melting plant in Bangladesh, where assets from three units were evaluated. The comparison between the fuzzy RBM and the traditional RBM approaches showed a close alignment, with discrepancies reduced by fine-tuning membership functions and fuzzy rules. Ultimately, this model helps prioritize assets according to their criticality, offering management a valuable tool to optimize maintenance strategies and mitigate risks across the plant.

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