APPLICATION OF FUZZY LOGIC SYSTEM TO ASSET MANAGEMENT: AN ADAPTATION FOR MAINTENANCE SCHEDULING

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Abstract: In asset management, failure mode and effects analysis together with maintenance cost play a key role in determining a proper maintenance policy on equipment. In this work, a methodology is developed that aids decision making process in selected equipment using fuzzy logic inference engine of MATLAB. A maintenance cost model was developed to determine the best maintenance policy on each component of the equipment. The maintenance cost and the risk priority number variable were deployed as the input to the framework to determine the maintenance decisions. The proposed framework was applied to three pumps in the production plant of iron ore concentrates in National Iron Ore Mining Company, Itakpe to illustrate its applicability and efficiency. Results showed that the bearing components of the pumps were of the highest risk numbers at 927, 801 and 809 while the shaft components had the most delicate decision indices of 0.785, 0.798 and 0.510. The technique demonstrated in this research can be applied to pumps used in engineering industries.

Keywords: Asset management, equipment, fuzzy logic, maintenance, risk priority number

Introduction

Asset management is defined as an act of maintaining demanded service level of an asset for present and future consumers based on the most economically effective management (IIMM, 2006). A production process line comprises of several equipment that needs to be constantly monitored and maintained in order to reduce downtime and cost. The production of iron ore concentrate comprises of equipment such as pumps, vibrating screens, concentrate filters, transmission belts, just to mention a few. In his report, Adebiyi (2007) asserts that breakdown times occur a lot because of failure of one or more of these equipment.

The Management of National Iron Ore Mining Company, Itakpe expect the equipment to deliver at minimum cost. This means that production utilities must satisfy quantitative reliability requirements, while at the same time try to minimize their costs. The predominant expenditure for a utility is the cost of maintaining system assets. An example of which is through adopting preventive measures, collectively called preventive maintenance (PM). Preventive maintenance measures can impact on reliability by either improving the condition of an asset or by prolonging the lifetime of an asset (Allan *et al.*, 1988). Research findings have shown that maintenance impacts on the reliability performance of a component. For concentrate production process systems which are made up of interconnected components, this will eventually affect the entire system (Langevine*et al.*, 2002). Many programs, such as failure effects analysis, an evaluation of needs and priorities, and flow charts for decision making, had been used to validate this fact (Bertling and He, 1998).

Beneficiation of iron ore concentrate is an important process in steel manufacture. Maintenance, availability, reliability and total maintenance reliability are some of the most important functions carried out in the beneficiation plant in order to bring about the optimum workability of the equipment. The plant improves the iron content of ores. These ores are used for steel making at Ajaokuta Steel Company. The main product of National Iron Ore Mining Company (NIOMCO) is ore concentrate (Duru and Agba, 2005)

Studies have shown that Mechanical equipment breakdown can significantly impact a business. A breakdown can cost thousands of Naira in repair bills, business interruption and lost income (Boiler, 2011).

The production process line consists of equipment such as pumps, mills, vibrating screens, reclaimer and magnetic screens that should function optimally in order to have few breakdown times which will lead to higher productivity. Unfortunately, these equipment do have a lot of breakdown time even with the scheduled maintenance policy presently being employed. This paper therefore addresses the issues of incessant breakdown of equipment by proposing a model to be used in the management of these assets.

Failure mode and effects analysis (FMEA) and Risk Priority Number (RPN) is intended to provide information for making asset risk management decisions. Detail procedures on how to carry out an FMEA and its various applications in different industries and specific equipment have been documented by Stamatis (1995).

Over the years, several variations of the traditional FMEA have been developed. Traditional FMEA has been criticized for having several drawbacks. One of the critically debated setbacks is the method that the traditional FMEA employs to achieve a risk ranking. The purpose of risk ranking in order of importance is to assign the limited resources to the most serious risk items. Traditional FMEA uses an RPN to evaluate the risk level of a component or process. The RPN is obtained by finding the multiplication of three factors, which are the probability of failure (S_f) the severity of the failure (S) and the probability of not detecting the failure (S_d). Representing this mathematically will give (Carl, 2014):

$$\text{RPN} = S_f \text{ x S x } S_d \tag{1}$$

The most critically debated disadvantage of the traditional FMEA is that various sets of $S_f\,, S \text{ and } S_d$ may produce an identical value of RPN, however, the risk implication may be totally different (Ben-Daya and Raouf, 1993). The other prominent disadvantage of the RPN ranking method is that it neglects the relative importance among $S_f\,, S \text{ and } S_d$. The three factors are assumed to have the same importance. This may not be the case when considering a practical application of the FMEA process. Several authors have incorporated or replaced the traditional FMEA model with more practical formulation for RPN.

A model using fuzzy rule base and grey relation theory was developed by Anand and Jin (2003). In their work, they explained that most failure systems can be likened to grey systems where the information, such as operation, mechanism, structure and behavior are neither deterministic nor totally unknown. The major drawback of using grey theory as reported by Shih *et al.* (1996) is that it deals with making decisions characterized by incomplete information. Part of this assumption is that it involves using information gathered from experts and integrating them in a formal way so as to reflect a subjective method of ranking risks.

Ying-Ming *et al.* (2009) in their work, fuzzy risk priority numbers (FRPNs) were proposed for prioritization of failure modes. The FRPNs were defined as fuzzy weighted geometric means of the fuzzy ratings for Occurrence, Severity, and Detection, which were computed using alpha-level sets and linear programming models. In their work, Ying-Ming *et al.* (2009) assumed that developers have expert knowledge and expertise in using and developing the model. It is well known that this may not always be the case. Zaifang and Xuenning (2011) went further to bridge several knowledge gaps in the evaluation, calculation, and ranking of fuzzy RPNs. In their study, a fuzzyRPNs based method integrating weighted least square method, the method of impression and partial ranking method was proposed to generate more accurate fuzzy RPNs and ensure robustness against uncertainty. A design example of a horizontal drilling machine was used to illustrate the application of the proposed model. They proclaimed that the model is applicable in real life application because it can consider the personal characteristics of decision makers. The fault in this presumption is the question of whether the decision makers are ready to disseminate their personal bias and traits in their analysis.

Rachieru*et al.* (2014) analyzed the RPN results from traditional method of risk ranking and compared this to the fuzzy approach for risk ranking. This work, however, developed a maintenance cost model. The RPN results of the three pumps being used in National Iron Ore Mining Company, Itakpe were simulated with the maintenance cost model and from the result of the simulation, the maintenance decisions were determined.

Methods and Materials

Step 1: Variables and membership function

Four linguistic variables were defined in order to find the RPN values of each components of the pumps. These variables are:

a. Severity (S) – input variable. The severity factor indicates how significant a consequence is on the end-user or internal customer. There are cases where financial effects can be considered as a criterion to rank the severity. Severity is evaluated using the 10-point scale; **Where:** 10 means that the failure consequence is tremendous; and 1 means that the failure consequence is very low and ignorable (Liu, 2013)

b. Occurrence (O) – input variable. Occurrence is the probability of a specific failure mode. The occurrence rating is scaled from 1 to 10, where 10 means the probability of failure modes is very high and 1 means the occurrence is very low (Liu, 2013).

c. Detection (D) – input variable. This index determines the probability of detection of failures by various methods like quality control measures and testing. A number between 1 and 10 is given for Detection. A 10 on the detection index means that a failure mode is almost impossible to detect and 1 means the detection of failure is almost certain (Rhee and Ishii, 2013)

d. Risk Priority Number (RPN)– output variable. The main purpose of the FMEA is to compute the Risk Priority Number (RPN) to assign limited resources and budget to the most serious risk items

For the purpose of this study, the trapezoidal Membership Function (MF) model type was adopted for severity, occurrence and RPN variables (Jang, *et al.*, 1997).

Trapezoidal MF is specified by four parameters (a, b, c, d) as expressed as:

$$\text{Trapezoidal } (x; a, b, c, d) = \begin{cases} 0, & x \le a \\ \frac{x-a}{b-a}, & a \le x \le b \\ 1, & b \le x \le c \\ 0, & d \le x \end{cases} \quad (2)$$

Where: a, b, c, d respectively indicate parameters which characterize the shape of the MF curve. These parameters are in crisp rating where c is the smallest value, from b to c, the range of the most promising value and d, the largest value that illustrate the fuzzy function.

Gaussian membership function model type was adopted for the detection variable (Jang *et al.*, 1997).

Gaussian MF is defined by two parameters (c, σ) expressed as:

$$\text{Gaussian } (x; c, \sigma) = e^{-[x-c]^2/2\sigma^2} \quad (3)$$

Where: c determines the centre of MF and σ represents the width of MF.

Step 2: Fuzzy rules

Fuzzy rules also known as If-Then rules have been prescribed as a key tool for describing pieces of information in fuzzy logic (Dubois and Prade, 1996).

A total number of 125 fuzzy rules are gathered from experts in the field of study (Rachieru *et al.*,2014). These are represented in matrix form in Table 1.

Table 1: Fuzzy Rules

Severity	Occurrence	Detection VM	M	A	H	VH
VM	VM	VM	VM	VM	VM	M
	M	VM	VM	VM	M	M
	A	VM	VM	M	M	A
	H	VM	M	M	A	A
	VH	M	M	A	A	H
M	VM	VM	VM	VM	M	M
	M	VM	VM	M	M	A
	A	VM	M	M	A	A
	H	M	M	A	A	H
	VH	M	A	A	H	H
A	VM	VM	VM	M	M	A
	M	VM	M	M	A	A
	A	M	M	A	A	H
	H	M	A	A	H	H
	VH	A	A	H	H	VH
H	VM	VM	M	M	A	A
	M	M	M	A	A	H
	A	M	A	A	H	H
	H	A	A	H	H	VH
	VH	A	H	H	VH	VH
VH	VM	M	M	A	A	H
	M	M	A	A	H	H
	A	A	A	H	H	VH
	H	A	H	H	VH	VH
	VH	H	H	VH	VH	VH

VM = Very Minor, M=Minor, A = Average, H=High, VH=Very High, these are the fuzzy sets defined for the inference engine

As an example, these fuzzy rules are presented in an if-then statement and read as:

Rule matrix 1: IF severity is very minor AND occurrence is average AND detection is minor, THEN RPN is very minor

Step 3: Defuzzification

The defuzzification model converts fuzzy output of the fuzzy interference engine to crisp or quantifiable outputs (Jang *et al.*, 1997). In order to obtain outputs from the fuzzy output, a defuzzification model is required.

There are several defuzzification methods, the centroid technique used with the Mamdani inference technique is the most popular. The adopted centroid defuzzification model as defined by Jang, *et al.* (1997) defined the centre of gravity (COG) of a fuzzy set expressed as:

$$COG = \frac{\int_a^b \mu_A(x) x dx}{\int_a^b \mu_A(x) dx} \qquad (4)$$

Where: $\mu_A(x)$ is the crisp value assigned to the fuzzy set A in the universal set x

The centroid defuzzification method finds a point representing the centre of gravity of the fuzzy set, A, on the interval $[a, b]$.

A reasonable estimate is then calculated over a sample of points

The Matlab model framework for the RPN is shown in Fig. 1.

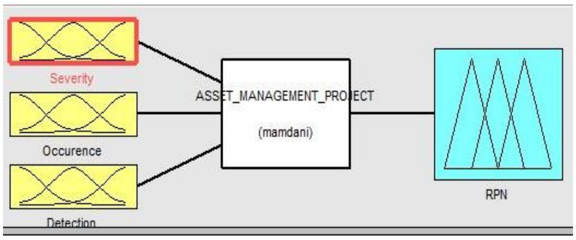

Fig. 1: Model framework for RPN

Step 4: Maintenance cost model

In order to determine the maintenance policy for the equipment analysis, it is pertinent to develop a maintenance cost model. The model was compared to the one developed by Nasrin (2016). The maintenance cost together with the calculated RPN will allow a meaningful decision to be made as regards the maintenance policy to choose, be it Corrective maintenance (CM), preventive maintenance (PM) or Condition-based maintenance (CBM).

Notations:

MC = Maintenance Cost
DC = Direct Cost
IC = Indirect Cost
W_m = Wage of Maintenance manpower/hr. (N)
T_r = Repair Time
C_s = Cost of spare parts
C_m = Cost of Materials and Energy
T_s = Downtime (hr)
P = production Capacity/hr.
C_p = Sales price
W_p = Wage of Production manpower/hr.

$$MC = DC + IC \qquad (5)$$
$$DC = W_m T_r + C_s + C_m \qquad (6)$$
$$IC = T_s P C_p + T_s W_p \qquad (7)$$

Therefore, $MC = T_s(PC_p + W_p) + W_m T_r + C_s + C_m$ (8)

Enumerated in Table 2 below are the forty-nine (49) fuzzy rules culled from the opinions of the experts in the field.

Table 2: Maintenance decision rules

MC/RPN	N	VL	L	M	H	VH	EH
N	CM	CM	CM	CM	CM	PM	PM
VL	CM	CM	CM	PM	PM	PM	PM
L	CM	PM	PM	PM	PM	PM	PM
M	CM	PM	PM	PM	PM	PM	CBM
H	PM	PM	PM	PM	PM	CBM	CBM
VH	PM	PM	PM	PM	CBM	CBM	CBM
EH	PM	CBM	CBM	CBM	CBM	CBM	CBM

CM = Corrective maintenance, Fuzzy range (-0.45 -0.05 0.05 0.45); PM = Preventive maintenance, Fuzzy range (0.05 0.45 0.55 0.95); CBM = Condition-based maintenance, Fuzzy range (0.55 0.95 1.05 1.45)

RPN and maintenance cost (MC) are designed as the inputs of the Mamdani fuzzy inference system (FIS). Gaussian's membership function was selected for RPN and MC input variables. Trapezoidal membership function was chosen for maintenance decision. This is the output variable. The rules are applied and simulated on the FIS.

From Table 2, N=Negligible, VL=Very Low, L= Low, M= Moderate, H = High and EH = Extremely High. The basis of choice of fuzzy values for CM, PM and CBM were derived from the simulation results of the maintenance cost and RPN variables in the fuzzy inference engine. As an illustration, when the maintenance cost on a component is defined as "Low" and its associated RPN result is "Medium", the maintenance decision would be preventive maintenance which is the fuzzy range of (0.05 0.45 0.55 0.95).

The Matlab model framework for the maintenance decision is shown in Fig. 2.

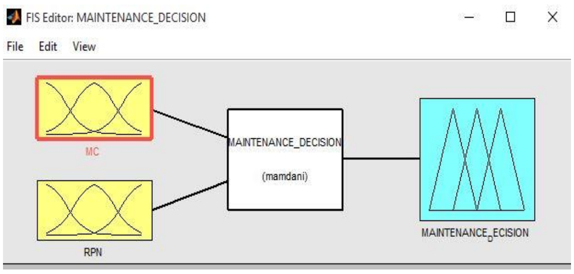

Fig. 2: Maintenance decision framework

Data Representation

A representation of the FMEA punctuation form is presented in Table 3. This shows the failure mode and effects analysis of one of the three pumps that is analyzed in this work. The severity, occurrence and detection on the pumps were observed over a period of ninety working days.

Table 3: FMEA of components of pump in National Iron Ore Mining Company

System Identification: Warman SP/SPR heavy duty cantilever sump pump								
Function	Description of system function: For clear and clarified water, thickener overflow water							
Component	Component function	Failure Mode	Severity	Failure cause	Failure effect	Occurrence	Detection	RPN(Crisp values)
1. Bearing	for lubrication to aid smooth running of drive shaft	1.1 Bearing damage	8	operational stress and wear, wrong bearing	a. Excessive pump vibration	6	5	**240**
		1.2 Lack of lubrication	8	worker's negligence of duty, over heated bearings	b. Pump Overload c. increased shaft radial movement d. pump shutdown	9	5	**240**
2. Impeller	Transfers energy from the motor to the fluid being pumped by accelerating the fluid outwards from the center of rotation	2.1 worn out impellers	6	pump cavitation	a. pump low efficiency	9	5	**270**
		2.2 Impeller O rings cut	5	wear, wrong rings used, wrong clearance between	b. vibration	10	6	**300**
		2.3 Inner liner wear	4	erosion by suspended solid particles contained in the fluid	c. failure in suction power and material blockage	8	5	**160**
3. Shaft	Transmit the torque encountered when starting and during operation while supporting the impeller and other rotating parts	3.1 shaft deformation	7	Misalignment, stress and tension	a. pump low efficiency	1	8	**56**
		3.2 Gland packing wear	5	loose packing, age	b. vibration	8	5	**160**
		3.3 Throat Bushing wear	3	very wrong throat bushing clearance	c. increased shaft radial movement	8	4	**96**
		3.4 Bad and worn	2	wrong sleeve installation, age and material wear	d. possible bearing damage e. excessive coupling failure	5	8	**80**
4. coupling	compensate the axial growth of the shaft and transmit torque to the impeller	4.1 Cover plate wear	6	High differential pressures between the discharges and suction sides of the impeller	a. losses of pump efficiency	7	7	**294**
		4.2 frame plate wear	6	excessive tightening causing cracks	b. noise and vibration of pump	6	7	**252**
		4.3 Faulty shaft coupling	9	lack of lubrication	c. possible seal damage d. material blockage	1	8	**72**
5. Casing	The volute that receives the fluid being pumped by the impeller slowing down the fluid's rate of flow and increasing fluid pressure	5.1 leaking casing	8	ambiet and environmental factors, loose tightening of casing	a. reduction in pumping rate	6	3	**144**
		5.2 leaking flanges	8	too much pressure and stress concentration at flange seals	b. corrosion on all pump components	9	6	**576**
6. Electric Motor	converts electrical energy to mechanical enery to drive the impeller	6.1 Motor fault	6	fluctuation in power supply	a. problem in startup of pump b. material bloackage	10	6	**360**
7. V- belt	transmission mechanism between the motor shaft and pump shaft	7.1 V-belt cut	9	low/high belt tension, misalignment	a. Lost man-hour due to breakdown	9	9	**729**

Table 4: Shape parameters for model variables

Fuzzy shape parameters for severity and occurrence (trapezoidal MF)	Fuzzy shape parameters for Detection (Gaussian MF)	Fuzzy shape parameters for RPN (trapezoidal MF)	Linguistic Term
-1.025 0.775 1.225 3.025	0.7644 9.775 0.7644 10.23	-223.8 -23.98 25.98 225.8	Very Minor (VM)
1.225 3.025 3.475 5.275	0.7664 7.525 0.7644 9.975	25.98 225.8 275.7 475.5	Minor (M)
3.5 5.3 5.75 7.55	0.7644 5.275 0.7644 5.725	275.7 475.5 525.5 725.3	Average (A)
5.725 7.525 7.975 9.775	0.7644 3.025 0.7644 3.475	525.5 725.3 775.2 975	High (H)
3.02 9.82 10.3 12.1	0.7644 0.775 0.7644 1.225	775.2 925 1025 1225	Very High (VH)

Table 4 above shows the fuzzy shape parameters for the severity, occurrence and detection variables. The Fuzzification of the values of these variables are used to determine the linguistic term that the RPN of each component falls into.

Results and Discussion

In running the model framework inference engine, the set of rules in Table 1 were applied to the punctuation form in Table 3 for severity, detection and occurrence variables, respectively. A simulated result for the three pumps is shown in Fig. 3 in graphical view.

The results of RPN in Fig. 3 above together with the maintenance cost derived from Equation (8) for each of the three pumps served as the input to the second fuzzy inference engine to determine the maintenance decision index. The graphical result of the maintenance decision index is shown in Fig. 4.

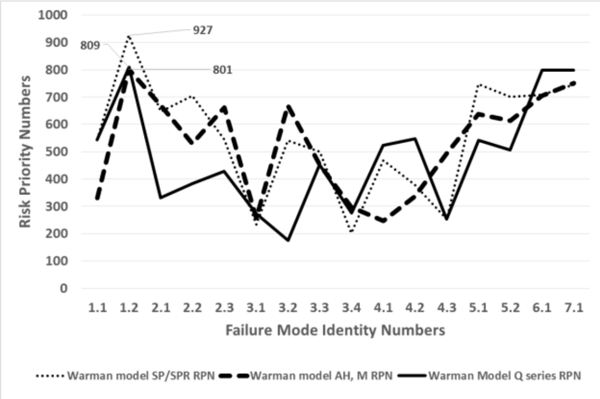

Fig. 3: Risk priority numbers result

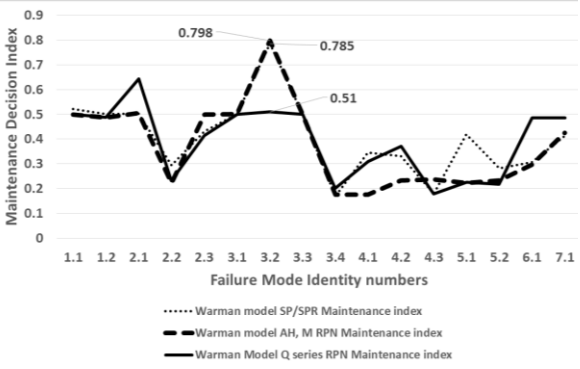

Fig. 4: Maintenance decision index results

The detailed maintenance decision result for the three pumps is presented in Table 4.

Table 5: Detailed maintenance decision results

Failure mode Identity numbers	Component	Maintenance decision (linguistic) Warman Model SP/SPR	Maintenance decision (linguistic) Warman Model AH, M	Maintenance decision (linguistic) Warman Q series
1.1	BEARING	PM	PM	PM
1.2		PM	PM	PM
2.1	IMPELLER	PM	PM	PM/CBM
2.2		CM	CM	CM
2.3		CM/PM	PM	PM
3.1	SHAFT	PM	PM	PM
3.2		PM/CBM	PM/CBM	PM
3.3		PM	PM	PM
3.4		CM	CM	CM
4.1	COUPLING	CM	CM	CM
4.2		CM	CM	CM
4.3		CM	CM	CM
5.1	CASING	CM/PM	CM	CM
5.2		CM	CM	CM
6.1	ELECTRIC MOTOR	CM	CM	PM
7.1	V BELT	CM/PM	PM	PM

Where CM, PM, and CBM are as earlier defined in the footnote of Table 2

Analyzing the graphical results for the three pumps, it was observed that the failure mode id captioned 1.2 known as "lack of lubrication" scored the highest RPN value for pump model SP/SPR, AH/M and Q series with RPN scores of 927, 801 and 809, respectively (Fig. 3). The failure mode in the three cases is due to lack of lubrication on the bearings. This signifies the criticality of this component and the possible negligent attitude of technical staff as regards lubrication of the bearing nipples.

Analysis of the graphical results shown in Fig. 4 and also Table 5 for the three pumps, peculiar maintenance decisions was suggested for different components. As observed, for the bearing component, in each of the equipment, preventive maintenance (PM) was suggested. For the impellers, PM was also suggested. For the shaft components with index 0.798 and 0.785, condition based maintenance (CBM) was advised. This could be a sensory system installed on the component in order to predict the equipment condition and predicting the failure time by monitoring techniques which is in line with Nasrin (2016) results from maintenance decisions using Fuzzy FMEA. The couplings, casings and electric motors should be left for corrective maintenance. This may be due to the fact that such components do not give way to wear and tear easily and could be run till a breakdown occurs. This will in turn save cost in contrast to PM policies on these components. Also from the results, PM policy is the best for V belts of the three pumps. The developed model was compared to the existing model used at National iron ore mining company, Itakpe. The advantages of the developed model indicate that issues of breakdown maintenance were constructively minimized. There is timely intervention to attend to maintenance schedule at all times.

Conclusion

In this research, an asset framework has been developed in order to analyze failure mode and effect and determine the maintenance policy techniques for selected equipment. The importance of risk priority numbers have been shown in maintenance policy determination. The results of the simulated framework showed that a high risk priority number does not necessarily mean that a more stringent and expensive maintenance policy need be adopted. Therefore, the maintenance cost function need to be considered.

During the course of this work, however, it was observed that the study area does not have a standard equipment record keeping culture. Keeping proper and necessary record on equipment will aid management, planning and maintenance of the equipment.

The developed model can be applied to equipment in manufacturing or production industries where there is no suitable maintenance policy in effect or where confusion exists as to which maintenance policy to adopt in any case.

In conclusion, the objective of developing an asset management for selected equipment has been accomplished.

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