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Development of a Risk Matrix and Extending the Risk-basedMaintenance Analysis with Fuzzy Logic Technology

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Abstract

In this article, loss of production, higher maintenance costs are major problems of manufacturing systems are discussed. Here certain investigating methods, like Risk-based maintenance (RBM), help to deal with such issues. An important element of the RBM planning is to assess the consequences of action and prioritization of maintenance tasks based on the risk of potential failures. The main purpose of this classification is the right choice for maintenance strategy, maintenance intervals, and a certain level of spare parts in the storage. This manuscript illustrates the use of fuzzy logic for the minimization of suboptimal classifications, and it suggests a fuzzy inference system (FIS) for overcoming the challenge mentioned above. Membership functions and the rule base are developed. It is possible to integrate the suggested approach to currently existing computer-aided maintenance management system (CMMS) in a manufacturing firm (MF).

Keywords: classification; fuzzy logic; manufacturing systems; risk-based maintenance; risk matrix

Introduction

The performance of production is heavily influenced by the maintenance productivity e.g. Parida and Kumar, which concerns significant endeavors that deal with inspections, scheduled cleaning, adjustments, repairs and replacements of machinery in the manufacturing firm to ensure operational reliability, and final product quality. The output of manufacturing process is dependent on the performance of machinery as defective products from previous machinery can accumulate or disturb the subsequent process and overall quality. This has been further exacerbated by the increasing trend on mechanization and automation and the role of machinery in production operations become significantly important factor. Hence, it is vital to keep the performance of machinery in an ideal condition and operate effectively.

Inherently, the equipment or machinery experiences aging and deteriorate with time and/or level of usage in a manufacturing process, which has direct/indirect impact on the overall quality of the manufactured products. In this context, it is possible to characterize the diminished product quality by increasing the rejection rate and declining the performance of particular machinery. As the rejected products cause the deterioration of the downstream process, it is not possible to segregate the maintenance tasks of machinery from the overall manufacturing process management tasks, Wenchi et al.. Moreover, the performing maintenance at the right time on the right machinery by the right personnel is crucial to restore them to an acceptable condition. Hence, it is vital using effective machinery prioritization approaches to schedule maintenance tasks and assign them into different maintenance strategies (i.e. preventive or corrective) as appropriately based on the risk [i.e. risk based maintenance (RBM)] of the potential failures. As shown in the work by Ratnayake et al.

Fig. 1 illustrates the machines classification matrix in relation to maintenance strategies.

Fig. 1. Screening matrix.

Currently, some of the MFs use empirical models to classify machinery for performing maintenance tasks; it was shown in the papers Ratnayake. However, it has been revealed that the empirical models based classification requires further fine prioritization of the machinery for allocation of existing resources for performing maintenance tasks. Hence, it is vital developing RMB approach for prioritization and classification of machinery for effective scheduling of maintenance tasks. First, this manuscript explains the weaknesses of the currently existing empirical model based approach. Then, it suggest a risk matrix to make machinery prioritization and classification by taking personal safety (PS), percentage non-conforming products (PNCP), time to failure elimination (TTFE), availability (A) of a machinery per month for manufacturing tasks, and failure frequency [i.e. number of breakdowns (NoB) per month] into consideration. Finally, it demonstrates a fuzzy logic

based approach that supports the use of risk matrix to make optimal prioritization and classification of machinery (i.e. how fuzzy logic enables to minimize s
ub-optimal classifications, when RBM scheduling is made with the support of a risk matrix).

Industrial challenge

It mainly manufactures plastic products for domestic usage (e.g. garden tools and technological tools). Currently the MF uses scheduling (or time based) or corrective maintenance strategies for each machine which has been used in the manufacturing process. At the end of each year of manufacture/production, the maintenance personnel are responsible to prepare a schedule for preventive maintenance inspection (Note: as a rule of thumb, every machine has to be inspected after 2700 machine hours) focusing on the manufacturing operations that have to be performed in the subsequent year. However, it has been that the maintenance tasks are not properly implemented. For instance, the maintenance tasks are not implemented according to the schedule. Because of that, the MF is currently experiencing a significantly large number of breakdowns and consequently the MF has to perform unplanned corrective maintenance or reactive maintenance (i.e. firefighting). It has also been noted that the selected MF has a computer-aided maintenance management system (CMMS). The CMMS allows gathering and organizing information relating to the production, generating different indicators and graphs, etc., to support/schedule maintenance tasks. It also provides the opportunity to access to the database facility and breath of information on each production batch and each process performed at the MF's premises. The supervision of the machines has been performed over the inspection of individual elements of the machineries by the technical staff in the maintenance department. However, until to the date of the current study, the MF has not established rules concerning time limits and a way to control the efficiency of machines, which resulted in an unplanned way of the monitoring tasks. In order to change the current circumstances, the MF has decided to change currently used maintenance models and strategies. The MF is in the process of changing the current maintenance strategies to risk based maintenance strategy. Hence, it is vital to develop risk matrix and an approach to make effective risk based machinery classification for deploying maintenance resources effectively.
Currently, the case study MF uses a

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classification model to classify the machines. The existing classification model is based on three criteria: the use of equipment in production process, availability and safety of the employee. Table 1 illustrates the description of the criteria used in the classification.

First criterion describes the time and the extent of a machine that has been used to produce finished products. Scale for this criterion ranges from 1 to 4 points. The second criterion for the classification is availability. This criterion is calculated as availability per month [%] (or availability is assessed using the number of failures per year). The scale for criterion ranged from 1 to 4 points. Point 1 is assigned for the machines that have the highest number of failures [i.e. very low availability (<40%)], and point 4 is assigned when the number of failures does not exceed 10 [i.e. the availability is very high (81-100%)]. The last criterion in this classification is the safety of the employee – Sp. Scale scores ranged from 1 to 3 points. Point 1 is assigned to devices whose failure will have a major impact on the health of the worker, and point 3 were awarded those whose failures have a negligible risk to workers' health. The C_V values is calculated using the empirical formula (1) to qualify a machine for a certain classification category.

$$Cv = w_1 Pt + w_2 Fm + w_3 \quad (1)$$

The parameters Pt, Fm, Sp are and the weights w_i shall be decided by the management of a particular MF based on their requirements. Where using formula (2),

$$\sum w_i = 1 \quad (2)$$

Based on the discussion carried out with the people responsible for carrying maintenance activities of the company, weights (w_i) of the formula (1) were decided. The formula (3) illustrates the used values of weights.

$$Cv = 0.4 + 0.3Fm + 0.3Sp \quad (3)$$

The currently existing classification model classifies all machines into three categories H–High, M–Medium and L–Low. Table 2 illustrates machine classification categories according to model.

Table 2. The range of classification categories.

After the machines have been classified, it has been revealed that 41% of machines are with priority – H, 34% machines are with priority – M, and 25% machines are with priority L. It is essential to have special control of all machines, which are with priority H. In practice, it is a significantly difficult task as the case study of MF is relatively small organization and it lacks adequate resources such as employees and equipment to take care properly of all the machines with priority H. Therefore, in order to allocate resources available for the maintenance tasks, it is vital to perform RBM prioritization of the existing machinery. Hence, it is vital developing a risk matrix together with an effective risk analysis process to optimize the maintenance resources allocation. The risk matrix has been developed on the base of the authors' experience, historical data from the case study manufacturing firm and with the support of maintenance supervisor. Table 3 illustrates ranges, ranks and linguistic terms for consequences and number of failures. Four types of consequences have been are defined: personal safety (PS), percentage of non-conforming products (PoNCP), time of failure elimination (ToFE), and machinery failure frequency that is designated as the number of breakdowns (NoB) per six months.

The ranges and ranks of input and output variables were utilized as the basis for input and output variables. These ranges and rules were developed using CMMS system. Then, based on the risk of potential loss of quality (i.e. NoB of machinery vs. PoNCP), personnel safety (i.e. NoB vs. PS), and production (i.e. NoB vs. ToFE), the machinery have been evaluated focusing on classifying them into groups (i.e. risk based prioritization of machinery) for performing maintenance activities. The overall risk scenarios are presented as a risk matrix in

VH= Very high; H = High; M-H = Medium to high; M-L = Medium to low; L = Low; VL = Very low

The potential use of the risk matrix has been verified together with personal maintenance in the case study of MF. If the values of both the number of failures and the consequences are in the middle of the each range, then it is not a challenge in estimating the level of risk. However, if a range value fall at the border of the particular range, then there is a high possibility for making suboptimal classification of the machinery during the risk based maintenance prioritizations. In addition, such uncertainty creates significant variability in the analysis depending on the available information, knowledge, and experience. In order to cater the aforementioned circumstances, it is vital to use fuzzy logic based approach for enhancing the RBM classification of the machinery. In this context, it is possible to use the risk matrix as the rule base for a fuzzy inference system.

1. Fuzzy logic assisted RBM assessment approach

The illustrative case presented in this manuscript utilizes a Mamdani-type fuzzy inference process. The membership functions are developed taking the ranges of the NoB and CoFs into consideration. However, it is possible to develop membership functions with the support of maintenance experts by examining how they perceive membership values along the ranges, Stadnicka et al.

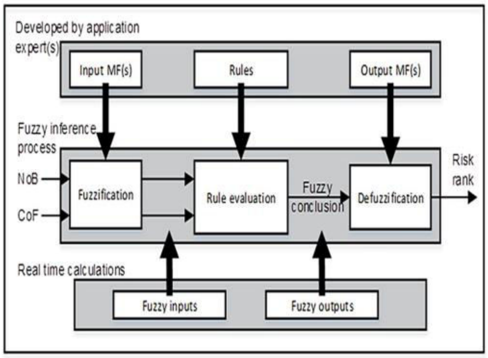

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Fig. 2. Overall view of the fuzzy RBM assessment process

The illustrative case has been demonstrated using triangular and trapezoidal membership functions. Fuzzy logic assisted risk rank calculation has been demonstrated using the NoB and a consequence of failure – PoNCP.

The input and output variables shall consist of quantitative, qualitative and judgmental (i.e. linguistic) data. Using an appropriate membership function, the user has "more confidence" that the input parameter lies in the center of the interval than at the edges. In this study, the authors has incorporated Gaussian membership functions, such in works Tay and Lee [11], Ratnayake [12] in order to minimize the gap between practical realities and mathematical modelling,

Where *c* represents the center and determines the width of the MFs. To model the membership functions, the Gaussian combination membership (GCMF) (i.e. "gauss2mf"), which is available in MATLAB (R2014b), has been utilized [13, 14]. The function "gauss2mf" is a combination of two

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parameters [i.e. (c, σ)] indicated in Equation (5). It follows the following syntax from Mathworks [13]:

$$y = \text{gauss2mf}\{x, [\sigma 1\ c1\ \sigma 2\ c2]\} \quad (5)$$

The first part of the function of the GCMF is specified by σ_1 and c_1, which determine the shape of the left-most curve. The second part of the GCMF, specified by σ_2 and c_2, determines the shape of the right-most curve. Whenever $c_1 \leq c_2$, the 'gauss2mf' function reaches a maximum value of 1. Otherwise, the maximum value is less than one. The order of the parameters is as follows: $[\sigma 1\ c1\ \sigma 2\ c2]$, [13]. Moreover, the other parameters of the fuzzy logic based expert system that have been selected for the current analysis are as follows: "AND" operator with "minimum", "OR" operator with "maximum", "Implication" with "minimum", "Aggregation" with "maximum" and "Defuzzification" with "centroid" algorithm. A fuzzy rule base has been developed using the table-look-up approach (see Table 4). The toolbox simulator tool of MATLAB (R2014b) has been utilized to execute the suggested fuzzy inference process in program Matlab [14].

2. Analysis, results and discussion

Fig. 3 illustrates Matlab R2014b based fuzzy logic designer used for calculating risk ranks in relation to NoB and PoNCP.

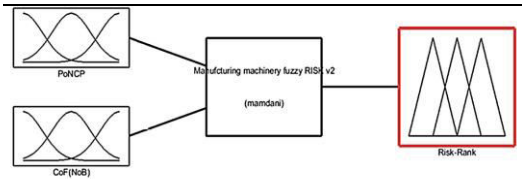

Fig. 3. Fuzzy logic designer.

The parameter values of GCMFs are presented in Table 5.

NoB	[2 30 2 30]	[4 25 1.75 25]	[3 15 3 15]	[1 7.5 2.5 7.5]	
PoNCP	[0.4 5 0.5 5]	[0.6 4 0.3 4			
Output variable	VH	H	M-H		
Risk rank	[0.2 0 0.2 0.5]	[0.3 1]			

The GCMFs for the PoNCP, NoB and Risk rank are illustrated in Fig. 4, Fig. 5 and Fig. 6 respectively.

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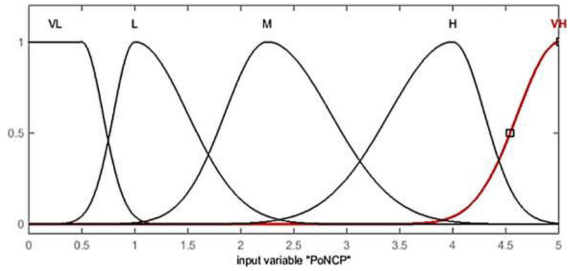


Fig. 4. GCMF of PoNCP.

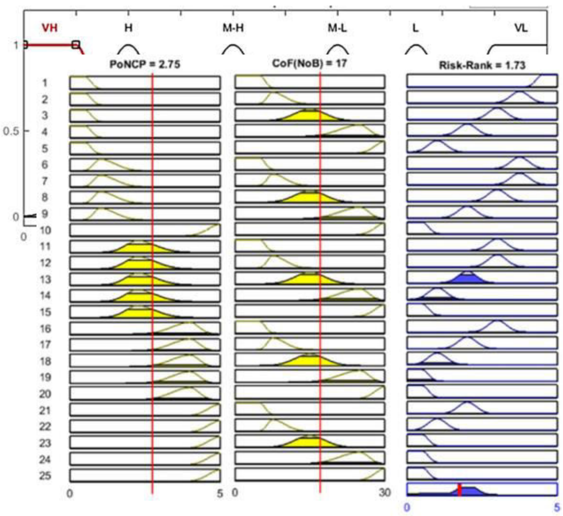


Fig. 6. GCMF of risk rank.

Fig. 7 illustrates a rule view and an example calculation of risk rank for machinery. The calculation has been carried out for the PoNCP=2.75 and NoB=17. The risk rank estimated by the fuzzy inference process is 1.73. The corresponding linguistic value is M-H (using the membership function

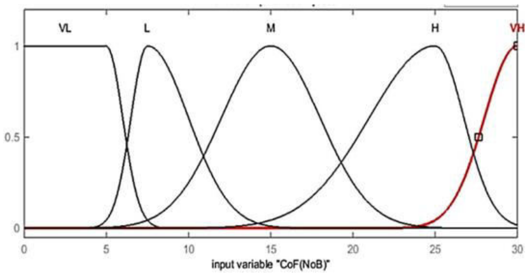
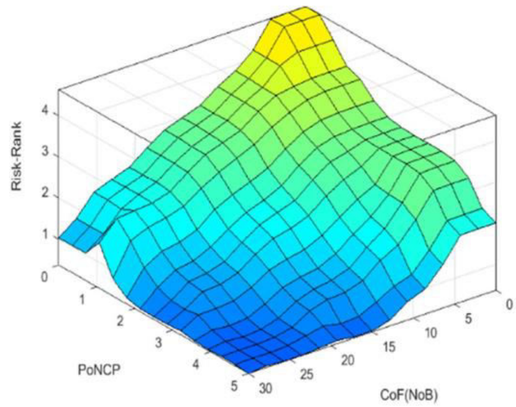


Fig. 5. GCMF of NoB.

in Fig. 6). This linguistic value shall be used for the classification of machinery into groups for allocating maintenance resources (i.e. machinery with high risk will be given main priority). Similar manner, it is possible to calculate the risk of potential failures for each piece of machinery. Based on the



manufacturing firm's risk philosophy, it is possible to prioritize 1. PS, 2. PoNCP and

3. ToFE or any other sequence. The aforementioned kind of prioritization is mostly dependent on how the particular manufacturing firms perceive risk in their operations' related health, safety, environment and quality (i.e. HSE&Q). Fig. 8 illustrates three dimensional (3D) risk profiles in

relation to PoNCP and NoB.

Fig. 7. A rule view and calculation [risk rank is 1.73 for PoNCP = 2.75 and NoB = 17].Fig. 8. 3D risk profile.

Conclusion

The manuscript has demonstrated RBM prioritization approach for the machinery utilized in a manufacturing process. It has been proposed as an alternative to currently existing empirical model based approach, which poses significant challenges in allocating limited resources available in the case study manufacturing firm. A risk matrix has been developed to overcome some of existing challenges. In addition, fuzzy logic based risk rank calculation approach has been presented. The suggested RBM approach together with fuzzy inferencing process enables to minimise suboptimal calculations, when the input values are at the boundaries of the particular ranges. Fuzzy membership functions together with the rule base enabled to insert numbers with least uncertainty. When the membership functions are revised with the support of maintenance experts, then it also enables to recycle the experts' knowledge in maintenance related decisions. Such recycling enables to minimize the variability in the final RBM prioritizations.

Future research shall be carried out to investigate the potentiality for developing membership functions with the support of artificial neural network (ANN).

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