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RISK ANALYSIS OF A REPAIRABLE UNIT IN SUGAR INDUSTRY: A HYBRID APPROACH USING FUZZY FMEA AND GRA

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Abstract

The purpose of this study is to develop a comprehensive risk assessment profile for a repairable unit in a sugar industry. The risk analysis of milling unit in the sugar industry often relies on uncertain data and subjective expert assessments, which could be biased. This highlights the need for careful interpretation as the data quality variations have great impact on the decision-making. By integrating risk analysis techniques like failure mode and effect analysis (FMEA), Grey relation analysis (GRA), and fuzzy theory, together with expert assessments for the very first time, the approach aims to prioritize risk management strategies of milling unit in Dhampur Sugar Mills Ltd., a sugar industry located in Western Uttar Pradesh, India. First of all, Root cause analysis (RCA) is conducted to detect in-depth potential failure modes of the unit. Further, FMEA is employed for risk identification and prioritization, with ranking of components based on their RPN (Risk Priority Number) scores. To address the limitations of FMEA, fuzzy FMEA supported by a fuzzy decision support system (FDSS) has been used to compute FRPN (Fuzzy Risk Priority Number) scores. Based on these scores, the components are ranked. Subsequently, GRA is employed within the fuzzy FMEA framework to intelligently assess the relative importance of key factors, i.e. probability of occurrence, severity effect, and probability of non-detectability of failure in order to determine optimal rankings of critical components. The implementation of fuzzy logic and grey approach with inputs of FMEA offers a more efficient and better way to make decision regarding risk priorities. This risk assessment approach is valuable for sugar industry where complex engineering systems are essential for production process, and the findings from this study will aid system specialists and analysts in future planning and maintenance strategies.

Keywords: Risk analysis, FMEA, fuzzy FMEA, FDSS, RPN, GRA.

I. Introduction

Risk assessment of complex systems across various process industries is essential for ensuring operational safety, reliability, and efficiency as the machinery and processes are susceptible to a

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wide range of potential failures, which can lead to disastrous consequences, including equipment damage, environmental harm, and accidents etc. By systematically identifying, analyzing, and prioritizing risks, targeted mitigation strategies can be implemented to enhance the persistence of operational uptime of systems. This dynamic approach not only helps in complying with regulatory requirements but also reduces operational downtime. Ultimately, effective risk assessment enables industries to safeguard their assets, protect their workforce, and maintain a competitive edge in the emerging global market.

The sugar industry is one of the most significant agro-based industries throughout the world. It plays a vital role in the socio-economic development of rural areas. This industry contributes significantly to the Indian economy, accounting for approximately 1% of the GDP. It is a lifeline for millions of farmers and laborers, providing employment to over 5 lakh skilled and semi-skilled workers across the nation. Within a sugar industry, the milling unit is one of the most vital components, as it is responsible for crushing sugarcane to extract juice, which forms the basis for all subsequent processes of sugar production. The crushing process demands precision and consistent performance, as any failure or inefficiency in the milling unit can lead to reduced juice extraction, operational delays, and significant financial losses. Therefore, it is important to conduct RAM analysis of milling unit in order to ensure its failure-free operation for the seamless functioning of sugar industry and for maintaining the stability of the national economy.

Various qualitative risk analysis techniques have been extensively explored in the literature, particularly for different industries and process plants. FMEA was introduced by NASA as a formal design technique in 1963. Besides this, it has also been widely employed by researchers as an effective tool for reliability and safety analysis of various industries [1-3], to mention a few. In this technique, failure causes are ranked using RPN. One of the major shortcomings of the RPN ranking technique is its inability to account for the relative significance of probabilities of occurrence, non-detection and severity effect of failure. Moreover, due to system complexity and ambiguous human verdicts, the impreciseness and uncertainty arise in the data regarding risk factors. To address this problem, the researchers used fuzzy approach in FMEA. Guimaraes and Lapa [4] demonstrated the use of the fuzzy technique in FMEA for the evaluation of the PWR chemical and volume control system in a nuclear power station. Sharma *et al.* [5] presented fuzzy logic based FMEA by developing a knowledge-based FDSS for prioritizing the risky components in a paper plant. Tay and Lim [6] used the fuzzy FMEA approach to evaluate the performance of some models in a semiconductor manufacturing plant. Wang *et al.* [7] proposed the fuzzy weighted geometric mean in FMEA to perform risk analysis. From these studies, it is deduced that fuzzy approach with FMEA overcomes the impreciseness in data but remains unable to balance the relative importance between risk factors. Therefore, to overcome these limitations many researchers utilized different multi-criteria decision making (MCDM) techniques such as Bayesian Network (BN), Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), Analytical Hierarchy Process (AHP), GRA, etc., and improved prioritization of risky components.

BN is probabilistic graphical model that represent dependencies among variables, making them useful for decision making under uncertainty. BN, while effective for probabilistic reasoning has its own drawbacks. The high computational complexity in inference is quite challenging to handle large scale problems and reliance on extensive prior data for accurate probability estimations makes the use of BN impractical in situations with limited failure history [8-9]. TOPSIS is a MCDM method that ranks alternatives based on their geometric distance from the ideal and worst solutions. AHP is a structured approach for decision making that uses pairwise comparison to determine criteria weights. Despite their effectiveness, both methods have notable limitations. TOPSIS is highly sensitive to the choice of normalization techniques and does not account for interdependencies among criteria, leading to ranking inconsistencies [10]. On the other hand, AHP suffers from rank reversal when alternatives are added or removed and its reliance on subjective pairwise comparison introduces potential bias [11]. Both AHP and TOPSIS, struggle with handling uncertainty, which has led researchers to integrate fuzzy logic and hybrid approaches to improve decision making robustness. Samvedi *et al.* [12] addressed the increasing complexity and uncertainty in supply chain risk management by proposing a composite risk index using an integrated fuzzy AHP–TOPSIS approach. Badida *et al.* [13] highlighted the effectiveness of fuzzy AHP and fuzzy TOPSIS to assess occupational health risks in hospitals, prioritizing workplace hazards by utilizing a fuzzy multi-criteria approach emphasizing the importance of fuzzy methods in complex risk evaluations.

GRA is another decision-making technique which offers a flexible and effective tool for reliability analysis, especially in uncertain, incomplete, or sparse data environment. Over the years, numerous researchers have applied GRA in various fields such as industry [14], forecasting [15-16], and engineering [17]. An integrated framework for understanding the qualitative behavior of a paper plant has been proposed by Sharma *et al.* [18]. They used fuzzy FMEA and GRA approaches to analyze the paper plant's qualitative performance and compared risk priority results with FMEA ranking results. A unique fuzzy multi-criterion decision making approach based on the grey relation technique has been presented by Dhal *et al.* [19] for the efficient identification of flexible manufacturing systems. In a geothermal power plant, Feili *et al.* [20] illustrated the use of FMEA approach for risk assessment. They investigated five primary components of the geothermal power plant, and on the basis of the findings, maintenance workers and system analysts were recommended corrective measures towards enhancing system reliability. To improve the purchasing process in a public hospital, Kumru and Kumru [21] have presented a study by implementing the fuzzy FMEA. The multidimensional model with fuzzy approach in FMEA was proposed by Silva *et al.* [22] for prioritization of various attributes of information security. Shankar *et al.* [23] identified socially-induced sustainability risks as the main threats to freight transportation systems and proposed a risk analysis model using intuitionistic fuzzy and D-number theory to help managers proactively address these risks and optimize resource allocation. Panchal and Shrivastava [24] presented an FMEA-GRA integrated approach for risk ranking in a CNG dispensing system. An enhanced grey FMEA was used by Yaşbayır and Aydemir [25] to identify risk priorities of a steel-door industry employing a new mass gravity law based RPN calculation technique. To improve aviation safety risk assessment, Wei *et al.* [26] integrated Fuzzy Cognitive Maps (FCM) and GRA enhancing GRA's ability to account for interactions between evaluation indices, making it more robust for complex decision-making scenarios. Sur and Kim [27] utilized a hybrid GRA and ordinal priority approach (OPA) to identify and rank the most dangerous types of accidents in marine operations. Soltani *et al.* [28] integrated Fuzzy Best-Worst Method (FBWM) and GRA for accurate risk assessment in blasting operations.

The risk analysis of milling unit in the sugar industry often relies on uncertain data and subjective expert assessments, which could be biased. Moreover, the sugar industry presents unique combination of industrial hazards compared to other sectors due to the presence of high-speed mechanical systems, combustible dust, high pressure steam and flammable byproducts like ethanol. These risks necessitate strict safety protocols, regular equipment maintenance and worker training to prevent catastrophic failures. In such a high-risk and variable environment, intervention of hybrid approach offering substantial advantages is needed. While standard FMEA may oversimplify failure prioritization through equal-weighted risk factor scoring, its integration with fuzzy theory and GRA allows for nuanced evaluation of failure modes under conditions of incomplete, uncertain, or qualitative data. This is particularly important in the sugar industry, which frequently operates with seasonal labor, limited instrumentation, and a combination of mechanical and biological process risks.

To the author's best knowledge, existing research on risk assessment in the sugar industry has primarily relied on standard FMEA or other qualitative methods, which do not adequately address subjective uncertainty and expert variability. While fuzzy FMEA has been widely applied in industries such as automotive, healthcare and manufacturing, its use in sugar industry maintenance and risk assessment remains largely unexplored. The purpose of this study is to develop a comprehensive risk assessment profile of milling unit in the sugar industry by applying risk analysis techniques namely fuzzy FMEA and GRA incorporating expert assessments for the first time. Unlike prior studies in highly automated and sensor-rich industries such as petrochemicals, thermal and pharmaceuticals, the hybrid approach using fuzzy FMEA and GRA in the sugar industry addresses the challenges of low data availability and high dependency on human expertise. As a result, it enables more context-sensitive and actionable risk prioritizations that align closely with real-world plant conditions that enhances maintenance decision making. This paper is organized in six sections as follows: Section II outlines some basic notions of fuzzy theory. Section III presents the system description. In Section IV, risk analysis for the identification of hazardous components of milling unit has been discussed. Section V presents the results and discussion of the study. Finally, in Section VI, the conclusion and managerial implications has been presented.

II. Fuzzy theory

Some basic notions of fuzzy theory that have been utilized in this study are discussed below:

I. Fuzzy set

For a universal set X, the fuzzy set $\tilde{A}$ is represented by

$$\tilde{A} = \{(x, \mu_{\tilde{A}}(x)) : x \in X\}$$

where, $\mu_{\tilde{A}}(x) \in [0,1]$ is the degree of membership of element x.

II. Triangular membership function

The triangular membership function $\mu_{\tilde{A}}(x)$ of a fuzzy set $\tilde{A}$ represented by the triplet (p_1, p_2, p_3) is described as

$$\mu_{\tilde{A}}(x) = \begin{cases} \frac{(x-p_1)}{(p_2-p_1)}, & p_1 \le x \le p_2 \\ \frac{(p_3-x)}{(p_3-p_2)}, & p_2 \le x \le p_3 \\ 0, & otherwise \end{cases} \quad . \tag{1}$$

III. Trapezoidal membership function

The trapezoidal membership function $\mu_{\tilde{A}}(x)$ of a fuzzy set $\tilde{A}$ represented by the quadruplet (q_1, q_2, q_3, q_4) is described as

$$\mu_{\tilde{A}}(x) = \begin{cases} \frac{(x-q_1)}{(q_2-q_1)}, & q_1 \le x \le q_2 \\ 1, & q_2 \le x \le q_3 \\ \frac{(q_4-x)}{(q_4-q_3)}, & q_3 \le x \le q_4 \\ 0, & otherwise \end{cases} \quad . \tag{2}$$

IV. Linguistic terms

To indicate the likelihood of uncertain events, experts utilize phrases such as 'low,' 'medium,' 'high,' etc. These expert opinions are expressed through linguistic terms or variables, and they convey their appraisal of the possibility that a particular event will occur. The analysts represent these events using well-defined fuzzy membership functions [29]. In this study, six linguistic terms - 'remote,' ‘minor’, 'low,' 'moderate,' 'high,' and 'very high' are employed to represent occurrence of events in the fuzzy FMEA and GRA approaches.

III. System description

This study conducts a risk analysis of the milling unit at Dhampur Sugar Mills Ltd., a sugar industry located in Western Uttar Pradesh, India. The mill has a crushing capacity of 23,500 MT/day of sugarcane. The left-over bagasse generates a good amount of electricity, totaling 121 MW/day. The sugar industry comprises several functional units: feeding, milling, refining, and crystallization. The milling unit being a crucial unit of sugar industry, its efficiency has great significance on overall plant efficiency. Its primary function is to crush sugarcane to extract juice, which is further processed into sugar by refining and crystallization units. This unit possesses a series of five heavy duty mills each consisting inter-rack carriers, roller pressure feeder and pumps connected in series configuration. These heavy-duty mills are designed to operate continuously under high pressure to maximize juice extraction. Failure of any mill or component of the mill can bring the whole milling unit to a halt. The function of each component in brief is as follows:

- **Inter-rack carrier (IRC):** IRC are used to transport crushed sugarcane or bagasse between mills, ensuring a smooth and continuous flow through the milling process.
- **Roller Pressure Feeder (RPF):** The RPF are used for juice extraction in sugar mills which may be basic, toothed roller pressure feeder (TRPF) or grooved roller pressure feeder (GRPF). TRPF and GRPF enhance juice extraction by gripping and compressing sugarcane with toothed and grooved rollers which apply additional pressure increasing efficiency of the mills.
- **Pumps:** Pumps transport primary juice from Mill 1 and secondary juice from Mill 2-5, to the raw juice tank. They also supply water and other liquids throughout the milling process, ensuring continuous flow and efficient processing of sugarcane juice.

The schematic diagram of the milling unit is depicted in figure 1.

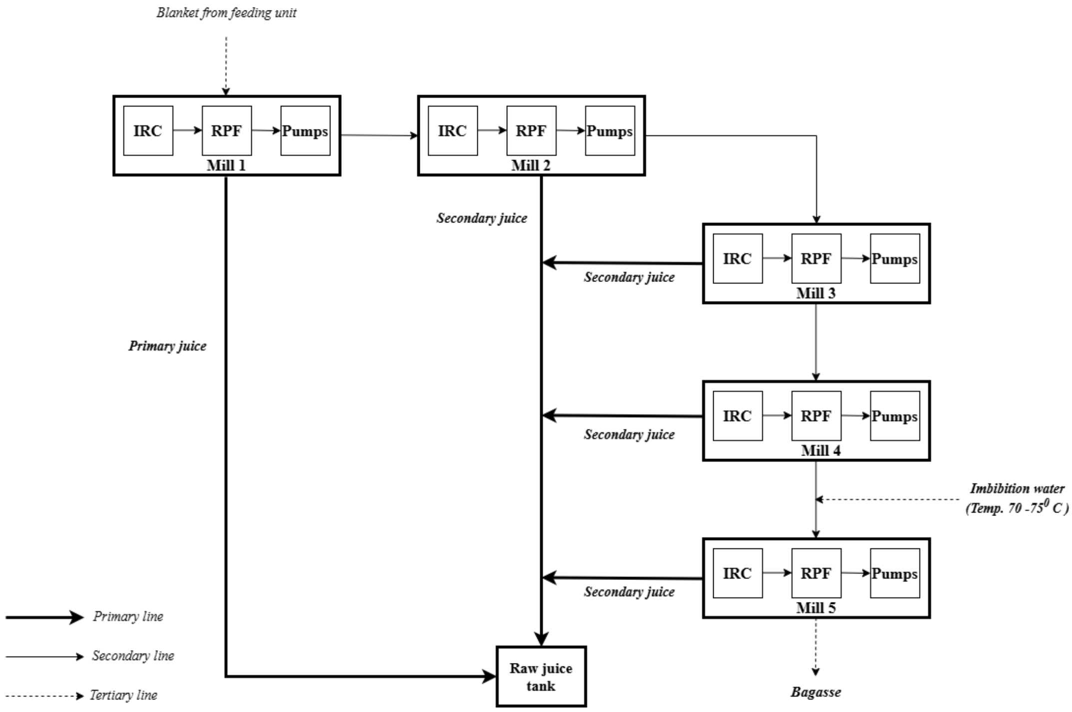

Figure 1: *Schematic diagram of the milling unit*

IV. Risk Analysis

This section presents an in-depth risk analysis of the milling unit in a sugar industry using fuzzy FMEA and GRA. This helps in prioritizing risk managerial strategies, enhancing the availability and safety ensuring long-term sustainability of the complex machines, equipments and processes in milling unit.

I. Failure mode and effect analysis (FMEA)

FMEA is a powerful tool to assess the potential failure mode and their effect so that corrective actions may be prioritized depending upon risk ranking. It is a systematic, bottom-up technique that investigates the effect of possible failure modes at one level on failure modes of the next sub-system level. The procedural steps of FMEA are shown in figure 2.

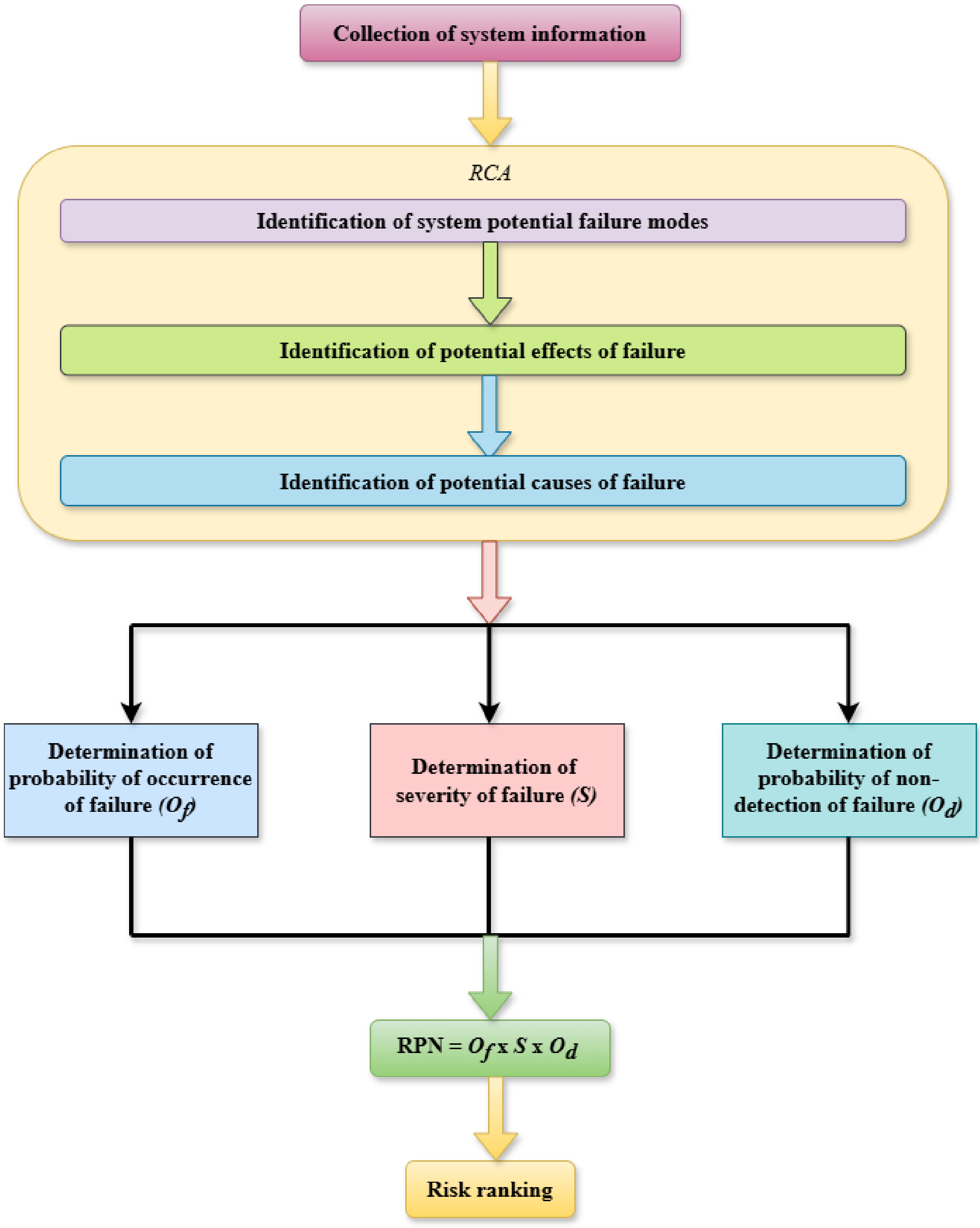

Figure 2: *Procedural steps of FMEA*

After collecting information of the system from various sources such as expert opinion, log book, computer records, etc., RCA has been performed to identify potential failure causes of each component (IRC, RPF, and Pumps) of the milling unit for preventing future failures. The root causes of problem issues, illustrated using a Fishbone diagram are represented in figure 3.

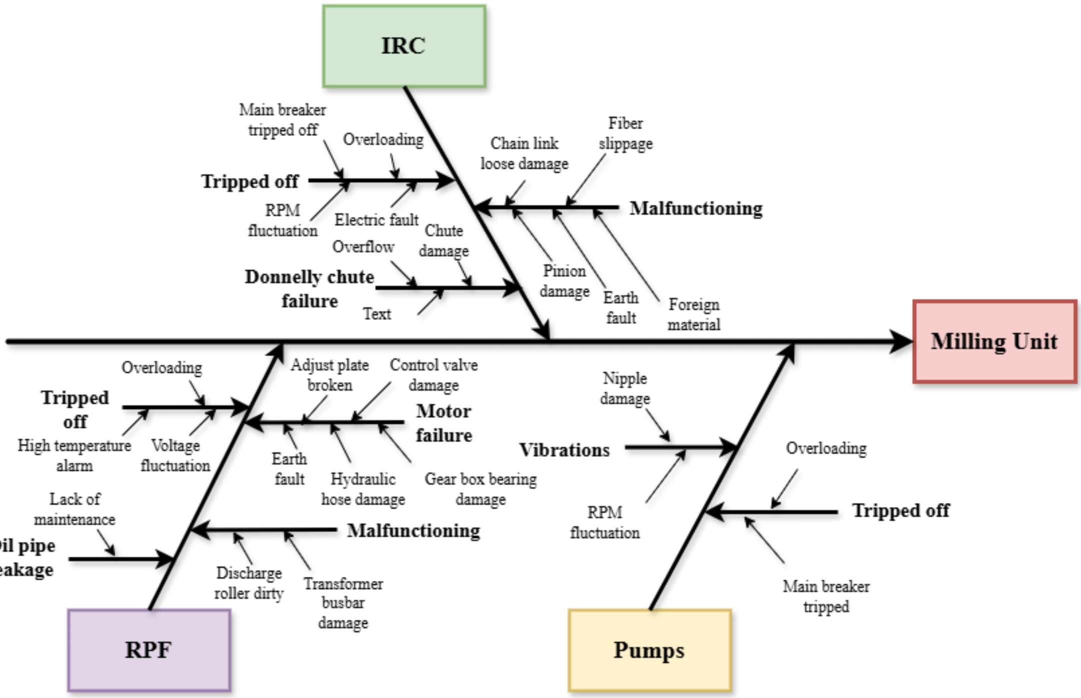

Figure 3: *RCA of milling unit*

Further, a fuzzy linguistic assessment scale (Table 1) has been generated to compute scores with the help of expert opinions regarding the probability of occurrence of failure (O_f), severity effect of failure (S) and probability of non–detection of failure (O_d) of distinct components of the milling unit [30].

Table 1: *Scale for probability of occurrence, severity effect and likelihood of non-detection of failure*

Linguistic terms	Symbol	Score	MTBF	Prob. of occurrence	Severity effect	Likelihood of non-detection (%)
Remote	R	0-1	>5 years	<0.01	Not noticed	0-5
Low	L	2-3	2-5 years	0.01-0.1	Minor hassle to the operator	6-25
Moderate	M	4-6	1-2 years	0.1-0.5	Minor fall in system efficiency	26-55
High	H	7-8	0.5-1 years	0.5-1	Significant loss in system efficiency	56-75
Very High	VH	9-10	<6 months	>1	Manufacturing loss	76-100

The scores of risk factors of distinct components of milling unit have been computed with the help of expert opinions. To mitigate bias in expert assessment, a diverse panel of experienced professionals was consulted from the sugar industry, including maintenance engineers, quality control specialists, and system analysts, ensuring a balanced and comprehensive assessment of risk factors. Further, to minimize individual biases in the computed scores by experts, Delphi technique

Table 2: *FMEA sheet for milling unit*

Function	Potential failure mode	Potential effect of failure	Potential cause of failure	O_f	S	O_d	RPN Score	Corrective actions
				IRC				
To carry blanket	Tripped off	Operational loss	Electric fault [MU_{11}]	7	3	5	105	Repairing insulation, Replace fuses
			Main breaker tripped off [MU_{12}]	5	3	6	90	Check overload settings, Examine motor health
			RPM fluctuation [MU_{13}]	7	3	3	63	Bearing replacement, Gearbox maintenance
			Overloading [MU_{14}]	7	5	3	105	Adjust feed rate, Upgrade motor capacity
	Donnelly chute failure	Fails to operate	Chute damage [MU_{15}]	4	4	4	64	Improve alignment
			Shaft damage [MU_{16}]	3	5	5	75	Material upgrade, Lubrication check
			Overflow [MU_{17}]	3	2	2	12	Clear choke points, Check juice channels
	Malfunc- -tioning	Cane carrier shut down	Chain link loose/ damage [MU_{18}]	4	5	2	40	Regular inspections, Timely replacement
			Fiber slippage [MU_{19}]	5	4	3	60	Adjust roller pressure, Improve fiber feeding
			Pinion damage [MU_{110}]	3	6	5	90	Lubrication improvement, Load adjustment
			Foreign material [MU_{111}]	4	7	2	5	Pre-sorting materials, Magnetic separation
			Earth fault [MU_{112}]	6	4	6	144	Inspect grounding system, Check insulation integrity
				RPF				
To separate juice and bagasse	Tripped off	Fails to squeeze juice	Voltage fluctuation [MU_{21}]	7	3	3	63	Install voltage stabilizer, Upgrade electrical wiring
			High temperature alarm [MU_{22}]	5	2	2	20	Temperature calibration, Coolant system check
			Overloading [MU_{23}]	7	5	3	105	Adjust feed rate, Monitor load sensors
	Oil pipe leakage	Breakage	Lack of maintenance [MU_{24}]	3	6	5	90	Scheduled maintenance
	Motor failure	Mill shut down/bypass	Adjust plate broken [MU_{25}]	2	5	6	60	Replace plate, Check alignment
			Control valve damage [MU_{26}]	3	6	6	108	Valve replacement, Pressure monitoring
			Hydraulic hose damage [MU_{27}]	3	6	7	126	Installation of quality hoses, Regular inspections
			Gear box bearing damage [MU_{28}]	3	5	7	105	Bearing inspection, Regular lubrication
			Earth fault [MU_{29}]	6	4	6	144	Inspect grounding system
	Malfunc- -tioning	Fails to operate	Transformer busbar damage [MU_{210}]	2	5	6	60	Busbar inspection, Transformer maintenance
			Discharge roller dirty [MU_{211}]	4	6	5	120	Increase cleaning frequency
				Pumps				
To transfer sugarcane juice	Tripped off	Operational loss	Main breaker tripped off [MU_{31}]	5	3	6	90	Inspect breaker, Reset system
			Overloading [MU_{32}]	7	5	3	105	Optimize load distribution
	Vibrations	Equipment damage	Nipple damage [MU_{33}]	3	6	6	108	Enhance Material Strength
			RPM fluctuation [MU_{34}]	7	3	3	63	Inspect drive belt, Calibrate RPM sensor

[31-32] is employed. Subsequently, an FMEA sheet (Table 2) has been generated, and scores related to O_f, S and O_d have been tabulated which are utilized to calculate the RPN score of each failure cause. Here, RPN = $O_f \times S \times O_d$.

In FMEA, the crisp values of O_f, S and O_d of different components are considered to calculate their RPN scores, which seems inappropriate, since probability of occurrence, non-detection and severity effect of failures are subjective and vague, being suggested by experts in natural language. Also, RPN ranking obtained using FMEA could potentially mislead analysts and maintenance professionals as the failure causes with the same RPN score might have different linguistic sets. On the other hand, some of the failure causes have the same linguistic set with different RPN scores, so that, the risk implications could differ significantly. Also, despite their actual significance in practical applications, the RPN ranking technique overlook the relative significance of O_f, S and O_d [21,30]. As a result, on the basis of RPN, system analysts may face challenges in determining risk priorities for corrective actions. Therefore, to address these drawbacks, a combination of the fuzzy logic and grey approach with inputs of FMEA is implemented to offer a more efficient and better way to make decisions regarding risk priorities.

II. Fuzzy FMEA

The fuzzy logic toolbox of MATLAB offers robust functionality for handling linguistic variables, rule-based systems, and complex multi-criteria decision-making models. Therefore, for the implementation of the fuzzy FMEA approach, the fuzzy logic toolbox in MATLAB (R2015a) has been employed to develop a knowledge–inferencing–based fuzzy decision support system (FDSS) for better decision-making in risk ranking. The three modules of the fuzzy inference system—the knowledge base module, input inference module, and output inference module are depicted in figure 4.

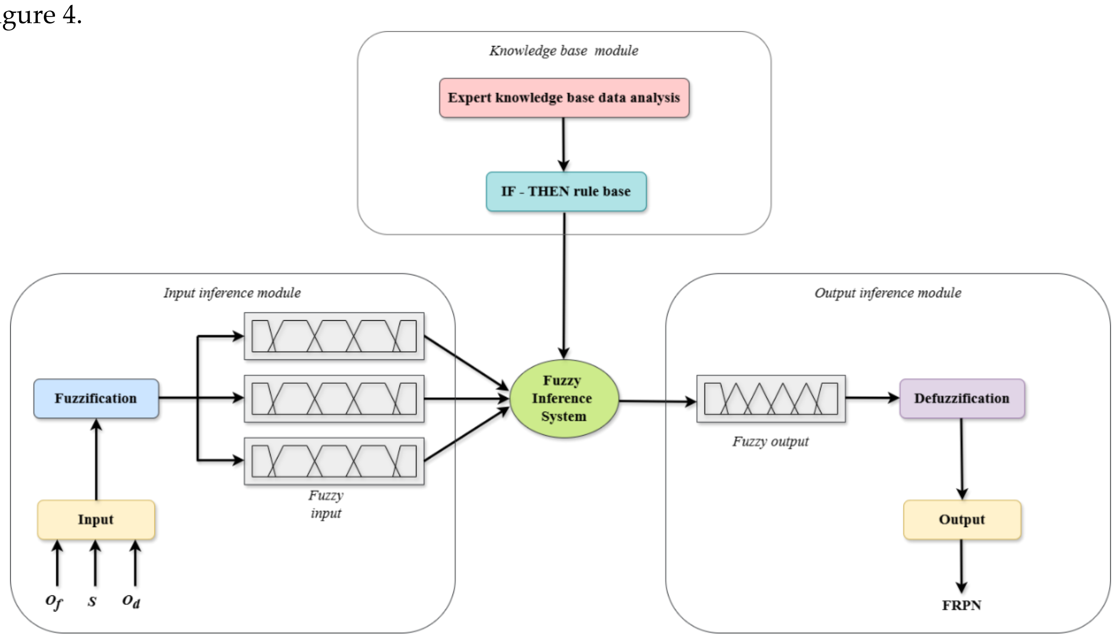

Figure 4: *Knowledge–inferencing–based FDSS*

The knowledge base module consists of a well-defined set of 'if-then' rules expressed in linguistic terms by employing a fuzzy model of the process and expert knowledge. For instance, a rule in the form of 'if-then' can be expressed as:

$\boldsymbol{R_1}$**: if** p is $\boldsymbol{P_i}$**, then** q is $\boldsymbol{Q_i}$**,** where i =1, 2, …, N

where, p and q are input and output linguistic terms; $\boldsymbol{P_i}$ and $\boldsymbol{Q_i}$ are antecedent and consequent linguistic constants.

For the input and output inferencing module, the trapezoidal membership function has been used to fuzzify crisp input values of O_f, S and O_d taken from the FMEA sheet. Here, the input membership function is defined with five linguistic terms 'Remote', 'Low', 'Moderate', 'High' and 'Very High' depicted in figure 5.

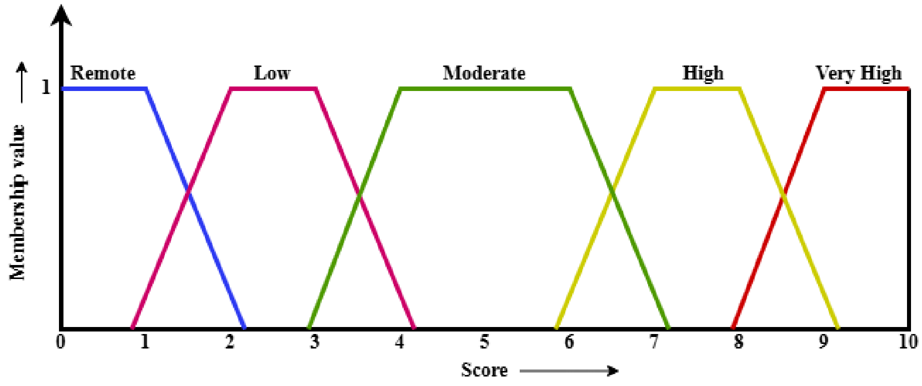

Figure 5: *Input membership function for O_f, S and O_d*

After combining three inputs and five linguistic terms, 125 'if-then' rules base has been generated. The fuzzy output i.e. FRPN is achieved by combining the inference mechanism with input variables and an 'if-then' set of 125 rules. The Mamdani min-max inferencing technique in fuzzy logic toolbox (figure 6) is used for inferencing, and fuzzy output is obtained using a triangular membership function defined with six linguistic terms 'Remote', 'Minor', 'Low', 'Moderate', 'High' and 'Very High', shown in figure 7.

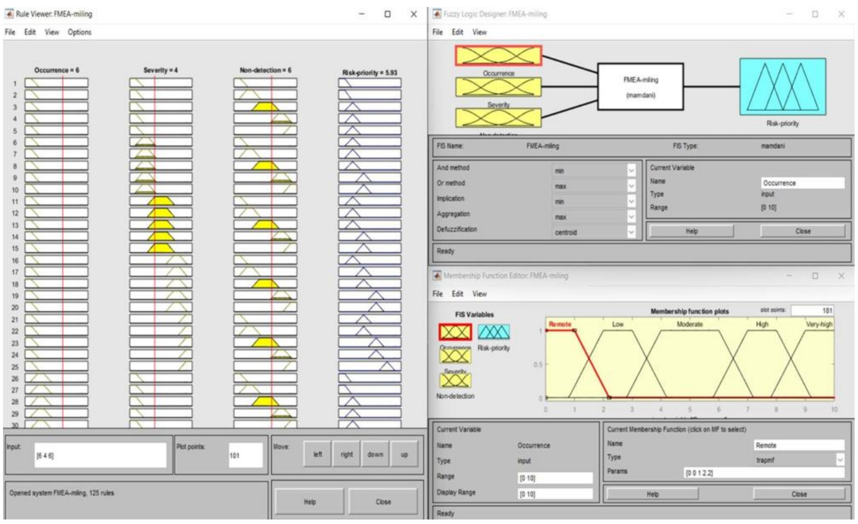

Figure 6: *Fuzzy logic toolbox*

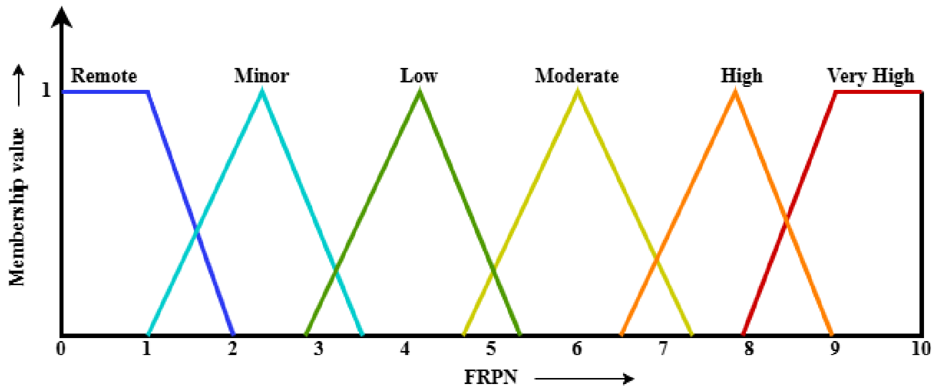

Figure 7: *Output membership function for fuzzy output*

To obtain crisp output, the fuzzy output has been defuzzified by employing the center of area (COA) method. According to this method, the defuzzified value ($\bar{x}$) for a fuzzy set Ã is given by

$$\bar{x} = \frac{\int_{x_1}^{x_2} x.\mu_{\tilde{A}}(x)dx}{\int_{x_1}^{x_2} \mu_{\tilde{A}}(x)dx} \quad (3)$$

where, $\mu_{\tilde{A}}(x)$ is the membership function of Ã defined on [x_1, x_2].

The obtained crisp values of FRPN have been used to assign risk priorities for better decision making. The results are compared with RPN obtained by FMEA and are tabulated in table 3. Moreover, to enable intelligent decision-making for relative importance between O_f, S and O_d and to determine the optimal ranking of critical components, GRA approach has been used.

Table 3: *Risk ranking results based on RPN and FRPN*

Component	Potential cause of failure	RPN	Ranking	FRPN	Fuzzy ranking
IRC	MU_{11}	105	5	4.45	7
	MU_{12}	90	6	5.01	5
	MU_{13}	63	9	3.26	9
	MU_{14}	105	5	4.45	7
	MU_{15}	64	8	4.99	6
	MU_{16}	75	7	6.00	2
	MU_{17}	12	14	2.40	10
	MU_{18}	40	12	5.55	4
	MU_{19}	60	10	5.55	4
	MU_{110}	90	6	5.55	4
	MU_{111}	56	11	4.07	8
	MU_{112}	144	1	5.93	3
RPF	MU_{21}	63	9	3.26	9
	MU_{22}	20	13	3.26	9
	MU_{23}	105	5	4.45	7
	MU_{24}	90	6	5.55	4
	MU_{25}	60	10	4.99	6
	MU_{26}	108	4	5.93	3
	MU_{27}	126	2	5.93	3
	MU_{28}	105	5	6.38	1
	MU_{29}	144	1	5.93	3
	MU_{210}	60	10	4.99	6
	MU_{211}	120	3	5.55	4
Pumps	MU_{31}	90	6	5.01	5
	MU_{32}	105	5	4.45	7
	MU_{33}	108	4	5.93	3
	MU_{34}	63	9	3.26	9

III. GRA

The GRA is a significant decision-making method introduced by Deng [33]. It offers a flexible and effective tool for reliability analysis, especially in the environment of uncertainty. It takes into account the multiple reliability metrics to rank and prioritize failure causes, system components and maintenance strategies which makes it highly valuable in process industries and complex engineering systems. For intelligent decision-making in prioritization, Chang *et al.* [34] employed grey theory into the fuzzy FMEA approach which gained popularity. In this study, the same linguistic terms which were used in fuzzy FMEA are applied in GRA to calculate the degree of relation, and the ranking outcomes are compared with the FRPN results. Figure 8 illustrates the steps of GRA.

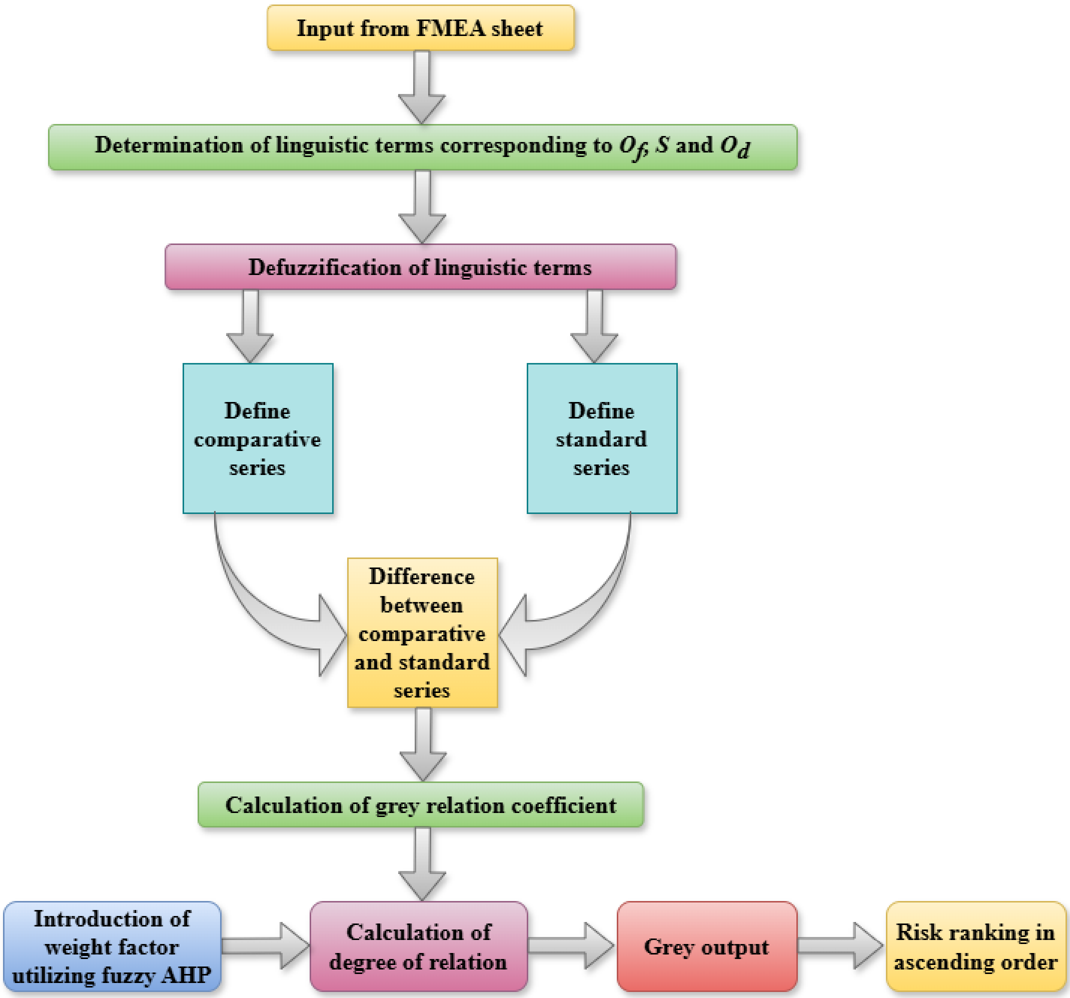

Figure 8: *Procedural steps of GRA*

The five linguistic terms established by experts for O_f, S and O_d in the fuzzy FMEA were defuzzified by employing the method given by Chen and Klein [35] to yield crisp values which are presented in table 4.

Table 4: *Crisp values for linguistic terms*

Linguistic term	Crisp value	Symbol
Remote (R)	0.0937	+ + +
Low (L)	0.2650	+ +
Moderate (M)	0.5118	+
High (H)	0.7272	–
Very high (VH)	0.9125	– –

The crisp values given in table 4 have been employed to generate the comparative series for different causes of failures of various components of the considered unit. For instance, comparative series of IRC component is represented by

$$\begin{bmatrix} - & ++ & + \\ + & ++ & + \\ - & ++ & ++ \\ - & + & ++ \\ + & + & + \\ ++ & + & + \\ ++ & ++ & ++ \\ + & + & ++ \\ + & + & ++ \\ ++ & + & + \\ + & - & ++ \\ + & + & + \end{bmatrix} = \begin{bmatrix} 0.7272 & 0.2650 & 0.5118 \\ 0.5118 & 0.2650 & 0.5118 \\ 0.7272 & 0.2650 & 0.2650 \\ 0.7272 & 0.5118 & 0.2650 \\ 0.5118 & 0.5118 & 0.5118 \\ 0.2650 & 0.5118 & 0.5118 \\ 0.2650 & 0.2650 & 0.2650 \\ 0.5118 & 0.5118 & 0.2650 \\ 0.5118 & 0.5118 & 0.2650 \\ 0.2650 & 0.5118 & 0.5118 \\ 0.5118 & 0.7272 & 0.2650 \\ 0.5118 & 0.5118 & 0.5118 \end{bmatrix}, \quad (4)$$

where, the matrices at left and right hand side, respectively, represent linguistic terms and crisp values of causes of failure. Further, a standard series for the failure causes of IRC component has been obtained by taking minimum level of linguistic terms (i.e. 'Remote' in this study), for three variables O_f, S and O_d since in FMEA, the RPN score is directly proportional to level of risk. The crisp value for 'Remote' is 0.0937, which represents the average value. The lowest possible value of term 'Remote' is 0. Thus, the standard series for failure causes of IRC component is

$$\begin{bmatrix} +++ & +++ & +++ \\ +++ & +++ & +++ \\ +++ & +++ & +++ \\ +++ & +++ & +++ \\ +++ & +++ & +++ \\ +++ & +++ & +++ \\ +++ & +++ & +++ \\ +++ & +++ & +++ \\ +++ & +++ & +++ \\ +++ & +++ & +++ \\ +++ & +++ & +++ \\ +++ & +++ & +++ \end{bmatrix} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}. \quad (5)$$

To calculate grey relation coefficient of IRC component, the difference D between comparative and standard series is obtained as

$$D = \begin{bmatrix} 0.7272 & 0.2650 & 0.5118 \\ 0.5118 & 0.2650 & 0.5118 \\ 0.7272 & 0.2650 & 0.2650 \\ 0.7272 & 0.5118 & 0.2650 \\ 0.5118 & 0.5118 & 0.5118 \\ 0.2650 & 0.5118 & 0.5118 \\ 0.2650 & 0.2650 & 0.2650 \\ 0.5118 & 0.5118 & 0.2650 \\ 0.5118 & 0.5118 & 0.2650 \\ 0.2650 & 0.5118 & 0.5118 \\ 0.5118 & 0.7272 & 0.2650 \\ 0.5118 & 0.5118 & 0.5118 \end{bmatrix}. \quad (6)$$

The grey relation coefficient for each linguistic term corresponding to each failure cause of the IRC component is obtained using

$$\gamma_{ij} = \frac{D_{min} + \xi D_{max}}{d_{ij} + \xi D_{max}}, \quad i = 1,2, \dots n; \; j = 1,2,3 \quad , \quad (7)$$

where, n = number of failure causes in component, D_{min} and D_{max} are the least and most possible values of factors in equation 6 and the identifier ξ is assumed to be 0.5. The matrix of grey relation coefficients for failure causes of IRC component is given as

$$\gamma = \begin{bmatrix} 0.4647 & 0.7625 & 0.5681 \\ 0.5681 & 0.7625 & 0.5681 \\ 0.4647 & 0.7625 & 0.7625 \\ 0.4647 & 0.5681 & 0.7625 \\ 0.5681 & 0.5681 & 0.5681 \\ 0.7625 & 0.5681 & 0.5681 \\ 0.7625 & 0.7625 & 0.7625 \\ 0.5681 & 0.5681 & 0.7625 \\ 0.5681 & 0.5681 & 0.7625 \\ 0.7625 & 0.5681 & 0.5681 \\ 0.5681 & 0.4647 & 0.7625 \\ 0.5681 & 0.5681 & 0.5681 \end{bmatrix}. \tag{8}$$

Similarly, the grey relation coefficient for each failure causes of other two components RPF and pumps have been obtained.

The degree of relation (δ), indicating the relationship between the potential causes and the optimal value of decision factors is given by

$$\delta = \beta_1\gamma_{i1} + \beta_2\gamma_{i2} + \beta_3\gamma_{i3}, \text{ with } \sum_{j=1}^{3}\beta_j = 1, \tag{9}$$

where, β_j is the weight coefficient corresponding to j^{th} factor.

The weight coefficients, β_j of the decision factors can be computed either based upon expert feedback or assumed directly. In present study, the fuzzy AHP has been employed to generate the fuzzy comparison matrix for three risk factors O_f, S and O_d using Wang's scale [36] shown in table 5, on the basis of suggestions given by maintenance engineers. The imprecise and uncertain assessments of them are translated into corresponding triangular fuzzy numbers given in comparison matrix (Table 6). This scale is particularly effective within the process industries, as it allows for nuanced pairwise comparisons in uncertain or imprecise environments. Its fuzzy linguistic scale is well-suited for dealing with subjective assessments and partial information, which are common in complex industrial processes. The fuzzy extent analysis method [37] has been used to determine weight coefficients β_j for fuzzy comparison matrix of risk factors presented in table 6.

Table 5: *Wang's scale for matrix generation*

Uncertain judgement	Fuzzy scale
Approximately important	(1/2, 1, 2)
Approximately X times more important[a]	(X-1, X, X+1)
Approximately X times less important	(1/X+1, 1/X, 1/X-1)
Between Y and Z times more important[b]	(Y, Y+Z/2, Z)
Between Y and Z times less important	(1/Z, 2/Y+Z, 1/Y)

[a] X = 2, 3, ……,9
[b] Y, Z = 1, 2, ……., 9 and Y < Z

Table 6: *Comparison matrix for risk factors*

	O_f	S	O_d	β_j
O_f	(1, 1, 1)	(1/4, 1/3, 1/2)	(1/2, 1, 2)	0.22
S	(2, 3, 4)	(1, 1, 1)	(1, 2, 3)	0.48
O_d	(1/2, 1, 2)	(1/3, 1/2, 1)	(1, 1, 1)	0.30

The weight coefficients so obtained are β_1 = 0.22, β_2 = 0.48, β_3 = 0.30. Further, the value of δ is calculated by using equation 9 for corresponding γ_{ij} and β_j.
For instance, for failure cause **MU_{11}:**

$$\delta_{11} = 0.4647\times0.22+0.7625\times0.48+0.5681\times0.30 = 0.6387$$

Similarly, the degree of relation δ i.e., grey output has been computed for each cause of each component of milling unit and ranking of risky components has been tabulated in table 7.

Table 7: *Grey relation coefficient and grey output for various failure causes*

Component	Failure causes	O_f	γ_{O_f}	S	γ_S	O_d	γ_{O_d}	Grey output	Grey ranking
IRC	MU_{11}	–	0.4647	++	0.7625	+	0.5681	0.6387	7
	MU_{12}	+	0.5681	++	0.7625	+	0.5681	0.6614	8
	MU_{13}	–	0.4647	++	0.7625	++	0.7625	0.6970	9
	MU_{14}	–	0.4647	+	0.5681	++	0.7625	0.6037	4
	MU_{15}	+	0.5681	+	0.5681	+	0.5681	0.5681	1
	MU_{16}	++	0.7625	+	0.5681	+	0.5681	0.6109	5
	MU_{17}	++	0.7625	++	0.7625	++	0.7625	0.7625	11
	MU_{18}	+	0.5681	+	0.5681	++	0.7625	0.6264	6
	MU_{19}	+	0.5681	+	0.5681	++	0.7625	0.6264	6
	MU_{110}	++	0.7625	+	0.5681	+	0.5681	0.6109	5
	MU_{111}	+	0.5681	–	0.4647	++	0.7625	0.5768	2
	MU_{112}	+	0.5681	+	0.5681	+	0.5681	0.5681	1
RPF	MU_{21}	–	0.4647	++	0.7625	++	0.7625	0.6970	9
	MU_{22}	+	0.5681	++	0.7625	++	0.7625	0.7197	10
	MU_{23}	–	0.4647	+	0.5681	++	0.7625	0.6037	4
	MU_{24}	++	0.7625	+	0.5681	+	0.5681	0.6109	5
	MU_{25}	++	0.7625	+	0.5681	+	0.5681	0.6109	5
	MU_{26}	++	0.7625	+	0.5681	+	0.5681	0.6109	5
	MU_{27}	++	0.7625	+	0.5681	–	0.4647	0.5789	3
	MU_{28}	++	0.7625	+	0.5681	–	0.4647	0.5789	3
	MU_{29}	+	0.5681	+	0.5681	+	0.5681	0.5681	1
	MU_{210}	++	0.7625	+	0.5681	+	0.5681	0.6109	5
	MU_{211}	+	0.5681	+	0.5681	+	0.5681	0.5681	1
Pumps	MU_{31}	+	0.5681	++	0.7625	+	0.5681	0.6614	8
	MU_{32}	–	0.4647	+	0.5681	++	0.7625	0.6037	4
	MU_{33}	++	0.7625	+	0.5681	+	0.5681	0.6109	5
	MU_{34}	–	0.4647	++	0.7625	++	0.7625	0.6970	9

V. Results and Discussion

To prioritize risk management strategies of milling unit, FMEA has been conducted. The FMEA sheet of milling unit together with the numerical values assigned to risk factors O_f, S and O_d are presented in table 2. The risk ranking of failure causes is measured using RPN scores. The higher is

RPN score, higher is risk ranking. It is observed that for IRC, the failure cause **MU_{111}** described by moderate probability of occurrence, higher severity and low probability of non-detection [**M, H, L**] has lower RPN score 56, while the failure cause **MU_{112}** for which all the risk factors are moderate [**M, M, M**] yields RPN score 144. This means that **MU_{112}** has higher priority than **MU_{111}**, which could be misleading for managers, as **MU_{111}** should have a higher priority than **MU_{112}** for corrective actions. Also, it is revealed that MU_{11} (low severity) and **MU_{14}** (moderate severity) have same RPN score 105; however, on the basis of severity, the risk implication for both of them may be totally different. Table 6 presents the defuzzified RPN using fuzzy FMEA and the grey outputs are tabulated in table 7. Further, the comparison of ranking results obtained from FMEA, fuzzy FMEA, and GRA methods has been depicted in table 8. From table 8, it is observed that the failure causes **MU_{111}** and **MU_{21}** represented by the linguistic terms **[M, H, L]** and **[H, L, L]** have defuzzified outputs as 4.07 and 3.26, respectively, and grey outputs as 0.5768 and 0.6970, respectively. This shows that **MU_{111}** should be given higher priority for corrective actions than **MU_{21}** (when severity is considered). On the other hand, the standard FMEA approach produces their RPN scores as 56 and 63, respectively, and ranks them 11th and 9th places, respectively. This suggests that **MU_{21}** has higher priority than **MU_{111}**, which could be misleading.

Table 8: *Risk ranking comparison of failure causes based on RPN, FRPN and grey output*

Component	Potential cause of failure	RPN	Ranking	FRPN	Fuzzy ranking	Grey output	Grey ranking
IRC	MU_{11}	105	5	4.45	7	0.6387	7
	MU_{12}	90	6	5.01	5	0.6614	8
	MU_{13}	63	9	3.26	9	0.6970	9
	MU_{14}	105	5	4.45	7	0.6037	4
	MU_{15}	64	8	4.99	6	0.5681	1
	MU_{16}	75	7	6.00	2	0.6109	5
	MU_{17}	12	14	2.40	10	0.7625	11
	MU_{18}	40	12	5.55	4	0.6264	6
	MU_{19}	60	10	5.55	4	0.6264	6
	MU_{110}	90	6	5.55	4	0.6109	5
	MU_{111}	56	11	4.07	8	0.5768	2
	MU_{112}	144	1	5.93	3	0.5681	1
RPF	MU_{21}	63	9	3.26	9	0.6970	9
	MU_{22}	20	13	3.26	9	0.7197	10
	MU_{23}	105	5	4.45	7	0.6037	4
	MU_{24}	90	6	5.55	4	0.6109	5
	MU_{25}	60	10	4.99	6	0.6109	5
	MU_{26}	108	4	5.93	3	0.6109	5
	MU_{27}	126	2	5.93	3	0.5798	3
	MU_{28}	105	5	6.38	1	0.5798	3
	MU_{29}	144	1	5.93	3	0.5681	1
	MU_{210}	60	10	4.99	6	0.6109	5
	MU_{211}	120	3	5.55	4	0.5681	1
Pumps	MU_{31}	90	6	5.01	5	0.6614	8
	MU_{32}	105	5	4.45	7	0.6037	4
	MU_{33}	108	4	5.93	3	0.6109	5
	MU_{34}	63	9	3.26	9	0.6970	9

Further, in standard FMEA, the failure causes described by different sets of linguistic terms may receive equal priority, while the failure causes described by same set of linguistic terms may receive different priorities. Such prioritization of failure causes may mislead the managers potentially in planning the maintenance strategies and maintenance resources may be misallocated. Fuzzy FMEA and GRA approaches overcome this limitation by refining rankings, making risk prioritization more accurate and ensuring that maintenance efforts are focused on genuinely high-risk failure causes rather than treating the failure causes equally critical with same RPN scores. For instance, for IRC and RPF, a significant discrepancy in ranking of failure causes **MU_{14}** and **MU_{28}** is highlighted. These failure causes, despite being described by different sets of linguistic terms [**H, M, L**] and [**L, M, H**], respectively, are assigned the same RPN score 105 and 5th rank using FMEA, which could be misleading as the risk implications for both the causes may be different. However, their defuzzified output is 4.45 and 6.38 respectively, while the grey output is 0.6037 and 0.5798, respectively. Therefore, fuzzy and grey approaches yield different outputs and different priorities for **MU_{14}** and **MU_{28}.** According to them, **MU_{28}** is given higher priority than **MU_{14}**. A similar pattern emerged for the RPF and pumps, where causes **MU_{24}** and **MU_{31}**, with different linguistic sets [**L, M, M**] and [**M, L, M**], respectively, produce the same RPN score 90 and 6th rank using FMEA. However, the defuzzified outputs are 5.55 (4th rank) and 5.01 (5th rank) and grey outputs are 0.6109 (5th rank) and 0.6614 (8th rank), respectively, for **MU_{24}** and **MU_{31}**. This suggests higher priority of **MU_{24}** than **MU_{31}** for corrective actions.

In contrast, for the failure causes **MU_{18}** and **MU_{19}** of IRC represented by the same linguistic terms [**M, M, M**], the defuzzified output is 5.55 and grey output is 0.6264 for both failure causes. This necessitates that both failure causes should be given the same priority for attention, but a variation in their RPN score is noted (40 and 60), suggesting higher priority for **MU_{19}** over **MU_{18}**, which could potentially mislead decision makers. However, in some cases, it is found that for failure causes represented by same linguistic terms, FMEA and fuzzy FMEA suggest different rankings, while GRA suggest same rankings. For instance, the failure causes **MU_{24}, MU_{25}** and **MU_{26}** of the RPF are represented by the linguistic terms **[L, M, M],** but distinct RPN rankings of 6th, 10th and 4th, respectively, are suggested by FMEA and 4th, 6th and 3rd positions, are suggested by fuzzy FMEA, while GRA ranks them at same priority level i.e. 5th position. Similarly, **MU_{15}** and **MU_{211}** with linguistic terms **[M, M, M]** are ranked 8th and 3rd, respectively, by FMEA, while, 6th and 4th, respectively, by fuzzy FMEA. On the other hand, the grey output places both at 1st position. Thus, the effect of weight coefficients in grey output is visible in the results. This shows that GRA takes into account the relative importance of O_f, S and O_d. Further, according to GRA, the failure causes **MU_{15}, MU_{112}, MU_{211}** and **MU_{29}** require the most attention, and **MU_{17}** requires the least attention. By resolving resulting ambiguities, this hybrid approach allows plant managers to prioritize the most critical maintenance action efficiently, leading to better resource allocation, reduced downtime and enhanced system reliability.

VI. Conclusion

This study developed a comprehensive risk assessment profile utilizing hybrid approach for accurately analyzing the qualitative performance of the milling unit in a sugar industry. The key failure causes affecting system availability have been identified and their associated RPN, FRPN and grey output scores have been calculated by employing respectively FMEA, FDSS and GRA to establish priorities. In standard FMEA, the failure causes described by different sets of linguistic terms may receive equal priority, while the failure causes described by same set of linguistic terms may receive different priorities, potentially leading to the misallocation of maintenance resources. For instance, for IRC and RPF, overloading and gear box bearing damage, despite being described by different sets of linguistic terms are assigned the same ranking using FMEA. However, the FRPN and grey analysis yield different rankings and accordingly gear box bearing damage is given higher priority than overloading. In contrast, the failure causes of RPF namely, lack of maintenance, adjust plate broken and control valve damage, are represented by the same linguistic terms but distinct RPN rankings are suggested by FMEA and fuzzy FMEA. They suggest that control valve damage should be given higher priority than lack of maintenance and adjust plate broken, which could mislead the analysts. On the other hand, GRA ranks them at same priority level. The effect of weight coefficients in grey output is visible in the results. For instance, the failure causes of IRC namely electric fault (low severity) and overloading (moderate severity) have same RPN scores and same defuzzified outputs. This could be misleading for managers, since the risk implication for both of these failure causes may be totally different on the basis of severity. However, the grey output suggests that overloading should be given high priority over electric fault for corrective actions. Thus, the combined use of FDSS and GRA provides more reliable and consistent ranking results for the key failure causes. Also, it is observed that failure causes such as chute damage, earth fault and discharge roller dirty require most attention, while overflow requires least attention.

In nutshell, the prioritization of failure causes allows system analysts to pinpoint the most vulnerable and high-risk components in the milling unit of sugar industry. The critical failure causes with top priorities should be addressed promptly, either by reducing or eliminating them, in order to improve overall system availability ultimately leading to better system reliability and prolonged operational life. The findings will be useful to develop an optimized maintenance policy, to enhance production efficiency and to reduce maintenance costs allowing sugar industries to allocate resources effectively and avoid unnecessary expenditures on low-priority issues. A well-maintained milling unit not only boosts overall productivity but also ensures a stable sugar supply, contributing to market stability and economic growth in sugar producing regions.

I. Managerial implications

Risk analysis of milling unit in the sugar industry often relies on uncertain data and subjective expert assessments, which could be biased. This highlights the need for careful interpretation as the data quality variations affect decision-making. The present analysis will prove to be beneficial for managers, to plan suitable maintenance policies, reduce maintenance and operational cost, and ensure long-term system availability of the sugar industry. Some of the managerial implications of present study are as follows:

- It helps in identifying the risky components of complex industrial systems using subjective judgments of experts.
- It prioritizes the key failure causes of an industrial system in a more promising way in the environment of uncertainty / subjective judgments.
- It helps to plan optimal maintenance strategies for the considered system for maintaining high availability of the industry.
- It helps to reduce maintenance costs by minimizing unplanned downtimes.
- It helps to enhance productivity of the considered system and overall industry.

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