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Research Article

Multicriteria FMECA Based Decision-Making for Aluminium Wire Process Rolling Mill through COPRAS-G

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This paper presents a multifactor decision-making approach based on "grey-complex proportional assessment (COPRAS-G) method" in a view to overcome the limitations of Failure Mode Effect and Criticality Analysis (FMECA). In this model, the scores against each failure mode are expressed in grey number instead of crisp values to evaluate the criticalities of the failure modes without uncertainty. The suggested study is carried out to identify the weights of major failure causes for bearings, gears, and shafts of aluminium wire rolling mill plant. The primary findings of the paper are that sudden impact on the rolls seems to be most critical failure cause and loss of power seems to be least critical failure cause. It is suggested to modify the current control practices with proper maintenance strategy based on achieved maintainability criticality index (MCI) for different failure causes. The outcome of study will be helpful in deriving optimized maintenance plan to maximize the performance of process industry.

1. Introduction

The reliability and maintenance engineering is important to maintenance practitioners and reliability engineers to keep the system in a state of readiness. Moreover, it helps to identify the condition based faults, compare possible failure patterns, and maximize effectiveness in maintenance plan. There are many techniques available for planning maintenance activities of process industries. Traditional Failure Mode Effect and Criticality Analysis (FMECA) has proved to be prominence tool among maintenance personnel, where failure modes are ranked on risk priority number (RPN), which is the product of chances of failure (C), degree of detectability (D), and degree of severity (S) to prioritize the maintenance activities.

Traditional FMECA is a widely accepted methodology for prioritizing failure modes; however, it has some limitations. It does not cover the interdependency of different failure modes and their effects. It considers only limited criteria like C, D, and S and does not cover some important criteria like maintainability (M), spare parts availability (SP), economic safety (ES), economic cost (EC), and so forth which may also influence the failure modes. Moreover, same importance will be given to C, D, and S ignoring their relative importance and even small variation in the value of C or D or S may change the value of RPN significantly due to multiplication rule.

It has been observed that past researchers have undergone various modifications for improving FMECA to overcome these drawbacks for different processing units. Sahoo et al. [1] show that failure modes, effects, and critique analysis (FMECA) is an integral part of the technical design of maintenance and it represents a strong tool to evaluate and improve system reliability and therefore reduces costs associated with maintenance that is used in a wide range of industry. Some researchers [2–5] incorporated a new factor called operating conditions in the field of power plant. Anish et al. [5] presented a multifactor decision-making approach for prioritizing failure modes for paper industry as an alternative using TOPSIS. Braglia et al. [6, 7] presented fuzzy TOPSIS and Xu et al. [8] presented fussy assessment based FMEA for engine system. Gargama and Chaturvedi [9] introduced fuzzy RPN applying level sets where the three risk factors are expressed into fuzzy linguistic variables. Adhikary et al. [10] presented multicriteria FMECA for coal-fired thermal power station using COPRAS-G method. Zhang [11] presented integration of both subjective weights and objective weights to avoid failure modes from being underestimated or overestimated based on fuzzy TOPSIS to get the closeness coefficient for each failure mode. Chanamool and Naenna [12] highlight the importance of fuzzy FMEA for prioritization and assessment of failures that likely occur in the working process of an emergency department of hospitals. Liu et al. [13] presented a novel approach for FMEA based on combination weighting and fuzzy VIKOR method where integration of fuzzy analytic hierarchy process (AHP) and entropy method is applied for risk factor weighting in this proposed approach to deal with the uncertainty and vagueness from humans' subjective perception and experience in risk evaluation process.

It has been observed that previous researchers did not consider COPRAS-G based multicriteria decision-making approach to process industries like aluminium wire rolling mill. In this paper COPRAS-G, a multicriteria decision-making tool, is applied to model FMECA in lieu of the traditional multiplication rule of the criticality factors.

2. COPRAS-G Methodology

The concept of grey number was basically derived from grey theory, which deals with the decisions of uncertainty experienced in real-world environment [14–19]. The grey number is having upper and/or lower limits whose exact value is unknown but the interval within which the value falls is known [15–17]. Hwang and Yoon, 1981 [20], highlight importance of multicriteria decision-making (MCDM) where multiple and conflicting criteria are under consideration in different areas like personal, public, academic, or business contents.

The COPRAS-G method for criticality evaluation of failure modes is expressed through the following steps [15–17]:

(1) Select the set of various criteria and failure modes and arrange them along the columns and the rows, respectively, in the decision matrix.

(2) Construct the decision-making matrix X which shows the criteria ranking in grey number intervals:

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

where x_{ij} is the lower value and y_{ij} is the upper value of the interval. $i = 1, 2, \dots, m$ which represents the failure modes along the row and $j = 1, 2, \dots, n$ which represents the criteria along the column in decision matrix.

(3) Normalize the decision matrix X, as follows:

$$x1_{ij} = \frac{x_{ij}}{(1/2)\left(\sum_{j=1}^{n} x_{ij} + \sum_{j=1}^{n} y_{ij}\right)},$$
$$y1_{ij} = \frac{y_{ij}}{(1/2)\left(\sum_{j=1}^{n} x_{ij} + \sum_{j=1}^{n} y_{ij}\right)}. \quad (2)$$

Normalized decision matrix $X1$ is as follows:

$$X1 = \begin{bmatrix} [x1_{11}; y1_{11}] & \cdots & [x1_{1n}; y1_{1n}] \\ \vdots & \ddots & \vdots \\ [x1_{m1}; y1_{m1}] & \cdots & [x1_{mn}; y1_{mn}] \end{bmatrix}. \quad (3)$$

(4) Calculate weight of each criterion based on Shannon's entropy concept where initially we have to calculate entropy e_j and from it weight w_j for jth criteria as follows:

$$e_{x_j} = -\frac{1}{\ln m}\sum_{i=1}^{m} x_{ij} \ln x_{ij},$$
$$e_{y_j} = -\frac{1}{\ln m}\sum_{i=1}^{m} y_{ij} \ln y_{ij},$$
$$w_{x_j} = \frac{1 - e_{x_j}}{\sum_{j=1}^{n}\left(1 - e_{x_j}\right)}, \quad (4)$$
$$w_{y_j} = \frac{1 - e_{y_j}}{\sum_{j=1}^{n}\left(1 - e_{y_j}\right)}.$$

(5) Determine weighted normalized matrix as per the following equations:

$$x2_{ij} = x1_{ij} \cdot w_{ij},$$
$$y2_{ij} = y1_{ij} \cdot w_{ij}. \quad (5)$$

Weighted normalized decision matrix $X2$ is as follows:

$$X2 = \begin{bmatrix} [x2_{11}; y2_{11}] & \cdots & [x2_{1n}; y2_{1n}] \\ \vdots & \ddots & \vdots \\ [x2_{m1}; y2_{m1}] & \cdots & [x2_{mn}; y2_{mn}] \end{bmatrix}. \quad (6)$$

(6) Calculate the weighted mean normalized sums P_i for beneficial criteria whose larger values are preferable and R_i for nonbeneficial criteria whose smaller values are preferable as follows:

$$P_i = -\frac{1}{2}\sum_{j=1}^{k}\left(x2_{ij} + y2_{ij}\right),$$
$$R_i = -\frac{1}{2}\sum_{j=k+1}^{k}\left(x2_{ij} + y2_{ij}\right), \quad (7)$$

where $i = 1, 2, \dots, m$, "k" is the number of beneficial criteria, and $(m - k)$ is the number of nonbeneficial criteria. All the beneficial criteria are placed in the decision-making matrix first and then the nonbeneficial criteria are placed.

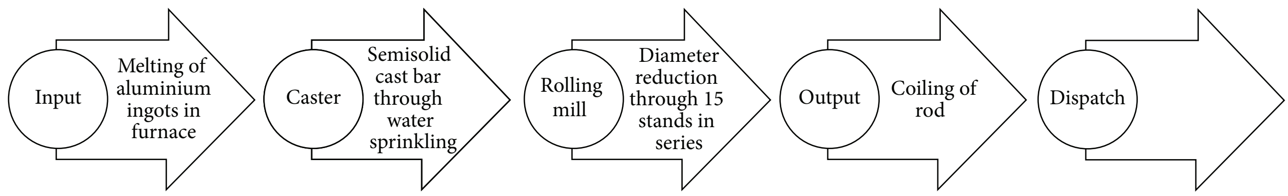

FIGURE 1: Layout of aluminium wire rolling mill process flow.

(7) Calculate the relative significance/weight MCI of each alternative as follows:

$$MCI = P_i + \frac{R_{\min} \sum_{i=1}^{m} R_i}{R_i \sum_{i=1}^{m} (R_{\min}/R_i)} = P_i + \frac{\sum_{i=1}^{m} R_i}{R_i \sum_{i=1}^{m} (1/R_i)}, \quad (8)$$

where $R_{\min}$ is the minimum value of all weighted mean normalized sums "R_i" of nonbeneficial criteria.

The criticality ranks (priorities) of alternatives are ranked according to the value of MCI in increasing order; that is, larger value of MCI is having higher priority than other alternatives. $MCI_{\max}$ is the maximum value of relative significance/weight among all alternatives.

(8) Calculate the degree of unity in percentage (%) contribution C_i for ith failure cause and assign rank based on value of MCI:

$$C_i = \frac{MCI_i}{MCI_{\max}} * 100, \quad (9)$$

where $MCI_{\max}$ is the maximum value of relative significance/weight among all alternatives.

3. Case Study

3.1. Introduction. The proposed model is applied to the aluminium wire rolling mill processing plant situated in Gujarat, India. The detailed layout of process is given in Figure 1. The aluminium wire is produced through Properzi Process where solid aluminium bar of 40 mm is fed into stands to gradually reduce diameter to 6 mm rod through fifteen stands in series. At each stand diameter of rod decreases by about 15–20%. It is concluded that bearings, gears, and primary and secondary shafts are identified as most critical components based on historical comprehensive failure and repair data.

To decide the score for each individual failure mode for every process input of critical components, the following methods are used:

(i) Historical failure data which gives comprehensive behavioral study of failure pattern of critical components.

(ii) Questionnaires to floor operators, managers, and maintenance personnel.

The score for chances of failure, detectability, maintainability, spare parts, economic safety, and economic cost is ranked as per Tables 1, 2, 3, 4, 5, and 6, respectively.

TABLE 1: Scores for chance of failure (C).

Occurrence	MTBF	Score
Almost never	More than three years	1
Very rare	Once every 2-3 years	2
Rare	Once every 1-2 years	3
Very low	Once every 11-12 months	4
Low	Once every 9-10 months	5
Medium	Once every 7-8 months	6
Moderate high	Once every 5-6 months	7
High	Once every 3-4 months	8
Very high	Once every 1-2 months	9
Extremely high	Less than 1 month	10

TABLE 2: Scores for detection of failure (D).

Chances of detection	Likelihood of nondetection (%)	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

3.2. Importance of Use of COPRAS-G. During brainstorming session, maintenance personnel score a criticality factor into different criticality levels so it is challenging to do criticality analysis of failure modes accurately. Hence this practical difficulty can be solved by expressing the scores of a criticality factor in an interval (grey number) instead of certain and exact value (white number). In this problem, COPRAS-G method, a multifactor decision-making tool, is used by expressing criticality factors with grey numbers in lieu of the traditional multiplication rule. The main idea of COPRAS-G method is to express the criteria values in intervals, which comes from real situation of decision-making.

3.3. Failure Mode Effect and Criticality Analysis with Assignment of Score in Grey Number Range. The potential failure modes, their causes, and failure effect of bearings, gears,

Table 3: Scores for maintainability (M).

Maintainability scope	Criteria for measure	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 4: 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 5: 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 6: 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

and primary and secondary shafts are generated through the root cause analysis method. 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 ranked on scale of 1–10 as per concept of grey number range in $[x_{ij}; y_{ij}]$ based on Tables 1–6, where x_{ij} is the lower value and y_{ij} is the upper value of the interval as reflected in Table 7. The scales of 1 to 10 signify from least to most consideration of impact of criteria and are assigned on basis of questionnaires and brainstorming session to floor operators, shop floor managers, and maintenance personnel for various individual failure causes (C1 to C14).

4. Results and Discussion

Table 8 shows the relative significance/weight of each alternative MCI and the degree of unity in percentage (%) contribution (C_i) for ith failure cause which is derived as per COPRAS-G methodology discussed in Section 2.

It has been observed from Table 8 that design defects and bearing dimension not as per specification (C3) seems to be most critical failure cause and overheating at gear mesh (C9) seems to be least critical failure cause. It is suggested to modify the current control practices as listed in Table 1 that failure causes (C3, C5, C10, C4, and C14) with large value of MCI should be kept under predictive maintenance, failure causes (C13, C8, C7, C1, and C2) with moderate value of MCI should be kept under preventive maintenance, and failure causes (C12, C6, C11, and C9) with low MCI should be kept under corrective maintenance.

Moreover, it has been observed that almost 70% down time is due to bearing failure and replacement practice is 100%, so it is recommended to select standardized bearing with appropriate specifications and mount them properly during every replacement to avoid bearing misalignment (C5) and minimizing reverse and repeated cyclic loading; thus shaft fatigue (C14) and gear tooth fracture (C10) can be avoided. Appropriate condition monitoring is suggested to continuously record the condition of bearing damage and shaft damage to prevent sudden breakdown and starting thrust on these components. Also, the condition of lubricants should be checked and replaced whenever necessary rather than routine clean-up. Hence, sudden impact on the rolls (C5), design defects with bearing dimension/specification (C3), foreign matters/particles (C4), excessive overload and cyclic stresses (C10), and reverse and repeated cyclic loading (C14) can be covered under recommendations. Failure causes with moderate and low MCI are controlled under preventive and corrective maintenance practices. Comparison matrix for deciding maintenance strategy is shown is Table 9.

5. Conclusion and Scope

This paper highlights multicriteria decision-making approach based on COPRAS-G to overcome the limitations of FMECA.

Table 7: COPRAS-G based FMECA.

Particulars					Decision matrix															
Key process input	Potential failure mode	Potential causes	Potential failure effects	Current controls	C		D		M		SP		ES		EC					
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)?	What are the existing *controls* and procedures that prevent either the cause or the failure mode?	Chance of failure		Detection probability of failure		Maintainability criteria		Spare parts criteria		Economic safety criteria		Economic cost criteria		Weighted mean normalized sum	Relative significance/weight	% contribution	Criticality rank
					x_{ij}	y_{ij}	x_{ij}	y_{ij}	x_{ij}	y_{ij}	x_{ij}	y_{ij}	x_{ij}	y_{ij}	x_{ij}	y_{ij}	P_i	MCI	C_i	Rank
Bearing failure	Bearing high temperature	Improper lubrication & defective sealing	Bearing gets jammed/bearing housing jammed	Lubricating the parts when occurred	8	9	7	8	1	2	2	3	3	4	3	4	0.1297	0.1297	60	9
	Bearing corrosion	Higher speed than specified	Increase in vibration & noise	Proper coolant	8	9	5	6	1	2	2	3	3	4	4	5	0.1244	0.1244	58	10
	Bearing fatigue	Design defects & bearing dimension not as per specification	Life reduction	Bearing replacement	9	10	7	8	6	8	3	5	9	10	9	10	0.2156	0.2156	100	1
	Roller balls wear-out	Foreign matters/particles	Sudden rise in thrust	Regular cleaning of parts	7	9	6	7	4	5	3	5	7	8	5	6	0.1662	0.1662	77	4
	Bearing misalignment & improper mounting	Sudden impact on the rolls	Shaft damage & impact damage on other parts	Routine check-up	8	10	5	6	6	7	5	7	9	10	9	10	0.2079	0.2079	96	2
	Electrical damage	Loss of power	Operation interrupted	Electrical wiring check-up	7	9	1	2	1	2	3	4	5	6	2	3	0.1062	0.1062	49	12
Rolling mill gearing failure	Gear teeth wear-out	Inadequate lubrication-dirt, viscosity issues	Rough operation & considerable noise	Routine check-up of lubrication	7	8	2	3	5	6	3	4	7	8	4	5	0.1401	0.1401	65	8
	Gear teeth surface fatigue (pitting)	Improper meshing, case depth & high residual stresses	Gear life reduction	Preventive maintenance	8	9	4	5	5	6	3	4	4	5	5	6	0.1444	0.1444	67	7
	Gear teeth scoring	Overheating at gear mesh	Interference & backlash phenomenon	Lubricating when needed	4	5	3	4	2	3	2	3	2	3	3	4	0.0863	0.0863	40	14
	Gear teeth fracture	Excessive overload & cyclic stresses	Sudden stoppage of process plant	Breakdown maintenance	9	10	2	4	6	7	3	4	7	8	7	8	0.1700	0.1700	79	3
	Gear teeth surface cold/plastic flow	High contact stresses due to rolling & sliding action of mesh	Slippage & power lose	Gear replacement when needed	3	4	6	7	3	4	3	4	2	3	3	4	0.1022	0.1022	47	13

TABLE 7: Continued.

Particulars					Decision matrix															
Key process input	Potential failure mode	Potential causes	Potential failure effects	Current controls	C		D		M		SP		ES		EC					
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)?	What are the existing *controls* and procedures that prevent either the cause or the failure mode?	Chance of failure		Detection probability of failure		Maintainability criteria		Spare parts criteria		Economic safety criteria		Economic cost criteria		Weighted mean normal-ized sum	Relative signifi-cance/weight	% con-tribution	Criticality rank
					x_{ij}	y_{ij}	x_{ij}	y_{ij}	x_{ij}	y_{ij}	x_{ij}	y_{ij}	x_{ij}	y_{ij}	x_{ij}	y_{ij}	P_i	MCI	C_i	Rank
Rolling mill shaft (primary & sec-ondary) failure	Shaft fretting	Vibratory dynamic load from bearing	Leads to sudden failure	Breakdown maintenance	5	6	4	5	3	5	3	4	3	4	3	4	0.1096	0.1096	51	11
	Shaft misalignment	Uneven bearing load	Vibration & fatigue	Preventive maintenance	8	9	4	5	5	6	4	5	4	5	5	6	0.1477	0.1477	68	6
	Shaft fracture (fatigue)	Reverse & repeated cyclic loading	Sudden stoppage of process	Preventive maintenance	9	10	2	3	6	7	3	4	5	6	6	7	0.1526	0.1526	71	5
					100	**117**	**58**	**73**	**54**	**70**	**42**	**59**	**70**	**84**	**68**	**82**				

Table 8: Criticality ranking based on MCI.

Failure cause versus criteria		Weighted mean normalized sum	Relative weight	% contribution	Criticality rank
Failure cause	Notation	P_i	MCI	C_i	Rank
Bearing high temperature	C1	0.1297	0.1297	60	9
Bearing corrosion	C2	0.1244	0.1244	58	10
Bearing fatigue	C3	0.2156	0.2156	100	1
Roller balls wear-out	C4	0.1662	0.1662	77	4
Bearing misalignment & improper mounting	C5	0.2079	0.2079	96	2
Electrical damage	C6	0.1062	0.1062	49	12
Gear teeth wear-out	C7	0.1401	0.1401	65	8
Gear teeth surface fatigue (pitting)	C8	0.1444	0.1444	67	7
Gear teeth scoring	C9	0.0863	0.0863	40	14
Gear teeth fracture	C10	0.1700	0.1700	79	3
Gear teeth surface cold/plastic flow	C11	0.1022	0.1022	47	13
Shaft fretting	C12	0.1096	0.1096	51	11
Shaft misalignment	C13	0.1477	0.1477	68	6
Shaft fracture (fatigue)	C14	0.1526	0.1526	71	5

Table 9: Comparison matrix for deciding maintenance strategy.

Sr. number	Failure cause	Suggested maintenance strategy	Impact of MCI & (C_i)
1	C3, C5, C10, C4, C14	Predictive (condition based) maintenance	High MCI & (C_i)
2	C13, C8, C7, C1, C2	Preventive maintenance	Moderate MCI & (C_i)
3	C12, C6, C11, C9	Corrective maintenance	Low MCI & (C_i)

The case study presented in this paper shows how to deal with the problems encountered in aluminium wire rolling mill processing plant with mix of maintenance practices. It is concluded that the study will be helpful in deriving optimized maintenance plan to improve plant efficiency as a whole. The similar work can be extended for process industries of same or of different kinds in a view to decide suitable maintenance strategies in coordination with failure analysis.

Competing Interests

The authors declare that they have no competing interests.

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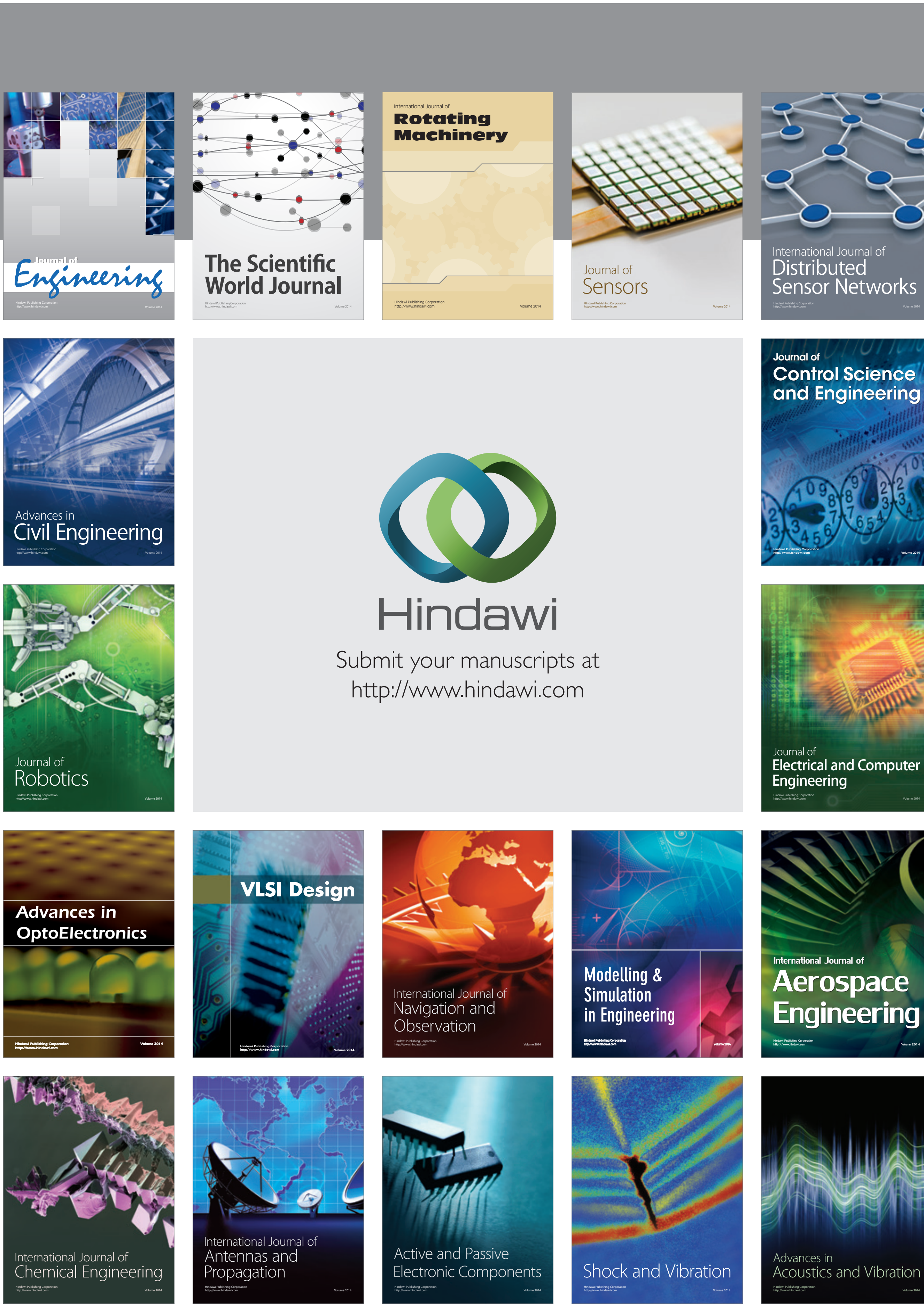
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