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QUALITY ENHANCEMENT IN MAINTENANCE PLANNING THROUGH NON-IDENTICAL FMECA APPROACHES

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Abstract: *The purpose of this paper is to investigate the scope of reliability improvement of aluminium wire rolling mill. This paper addresses the performance reliability of continuous process industry of interest to many applications in maintenance planning where multi-attribute decision making (MADM) approaches are very useful. The paper addresses the process of discriminating critical components through substantial shop-floor failure data. The research work narrates a method for evaluating risk priority number (RPN) traditionally. Moreover, the maintainability criticality index (MCI) for each failure cause of identified critical components is evaluated through two disparate MADM failure models: technique for order preference by similarity to ideal solution (TOPSIS) and preference section index (PSI) to overcome the limitations of more traditional approaches. The primary findings of this research work are to enhance quality in planning the maintenance activities of critical components of targeted process industry through traditional as well as non-traditional failure analysis models. The research work is focused on potential failure causes of critical components like; bearings, gears, and shafts of aluminium wire rolling mill which are commonly representing the most critical components in a large range of industrial processes including aluminium wires. The proposed work will illustrate the working lives of components and associated failures. It will help to elucidate maintenance issues of major process industries and recommended deliverable keys.*

Keywords: *Shop-floor Failure Data Analysis, FMECA, Reliability Engineering, Maintenance Planning, TOPSIS, PSI, Process Industry*

1. Introduction

The reliability and maintenance issues are very crucial to all major process industries like rolling and textile mill, dairy and fertilizer plant, sugar and paper industry. Out of various process industries stated as earlier, the aluminium wire rolling mill is selected for study because aluminium transmission wire market size was about 6.5 lacs metric tons in volume terms in financial year 2015 in India (IEEMA's 68th annual report 2014-

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15). It is likely to grow at a compound annual growth rate (CAGR) of 13.5% between financial year 14-19 due to inter-regional transmission network expansion, infrastructure, industrial demand and Government of India's "power for all" initiative (Indian electrical equipment industry mission plan 2012-22). It has been observed from the facts about aluminium wire rolling mill that approximately 20 to 25 % of possible production time goes towards maintenance of equipment i.e. loss of reliability due to poor maintenance practices. Therefore, it is vital to enhance quality of current control practices associated with maintenance system with a view to increasing the effective utilization of resources with little or no cost. In fulfillment of reaching this goal, it is necessary to examine and scan historical failure data. This will help to execute more modified FMECA based maintenance plan.

Searching in the literature review, it seems many researchers have done various modifications for improvement of FMECA for different process industries. It is based on the systematic brainstorming session to recognize the failures which may occur in system or process (Vandenbrande, 1998). It is devoted to determining the design reliability by considering the potential causes of failures and their effects on the system under study (Dhillon, 1985 and O'Conner, 2002). Hwang and Yoon (1981) highlighted the importance of MCDM, where multiple and conflicting criteria are under consideration in different area like personal, public, academic or business contents. Gilchrist (1993) introduced economic considerations into his modified FMECA model while incorporating failure cost to form an expected cost model; Bevilacqua et al. (2000) incorporated a new factor called operating conditions in the field of a power plant; Braglia (2000) developed a new tool for reliability and failure mode analysis by integrating the conventional aspects of FMECA with economic consideration. Xu et al. (2002) presented FMEA of engine system based on fussy assessment concept. Braglia et al. (2003) presented fuzzy TOPSIS. Sahoo et al. (2004) showed that FMECA is a basic part of the maintenance plan and shows a strong tool to evaluate and improve system reliability with reduction of overall maintenance cost. Sachdeva et al. (2009) presented a multi-criteria decision-making approach to prioritizing failure modes for paper industry using TOPSIS. Maniya and Bhatt (2011) presented the multi-criteria decision making method to solve problems of facility layout design selection based on preference selection index (PSI) method. Zammori and Gabbrielli (2011) presented MCDM based advanced FMCEA by integrating it with analytical network process (ANP) and reported case study to show comprehensive criticality analysis. Liao et al. (2012) proposed cloud model based FMECA to prioritize potential failure causes of power transformer with numerical illustrations. Feili et al. (2013) discussed FMEA to determine, classify and analyze common failures of major components of geothermal power plant. Adhikary and Bose (2014) presented multi-factor FMECA through COPRAS-G method for coal-fired thermal power plant. Fragassa et al. (2014) presented an advanced application of FMECA used in integration with other quality tools (FTA, RDA) for recognizing critical functions on diesel intake manifold in a view to optimizing industrial processes where several parts are realized in aluminium (including wires). Mobin et al. (2015) proposed an integration of a fuzzy analytic hierarchy process (FAHP) and the complex proportional assessment of alternatives to Grey relations (CORPAS-G) to prioritize suppliers in an Iranian manufacturing industry. Zhang (2015) deduced closeness coefficient for failure modes by integrating both subjective and objective weights to avoid over or under estimation though fuzzy TOPSIS. Chanamool and Naenna (2016) highlighted the importance of Fuzzy FMEA to prioritize and assess failures associated with working process of hospital's emergency department. Mittal et al. (2016) described the ranking of major problems of plywood industries through multiple-attribute decision-making (MADM) approach based fuzzy TOPSIS. Rathi et al. (2016) presented fuzzy MADM for prioritizing six sigma projects through fuzzy VIKOR in the Indian auto sector. Rastegari et al. (2017) addressed condition-based maintenance and its implementation with vibration monitoring techniques in order to plan maintenance activities of the spindle units of the automobile gear box manufacturing company in Sweden.

Literature review seems that past researchers have not yet considered the instance of planning the maintenance activities through both traditional and non-traditional ways in consultation with substantial historical failure data. This research work emphasized non-traditional FMECA models to enhance quality in maintenance practices effectively over current control practices. Table 1 shows the proposed contribution to present a strong case in developing the maintenance plan effectively to any kind of process industries as a whole.

Table 1. Comparison of some researcher's contributions with presented work

	Feili et.al	**Sachdeva et al.**	**Adhikari and Bose**	**Presented Work**
Targeted Process Industry	Geothermal Power Plant	Paper manufacturing unit	Thermal power plant	Aluminium wire rolling mill
Methods	Traditional FMECA with only three basic criteria	TOPSIS with weighted attributes including maintainability, economic cost and safety criteria with basic criteria	COPRAS-G with weighted attributes including some process criteria with basic criteria	(i) Traditional FMECA (ii) TOPSIS with weighted attributes including maintainability, economic cost and safety criteria with basic criteria (iii) PSI with concept of statistics rather than assignment of weight attributes also.
Novel contribution	Drawback of multiplication of scores to find RPN with limited basic criteria	Only weighted attributes presented	Only weighted attributes presented	Criticalities are presented based on basic RPN, weighed attributes as well as with the concept of statistics where subjective weight is not required to prove competency.

2. Overview of rolling mill and discriminating its critical components

In this work, research is focused on reliability and maintenance issues of the identified aluminium wire rolling mill plant. The Figure 1 highlights the understanding of process flow of rolling mill plant and functional details of it as discussed below:

1) Furnaces**:** In aluminium rolling mill, there are two units of furnaces of 12 ton and 15 ton each. Both the

furnaces used furnace oil to melt aluminium ingots to a temperature range of about 750-800 ^{0}C to convert it into liquid aluminium.

2) Caster Wheel**:** It is about 1400 mm in diameter made of cast iron through which liquid aluminium is feed by continuous casting process to convert it into 40 mm diameter bar. In this process, water spray is used as cooling medium.

3) Rolling Machine**:** It is the main component of rolling mill where aluminium wire drawn through fifteen stands in series to reduce the diameter of the wire to 6 mm.

Figure 1. Rolling mill process flow

In this paper, the work is emphasized on fifteen stands of rolling machine, where reliability and maintenance issues played a crucial role. The rolling machine consists of thirty-one components as listed in Table 2 whose comprehensive historical failure data are recorded and analyzed in a view to discriminating the most critical components based on their downtime and frequency of failures.

Table 2. Part Wise Failure Data of Aluminium Wire Rolling Mill

Part No.	Part Name	Run time (Hrs.) (24 X7)	Up Time (Hrs.)	Down Time (hrs.)	Freq. of Failure(n)
1	Primary Shaft	8472	8388	84	21
2	Secondary Shaft	8472	8432	40	20
3	Bearing Secondary Housing	8472	8448	24	12
4	Primary Bevel gear Spigot end	8472	8394	78	23
5	Primary Bevel gear Taper end	8472	8400	72	18
6	Secondary Bevel gear Ring	8472	8418	54	27
7	Pin for Entry Guide Roller	8472	8447	25	154
8	Main Chuck Nut for primary shaft	8472	8446	26	13
9	Spline Side Chuck Nut	8472	8452	20	10
10	Chuck Nut for BRG	8472	8448	24	12
11	Bottom Nut for secondary shaft	8472	8444	28	14
12	Shear Pin for Drive Assembly	8472	8472	0	0
13	Top Nut for secondary shaft	8472	8469	3	36
14	Lock Nut Bearing side	8472	8461	11	11
15	Cylinder Pin for Primary Assembly	8472	8412	60	15
16	Special Bolt for Secondary	8472	8472	0	0
17	Spacer for Outer	8472	8472	0	0
18	Spacer for Inner	8472	8472	0	0

Table 2. Part Wise Failure Data of Aluminium Wire Rolling Mill (continued)

Part No.	Part Name	Run time (Hrs.) (24 X7)	Up Time (Hrs.)	Down Time (hrs.)	Freq. of Failure(n)
19	Secondary Block Housing	8472	8472	0	0
20	Bearing Housing 110ϕ for Primary	8472	8456	16	8
21	Bearing Housing 120ϕ for Primary	8472	8448	24	12
22	Bearing No. 32308	8472	8136	336	168
23	Bearing No. 30310	8472	8140	332	166
24	Bearing No. 6213	8472	8136	336	168
25	Bearing No. 32222	8472	8000	472	118
26	Oil Seal. 701010 (replace with P.no.24)	8472	8472	0	0
27	Oil Seal. 608010 (replace with P.no.23)	8472	8472	0	0
28	Oil Seal. 629010 (replace with P.no.22)	8472	8472	0	0
29	Coiler Bolt	8472	8472	0	18
30	Casting Bolt	8472	8436	36	12
31	Coupler Bolt	8472	8456	16	8

Figure 2 shows the criticality analysis based on downtime and frequency of failures. The analysis of the data interpreted the major critical components as bearings - designation number 32308, 30310, 6213, 32222 (70 %), gears – primary & secondary bevel gears with spigot and taper end (4 %) and shafts – primary & secondary (4%).

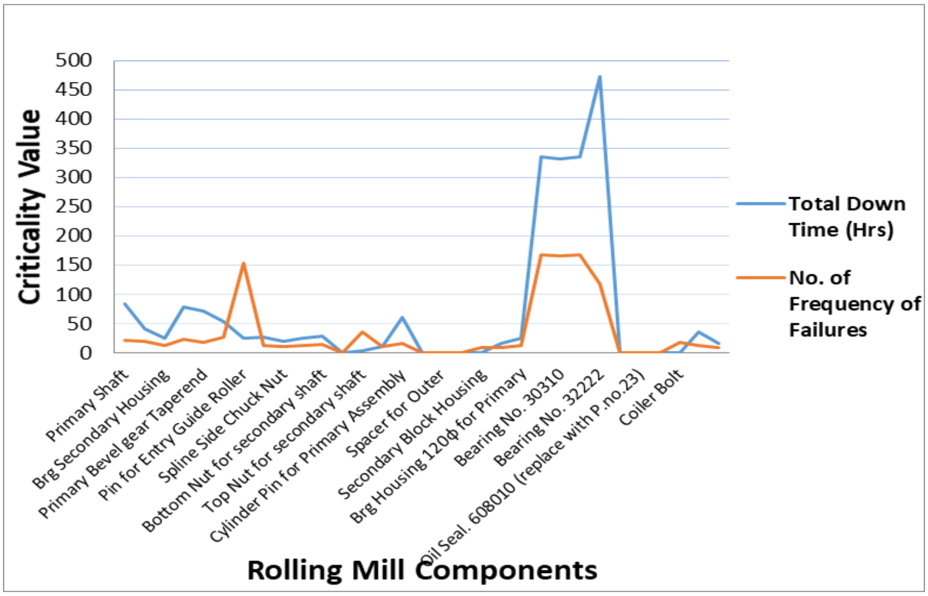

Figure 2. Part-wise downtime and frequency of failure

These components are commonly representing the most critical components in a large range of industrial processes. The remaining components cover of about 22 % reliability loss with no significant effect.

3. Failure analysis models

3.1. General FMEA

In this research, the MADM based TOPSIS and PSI FMECA models are employed to major critical components as identified through criticality analysis earlier: bearings (70 %), gears (4 %) and shafts – primary and secondary (4 %) of aluminium rolling mill. Failure mode effect analysis (FMEA) for these components is prepared based on historical failure data and questionnaires and discussion to shop-floor operators, managers, maintenance personnel. Table 2 shows the FMEA of identified critical components.

Table 3. FMEA of identified critical components

Key Process Input	**Potential Failure Mode**	**Potential Causes**	**Potential Failure Effects**	**Notation**
What is the Process Input?	In what ways can the Process Input fail?	What causes the Key Input to go wrong?	What is the impact on the Key Output Variables once it fails (customer or internal requirements)?	
Rolling Mill Bearing Failure	Bearing high temperature	Improper lubrication & defective sealing	Bearing gets jammed/Bearing housing jammed	C1
	Bearing corrosion	Higher speed than specified	Increase in vibration & noise	C2
	Bearing fatigue	Design defects, Bearing dimension not as per specification	Life reduction	C3
	Roller balls wear- out	Foreign matters/particles	Sudden rise in thrust	C4
	Bearing misalignment & improper mounting	Sudden impact on the rolls	Shaft damage & Impact damage on other parts	C5
	Electrical damage	Loss of power	Operation interrupted	C6
Rolling Mill Gearing Failure	Gear teeth wear-out	Inadequate lubrication - Dirt, viscosity issues	Rough operation & considerable noise	C7
	Gear teeth surface fatigue (Pitting)	Improper meshing, case depth & high residual stresses	Gear life reduction	C8
	Gear teeth scoring	Overheating at gear mesh	Interference & backlash phenomenon	C9
	Gear teeth fracture	Excessive overload & cyclic stresses	Sudden stoppage of process plant	C10
	Gear teeth surface cold/plastic flow	High contact stresses due to rolling & sliding action of mesh	Slippage & power loss	C11
Rolling Mill Shaft (Primary & Secondary) Failure	Shaft fretting	Vibratory dynamic load from bearing	Leads to sudden failure	C12
	Shaft misalignment	Uneven bearing load	Vibration & fatigue	C13
	Shaft fracture (Fatigue)	Reverse & repeated cyclic loading	Sudden stoppage of process	C14

3.2. Assignment of scores to each failure cause

In this research study, each failure cause of three critical components (bearings, gears and shafts) are evaluated based on different criteria like: chances of failure (C), degree of detectability (D), degree of severity (S), degree of maintainability (M), spare parts (SP), economic safety (ES) and economic cost (EC). The Chances of failure (C) criteria represents the probability of frequency of failure occurs. The higher score shows higher criticality of the components. The Detection of failure (D) criteria represents the ability of shop-floor operator or maintenance personnel to detect failure through observations or by other condition monitoring aids. The higher score shows difficult to detect. The degree of severity (S) criterion indicates how the effect of failure cause is severe to component performance or service. A higher score indicates more downtime or service time required to restore the components. The Maintainability (M) criterion represents the probability of equipment to be restored back to its up state. A higher score indicates that it is difficult to maintain the components. The Spare part (S) criterion represents the availability of spares during a breakdown. The lower score shows spare parts are easily available. An economic safety (ES) criterion is referring personnel and equipment safety in the plant. A higher score represents less safety. An economic cost (EC) criterion is based on production loss cost, spare parts costs and manpower cost etc. Higher score presents higher cost.

The scores for each failure cause for every different criterion are ranked on a scale of 1 – 10. The scale of 1 to 10 refers from least to most consideration of the impact of criteria. The scores for probability of occurrence (P), degree of detectability (D),) and severity (S) are shown in Table 4, Table 5 and Table 6 respectively for traditional FMECA. The scores for chances of failure (C), degree of detectability (D), degree of maintainability (M), spare parts (SP), economic safety (ES) and economic cost (EC) for various failure causes are as per Table 4, Table 5, Table 7, Table 8, Table 9 and Table 10 respectively. It is in crisp values for both MADM models discussed here.

Table 4. Scores for chances of failure (C)

Occurrence	**Criteria for occurrence**	**Score**
Almost never	More than three year	1
Very Rare	Once every 2-3 year	2
Rare	Once every 1-2 year	3
Very Low	Once every 11-12 month	4
Low	Once every 9-10 month	5
Medium	Once every 7-8 month	6
Moderate High	Once every 5-6 month	7
High	Once every 3-4 month	8
Very High	Once every 1-2 month	9
Extremely High	Less than 1 month	10

Table 5. Scores for detection of failure (D)

Chances of detection	Likelihood of Non detection (%)	Score
Immediate	< 10	1
Best	10 to 20	2
Better	21 to 30	3
Good	31 to 40	4
Easy	41 to 50	5
Occasional	51 to 60	6
Late	61 to 70	7
Difficult	71 to 80	8
Very Difficult	81 to 90	9
Impossible	91 to 100	10

Table 6. Scores for severity (S)

Effect of severity	Service duration affected	Score
Almost nil	< 30 min.	1
Very rare	1 hour	2
Rare	2 hour	3
Very Low	3 hour	4
Low	4 hour	5
Medium	5 hour	6
Moderate High	6 hour	7
High	7 hour	8
Very High	8 hour	9
Extremely High	>8 hour	10

Table 7. Scores for maintainability (M)

Chances of detection	Likelihood of Non detection (%)	Score
Extremely High	< 10	1
Very High	10 to 20	2
High	21 to 30	3
Moderate High	31 to 40	4
Medium	41 to 50	5
Low	51 to 60	6
Very Low	61 to 70	7
Rare	71 to 80	8
Very Rare	81 to 90	9
Almost Nil	91 to 100	10

Table 8. Scores for spare parts (SP)

Criteria for availability and requirement	**Score**
Easily available & Desirable	1
Easily available & Essential	2
Easily available & Very essential	3
Hard to procure but Desirable	4
Hard to procure but Essential	5
Hard to procure but Very essential	6
Scarce and Desirable	7
Scarce and Essential	8
Scarce and Very essential	9
Impossible and Urgent	10

Table 9. Scores for economic safety (ES)

Criteria for economic safety	**Score**
Extremely low	1
Very low	2
Low	3
Fair	4
Average	5
Medium	6
Moderately high	7
High	8
Very high	9
Extremely high	10

Table 10. Scores for economic cost (EC)

Criteria for economic cost	**Score**
Extremely low	1
Very low	2
Low	3
Fair	4
Average	5
Medium	6
Moderately high	7
High	8
Very high	9
Extremely high	10

3.3. Traditional FMECA

The FMECA is an engineering approach for defining, identifying and eliminating potential problems from system/sub-system or components of the processing plant. The FMECA is composed of two steps: the first of these is the FMEA. In FMECA, the risk is calculated using risk priority number (RPN). The RPN is obtained by multiplying the chances of failure (C), detectability (D) and Severity (S) (Fragassa, 2016).

In criticality analysis, the decision matrix is devised by assigning the score to each failure cause (C1 to C14) against three profit criteria (C, D, S) as discussed in Section 3.2. Table 11 highlights the decision matrix to calculate RPN. The RPN for each failure cause of critical components presented in this research work is evaluated by multiplying scores of these three criteria as per following equation.

$$RPN = [a_{ij} \,.\, b_{ij} \,.\, c_{ij}] \quad (1)$$

where; ith alternative – failure modes (i = 1, 2,….., n) is evaluated for jth criteria – criticality factor (j = 1, 2,….., m).

Table 11. Decision Matrix – X for traditional FMECA

	C	**D**	**S**
Potential Failure Causes	Probability of Chance of failure	Degree of Detectability	Degree of Severity
	a_{ij}	b_{ij}	c_{ij}
C1	9	8	1
C2	8	6	2
C3	10	7	6
C4	9	6	5
C5	10	5	6
C6	9	1	1
C7	7	3	5
C8	8	5	5
C9	5	4	2
C10	9	2	6
C11	3	6	3
C12	5	5	4
C13	8	5	5
C14	9	2	6

Table 12 displays RPN obtained through traditional FMECA

Table 12. Risk priority number (RPN) for traditional FMECA

Notation	**Potential Failure Causes**	$\boldsymbol{RPN}$	***Rank***
C1	Improper lubrication & defective sealing	280	7
C2	Higher speed than specified	72	12
C3	Design defects, Bearing dimension not as per specification	630	1

Table 12. Risk priority number (RPN) for traditional FMECA (continued)

Notation	Potential Failure Causes	*RPN*	*Rank*
C4	Foreign matters/particles	336	4
C5	Sudden impact on the rolls	320	5
C6	Loss of power	14	14
C7	Inadequate lubrication - Dirt, viscosity issues	50	13
C8	Improper meshing, case depth & high residual stresses	320	6
C9	Overheating at gear mesh	168	9
C10	Excessive overload & cyclic stresses	384	3
C11	High contact stresses due to rolling & sliding action of mesh	75	11
C12	Vibratory dynamic load from bearing	150	10
C13	Uneven bearing load	392	2
C14	Reverse & repeated cyclic loading	224	8

3.4. Limitations of traditional FMECA

The limitations of FMECA are that it deals with a limited number of criteria. Moreover, the same weight is given to each criterion without considering their relevance. Finally, even small tolerance in the indexes (C, D or S) may change the value of RPN considering the effect of multiplication. In a view to overcoming the limitations of traditional FMECA, multi-criteria decision-making based failure analysis models are applied.

3.5. TOPSIS based FMECA

TOPSIS is a multi-attribute decision-making method based on the measurement of Euclidean distance of each criterion from the ideal value. It was first discussed in crisp version by Hwang and Yoon (1981). The maintainability criticality index for each failure cause of critical components of identified process industry presented in this research work is evaluated based on following procedure (Sachdeva et al., 2009):

Step 1. *Selection of a set of various criteria and failure modes and arranging them in the columns and the rows respectively in the decision matrix.*

The set is selected for each failure mode (C1 to C14) with six profit criteria (C, D, M, SP, ES, EC) as discussed in section 3.1.

Step 2. *Generation of decision matrix –X.*

$$X = [x_{ij}] \tag{2}$$

where; i[th] alternative – failure modes (i = 1, 2,….., n) is evaluated for j[th] criteria – criticality factor (j = 1, 2,….., m).

The decision matrix –X as shown in Table 13 is prepared by assigning score to each failure mode (C1 to C14) with six profit criteria (C, D, M, SP, ES, EC) as discussed in Section 3.2.

Table 13. Decision Matrix – X for TOPSIS

	C	D	M	SP	ES	EC
Potential Failure Causes	Chance of failure	Detection probability of failure	Maintainability criteria	Spare parts criteria	Economic safety criteria	Economic cost criteria
	x_{ij}	x_{ij}	x_{ij}	x_{ij}	x_{ij}	x_{ij}
C1	9	8	1	3	3	3
C2	8	6	2	2	4	3
C3	10	7	6	3	10	9
C4	9	6	5	3	7	5
C5	10	5	6	5	9	10
C6	9	1	1	3	5	2
C7	7	3	5	3	7	4
C8	8	5	5	3	5	5
C9	5	4	2	3	3	3
C10	9	2	6	4	7	7
C11	3	6	3	3	3	3
C12	5	5	4	3	3	3
C13	8	5	5	3	6	6
C14	9	2	6	4	6	7

Step 3. *Normalization of decision matrix –* X

Normalizing of decision matrix is done by equation of Deng et al. (2000) and method discussed by Salabun (2013) for linear and profit criteria as displayed in Table 14:

$$r_{ij} = \frac{x_{ij}}{\sum_{i=1}^{n} x_{ij}} \tag{3}$$

Table 14. Normalization of Decision Matrix – X for TOPSIS

	C	D	M	SP	ES	EC
Potential Failure Causes	Chance of failure	Detection probability of failure	Maintainability criteria	Spare parts criteria	Economic safety criteria	Economic cost criteria
	r_{ij}	r_{ij}	r_{ij}	r_{ij}	r_{ij}	r_{ij}
C1	0.0826	0.1231	0.0175	0.0667	0.0385	0.0429
C2	0.0734	0.0923	0.0351	0.0444	0.0513	0.0429
C3	0.0917	0.1077	0.1053	0.0667	0.1282	0.1286
C4	0.0826	0.0923	0.0877	0.0667	0.0897	0.0714
C5	0.0917	0.0769	0.1053	0.1111	0.1154	0.1429
C6	0.0826	0.0154	0.0175	0.0667	0.0641	0.0286
C7	0.0642	0.0462	0.0877	0.0667	0.0897	0.0571
C8	0.0734	0.0769	0.0877	0.0667	0.0641	0.0714

Table 14. Normalization of Decision Matrix – X for TOPSIS (continued)

	C	D	M	SP	ES	EC
Potential Failure Causes	Chance of failure	Detection probability of failure	Maintainability criteria	Spare parts criteria	Economic safety criteria	Economic cost criteria
C9	0.0459	0.0615	0.0351	0.0667	0.0385	0.0429
C10	0.0826	0.0308	0.1053	0.0889	0.0897	0.1000
C11	0.0275	0.0923	0.0526	0.0667	0.0385	0.0429
C12	0.0459	0.0769	0.0702	0.0667	0.0385	0.0429
C13	0.0734	0.0769	0.0877	0.0667	0.0769	0.0857
C14	0.0826	0.0308	0.1053	0.0889	0.0769	0.1000

Step 4. *Selection of positive and negative ideal solution s^+ and s^- respectively for each criterion.*
In this method, s^+ and s^- are calculated by considering set of six criteria as benefit criteria through equation discussed by Salabun (2013) as follows:

$$s^+ = [\max(r_{i1}), \max(r_{i1}), \max(r_{i3}), \ldots, \max(r_{in})] = (S_1^+, S_2^+, S_3^+, \ldots, S_n^+) \quad (4)$$

$$s^- = [\min(r_{i1}), \min(r_{i1}), \min(r_{i3}), \ldots, \min(r_{in})] = (S_1^-, S_2^-, S_3^-, \ldots, S_n^-) \quad (5)$$

Step 5. *Calculation of weights for each criterion.*

The weight of each criteria is calculated by introducing Shannon's entropy concept, Here e_j represents the entropy of j[th] criteria. Initially, e_j is calculated for each criterion as per following equation;

$$e_j = -\frac{1}{\ln n} \sum_{i=1}^{n} r_{ij} \ln r_{ij} \quad (6)$$

Then, weight is calculated as follows;

$$w_j = \frac{1 - e_j}{\sum_{j=1}^{m}(1 - e_j)} \quad (7)$$

Step 6. *Calculation of distance between positive and negative ideal solution d_i^+ and d_i^-.*

The distance between positive and negative ideal solution d_i^+ and d_i^- is calculated as per following equations.

$$d_i^+ = \sqrt{\sum_{j=1}^{m} w_j \ (s_j^+ - r_{ij})^2} \quad (8)$$

$$d_i^- = \sqrt{\sum_{j=1}^{m} w_j \ (r_{ij} - s_j^-)^2} \quad (9)$$

where; i = 1,2,…..,n and j = 1, 2,…..,m

Table 15 shows the distances between positive and negative ideal solution.

Step 7. *Calculation of Maintainability Criticality Index MCI_{topsis}*

$$MCI_{topsis} = \frac{d_i}{d_i^+ + d_i^-} \quad (10)$$

Where; MCI_{topsis} is maintainability criticality index for TOPSIS. Table 16 shows obtained value of MCI_{topsis} and its criticality rank.

Table 15. Distances between Positive & Negative Ideal Solution

	C		D		M		SP		ES		EC	
Potential Failure Causes	**Chance of failure**		**Detection probability of failure**		**Maintainability criteria**		**Spare parts criteria**		**Economic safety criteria**		**Economic cost criteria**	
	d_i^+	d_i^-	d_i^+	d_i^-	d_i^+	d_i^-	d_i^+	d_i^-	d_i^+	d_i^-	d_i^+	d_i^-
C1	0.0005	0.0170	0.0000	0.0634	0.0418	0.0000	0.0111	0.0028	0.0444	0.0000	0.0545	0.0011
C2	0.0019	0.0118	0.0052	0.0323	0.0268	0.0017	0.0251	0.0000	0.0327	0.0009	0.0545	0.0011
C3	0.0000	0.0231	0.0013	0.0466	0.0000	0.0418	0.0111	0.0028	0.0000	0.0444	0.0011	0.0545
C4	0.0005	0.0170	0.0052	0.0323	0.0017	0.0268	0.0111	0.0028	0.0082	0.0145	0.0278	0.0100
C5	0.0000	0.0231	0.0117	0.0207	0.0000	0.0418	0.0000	0.0251	0.0009	0.0326	0.0000	0.0711
C6	0.0005	0.0170	0.0635	0.0000	0.0418	0.0000	0.0111	0.0028	0.0227	0.0036	0.0712	0.0000
C7	0.0042	0.0076	0.0324	0.0052	0.0017	0.0268	0.0111	0.0028	0.0082	0.0145	0.0401	0.0044
C8	0.0019	0.0118	0.0117	0.0207	0.0017	0.0268	0.0111	0.0028	0.0227	0.0036	0.0278	0.0100
C9	0.0118	0.0019	0.0207	0.0116	0.0268	0.0017	0.0111	0.0028	0.0444	0.0000	0.0545	0.0011
C10	0.0005	0.0170	0.0466	0.0013	0.0000	0.0418	0.0028	0.0112	0.0082	0.0145	0.0100	0.0278
C11	0.0231	0.0000	0.0052	0.0323	0.0151	0.0067	0.0111	0.0028	0.0444	0.0000	0.0545	0.0011
C12	0.0118	0.0019	0.0117	0.0207	0.0067	0.0151	0.0111	0.0028	0.0444	0.0000	0.0545	0.0011
C13	0.0019	0.0118	0.0117	0.0207	0.0017	0.0268	0.0111	0.0028	0.0145	0.0081	0.0178	0.0178
C14	0.0005	0.0170	0.0466	0.0013	0.0000	0.0418	0.0028	0.0112	0.0145	0.0081	0.0100	0.0278

Table 16. Maintainability Criticality Index MCI_{topsis} and criticality rank for TOPSIS

Notation	Potential Failure Causes	MCI_{topsis}	*Rank*
C1	Improper lubrication & defective sealing	0.4265	9
C2	Higher speed than specified	0.3640	10
C3	Design defects, Bearing dimension not as per specification	0.7986	2
C4	Foreign matters/particles	0.5794	3
C5	Sudden impact on the rolls	0.8051	1
C6	Loss of power	0.2499	14
C7	Inadequate lubrication - Dirt, viscosity issues	0.4419	8
C8	Improper meshing, case depth & high residual stresses	0.4981	7
C9	Overheating at gear mesh	0.2515	13
C10	Excessive overload & cyclic stresses	0.5636	4
C11	High contact stresses due to rolling & sliding action of mesh	0.3460	12
C12	Vibratory dynamic load from bearing	0.3525	11
C13	Uneven bearing load	0.5505	5
C14	Reverse & repeated cyclic loading	0.5455	6

3.6. PSI based FMECA

The concept of preference selection index (PSI) method was basically proposed by Maniya and Bhatt (2011). The maintainability criticality index for each failure cause of critical components of identified process industry presented in this research work is evaluated based on following procedure:

Step 1. *Selection of the set of various criteria and failure modes and arrange them along the columns and the rows respectively in the decision matrix.*

The set is selected for each failure mode (C1 to C14) with six profit criteria (C, D, M, SP, ES, EC) as discussed in Section 3.1.

Step 2. *Construction of decision making matrix - X with criteria rank in crisp value;*

$$X = [x_{ij}] = \begin{bmatrix} [x_{11}] & \cdots & [x_{1n}] \\ \vdots & \ddots & \vdots \\ [x_{m1} & \cdots & [x_{mn}] \end{bmatrix} \quad (11)$$

where x_{ij} is the index value. i = 1,2,….,m which represents the failure modes along the row and j = 1,2,….,n which represents the criteria along the column in decision matrix.

The decision matrix –X as shown in Table 17 is prepared by assigning score to each failure mode (C1 to C14) with six profit criteria (C, D, M, SP, ES, EC) as discussed in Section 3.2.

Table 17. Decision Matrix – X for PSI

	C	**D**	**M**	**SP**	**ES**	**EC**
Potential Failure Causes	Chance of failure	Detection probability of failure	Maintainability criteria	Spare parts criteria	Economic safety criteria	Economic cost criteria
	x_{ij}	x_{ij}	x_{ij}	x_{ij}	x_{ij}	x_{ij}
C1	9	8	1	3	3	3
C2	8	6	2	2	4	3
C3	10	7	6	3	10	9
C4	9	6	5	3	7	5
C5	10	5	6	5	9	10
C6	9	1	1	3	5	2
C7	7	3	5	3	7	4
C8	8	5	5	3	5	5
C9	5	4	2	3	3	3
C10	9	2	6	4	7	7
C11	3	6	3	3	3	3
C12	5	5	4	3	3	3
C13	8	5	5	3	6	6
C14	9	2	6	4	6	7

Step 3. *Normalization of decision matrix - X.*

Normalizing of decision matrix –X is done as per following equation as displayed in Table 18.

If the expectancy of the criteria is considered better when large;

$$N_{ij} = \frac{x_{ij}}{x_{ijmax}} \quad (12)$$

If the expectancy of the criteria is considered better when small;

$$N_{ij} = \frac{x_{ijmin}}{x_{ij}} \quad (13)$$

where; x_{ijmax} and x_{ijmin} are the maximum and minimum value of each alternative respectively.

Normalized decision matrix $X1$ is as follows;

$$X1 = \begin{bmatrix} [N_{11}] & \cdots & [N_{1n}] \\ \vdots & \ddots & \vdots \\ [N_{m1}] & \cdots & [N_{mn}] \end{bmatrix} \quad (14)$$

Table 18. Normalized Decision Matrix – $X1$ for PSI

	C	D	M	SP	ES	EC
Potential Failure Causes	Chance of failure	Detection probability of failure	Maintainability criteria	Spare parts criteria	Economic safety criteria	Economic cost criteria
	N_{ij}	N_{ij}	N_{ij}	N_{ij}	N_{ij}	N_{ij}
C1	0.9000	1.0000	0.1667	0.6000	0.3000	0.3000
C2	0.8000	0.7500	0.3333	0.4000	0.4000	0.3000
C3	1.0000	0.8750	1.0000	0.6000	1.0000	0.9000
C4	0.9000	0.7500	0.8333	0.6000	0.7000	0.5000
C5	1.0000	0.6250	1.0000	1.0000	0.9000	1.0000
C6	0.9000	0.1250	0.1667	0.6000	0.5000	0.2000
C7	0.7000	0.3750	0.8333	0.6000	0.7000	0.4000
C8	0.8000	0.6250	0.8333	0.6000	0.5000	0.5000
C9	0.5000	0.5000	0.3333	0.6000	0.3000	0.3000
C10	0.9000	0.2500	1.0000	0.8000	0.7000	0.7000
C11	0.3000	0.7500	0.5000	0.6000	0.3000	0.3000
C12	0.5000	0.6250	0.6667	0.6000	0.3000	0.3000
C13	0.8000	0.6250	0.8333	0.6000	0.6000	0.6000
C14	0.9000	0.2500	1.0000	0.8000	0.6000	0.7000

Step 4. *Calculate preference variation value p_j for all criteria.*

The preference variation value p_j for all criteria is calculated as per following equations;

$$p_j = \sum_{i=1}^{m} [N_{ij} - N_j] \quad (15)$$

where;

$$N_j = \frac{1}{m}\sum_{i=1}^{m} N_{ij} \quad (16)$$

Step 5. *Calculate deviation in preference value dj for all criteria.*

The deviation in preference value d_j for all criteria is calculated as per following equations;

$$d_j = [1 - p_j] \quad (17)$$

Step 6. *Calculate overall preference value o_j for all criteria.*

The overall preference value o_j for all criteria is calculated as per following equations;

$$o_j = \frac{d_j}{\sum_{j=1}^{n} d_j} \tag{18}$$

Table 19 shows the matrix obtained by multiplying value of N_{ij} and o_j for each criterion.

Table 19. Multiplication Matrix of N_{ij} and o_j

	C	D	M	SP	ES	EC
Potential Failure Causes	Chance of failure	Detection probability of failure	Maintainability criteria	Spare parts criteria	Economic safety criteria	Economic cost criteria
	$N_{ij} . o_j$	$N_{ij} . o_j$	$N_{ij} . o_j$	$N_{ij} . o_j$	$N_{ij} . o_j$	$N_{ij} . o_j$
C1	0.2497	0.1071	-0.0322	0.2845	0.0621	0.0381
C2	0.2220	0.0804	-0.0643	0.1897	0.0828	0.0381
C3	0.2775	0.0938	-0.1930	0.2845	0.2071	0.1144
C4	0.2497	0.0804	-0.1608	0.2845	0.1450	0.0636
C5	0.2775	0.0670	-0.1930	0.4741	0.1864	0.1272
C6	0.2497	0.0134	-0.0322	0.2845	0.1035	0.0254
C7	0.1942	0.0402	-0.1608	0.2845	0.1450	0.0509
C8	0.2220	0.0670	-0.1608	0.2845	0.1035	0.0636
C9	0.1387	0.0536	-0.0643	0.2845	0.0621	0.0381
C10	0.2497	0.0268	-0.1930	0.3793	0.1450	0.0890
C11	0.0832	0.0804	-0.0965	0.2845	0.0621	0.0381
C12	0.1387	0.0670	-0.1287	0.2845	0.0621	0.0381
C13	0.2220	0.0670	-0.1608	0.2845	0.1243	0.0763
C14	0.2497	0.0268	-0.1930	0.3793	0.1243	0.0890

Step – 7: Calculate the maintainability criticality index MCI_{psi} of each alternative.

The maintainability criticality index MCI_{psi} of each alternative as follow;

$$MCI_{psi} = \sum_{j=1}^{n}[N_{ij} . o_j] \tag{19}$$

The criticality ranks (priorities) of alternatives are given according to the value of MCI_{psi} in increasing order i.e. the larger value of MCI_{psi} is having higher priority than other alternatives.

Table 20 shows the MCI_{psi} and criticality rank for each failure cause.

Table 20. Maintainability criticality index MCI_{psi} and rank for PSI

	Potential Failure Causes	MCI_{psi}	***Rank***
C1	Improper lubrication & defective sealing	0.7095	3
C2	Higher speed than specified	0.5486	11
C3	Design defects, Bearing dimension not as per specification	0.7842	2
C4	Foreign matters/particles	0.6623	6

Table 20. Maintainability criticality index MCI_{psi} and rank for PSI

	Potential Failure Causes	MCI_{psi}	*Rank*
C5	Sudden impact on the rolls	0.9391	1
C6	Loss of power	0.6444	7
C7	Inadequate lubrication - Dirt, viscosity issues	0.5539	10
C8	Improper meshing, case depth & high residual stresses	0.5797	9
C9	Overheating at gear mesh	0.5127	12
C10	Excessive overload & cyclic stresses	0.6968	4
C11	High contact stresses due to rolling & sliding action of mesh	0.4519	14
C12	Vibratory dynamic load from bearing	0.4618	13
C13	Uneven bearing load	0.6131	8
C14	Reverse & repeated cyclic loading	0.6761	5

3.7. Significance of PSI

In preference selection index method, preference values of each attribute are calculated using the concept of statistics rather than assignment of weight attributes in other MCDM approaches like; TOPSIS. This method is very helpful in deciding the relative importance between attributes when situation of the conflict occurred.

4. Results, discussion and suggestions

4.1. Achievements from criticality analysis

In this research study, the historical failure data of thirty-one components of aluminium wire rolling mill are collected and analyzed in a view to understanding behavioral failure pattern of such components. Moreover, major reliability parameters are calculated as a part of reliability analysis. The results of criticality analysis show that bearings (70 %), gears (4 %) and shafts – primary and secondary (4 %) are most critical components.

4.2. Achievements from traditional FMECA

Based on achieved RPN and analysis of existing maintenance strategies; revised and effective maintenance methodology have been suggested. Looking to the outcome of traditional FMECA; Failure modes with RPN more than 500 are considered most critical and required to perform predictive maintenance, RPN from 250 to 500 are considered critical and recommended preventive maintenance and less than 250 are considered normal failures which are recommended corrective maintenance.

4.3. Achievements from TOPSIS based FMECA

It has been observed from the Table 16 that sudden impact on roll (C5) seems to be the most critical failure cause and loss of power (C6) seems to be the least critical failure cause. It is suggested to modify the current control practices that failure causes (C5, C3, C4, C10, C13) with large value of $MCItopsis$ should be kept under predictive maintenance, failure cause (C14, C8, C7, C1, C2) with moderate value of $MCItopsis$ should be kept under preventive maintenance and failure causes (C13, C11, C12, C6) with low $MCItopsis$ should be kept under corrective maintenance.

4.4. Achievements from PSI based FMECA

Table 20 shows results obtained from maintainability criticality index of each alternative MCI_{psi}; derived from multi-criteria decision making based PSI approach as discussed in Section 3.6. The comprehensive analysis of PSI approach shows that sudden impact on the rolls (C5) due to bearing misalignment and improper mounting seems to be most critical failure cause and high contact stresses due to rolling and sliding action of mesh (C11) seems to be least critical failure cause. It is suggested to modify the current control practices that failure causes (C5, C3, C1, C10, C14) with large value of MCI_{psi} should be kept under predictive maintenance, failure cause (C4, C6, C13, C8, C7) with moderate value of MCI_{psi} should be kept under preventive maintenance and failure causes (C2, C9, C12, C11) with low MCI_{psi} should be kept under corrective maintenance.

Table 21 shows the suggested maintenance planning activities over current control practices based their criticalities obtained from both MCDM failure models. Figure 3 displays the comparison of MCIs evaluated through both failure models discussed in this paper.

Table 21. Non-identical FMECA based Maintenance Planning over Current Control Practices

Notation	Potential Failure Effects	Current Controls	Suggested improvement in maintenance plan		
			Traditional FMECA	TOPSIS	PSI
C1	Improper lubrication & defective sealing	Lubricating the parts when occurred	Preventive Maintenance	Preventive Maintenance	Predictive Maintenance
C2	Higher speed than specified	Proper coolant	Corrective Maintenance	Preventive Maintenance	Corrective Maintenance
C3	Design defects, Bearing dimension not as per specification	Bearing replacement	Predictive Maintenance	Predictive Maintenance	Predictive Maintenance
C4	Foreign matters/particles	Regular cleaning of parts	Preventive Maintenance	Predictive Maintenance	Preventive Maintenance
C5	Sudden impact on the rolls	Routine check up	Preventive Maintenance	Predictive Maintenance	Predictive Maintenance
C6	Loss of power	Electrical wiring check up	Corrective Maintenance	Corrective Maintenance	Preventive Maintenance
C7	Inadequate lubrication – Dirt, viscosity issues	Routine check-up of lubrication	Corrective Maintenance	Preventive Maintenance	Preventive Maintenance
C8	Improper meshing, case depth & high residual stresses	Preventive maintenance	Preventive Maintenance	Preventive Maintenance	Preventive Maintenance
C9	Overheating at gear mesh	Lubricating when needed	Corrective Maintenance	Corrective Maintenance	Corrective Maintenance
C10	Excessive overload & cyclic stresses	Break down maintenance	Preventive Maintenance	Predictive Maintenance	Predictive Maintenance

Table 21. Non-identical FMECA based Maintenance Planning over Current Control Practices (continued)

Notation	Potential Failure Effects	Current Controls	Suggested improvement in maintenance plan		
			Traditional FMECA	TOPSIS	PSI
C11	High contact stresses due to rolling & sliding action of mesh	Gear replace when needed	Corrective Maintenance	Corrective Maintenance	Corrective Maintenance
C12	Vibratory dynamic load from bearing	Break down maintenance	Corrective Maintenance	Corrective Maintenance	Corrective Maintenance
C13	Uneven bearing load	Preventive maintenance	Preventive Maintenance	Predictive Maintenance	Preventive Maintenance
C14	Reverse & repeated cyclic loading	Preventive maintenance	Preventive Maintenance	Preventive Maintenance	Predictive Maintenance

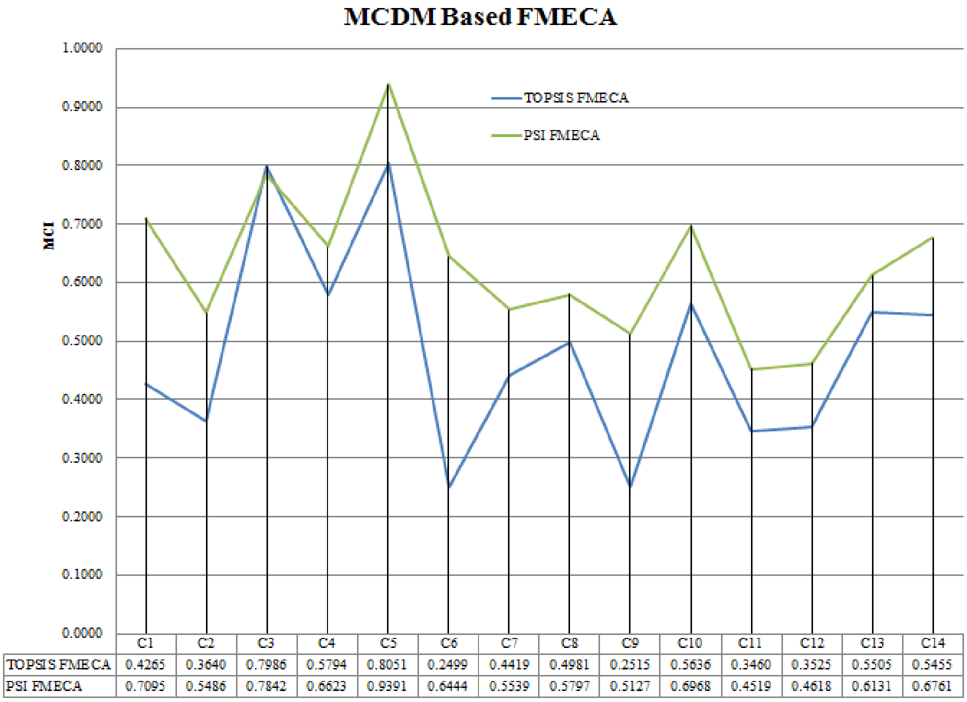

Figure 3. Comparisons of MCIs (TOPSIS and PSI)

5. Conclusion and scope of work

The major critical components like; bearings, gears, and shafts are discriminated with their potential failure causes through actual shop floor conditions. The failure pattern of these components mill is demonstrated in this paper. To overcome the limitations of more traditional failure analysis models, multi-criteria decision-making based TOPSIS and PSI models are discussed. It is concluded from outcome of different failure models that C3, C5 and C10 are considered most critical failure causes and will be recommended special care. Table 22 shows the priority of different failure causes obtained through both failure analysis models and ensure the importance of non-traditional model in planning maintenance activities of major process industries. It is concluded that the study will be helpful to enhance quality in planning the maintenance activities.

Table 22. Comparison of Priority for Non-identical FMECA Approaches

	FMECA	Traditional	TOPSIS	PSI
Priority of Failure Causes	Most Critical	C3	C5, C3, C4, C10, C13	C5, C3, C1, C10, C14
	Critical	C13, C10, C4, C5, C8, C1	C14, C8, C7, C1, C2	C4, C6, C13, C8, C7
	Normal	C14, C9, C12, C11, C2, C7, C6	C13, C11, C12, C6	C2, C9, C12, C11

The limitations of the proposed study is that presented failure model may not represent failures due to the first point as adequate of design for such components are not checked for high failure rate. Also, some criteria like; manpower skill, operating conditions, environmental effect etc. is not considered during modeling of FMEA and scores.

Similar work can be extended to other process industries such as; petrochemical plant, textile mill etc. with other MCDM based approaches like; analytical hierarchy process (AHP), qualitative flexible multi-criteria (QUALIFLEX), measuring attractiveness by a categorical-based evaluation technique (MACBATH) etc. Moreover, the results can be validated with similar or different kinds of process industries to prove competency of MCDM based failure analysis models as a future work.

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References:

Bevilacqua, M., Braglia, M., & Gabbrielli, R. (2000). Monte Carlo simulation approach for modified FMECA in a power plant. *Quality and Reliability Engineering International, 16*, 313-324.

Braglia, M. (2000). MAFMA: multi-attribute failure mode analysis. *International Journal of Quality & Reliability Management, 17*, 1017-1033.

Chanamool, N., & Naenna, T. (2016). Fuzzy FMEA application to improve decision-making process in an emergency department, *Applied Soft Computing, 43*, 441-453.

Chang C. L., Wei C. C., & Lee Y. H. (1999). Failure mode and effects analysis using fuzzy method and grey theory, *Kybernetes, 28*(9), 1072-1080.

Adhikary, D. D, & Bose, K. G. (2013). Multi Criteria FMECA for Coal-fired Thermal Power Plants using COPRAS-G. *International Journal for Quality & Reliability Management, 31*(5), 601-614.

Deng, J. L., (1989). Introduction to Grey System Theory. T*he Journal of Grey Theory, 1*(1), 1-24.

Dhillon, B. S. (1985). *Quality control, reliability, and engineering design*. New York: Dekker.

Feili, H. R., Akar, N., Lotfizadeh, H., Bairampou,r M., & Nasiri S., (2013). Risk analysis of geothermal power plants using Failure Modes and Effects Analysis (FMEA) technique. *Journal of energy conservation and management, 72*, 69-76, DOI: 10.1016/j.enconman.2012.10.027.

Zhang, F. (2015). Failure Modes and Effects Analysis based on Fuzzy TOPSIS. *IEEE International Conference on Grey System and Intelligent Services (GSIS), Leicester*, ISSN: 2166-9420, pp. 588-593.

Fragassa, C., Pavlovic, A., & Massimo, S. (2014). Using a total quality strategy in a new practical approach for improving the product reliability in automotive industry. *International Journal for Quality Research, 8*(3), 297-310.

Gilchrist, W. (1993). Modeling failure modes and effects analysis, *International Journal of Quality & Reliability Management*, 10, 16-23.

Hwang, C. L., & Yoon, K. (1981). *Multiple attribute decision making: methods and applications*. New York: Springer.

Liao, R., Bian, J., Yang, L., & Grzybowski, S. (2012). Cloud model-based failure mode and effects analysis for prioritization of failures of power transformer in risk assessment, *International transactions on electrical energy systems*, *23*, 1172-1190. doi:10.1002/etep.1647.

Lin, Y. H., Lee, P. C., & Ting, H. I. (2008). Dynamic multi-attribute decision-making model with grey number evaluations. *Expert Systems with Applications*, *35*(4), 1638-1644.

Maity, S. R., Chatterjee, P., & Chakraborty, S. (2012). Cutting tool material selection using grey complex proportional assessment method. *Materials and Design, 36*, 372-378.

Maniya, K. D., & Bhatt M. G. (2011). A selection of Material using a Novel type Decision making Method: Preference Selection Method, *Materials and Design, 31*, 1785-1789.

Mittal, K., Tiwary, P. C., Khanduja, D., & Kaushik, P. (2016). Application of Fuzzy TOPSIS MADM approach in ranking & underlining the problems of plywood industry in India. *Journal of Cogent Engineering, 3*(1). DOI: 10.1080/23311916.2016.1155839.

Mobin, M., Roshani, A., Saeedpoor, M., & Mozaffari, M. M. (2015). Integrating FAHP with COPRAS-G method for supplier selection (Case study: An Iranian manufacturing company). *Proceedings of the American Society for Engineering Management 2015 International Annual Conference, At Indiana, USA,* Retrieved from https://www.researchgate.net/ publication/282819416.

O'Connor, P. (1981). *Practical reliability engineering.* London: Heyden.

Rastegari, A., Archenti, A., & Mobin, M. (2017). Condition-based maintenance of machine tools: Vibration monitoring of spindle units. *IEEE Reliability and Maintainability Symposium (RAMS*), Florida (FL), USA, 1-8.

Rathi, R., Khanduja, D., & Sharma, S. K. (2016). A fuzzy-MADM based approach for prioritising Six Sigma projects in the Indian auto sector. *International Journal of Management Science and Engineering Management*, 1-8. http://dx.doi.org/10.1080/ 17509653.2016.1154486.

Anish, S., Kumar, D., & Kumar, P. (2009). Multi-factor Failure Mode Criticality Analysis using TOPSIS. *Journal of Industrial Engineering, 5*, 1-9.

Salabun, W. (2013). The mean error estimation of TOPSIS method using a fuzzy reference models. *Journal of Theoretical and Applied Computer Science, 7*(3), 40-50.

Sahoo, T., Sarkar, P. K., & Sarkar, A. K. (2014). Maintenance Optimization for Critical Equipments in Process Industry Based on FMECA Method. *International Journal of Engineering and Innovative Technology, 3*(10), 107-112.

Vandenbrande, W. W. (1998). How to use FMEA to reduce the size of your quality toolbox. *Quality Progress, 31*(11), 97-100.

Xu, K., Tang, L. C., Ho, M. S. L., & Zhu, M. L. (2002). Fuzzy assessment of FMEA for engine systems. *Reliability Engineering & System Safety, 75*, 17-29.

Zammori, F., & Gabbrielli, R. (2011). ANN/RPN: a multi criteria evaluation of the risk priority number. *Journal of quality and reliability engineering, 28*, 85-104. doi:10.1002/qre.1217.

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