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Development of a Fuzzy Risk Model for Criticality Analysis of TSP Complex Limited

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ABSTRACT

Assets failure is widely considered as one of the main causes of major accidents in chemical industries such as fires, explosions, and toxic gas releases. Asset criticality analysis is vital to prevent such accidents. This paper aims to model the asset criticality using traditional risk-based maintenance (RBM) and fuzzy RBM model. A case study has been performed on three main plants of TSP Complex Limited. Both models have been developed considering the factors like operational impact, operational flexibility, maintenance cost, safety and environment factor. Sulfuric acid (SA) plant has 2 critical assets, 10 semi-critical assets and 18 non-critical assets and has been found in semi-critical condition. On the other hand phosphoric acid (PA) plant and water treatment (WT) plant have been found as non-critical state as they have no critical assets. A fuzzy critical surface has been developed describing the transitional conditions from one criticality level to another criticality level. The proposed model can be used to prioritize the assets according to their critical value which enables to prepare the precedence list for taking action. This model is also applicable to other industries.

1. Introduction

In developing countries like Bangladesh, main focus is given on greater production. Owners take the regulatory compliances and associated expenses as constraining to productivity. The scenario is changing but not at a promising rate [1]. Chemical companies handle many hazardous materials and as a result, they can be classified as a high-risk industry. The complexities in managing chemical assets have led to many major accidents because of the frequent risks that accompany their process operations. This study emphasizes on the use of fuzzy logic to develop a tool for prediction of accidents in the chemical industries. With suitable risk identification model and risk control model accidents can be significantly mitigated. Though there are some lack of consensus regarding the selection of safety models to be used in risk identification, it will be advantageous in building more applicable risk models using a different approach like fuzzy logic.

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Very few researches have been done on safety performance using a fuzzy approach. Azadehaet al. designed a fuzzy expert system for performance assessment of health, safety, environment (HSE) and ergonomics system factors in a gas refinery in which they introduced an integrated HSE and ergonomic expert system through fuzzy logic whereas previous studies had introduced HSE expert system [2]. The importance of this study stems from the current lack of formal integrated methodologies for interpreting and evaluating performance data for HSE and ergonomics. Tah and Carr presented a methodology for evaluating the risk exposure, considering the consequences in terms of time, cost, quality, and safety performance measures of a project based on fuzzy estimates of the risk components [3]. Grassiaet al. integrated an estimative approach based on the fuzzy logic theory, which permits more coherence in the evaluation process, producing a very suitable final rank of hazardous activities [4].

A case study is performed on TSP Complex Limited to check the proposed model. Triple Super Phosphate Complex Limited (TSPCL) is a public sector enterprise under the administrative control of Bangladesh Chemical Industrial Corporation (BCIC), one of the largest public sector corporation of the country having big and medium sized industries covering at present nitrogenus and phosphatic fertilizer, paper, cement, chemical sanitary ware etc. The industry mainly produces Triple Super Phosphate (TSP) fertilizer, also sulfuric acid and phosphoric acid as intermediate product and gypsum as by-product. TSP Complex Limited consists of sulfuric acid plant, phosphoric acid plant, water treatment plant, TSP plant and SSP plant. Among them, sulfuric acid (SA) plant, phosphoric acid (PA) plant and water treatment (WT) plant are the main plants that are considered in this study.

The objective of this paper is to develop a framework to predict different types of hazards in industries when sufficient relevant data are not available. It also includes development of a fuzzy criticality assessment model along with traditional risk-based maintenance (RBM) model, comparing both model to help management and authority to take decisions regarding critical assets with more accuracy.

2. Methodology

2.1 Framework of the working process

At the beginning, all data are collected from TSP Complex Limited under BCIC (Bangladesh Chemical Industrial Corporation). A fuzzy RBM model is developed for asset criticality assessment. After that, the fuzzy RBM model is compared with the traditional RBM model to prioritize the assets based on their criticality level. All the operations are performed to take necessary actions for mitigating risks of the particular industry.

2.2 The RBM model

Maintenance management techniques have been a major process of transformation, from focusing on periodic overhauls to the use of condition monitoring, reliability-centered maintenance and expert systems. Nowadays, risk-based maintenance methodologies are starting to emerge.Risk-based maintenance method provides a tool for maintenance planning and decision making to reduce the probability of failure and its consequences. It is a methodology for determining the most economical use of maintenance resources [5]. This is done so that the maintenance effort across a facility is optimized to minimize any risk of a failure. The resulting maintenance program maximizes the reliability of the equipment and minimizes the cost of the total maintenance cost.
Different types of data were collected for this study:

1. Operational impact (OI)
2. Operational flexibility (OF)
3. Maintenance cost (MC)
4. Impact on safety and environmental factor (ISE)

The assessment of critical value (CV) for each asset is determined from the product of the failure frequency (FF) and effect (E) of failure. Mathematically,

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

2.3 The FRBM model

Fuzzy logic is a form of many-valued logic in which the truth values of variables may be any real number between 0 and 1 inclusive. It is employed to handle the concept of partial truth, where the truth value may range between completely true and completely false [6]. A fuzzy inference system (FIS) uses a collection of fuzzy membership functions and rules, instead of Boolean logic. In fuzzy theory, a fuzzy set A, of universe X, is thus defined by function, $\mu_A(x): X \rightarrow [0, 1]$ where,

$\mu_A(x) = 1$, if x is totally in A;

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

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

In this study, Mamdani fuzzy inference system is used to build a fuzzy inference system. In fuzzy modeling, the input-output variables are defined as linguistic variables. The fuzzification process decomposes the input and output variables and maps the crisp values into fuzzy sets. Figure 1 represents a typical fuzzy inference system.

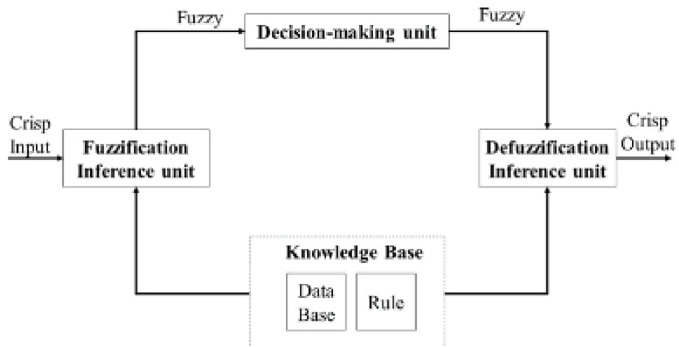

Figure 1. Fuzzy inference system.

A membership function (MF) is a curve that specifies the degree to which a given input belongs to a set. These functions are used in fuzzification and defuzzification steps of a fuzzy logic system to map the non-fizzy input values to fuzzy linguistic terms and vice versa [7]. There are different forms of membership functions: triangular, trapezoidal, gaussian etc. Equation 2 [13,14] and equation 3 [12] represent trapezoidal membership function and triangular membership function respectively.

$$\text{trapezoid}(x; a, b, c, d) = \begin{cases} 0, & x \leq a \\ \dfrac{x-a}{b-a}, & a \leq x \leq b \\ 1, & b \leq x \leq c \\ \dfrac{d-x}{d-c}, & c \leq x \leq d \\ 0, & d \leq x \end{cases} \tag{2}$$

$$\text{triangle}(x; a, b, c) = \begin{cases} 0, & x \leq a. \\ \dfrac{x-a}{b-a}, & a \leq x \leq b. \\ \dfrac{c-x}{c-b}, & b \leq x \leq c. \\ 0, & c \leq x. \end{cases} \tag{3}$$

The last step in the fuzzy inference system is defuzzification. Defuzzification is the process of weighting and averaging the outputs from all the individual fuzzy values, resulting in one single output decision or signal [8]. The final output of the system is the weighted average of all the criticality output.

2.4 Data analysis

In this study, all data are collected from TSP Complex Limited. For this study, the main three plants- sulfuric acid (SA) plant, phosphoric acid (PA) plant and water treatment (WT) plant are considered. By discussing with the chief plant engineer of the respective plants, all the data are taken. Some of the data related to maintenance and operations are also collected from the head of maintenance and operational engineer. All the RBM factors are localized and an asset criticality chart is prepared to perform traditional RBM model and fuzzy RBM model.

2.4.1 Factor values for RBM model

A Delphi team was formed with six members including maintenance engineer, operational engineer, process engineer, health and safety engineer and academician. All the RBM factors such as *OI, OF, MC and ISE* were localized and an asset criticality chart was prepared to perform two round of Delphi. The Delphi team established a classification and scale for the frequency of failure (F) for the different assets of a particular unit of the plant. The failure frequency scales are classified according to the number of failures per year [5,10], as listed in Table I.

Table I: Classification and scales of frequency and effect

Failure Frequency (FF)	Failures/year	Model scale
Poor	Greater than 4	4
Average	2-4	3
Good	1-2	2
Excellent	Less than 1	1

There are some operational impacts on the plant for any failure. The impacts are classified in five scales from immediate plant shutdown to no significance impact in operation is shown in Table II.

Table II: Classification and scales of operational impact factor

Operational Impact (OI)	Effect	Model scale
Extremely High	Immediate plant shut down	10
Very High	Partial plant shut down	6
High	Impact on production level or quality	4
Average	Operational cost associated with unavailability	2
Low	No significant impact in operation	1

Operational flexibility for the assets is categorized depending on the availability of the spare parts for a failure. OF is classified into three scales and tabulated in Table III.

Table III: Classification and scales of the operational flexibility factor

Operational Flexibility (OF)	Effect	Model scale
High	No spare/no alternative	4
Average	Spare shared	2
Low	Spare available	1

Each failure occurrence involves some unavoidable maintenance cost. So, the maintenance cost is localized in three scales as high, medium and low which may vary depending of the type of the industry and the economic condition of the country. The scales are listed in Table IV.

Table IV: Classification and scales of maintenance cost factor

Maintenance Cost (MC)	Effect	Model scale
High	>18 lakhs taka	2
Medium	10 to 18 lakhs taka	1.5
Low	<10 lakhs taka	1

Failure of different assets has a large impact on safety of the industry and the environment around the industry. Every industry should maintain proper environment condition and work condition. Six scales are assigned for the impact of safety and environment factor ranging from 0 to 8 which are listed in Table V.

Table V: Classification and scales of impact on safety and environment factor

Impact of safety and environment (ISE)	Effect	Model scale
Extremely High	Impact on internal and external human safety requiring notification to public institutions	8
Very High	Irreversible environmental affection	6
High	Impact operation facilities causing severe damage	4
Average	Minor accidents and incidents	2
Low	Environmental affection without laws violation	1
Very Low	No impact to human, environment nor operation facilities	0

Replacing the highest values for all the factors in equation 1, the maximum critical value for an asset is set to be 200. Three ranges are assigned to identify the criticality level for an asset in Table VI [11].

Table VI: Classification of criticality level

Asset Criticality level	Critical value
Critical	CL>100
Semi-Critical	40<CL<100
Non Critical	CL<40

2.4.2 Factor values of FRBM model

To develop the fuzzy logic expert system based intelligent model for the determination of the asset risk value, two parameters namely failure frequency (FF) and effect (E) were used as input parameters and criticality level (CL) was the output meter.

Table VII: Classification and the scale of assets

Linguistic variables	**Linguistic value**	**Linguistic Terms**	**Numerical range**
Failure Frequency (FF)	Excellent	E	[0 0 1 1.5]
	Good	G	[0.75 2 2.5]
	Average	A	[1.75 3 3.5]
	Poor	P	[2.75 4 4]
Effect (E)	Very Low	VL	[0 0 10 20]
	Low	L	[10 20 30]
	Medium	M	[20 30 40]
	High	H	[30 40 50]
	Very High		[40 50 60 60]
Criticality Level (CL)	Non Critical	NC	[0 0 30 50]
	Semi Critical	SC	[35 70 110]
	Critical	C	[100 200 200]

The different fuzzy membership functions give different fuzzy risk outputs. Type of the membership function and all the fuzzy numbers are determined according to the traditional RBM factor.

Fuzzification of the input-output parameters is carried out with the help of the functions as described in equation 4-6.

$$FF(i_1) = \begin{cases} i_1, & 1 \leq i_1 \leq 4 \\ 0, & otherwise \end{cases} \tag{4}$$

$$E(i_2) = \begin{cases} i_2, & 10 \leq i_2 \leq 50 \\ 0, & otherwise \end{cases} \tag{5}$$

$$CL(o_1) = \begin{cases} o_1, & 30 \leq o_1 \leq 200 \\ 0, & otherwise \end{cases} \tag{6}$$

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*).

The fuzzy logic toolbox in MATLAB (R2016b) is used to develop the input-output membership functions according to the collected data and expert's opinion.

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,

$$\mathrm{N} = \mathrm{m} \times \mathrm{n} \tag{7}$$

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);

By using the equation 7, A total of twenty ‘if-then’ fuzzy rules are formed based on expert’s knowledge and experience which are tabulated in Table VIII.

Table VIII: Fuzzy rules

Rules	**Input variables**		**Output variables**
Serial No.	**Failure Frequency (FF)**	**Effect (E)**	**Criticality Level (CL)**
1	Poor	Very Low	Non Critical
2	Poor	Low	Semi Critical
3	Poor	Medium	Semi Critical
4	Poor	High	Critical
5	Poor	Very High	Critical
6	Average	Very Low	Non Critical
7	Average	Low	Semi Critical
8	Average	Medium	Semi Critical
9	Average	High	Critical
10	Average	Very High	Critical
11	Good	Very Low	Non Critical
12	Good	Low	Non Critical
13	Good	Medium	Semi Critical
14	Good	High	Semi Critical
15	Good	Very High	Semi Critical
16	Excellent	Very Low	Non Critical
17	Excellent	Low	Non Critical
18	Excellent	Medium	Non Critical
19	Excellent	High	Non Critical
20	Excellent	Very High	Semi Critical

3. Results and Discussion

3.1 Criticality level of assets

The sulfuric acid (SA) plant, the phosphoric acid (PA) plant and the water treatment (WT) plant are taken into consideration to determine asset criticality. The critical value for each asset of all three plants is measured using RBM model and then compared with the proposed fuzzy model.

3.1.1 Sulfuric acid (SA) plant

The sulfuric acid plant has 30 assets which are involved in the production operation of sulfuric acid. The assets are tabulated in Table IX. The effect of each of the asset present in SA plant is calculated using equation 1. Waste heat boiler E1201 has the highest effect due to its high operational impact and high impact on safety and environment on any failure. On the other hand, boiler feed water pump J1202A, boiler feed water pump J1202B, boiler feed water pump J1202C have the minimum result. Figure2 shows the graphical representation of both RBM and FRBM value.

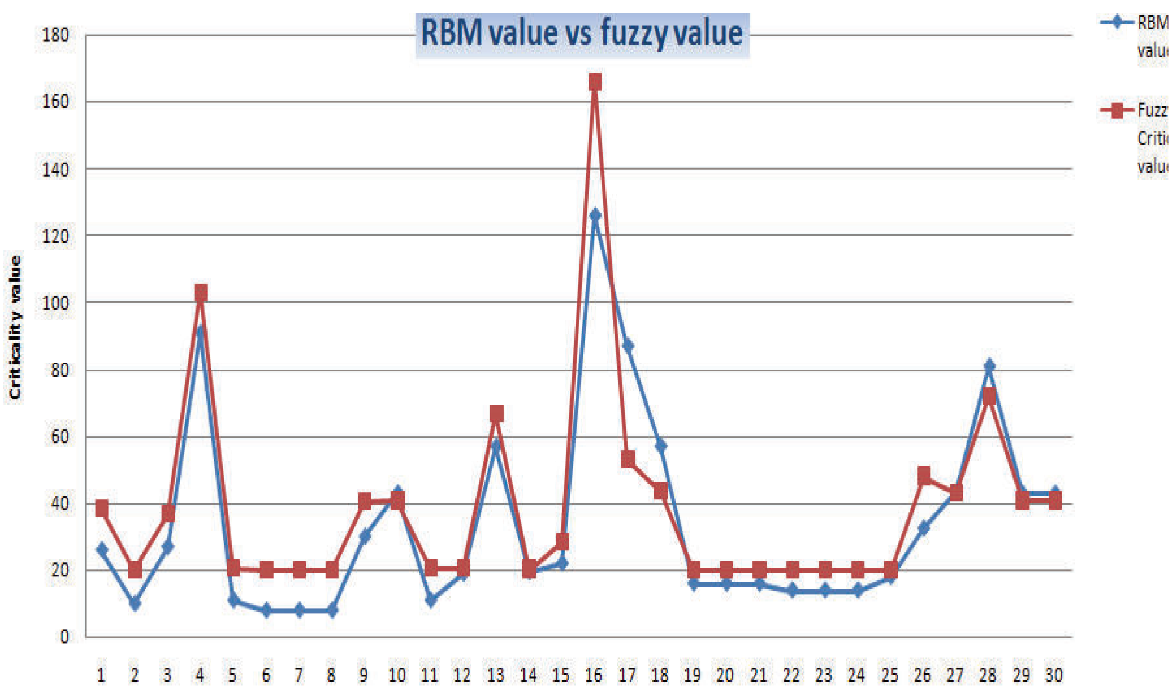

Figure 2. Graphical representation of both RBM and fuzzy critical value.

3.1.2 Phosphoric acid (PA) plant

The phosphoric acid (PA) plant has 25 assets which are involved in the process operation of phosphoric acid plant. The assets are tabulated in Table X. The result of each of the asset present in PA plant is calculated using equation 1. Circulation pump J2501 and slurry pump J2301 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, pre-mixer V2302 has the minimum result. Figure 3 shows the graphical representation of both RBM and FRBM value.

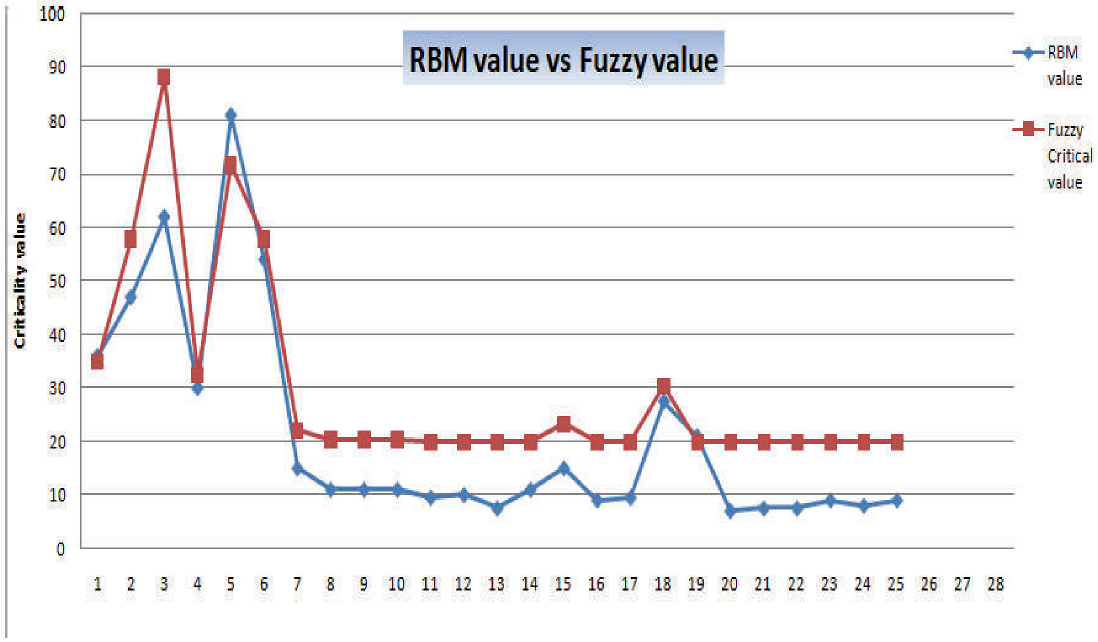

Figure 3. Graphical representation of both RBM and fuzzy critical value.

3.1.3 Water treatment (WT) plant

The water treatment has 34 assets which are involved in the process of water treatment process operation. The assets are tabulated in Table XI. The result of each of the asset present in PA plant is calculated using equation 1. Demiwater valve V4101 has the highest result due to its low operational impact and high impact on safety and environment on any failure. Figure4 shows the graphical representation of both RBM and FRBM value.

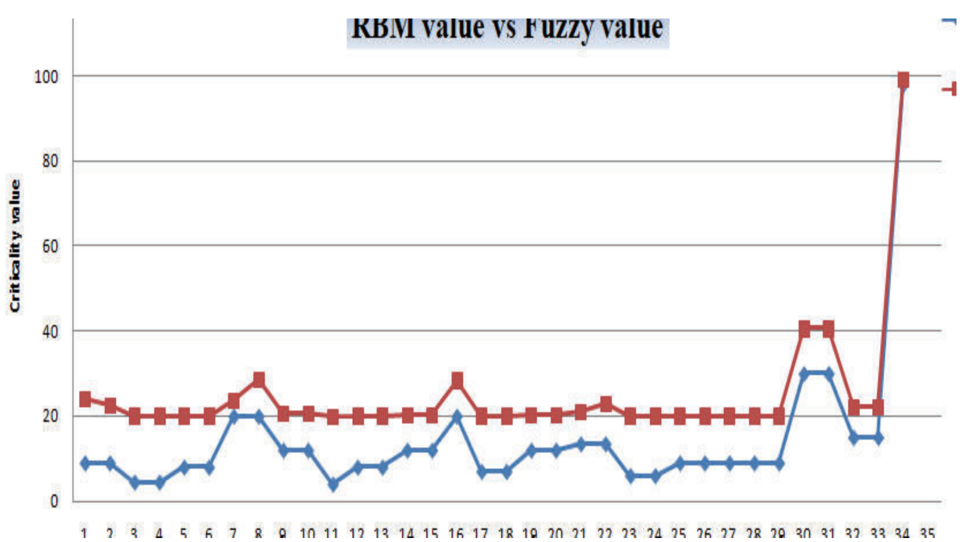

Figure 4. Graphical representation of both RBM and fuzzy critical value.

3.2 Comparison of Fuzzy Critical Value and RBM Critical Value

Table IX, table X and table XIlisted below represent the comparison of fuzzy critical value and RBM value for SA plant, PA plant and WT plant. Criticality level in both cases is almost same. Some of them show different results. It means that fuzzy RBM is more sensitive than the traditional RBM [10, 11]. The precision of the data will help to enrich the accuracy level of the proposed model.

Table IX: Comparison of fuzzy critical value and RBM critical value for SA plant

Serial No.	Name of the equipment	Critical value CV=FF×E	Criticality level	Fuzzy Critical value	Fuzzy Critical level
1	Sulfur Pit V1202	26	NC	38.3	NC
2	Sulfur Melting Coil E1202	10	NC	19.9	NC
3	Sulfur Furnace D1201	27	NC	36.5	NC
4	Waste Heat Boiler E1201	91	SC	103	C
5	Deaerator V1203	11	NC	20.3	NC
6	Boiler Feed water Pump J1202A	8	NC	19.9	NC
7	Boiler Feed water Pump J1202B	8	NC	19.9	NC
8	Boiler Feed water Pump J1202C	8	NC	19.9	NC
9	Gas Filter P1201	30	NC	40.5	SC
10	Converter F1301	43	SC	40.6	SC
11	Heat Exchanger E1301	11	NC	20.3	NC
12	Economizer E1302	19	NC	20.3	NC
13	Economizer E1303	57	SC	66.7	SC
14	A.T Tower F1401	19.5	NC	20.1	NC
15	A.T Pump Tank V1401	22	NC	28.2	NC
16	A.T Circulation Pump J1401	126	C	166	C
17	A.T Acid Cooler E1401	87	SC	53.1	SC
18	Product Cooler E1403	57	SC	43.6	SC
19	Product Transfer Pump J1403A	16	NC	19.9	NC
20	Product Transfer PumpJ1403B	16	NC	19.9	NC
21	Product Transfer Pump J1403C	16	NC	19.9	NC
22	Storage Tank V1403A	14	NC	19.9	NC
23	Storage Tank V1403B	14	NC	19.9	NC
24	Storage Tank V1403C	14	NC	19.9	NC
25	Air Fan K1301	18	NC	19.9	NC
26	Air Blower K1201	32.5	NC	47.9	SC
27	Drying Tower F1402	43.5	SC	43.1	SC
28	D.T Pump Tank V1402	81	SC	71.8	SC
29	D.T Circulation Pump V1402	43	SC	40.6	SC
30	D.T Acid Cooler E1402	43	SC	40.6	SC

Table X: Comparison of fuzzy critical value and RBM critical value for PA plant

Serial No.	Name of the equipment	Criticalvalue CV=FF×E	Criticality level	Fuzzy Critical value	Fuzzy Critical level
1	Bucket Elevator O2105	36	NC	34.9	NC
2	Pre-mixer V2302	47	SC	57.9	SC
3	Digester V2303	62	SC	88.2	SC
4	Crystallizer V2304	30	NC	32.5	NC
5	Filter M2401	81	SC	71.8	SC
6	Crystallizer Exhaust Fan K2303	54	SC	57.9	SC
7	Vacuum Pump K2403	15	NC	22.1	NC
8	Heat Exchanger E2301	11	NC	20.3	NC
9	Cooling Blower K2302	11	NC	20.3	NC
10	Heat exchanger E2302	11	NC	20.3	NC
11	Evaporator V2501	9.5	NC	19.9	NC
12	Circulation Pump J2501	10	NC	19.9	NC
13	Condenser V2402	7.5	NC	19.9	NC
14	Filtrate Storage Tank V2504	11	NC	19.9	NC
15	Slurry Pump J2301	15	NC	23.3	NC
16	Gypsum Slurry Tank V2414	9	NC	19.9	NC
17	R.A Tank V2409	9.5	NC	19.9	NC
18	Sealed Tank V2405	27.5	NC	30.3	NC
19	Gypsum Slurry Pump J2405	21	NC	19.9	NC
20	Density Measuring Box V2408	7	NC	19.9	NC
21	Receiver Tank V2403	7.5	NC	19.9	NC
22	Slurry Distributor V2401	7.5	NC	19.9	NC
23	Cape Blower K2401	9	NC	19.9	NC
24	Cloth Drying Fan K2402	8	NC	19.9	NC
25	Aeration Blower K2205	9	NC	19.9	NC

Table XI: Comparison of fuzzy critical value and RBM critical value for WT plant

Serial No.	Name of the equipment	Critical value CV=FF×E	Criticality level	Fuzzy Critical value	Fuzzy Critical level
1	Alum Pump V4102A	9	NC	19.2	NC
2	Alum Pump V4102B	9	NC	19.2	NC
3	Caustic Aid Pump V4103A	4.5	NC	19.9	NC
4	Caustic Aid Pump V4103B	4.5	NC	19.9	NC
5	Coagulated Aid Pump V4104A	8	NC	19.9	NC
6	Coagulated Aid Pump V4104B	8	NC	19.9	NC
7	Caustic Soda Pump J4203A	20	NC	23.5	NC
8	Caustic Soda Pump J4203B	20	NC	23.5	NC
9	Cleared Water Pump J4105A	12	NC	20.6	NC
11	Back Washing Pump J4108	4	NC	19.8	NC
12	Bleach Dissolving Pump V4117A	8	NC	19.9	NC
13	Bleach Dissolving Pump V4117B	8	NC	19.9	NC
14	Sodium Phosphate Pump V4113A	12	NC	20.1	NC
15	Sodium Phosphate Pump V4113B	12	NC	20.1	NC
16	Vacuum Pump J4204	20	NC	28.3	NC
17	Alum Dosing Pump J4113A	7	NC	19.9	NC
18	Alum Dosing Pump J4113B	7	NC	19.9	NC
19	Makeup Water Pump J4106A	12	NC	20.1	NC
20	Makeup Water Pump J4106B	12	NC	20.1	NC
21	Filtered Water Pump J4107A	13.5	NC	21	NC
22	Filtered Water Pump J4107B	13.5	NC	19.9	NC
23	Intermediate Pump J4111A	6	NC	19.9	NC
24	Intermediate Pump J4111B	6	NC	19.9	NC
25	Regeneratıon Pump J4120	9	NC	19.9	NC
26	Sulfuric Acid Pump J4122A	9	NC	19.9	NC
27	Sulfuric Acid Pump J4122B	9	NC	19.9	NC
28	Sulfuric Acid Pump J4122C	9	NC	19.9	NC
29	Sulfuric Acid Pump J4122D	9	NC	19.9	NC
30	Cooling Water Pump J4203A	30	NC	40.5	SC
31	Cooling Water Pump J4203B	30	NC	40.5	SC
32	Process Water Pump J4109A	15	NC	22.1	NC
33	Process Water Pump J4109B	15	NC	22.1	NC
34	Demiwater Valve V4101	98	SC	99.1	C

3.3 Fuzzy criticality level and risk matrix

The unified risk number of the topping unit is calculated by equation 3 and the unified Fuzzy risk calculated by equation 2 for failure of the topping unit. The topping unit is entirely in the semi-critical condition according to the criticality levels mentioned in table VI. A criticality surface is a useful tool for qualitative criticality assessment including categorizing the criticality levels for controlling measures. The Surface Viewer is a graphical interface that examines the output surface of an FIS for any one or two inputs [9]. Fuzzy criticality surface provides more precise and reliable results than the traditional criticality matrix. Figure 5 represents fuzzy criticality surface. It is observed that fuzzy criticality surface is more suitable for the practical applications to overcome uncertainties in contrast to the traditional one.

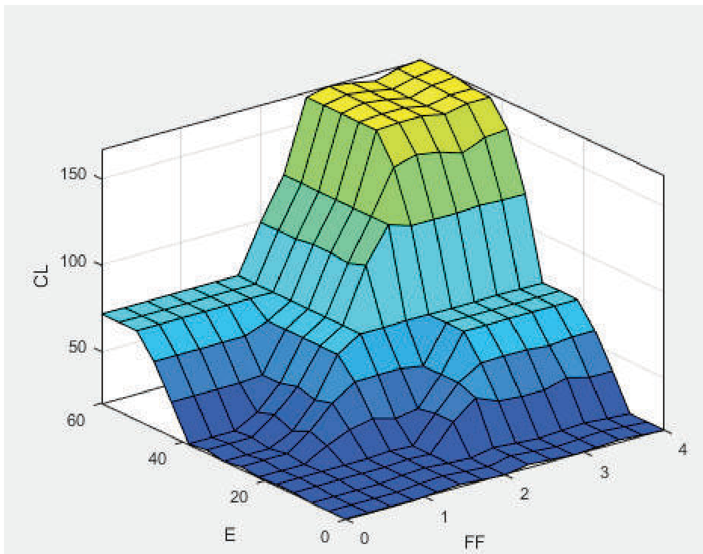

Figure 5. Fuzzy criticality surface

4. Conclusion

In this work, criticality modeling of process operations in chemical plants is proposed using risk-based maintenance (RBM) and fuzzy RBM approaches. The proposed model is strongly dependent on the real situation of the process operations. The case study has been performed in Chittagong TSP complex to check the proposed model. Assets of the three units of the plant were taken into consideration for the study of the model and Delphi method was used for the calculation of the information of each asset. Criticality level of each asset was selected from their corresponding risk value. The findings of the present study are summarized as follow:

- SA Plant: 2 critical assets, 10 semi-critical assets and 18 non-critical assets. It is in semi-critical state.
- PA Plant:No Critical asset, 4 Semi-critical assets and 21 Non-critical assets. It is in non-critical state.
- WT Plant:No Critical asset, 3 Semi-critical assets and 31 Non-critical assets. It is in non-critical state.

The proposed model has been compared with the traditional RBM approach efficiently and results obtained good enough to converge with the traditional one. The deviations in the comparison can be minimized by varying the membership functions and fuzzy rules. This model can be an excellent tool for the management to take the maintenance strategy for the plant which will reduce risk of the entire plant.

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