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Application of a Taguchi-fuzzy approach for prediction of maintenance-production workforce parameters of manufacturing systems

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Abstract

Maintenance workforce evaluation has recently received increased attention due to its significant positive influence on manufacturing. Much theoretical and practical work has been done in this area. However, its optimisation considering uncertainties has not been adequately addressed. The current study develops a novel approach providing an understanding of the uncertainties while including factors for workforce size determination using an integrated Taguchi-fuzzy technique. The feasibility of a fuzzy maintenance workforce model as an expert tool was investigated and the results were validated using a literature model. The current study observed that the developed fuzzy workforce prediction and optimisation tool can be used to avoid complex mathematical expressions for workforce size prediction. Compared to ARIMA, the model offers comparable results and can be easily used by maintenance mangers.

Keywords: Taguchi-fuzzy method, Workforce maintenance-production parameters, Manufacturing system, ARIMA

1. Introduction

Nowadays, the prediction of workforce size, utilisation of the workforce and its optimisation [1] for the maintenance function are important concerns [2-4] considered to be very serious by the management of organisations and systems [5-6] in the face of the stiff competition in the product market. This, however, calls for prudence in the management of maintenance resources. Thus, the application of workforce prediction models in such environments will aid control of excessive workers in a system. The workforce issues in the maintenance organisation mentioned motivate organisational management to initiate schemes and polices [7-9] that monitor and control maintenance workforce activities in a way that avoid wastes and capture as precisely as possible maintenance and production information.

During workforce planning activities for maintenance and production departments, the workforce size for these two departments is specified by decision makers. Based on the levels of production and maintenance activities, further specification of workforce size for maintenance and production department is made. The model in this study is based on a general group of maintenance and production workforce size. However, the analysis of the model is maintenance activity focused.

In the past, numerous maintenance workforce predictive analysis and evaluation tools have been constructed for maintenance workforce [10-12]. Most of these model methodologies have complex interrelationships in generating information effective for decision-making in maintenance system. They involve large amount of information that may be uncertain, imprecise and vague. Certain issues concerning workforce in maintenance has partial truth in them, and may be without boundaries that are distinct. Thus available studies in literature have been on workload, cost and schedules.

The situation is that much attention is not being paid to the mentioned attributes of information available in maintenance. Such data are regularly used for prediction analysis of the workforce size and other parametric issues. Apart from this problem that is the characteristic of maintenance systems, which available models cannot solve, the scope of the data analysis for workforce prediction in literature has not covered other important areas such as the level of machine availability, historical cost and number of defective products produced from machines, machine utilisation and workforce idle time [10-11]. Other omissions in previous investigations are the prevailing interest on loans and taxation issues.

In other words, the principal drive in having an acceptable framework of a workforce predictive approach is not limited to meeting the workload targets but by accounting for the technical, economic and financial issues of maintenance workforce prediction. Applied to this study, fuzzy logic should have the unique contribution of providing a practical framework to the modelling of complex interrelationships is considered. Fuzzy logic provides an avenue in which vague information obtained by the maintenance managers' evaluations could be analysed in solving the maintenance problem.

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Few techniques are being studied in maintenance optimisation for maintainable systems. Current research has seen efforts to relate workforce issues to genetic algorithm and maintenance cost [11]. Also, investigations have been conducted on a method of using scheduling analysis for aircrafts maintenance [10]. Ighravwe and Oke [12] proposed a non-linear programming technique for sizing workforce with worker's idleness consideration. In sum, these techniques which are based on the assumption of certainties, that are violated by the limiting factors, including machine breakdowns (causing high cost and frequently-produced defectives, low machine availability). The cost of defectives is a major concern to the maintenance manager and the problem is how to minimise the cost of defectives and reworks as well as machine unavailability.

Given the prevalence of these uncertainties in the maintenance system, the maintenance problem could be formulated by the applicability of fuzzy logic as a solution. This solution would be enhanced by integrating the Taguchi method into the framework. To further establish that uncertainties are prevalent in maintenance systems, other factors that introduce uncertainties to the maintenance system set-up include staff problems (such as absenteeism, moral issues, which causes shortage in production outputs or even non-attainment of maintenance workload targets and tasks as well as a carry-over of domestic issues that the worker has at home to the workplace). Other uncertainties in maintenance systems are attributed to operator's problems (poor skills, turnover, competence lacks, training deficiencies and motivational issues), cancellation of existing orders and more [13]. To minimise these uncertainties, adequate provisions for workforce size is required.

Furthermore, other uncertainties in maintenance include the cost of inventory and machine usage as well as achieved machine availability. All these have direct and indirect impacts on the maintenance system performance and the income that the organisation would make. The prevailing interest on loans and the workforce to maintenance ratio in this turbulent period is often a challenge, which may be resolved using fuzzy logic. Thus, if the maintenance system would remain efficient in its service delivery to the production system, then the maintenance workforce must be optimally managed. To address these challenging tasks, a fuzzy logic approach in generating an expert system that can be used in predicting the optimal workforce size of maintenance workforce is essential. Such an expert system could be enhanced by embedding design of experiments framework which (Taguchi method) into a fuzzy inference system (FIS). Fuzzy logic has been utilised to study uncertainty in multi-objective non-linear programming model [13]. Abbas and Elsayed [13] study combined different factors (objectives) at different levels using the Taguchi's design of experiment.

A brief account of research related to this work is given as follows: A study that utilised Mandani-style fuzzy model and centre-of-mass defuzzification method in designing of an expert system for hydroelectric power plant predictive maintenance was presented by Marcos et al. [5]. Pavement age and drop in pavement quality was used by Suman and Sinha [6] in investigating the suitability of fuzzy inference system for planned pavement maintenance treatment evaluation. The conclusions of their study showed that under uncertainty, fuzzy logic model has the capacity to select maintenance treatment for pavement maintenance. An expert system for addressing the problem of just-in-time maintenance system for production facilities was presented by Sahoo et al. [14] using fuzzy logic-based If-Then rules. Their investigation revealed that equipment availability can be improved using fuzzy model which has the capacity to forecast the number of defects, weaknesses and anomalies in installed equipment.

Tahir et al. [1] identified triangular and trapezoidal membership functions as two membership functions which can be used in mapping maintenance problems. This study combined these membership functions for the inputs and output based on triangular and trapezoidal membership functions. Tahir et al. [1] proposed a decision support system for maintenance activities in small-and-medium-scale firms using a combined fuzzy logic and analytical hierarchy process approach. Frequency of maintenance and downtime of equipment were taken as premises that can be used for selecting the type of maintenance strategy for different machines in a system. The outcome of their study showed that fuzzy modelling approach has the capacity of improving decision making process in maintenance systems. A fuzzy optimisation model for maintenance system under a multi-objective maintenance system was developed by Akhshabi [7]. Maintenance workers, policies, budget and spare parts risk were used in restraining the developed model. It was observed that the developed model has the capacity to identify spare parts policy for a maintenance system.

This study presents the development of a fuzzy logic knowledge-oriented approach for the continuous evaluation and progress of a maintenance system for a manufacturing system for the optimum performance of system through an account for the process uncertainties. The output of the fuzzy system developed will permit the proper prediction of the workforce. The prediction framework adopts fuzzy rule in the model build-up. Orthogonal array was then applied as a function to evolve an overall framework. The combined fuzzy logic and Taguchi orthogonal array provides an innovation application in the field of maintenance engineering practice for maintenance data analysis.

The remaining sections of this study are arranged as follows: In section 2, the application of the proposed fuzzy logic model and Taguchi method for workforce prediction are presented. Section 3 contains the application of the proposed fuzzy model while section 4 presents the discussion of results. The conclusions of this study is in section 5.

2. Research methodology

This study proposes Figure 1 as the flowchart for maintenance-production workforce size prediction. The first step for designing the proposed fuzzy logic model deals with the number of fuzzy rules for determining the value of the workforce size. This problem was addressed using factors and levels combinations. Full design of experiment is not considered because it lacks the capacity to reduce the time required to generate information for a system. Rather Taguchi method is considered [15]. This study used Taguchi method in combining different factors at different level in generating different maintenance-production workforce size [16]. Another benefit of Taguchi orthogonal array is that the same combination of factors and levels type can be used by different people in carrying out the same experiment results based on standard orthogonal array table [15-16].

Taguchi method is an experiment method that combines factors and levels in an experiment using orthogonal array. The aim of Taguchi method is to reduce the number of experiments required to study a dependent variable in an experiment. Four objectives or premises (factors) were

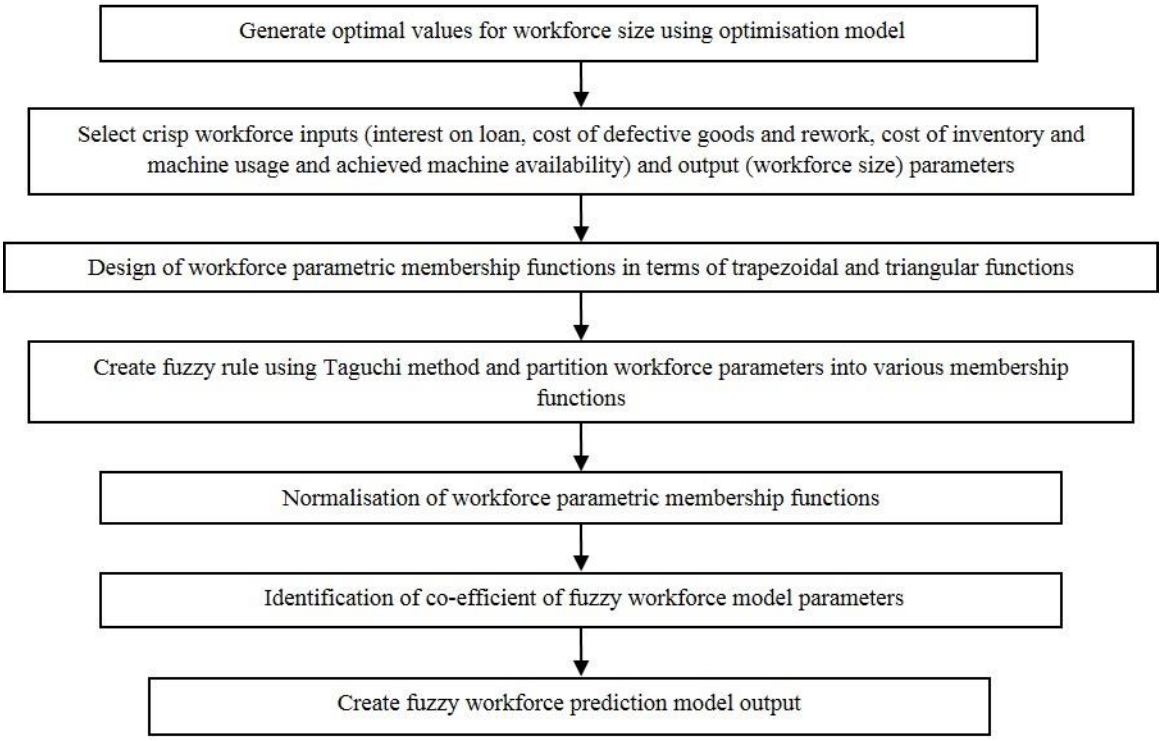

Figure 1 Taguchi-fuzzy workforce prediction model

Table 1 L_{27} orthogonal array

Experiment Number	**Factors**			
	A	***B***	***C***	***D***
1	1	1	1	1
2	1	1	1	2
3	1	1	1	3
4	1	1	2	1
5	1	2	2	2
6	1	2	2	3
7	1	2	3	1
8	1	2	3	2
9	1	3	3	3
10	2	3	1	1
11	2	3	1	2
12	2	3	1	3
13	2	1	2	1
14	2	1	2	2
15	2	1	2	3
16	2	1	3	1
17	2	2	3	2
18	2	2	3	3
19	3	2	1	1
20	3	2	1	2
21	3	3	1	3
22	3	3	2	1
23	3	3	2	2
24	3	3	2	3
25	3	1	3	1
26	3	1	3	2
27	3	1	3	3

Table 2 Inputs and output with their fuzzy and fuzzy intervals

S/No.	Linguistic Variables	Variables	Units	Linguistic values
1	Input 1	Interest on loan (x_1)	Naira	Low (L) Medium (M) High (H)
2	Input 2	Cost of defective goods and rework (x_2)	Naira	Low (L) Medium (M) High (H)
3	Input 3	Cost of Inventory and machine usage (x_3)	Naira	Low (L) Medium (M) High (H)
4	Input 4	Achieved machine availability (x_4)	-	Low (L) Medium (M) High (H)
5	Output	Workforce size (y)	-	Satisfactory(S) Average (A) Unsatisfactory (U)

considered at three levels. Twenty-seven experiments are generated (Table 1). The 27 experiments are used in generating If-Then fuzzy rules. FIS was established based on four core operations that involve fuzzification, knowledge base, inference system and defuzzification in mapping a set of input parameters to a set of output parameters [6, 17].

A fuzzification operation involves the conversion of real (crisp) value to linguistic terms while defuzzification deals with conversion of linguistic terms into crisp value. These linguistic terms are expressed using adjective of quantification and mapped to fall within a range of 0 and 1. This study considered interests on loan used to cater for workers' expenses, cost of defectives and reworks, and costs of inventory as well as machine usages and achieved machine availability as input parameters for the FIS. Workforce size was considered as output for the FIS (Table 2).

The various parameters membership functions in the proposed fuzzy model are normalised to lie between 0 and 1 based on Equation (1). Similar normalisation procedure is used for the output parameter.

$$\hat{x}_i = \frac{x_i - x_{i,\min}}{x_{i,\max} - x_{i,\min}}\left(x_{\min} - x_{\max}\right) + x_{\min} \qquad (1)$$

where $\mathcal{X}_i$ stands for the actual value of parameter $i, \hat{\mathcal{X}}_i$ represents the normalised value of parameter $i, \mathcal{X}_{i,\min}$ stands for the minimum value of parameter $i, \mathcal{X}_{i,\max}$ represents the maximum value of parameter $i, \mathcal{X}_{\min}$ stands for new minimum limit of parameter i, and $\mathcal{X}_{\max}$ represents new maximum limit parameter i [16].

During the application of fuzzy logic, the membership functions (linear, triangular and trapezoidal) designed is based on expert judgement. There is no rule on the type of membership function to be used in partitioning a parameter. The minimum and maximum values for a parameter need to be known. This study fixed the normalised minimum values for inputs as 0, while the normalised maximum values of input is 1. The triangular membership function is used to represent the low and medium values of input 1, while trapezoidal membership function is used to represents high values of input 1 (Figure 2). The characteristic equation for low values of input 1 is expressed as Equation (2), while the medium values characteristic equation is expressed as Equation (3). The characteristic equation for high values of input 1 is expressed as Equation (4).

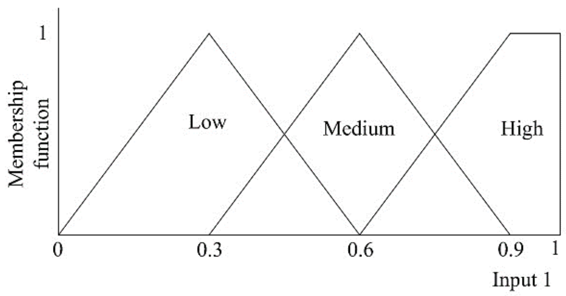

Figure 2 Membership functions for input 1

$$\mu_L(x_1) = \begin{cases} \dfrac{x_1}{0.3} & 0 \le x_1 \le 0.3 \\ \dfrac{0.6 - x_1}{0.3} & 0.3 \le x_1 \le 0.6 \\ 0 & 0.6 \le x_1 \le 1 \end{cases} \qquad (2)$$

$$\mu_M(x_1) = \begin{cases} 0 & 0 \le x_1 \le 0.3 \\ \dfrac{x_1}{0.3} - 1 & 0.3 \le x_1 \le 0.6 \\ \dfrac{0.9 - x_1}{0.3} & 0.6 \le x_1 \le 0.9 \\ 0 & 0.9 \le x_1 \le 1 \end{cases} \qquad (3)$$

$$\mu_H(x_1) = \begin{cases} 0 & 0 \le x_1 \le 0.6 \\ \dfrac{x_1}{0.3} - 2 & 0.6 \le x_1 \le 0.9 \\ 1 & 0.9 \le x_1 \le 1 \end{cases} \qquad (4)$$

The membership functions for low and high values of input 2 is represented with trapezoidal membership function. Triangular membership function is used to represent the medium values of input 2 (Figure 3). The characteristic expression for low values of input 2 is expressed as Equation (5), while Equation (6) represents the characteristic equation for medium values of input 2. The characteristic equation for high values of input 2 is expressed as Equation (7).

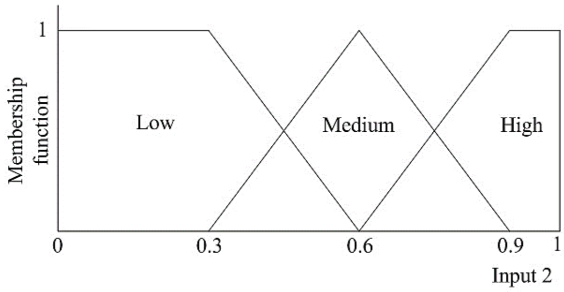

Figure 3 Membership functions for input 2

$$\mu_L(x_2) = \begin{cases} 1 & 0 \le x_2 \le 0.3 \\ \dfrac{0.6 - x_2}{0.3} & 0.3 \le x_2 \le 0.6 \\ 0 & 0.6 \le x_2 \le 1 \end{cases} \tag{5}$$

$$\mu_M(x_2) = \begin{cases} 0 & 0 \le x_2 \le 0.3 \\ \dfrac{x_2}{0.3} - 1 & 0.3 \le x_2 \le 0.6 \\ \dfrac{0.9 - x_2}{0.3} & 0.6 \le x_2 \le 0.9 \\ 0 & 0.9 \le x_2 \le 1 \end{cases} \tag{6}$$

$$\mu_H(x_2) = \begin{cases} 0 & 0 \le x_2 \le 0.6 \\ \dfrac{x_2}{0.3} - 2 & 0.6 \le x_2 \le 0.9 \\ 1 & 0.9 \le x_2 \le 1 \end{cases} \tag{7}$$

Input 3 low values are represented with triangular membership function. Trapezoidal membership function is used to represent the medium and high values of input 3. Equation (8) is used to express the characteristic equation for low values of input 3. The characteristic equation for medium values of input 3 is expressed as Equation (9), while Equation (10) expressed the characteristic equation for high values of input 3 (Figure 4).

For input 4, the triangular membership function is to represent the membership function for low, medium and high values (Figure 5). The characteristic equation for low values of input 4 is expressed as Equation (11), while medium values of input 4 characteristic equation is expressed as Equation (12). The characteristic equation for high values of input 4 is expressed as Equation (13).

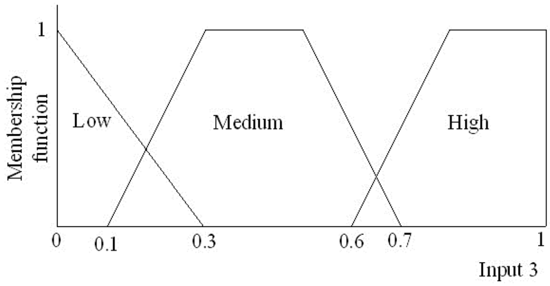

Figure 4 Membership functions for input 3

$$\mu_L(x_3) = \begin{cases} 1 - \dfrac{x_3}{0.3} & 0 \le x_3 \le 0.3 \\ 0 & 0.6 \le x_3 \le 1 \end{cases} \tag{8}$$

$$\mu_L(x_3) = \begin{cases} 0 & 0 \le x_3 \le 0.1 \\ 1 - \dfrac{0.3 - x_3}{0.2} & 0.1 \le x_3 \le 0.3 \\ 1 & 0.3 \le x_3 \le 0.5 \\ \dfrac{0.7 - x_3}{0.2} & 0.5 \le x_3 \le 0.7 \\ 0 & 0.7 \le x_3 \le 1 \end{cases} \tag{9}$$

$$\mu_L(x_3) = \begin{cases} 1 & 0 \le x_3 \le 0.6 \\ 1 - \dfrac{0.8 - x_3}{0.2} & 0.6 \le x_3 \le 0.8 \\ 1 & 0.8 \le x_3 \le 1 \end{cases} \tag{10}$$

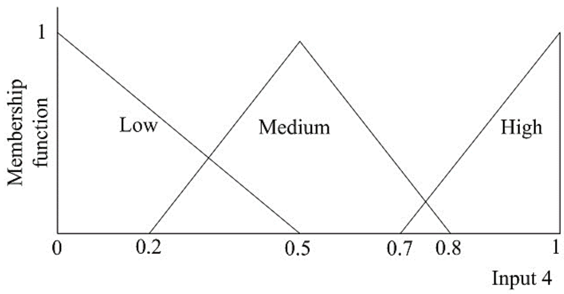

Figure 5 Membership functions for input 4

$$\mu_L(x_4) = \begin{cases} 1 - \dfrac{x_4}{0.5} & 0 \le x_4 \le 0.5 \\ 0 & 0.5 \le x_4 \le 1 \end{cases} \tag{11}$$

$$\mu_M(x_4) = \begin{cases} 0 & 0 \le x_4 \le 0.2 \\ \dfrac{0.5 - x_4}{0.3} - 1 & 0.2 \le x_4 \le 0.5 \\ \dfrac{0.8 - x_4}{0.3} & 0.5 \le x_4 \le 0.8 \\ 0 & 0.8 \le x_4 \le 1 \end{cases} \tag{12}$$

$$\mu_H(x_4) = \begin{cases} 0 & 0 \le x_4 \le 0.8 \\ 1 - \dfrac{1-x_m}{0.2} & 0.8 \le x_4 \le 1 \end{cases} \tag{13}$$

During the partitioning of the output parameter, satisfactory and unsatisfactory output values are represented using trapezoidal membership functions. The membership function for 'ok' output is triangular (Figure 6). The graphically representations for the output membership functions are in Figure 6. The membership function for satisfactory membership function is expressed as Equation (14). The 'ok' membership function is expressed as Equation (15). The unsatisfactory membership function is expressed as Equation (16).

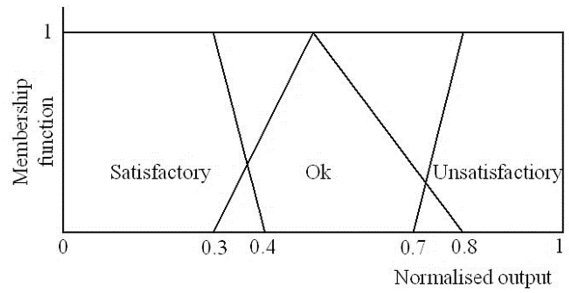

Figure 6 Membership functions for output

$$\mu_{yS} = \begin{cases} 1 & 0 \le y \le 0.3 \\ \dfrac{0.4-y}{0.1} & 0.3 \le y \le 0.4 \\ 0 & 0.4 \le y \le 1 \end{cases} \tag{14}$$

$$\mu_{yA} = \begin{cases} 0 & 0 \le y \le 0.3 \\ 1 - \dfrac{0.5-y}{0.2} & 0.3 \le y \le 0.5 \\ \dfrac{0.8-y}{0.3} & 0.5 \le y \le 0.8 \\ 0 & 0.8 \le y \le 1 \end{cases} \tag{15}$$

$$\mu_{yU} = \begin{cases} 0 & 0 \le y \le 0.7 \\ 1 - \dfrac{y-0.7}{0.1} & 0.7 \le y \le 0.8 \\ 1 & 0.8 \le y \le 1 \end{cases} \tag{16}$$

Aggregate method is used as the defuzzification method (Equation 18) for determining the output value when combining different input parameters [18-19].

$$y = \frac{\sum_{i=1}^{N} \mu_{x_i}(x_i) x_i}{\sum_{i=1}^{N} \mu_{x_i}(x_i)} \tag{17}$$

Autoregressive integrated moving average (ARIMA) is a forecasting model, it implementation involves the determination of different parameters. The basic steps for ARIMA implementation can be summarised as follows [20]:

Step 1: Determination of degree of differencing for a time series

Step 2: Elimination of nonzero mean from a differenced series;

Step 3: Determination of moving average and autoregressive orders for a time series;

Step 4: Determination of co-efficient for autoregressive and moving average models; and

Step 5: Generation of forecasting results.

The difference between ARIMA and the proposed method is that in ARIMA outputs are generated based on the combination of moving average, auto-regression and integrated difference of sets of data. This often requires the judgment of an expert. The proposed method is based on the contributions of different experts in designing membership functions. This does not involve complex mathematics analysis unlike ARIMA.

3. Model application

Practical data from a production company which produces household utensils is used in testing the proposed model. The company uses two production lines and utilizes about 16,000 tones of molten metal annually. The rest periods for workers in the manufacturing system lies between 15 and 20 min/shift while the busy periods are fixed at 94% of allocated daily operational time. The number of working days per month is 26 days and they operate two shifts per day. The maintenance department is divided into two main groups. The duration for preventive and corrective maintenance is between 15 to 30 min, while machine breakdown arrival time is 48 hr. The ratio of production activities between the machines is 60:40. Ighravwe and Oke [21] model is used in generating the values of the output parameter at three levels (Table 3).

Table 3 Levels for the factors

Level	x_1	x_2	x_3	x_4
1	3,102,039.75	490,562.02	106,619,016.37	0.583
2	3,186,222.50	501,728.40	107,914,835.04	0.585
3	3,240,654.00	516,841.94	109,636,975.69	0.586

To apply Taguchi method in generating the IF-THEN rules for four factors at three levels L_{27} orthogonal array is applied in generating the training data set. The testing data set are combinations of factors not contained in the L_{27} array. The interpretations of the IF-THEN rules for the L_{27} are as follows:

R1: If x_1 is low and x_2 is low and x_3 is low and x_4 is Low then y is unsatisfactory

R2: If x_1 is low and x_2 is low and x_3 is low and x_4 is medium then y is unsatisfactory

R3: If x_1 is low and x_2 is low and x_3 is low and x_4 is high then y is satisfactory

R4: If x_1 is low and x_2 is low and x_3 is medium and x_4 is low then y is ok

R5: If x_1 is low and x_2 is medium and x_3 is medium and x_4 is medium then y is ok

R6: If x_1 is low and x_2 is medium and x_3 is medium and x_4 is high then y is ok
R7: If x_1 is low and x_2 is medium and x_3 is high and x_4 is low then y is unsatisfactory
R8: If x_1 is low and x_2 is medium and x_3 is high and x_4 is medium then y is unsatisfactory
R9: If x_1 is low and x_2 is high and x_3 is high and x_4 is high then y is unsatisfactory
R10: If x_1 is medium and x_2 is high and x_3 is low and x_4 is low then y is satisfactory
R11: If x_1 is medium and x_2 is high and x_3 is low and x_4 is medium then y is satisfactory
R12: If x_1 is medium and x_2 is high and x_3 is low and x_4 is high then y is satisfactory
R13: If x_1 is medium and x_2 is low and x_3 is medium and x_4 is low then y is ok
R14: If x_1 is medium and x_2 is low and x_3 is medium and x_4 is medium then y is ok
R15: If x_1 is medium and x_2 is low and x_3 is medium and x_4 is high then y is ok
R16: If x_1 is medium and x_2 is low and x_3 is high and x_4 is low then y is unsatisfactory
R17: If x_1 is medium and x_2 is medium and x_3 is high and x_4 is medium then y is unsatisfactory
R18: If x_1 is medium and x_2 is medium and x_3 is high and x_4 is high then y is unsatisfactory
R19: If x_1 is high and x_2 is medium and x_3 is low and x_4 is low then y is unsatisfactory
R20: If x_1 is high and x_2 is medium and x_3 is low and x_4 is medium then y is satisfactory
R21: If x_1 is high and x_2 is high and x_3 is low and x_4 is high then y is satisfactory
R22: If x_1 is high and x_2 is high and x_3 is medium and x_4 is low then y is ok
R23: If x_1 is high and x_2 is high and x_3 is medium and x_4 is medium then y is ok
R24: If x_1 is high and x_2 is high and x_3 is medium and x_4 is high then y is ok
R25: If x_1 is high and x_2 is low and x_3 is high and x_4 is low then y is unsatisfactory
R26: If x_1 is high and x_2 is low and x_3 is high and x_4 is medium then y is unsatisfactory
R27: If x_1 is high and x_2 is low and x_3 is high and x_4 is high then y is unsatisfactory

The IF-THEN rules for the testing data sets are interpreted as follows:

R1: If x_1 is low and x_2 is high and x_3 is low and x_4 is high then y is satisfactory
R2: If x_1 is low and x_2 is high and x_3 is medium and x_4 is high then y is satisfactory
R3: If x_1 is low and x_2 is high and x_3 is high and x_4 is medium then y is satisfactory
R4: If x_1 is medium and x_2 is medium and x_3 is low and x_4 is medium then y is satisfactory
R5: If x_1 is medium and x_2 is medium and x_3 is medium and x_4 is low then y is satisfactory
R6: If x_1 is medium and x_2 is medium and x_3 is high and x_4 is low then y is unsatisfactory
R7: If x_1 is high and x_2 is low and x_3 is high and x_4 is high then y is satisfactory
R8: If x_1 is high and x_2 is low and x_3 is medium and x_4 is high then y is satisfactory
R9: If x_1 is high and x_2 is low and x_3 is low and x_4 is medium then y is satisfactory

By using the above If-Then rules, an ARIMA model was developed based on the crisp values of input and output parameters. Based on expert modeller in SPSS software, ARIMA (1, 0, 0) was selected for the workforce size problem. This implies that the degree of autoregressive is 1, integrated difference is 0 and moving averages is 0. The predicted values of workforce size using training data are in Figure 7.

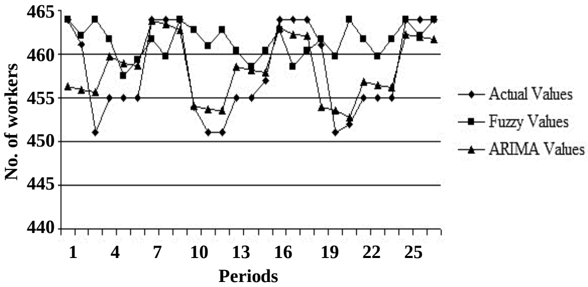

Figure 7 Actual and predicted values of optimal workforce size using training data

Based on the developed ARIMA and FIS models, predictions for the workforce size using the testing data were generated (Table 4).

Table 4 Actual and predicted workforce size using the testing data

Experiment number	Actual values	Fuzzy values	ARIMA values
1	452	464	455
2	455	462	463
3	464	462	463
4	451	459	454
5	455	458	458
6	464	460	463
7	451	464	454
8	455	462	457
9	455	462	454

4. Discussion of results

Based on the combination of factors and levels in Table 1, the results for workforce size showed that the number of unsatisfactory workforce size is twice that of satisfactory workforce size (6) and one and half times that of 'ok' workforce size (9). The testing data results revealed that the ratio of satisfactory workforce size to unsatisfactory workforce size is 8:1. It can be inferred the testing data sets combinations reduces the search for feasible combination of near-optimal solution that will generate satisfactory workforce size. From the testing data sets results, an IF-THEN rule of 'If x_1 is medium and x_2 is medium and x_3 is low and x_4 is medium then y ' or 'If x_1 is high and x_2 is low and x_3 is high and x_4 is high then y' can be used to determine the system maintenance-production workforce size.

The pattern of the results obtained for workforce size using training data (Figure 4) was close to actual value for both the proposed fuzzy and ARIMA models. However, ARIMA (1 0 0) pattern is similar to actual training data than the proposed fuzzy system. From the results in Figure 7 and Table 4, the application of fuzzy logic model in determining amount of maintenance-production workers that will be required to achieve sets objectives of management is justified. This study has also been able to shows that linguistic terms used for modelling the IF-THEN rules has the capacity of generating realistic results for a real system. In order to determine accuracy of the proposed expert system, mean absolute percentage error (MAPE) is selected as a statistical measure in this study (Table 5).

Table 5 Mean absolute percentage error predictive models

	Fuzzy model	**ARIMA model**
In-sample datasets	1.05	0.57
Out-sample datasets	1.51	0.061

Based on the Lewis's interpretation of MAPE [22], we observed that the fuzzy system has a high predictive capacity for workforce size prediction. The ARIMA model results outperformed those of the fuzzy system. The use of fuzzy modelling technique was satisfactory (i.e., MAPE < 10%) according to Lewis's study. Since the MAPE of the FIS model gave a satisfactory result, the use of optimisation model to determine the approximated value of a workforce for maintenance and production activities can be omitted. Thus, there is no need to re-formulate an optimisation model for workforce size determine whenever there is the need to combine new set of parameters.

This study shed more light on the debate for maintenance workforce evaluation for the possible ways of enhancing the performance metrics and attainment levels. This investigation therefore has significant practical implications for managers of maintenance industries and the benefits offered by the proposed model are performance-enhancing. By recalling the literature review outcome earlier mentioned, the gap, which includes the non-inclusion of level of machine availability, inventory cost and number of defective products produced from machine and machine utilisation has been bridged. Hence, managers are advised to use the model to control idleness of workers. This obviously has a direct productivity implication if monitoring is done with success.

Also, the use of interest rate as an input in the model provides a consciousness to all maintenance resources, including the hours invested in servicing and related operations, their use of resources in a waste-avoidance manner need to be prudently managed. The consciousness of taking corrective actions when they observe that certain company's resources are negligently handled (including equipment and tools that may need replacement when damaged) is created in all staff. This will obviously reduce expenditure and indirectly improve the company's profit margin. The indirect implication of this is that despite being in a fierce competitive environment, the company could survive and the labour force would retain their jobs.

Taking a close look at the proposed model, it is noted that to use the model for workforce size determination, it does not need any retraining activities. The model is appealing to the maintenance manager in being easy to use. Now, considering the model framework, the use of Taguchi method in combining different levels of the input parameters is a means in which decision makers would simulate different scenarios and generate results that will be within acceptable range. Furthermore, the novel contribution that fuzzy logic makes could be found in aiding the automation of huge and seemingly compound raw data which could be interpreted. Without the application of the model, the human experts would be saddled with the responsibility of managing this data, which is challenging. It could be added that the exclusion of uncertainties as a concept, and fuzzy logic model was excluded from analysis, the outcome may not adequately reveal the reality of the maintenance workforce situation in terms of performance with a consequent outcome of inappropriate results.

A further probing of the model could provide deeper insights on possible extensions on the use of fuzzy logic model for the workforce size prediction problem, which reflects the combination of multi-objective in the determination of workforce size. The information obtained from further probing may help in cost management activities. Further investigation of efforts in future could bring out results in the redesign of organogram of a system when complemented with the theory of span of control. The outputs from the proposed fuzzy system may then enhance downsizing and rightsizing activities of maintenance workforce.

Scarcely found in literature, as a frontline research the current work goes beyond the limitations, which emerged from the literature review. New grounds relating to the interaction of fuzzy logic and Taguchi method with respect of maintenance workforce was broken. The exciting result of this study activates some thought-provoking issues to members of the academic community and practitioners in the industry. Through the outcomes of this study, a deeper debate relating to some technical issues and their impacts on the workforce performance could commence. The approach reveals that uncertainties in the maintenance workforce activities could be accepted in view of the existing results obtained. Furthermore, optimisation has been considered by way of Taguchi method such that savings in terms of experimental data cost requirements for continuous performance analysis and improvement could be achieved.

This investigation has brought to light some computational issues not studied but are worth of further and deeper enquires. For instance, job evaluation, by considering the worth points of maintenance jobs and assigning monetary rewards according to the risk involved in executing the maintenance job is an aspect of research crying for empirical and modelling effort. The scales could be linked to the present scheme of Taguchi-fuzzy analysis. Thus, for periodic evaluations of maintenance personnel for promotion exercise, comparison of results obtained with standards could serve as a basis for promotion or otherwise of the concerned staff. The outcomes of this investigation are significant for academic and practitioners also.

Few studies have explored the significance influence of uncertainties in maintenance of manufacturing concerns. Fewer investigations have been tailored to the workforce aspect of maintenance and this study is front-line in considering uncertainties in maintenance workforce analysis. However, a number of limitations could be kept in mind from the implementation of this study. In the first instance, the investigation utilises information from a company. Thus, the outcomes may change in different companies with different product orientations. For instance, it is unclear if the maintenance system considered is centralised or decentralised for a small, medium or large-sized organisation, or whether part (significant or insignificant) or full maintenance tasks are outsourced to external contractors. Further data collection, analysis and interpretation with respect to these concerns are needed for deeper understanding of the concept sold in the current paper. Again, such data could assist with possible implementations in other settings. Academics could also investigate if the above-mentioned framework including nature of maintenance could be integrated into job evaluation framework earlier proposed for extension.

It is known that the motivation for tracking uncertainties in maintenance workforce is that they influence the values of decision made by decision makers in all aspects- technical and non-technical concerns of work. This may lead to reduced performance on the job by the maintenance workforce if not incorporated into the modelling framework. The question of by how much this deviation has always been taken for granted; more often, the quantity or dimensions of these effects are not measured from the Naira (or dollars) contributions of maintenance activities breakdowns. This aspect warrants investigations. A further study may be considered that minimises the discrepancies between the fuzzy model and ARIMA model results using neuro-fuzzy model. A fuzzy-based expert system can be design for aiding maintenance actions on spare parts repair and replace as a further study.

5. Conclusions

This study has proposed the combined fuzzy logic technique and Taguchi method a framework for workforce prediction. The proposed model is an addition to the workforce research paradigm. The value of the approach in contrast with ARIMA as an established predictive paradigm in manufacturing industry was discussed and analysed. We utilised real industry data to test the model. The experimental tests showed that the fuzzy model results were close to those of ARIMA model. Despite the better results from the ARIMA model, the proposed model ability to group organisation objectives using linguistic terms makes it a promising workforce predictive tool. The proposed model has the capacity to improve the efficiency of generating workforce information because it is Taguchi-based [15]. The contribution of this paper is that it provides decision makers with the good knowledge on combinations of factors and levels for selecting parameters that determines workforce size. The novelty of this study is that it provides a means for combining optimisation model, Taguchi method and fuzzy logic in designing an expert system for workforce size determination. This new approach when combined with intuition will improve staffing decision in maintenance systems.

6. References

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