Applying Fuzzy Multi-Criteria Decision-Making Framework in Evaluating Maintenance Systems with an Emphasis on Human Tasks and Errors

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Abstract. *Human errors are responsible for a substantial percentage of the manufacturing accidents and incidents across the globe. But serious injuries, lost days-of-work, damages to assets and deaths of employees should be avoided in manufacturing practices. Notwithstanding, most research on maintenance system evaluation addresses the preventive maintenance strategy, analysing its effectiveness and efficiency while ignoring the human factor aspects. A deviation from the literature is attempted by employing the use of multi-criteria decision making approaches and incorporating the human factors into maintenance system evaluation. The fuzzy logic, analytic hierarchy process (AHP), grey relational analysis (GRA) and the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) were used based on some key indicators. The novelty of the paper in maintenance system evaluation is by integrating safety, maintenance task and errors with human relation and equipment factors using a fuzzy multi-criteria approach. The proposed framework was tested in four different manufacturing systems and the results showed that the highest- and least-ranked maintenance system were a cement production plant and a pharmaceutical company, respectively. It is thought that human error evaluation might provide a new approach for maintenance managers to meet the zero accident goals of organisations.*

Received by	27 December 2020
Revised by	25 January 2021
Accepted by	17 February 2021

Keywords:
Ergonomics tools and methods**,** task analysis**,** advanced manufacturing systems**,** human error, fuzzy-TOPSIS

1. Introduction

Human factor offers a prominent contribution to the analysis of maintenance performance, cost-efficiency, and the safety of processes with production orientations [1]. Human factor also occupies a significant function in an effort to predict the safety of a system. It is the human element that could be responsible for triggering hazards into accidents either intentionally as revenge to organisational denials of the employee's privileges. Human beings could also be carelessness or the employee's inexperience could lead to accidents and loss of productive hours. In [2], it is declared that the employee is the principal culprit in accident cases. Whatever be the cause of accidents, either intentionally performed or unintentional, everybody suffers the losses, including the employees, the investors, governments and stakeholders. Note that such consequences often lead to serious injuries, lost days-of-work, damages to assets and even death of several employees as well as the possible closure of the business in the short, medium or even the long-run. The effect of accidents is grievous in high-risk systems. By ignoring intentional errors of human on the assumption that the employees and the system both have integrity, we concentrate on human errors as a natural phenomenon that is often referred to as a mistake. It is reasonable to state that human error is the consequential effect of the design of human brains as well as its shortcoming. Recognising the human error as critical in manufacturing, correct and precise details about the employee capabilities as well as behaviour have been found to be very useful if used methodically to improve the safety of a manufacturing facility.

The operational system of maintenance in an organisation is pivoted to the achievement of goals in the system. This maintenance system significantly influences the reduction of frequency and cost of equipment downtime, quality enhancement, and productivity index improvement. The proper choice of the working crew in terms of skill possession and other enablement are critical considerations in the achievement of the above-stated benefits. Poor maintenance consequently yields escalating and unbearable thresholds of equipment failures as well as associated penalties. The maintenance personnel's evaluation, obtained through the utilisation of a selected few measures, reveals an inadequate approach and wrong decision on the maintenance manpower.

The evaluation of human performance in a maintenance system is a multi-dimensional issue which consists of conflicting criteria. There is a necessity to, therefore, direct attention and resources in applying multi-criteria decision making approaches. The purpose of the current paper is to develop and apply a hybrid multi-criteria decision-making approach for the evaluation of human performance in maintenance systems. The evaluation of human performance in a maintenance system is a composite function of various criteria, many of which present challenge in measurements. There is a critical challenge of the intangible attribute of the effecting criteria; the vague nature and the uncertain forms of the criteria all cause insufficient and imprecise tracking of the assessments of policy and decision-makers.

There is abundant evidence in literature to support the employment of fuzzy linguistic evaluation in problems similar to the one described in this study. The argument has always been that the tool has a close link to human reasoning, and its benefits and simplicity are known to surpass other crisp number-based approaches. Consequently, an approach that integrates the fuzzy logic, grey relational analysis (GRA) and the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) to evaluate human performance in maintenance systems demands urgent and necessary attention. The advanced methodology is premised on the idea of fuzzy logic, analytical hierarchy process (AHP), GRA and TOPSIS.

Several investigators have attempted to evolve approaches to monitor the health status of maintainable systems such as manufacturing and railway transportation, among others. Capasso M. et al. [3] employed the principles of acquisition and status currents' post-processing information from induction traction motor coupled with the elimination of noise and the employment of independent components analysis, predicted motor condition. Kaplanoghu et al. [4] made an effort to define a scheduling approach that could and maintain a good health status of equipment based on multi-agent systems. The method's basis is to schedule single machines as the nature of the arrival of jobs is assumed to be dynamic. The approach's philosophy is that there is no need to model and solve the problem in a central manner again. TOPSIS, a prioritisation tool of artificial intelligence, provides a new perspective to solving maintenance problems in a situation where several choice factors are involved. TOPSIS is a tool found tremendously useful in cases where the maintenance manager, through his/her specialised knowledge, consider it essential to scale the technical issues from the most to the least important concerns. This attribute of TOPSIS makes it a good candidate to handle prioritisation problems. The TOPSIS, as applied in this communication, is advanced and built-up for the evaluation of the human performance in maintenance systems. Comparative analysis of the advanced methodology is made and employed in the assessment of strengths and weakness of the likely human performance by a relative comparison of the structure in relation to the adequate criteria. The advanced TOPSIS method was demonstrated in applicability using a case study obtained from a process industry engage in drinks production.

In this communication, a TOPSIS approach, which is integrated with fuzzy logic is proposed. This method, conceived as being advanced, permits prioritisation of technical issues under linguistic preferences. The unique application mechanism of the integrated TOPSIS and fuzzy logic to maintenance systems when considering human tasks, as well as errors, is certainly the contribution of this communication as the mechanism permits a strategic classification and prioritisation scheme. The method utilises the collaborative assistance of the analytical hierarchy process with the grey relational analytical properties to achieve the paper's primary goal. The method is value-adding and supports maintenance decision making innovatively. The fuzzy logic framework was combined with TOPSIS and advanced as TOPSIS to get rid of the uncertainty and the vague attribute of the system's decision-maker in the course of comparing items pair-wisely. The advanced framework could potentially be useful to assess human systems in other maintenance systems such as in roofing sheets as well as pot production processes.

Thus, this study's principal aim is to obtain a merit-driven scientific approach that could help plan in a multi-central problem environment. The organisation of this communication follows this order. The introductory part of the paper, detailing the study's motivation and specifying the study's objective, has been accomplished in the first section. Section 2 of the communication aims at revealing the literature gaps that motivated the current study and how this work has responded positively to the gaps by proffering a solution by way of a new approach to solving the problem. Section 3 is a presentation of the methodology of the advanced approach. In section 4, the practical application of the proposed approach is verified in a case investigation. Section 5 is the concluding remarks on the article.

2. Literature Review

The literature has established that human errors play an influential part in manufacturing operations and as a key determinant of maintenance success or failure. This assertion was validated in a report presented by Ruckart and Burgess [5]. Rashid et al. [6] also recognised the part played by human errors in disrupting organisational goals and identified three principal areas that they are prevalent in it, including during design activities, in manufacturing processes as well as in maintenance-related activities. Kubota et al. [7] has for many years recognised that organisations could produce human errors and illustrated this with a scheme referred to as CREAM. All over the globe, a significant portion of accidents are associated with human error and many of these accident cases occur during maintenance, at the pre-maintenance stage, as well as the post-maintenance stage when the equipment that is expected to be as good as new is handed over to the production function for regular production activities. Though a number of factors are usually attributed to mistakes by human at any time that they occur, including inexperience in the operation of equipment, facility or tools, and others may be poor training, employee deviation from accepted principles in operating equipment, etc. It is compelling and important to evaluate the possibility of mistakes such that accidents, incidents, their cost and consequences could be optimised in the event of maintenance tasks in manufacturing operations.

The literature that deals with the subject of human errors in maintenance is still growing and aggressive research efforts need to be committed to bring it up to maturity as soon as possible. This is in view of the critical need for information on such systems due to increasing stringent manufacturing environmental conditions that requires probes, improvement and optimisation of maintenance tasks. Here, a brief review of the academic literature on human error as they relate to manufacture is given. A first observation from the literature is that knowledge on human errors has recognised the need to link maintenance activities to production. In fact, this idea is very recent, contributed by two novel articles in 2016. The articles by Emami-Mehrgani et al. [8] and Lu et al. [9] are mentioned here. In the first article, Emami-Mehrgani et al. [8] investigated repairable systems in manufacturing in association with human errors. The system's special attributes considered are that the furtive of the equipment is random while the assumption of the planning period being non-fictive was considered.

Furthermore, a link was established with the capacity of the system and the policies adopted by the organisation on inventories. It was concluded that the policy proposed was efficient. A second article that emphasised linkage of production with maintenance in the development of a model is credited to Lu et al. [9]. In the article, the quality issue, which is mostly regarded as a production function, was elaborated upon. Drawing on the observation from these two important articles as regards a fruitful trend of research in the aspect of combinations and linkages of aspects of manufacturing, the current work takes a further step to extend them to more than two aspects, incorporating safety issues. This issue is a novel idea that the manufacturing system of the current dispensation needs in order to progress and operate at the optimum.

Other literature that contributed to the debate on human errors in maintenance include Singh and Kumar [10], Hammed et al. [11], Chui and Hsieh [12], In the case of hammed et al. [11], a risk-oriented approach that approximated maintenance interval as well as the maintenance inspection to carry out was proposed in a form that the argumentation of human errors was made with a retarding framework in a processing system. The authors employed the success likelihood approach in a processing facility of hydrocarbon origin. The conclusion revealed the feasibility of applying the approach in similar oil installations. Chui and Hsieh [12] proposed a system of human error methodical approach described as being latent. The authors applied the novel idea advanced to establish a strategy employed to analyse human error by applying fuzzy TOPSIS. Singh and Kumar [10] introduced a case study-oriented on the maintenance of railway bogie where the HEART (human error assessment and reduction technique) model was tested and found valid.

In another inquiry, Kim and Park [13] presented a scheme for forecasting human worker potentials to errors. The scheme was evaluated in a situation in which maintenance workers actualise test or maintenance tasks taking direction from a work plan or job procedure. The conclusion was on the possibility of reducing human errors in the application of the model. Carr and Christer [14] introduced the concept of human error in delay-time modelling with respect to inspection in maintenance tasks. The human error cost analysis was embarked upon and reported. Azadeh et al. [15] optimised the tasks involved in maintenance for a production organisation by including operator error, viewing the cost dimension as well expatiating on the learning effects. A novel framework, incorporating AHP and TOPSIS was exhibited, tested and verified to be applicable in a real production system.

3. Research Methodology

In evaluating a maintenance system, the current approach in literature is to base judgment on the state of technical matters such as system safety criteria, measures due to maintenance, job executions and measures on equipment repairs. This assessment methodology is short-sighted and inconsistent with all the system's parameters, omitting important human factors issues. The implication is that a full perception of the system's performance is not gained. Thus, the conceptualisation approach should be changed. The current paper suggests that the human factors, including two major criteria of human relations and maintenance errors, should be incorporated into a model to serve as a new way of evaluating maintenance systems. We argue strongly, following Burley's [16] viewpoints and Dunn [17] that ignoring the human factor elements in terms of human relations and human error is at the peril of the organisation. Burley [16] emphatically stated that mistakes are costly events in maintenance and have been closely associated with safety and environmental performance decline, increased rework quantities and rates, added periods of down-time, poor customer service and declining business competitiveness.

Therefore, it is important to incorporate some or all of these issues into new and emerging models of maintenance performance evaluation. Unfortunately, despite being acknowledged as a principal factor that accounts for a major dimension of failure modes [16], and as noted in the classic work of Burley [16] that all humans in maintenance systems make a mistake but that the view-point in current maintenance analysis literature is that mistake is bad and not tolerated. The team that commits errors or mistakes is painted in shame and blamed and punished for the error. It is very unusual to incorporate factors of human errors into performance metrics, and this is strongly worked against in the current paper. The current paper advocates against the position of current literature, arguing that humans in maintenance should not be punished, may not be blamed and should not be shamed for any errors but rather a system that eliminates, reduces or mitigate the influence of occurrence of errors should be developed. In addressing the human error issue in maintenance, Burley [16] suggested focus on (1) The way the minds of the maintenance crew works by considering the short and long term memory of the mind; (2) The quantum of maintenance information that the team successfully tackles; (3) The threshold of the corporate levels of errors; (4) Consideration of the blame game; (5) Slips, lapses and deviations.

The proposed framework used to evaluate the maintenance system comprises AHP, TOPSIS and fuzzy logic (Fig. 1). The descriptions of these tools as applied to maintenance evolution are presented as shown in Fig.1.

System safety is a system engineering branch of learning which aids the procedural risk management process within the complicated maintenance system. The two criteria, human relations and maintenance errors, are founded on the premise that while many modern maintenance systems are built so that automatic correction of faults and repairs are made, several tasks are human-oriented and must be performed by humans (Table 1).

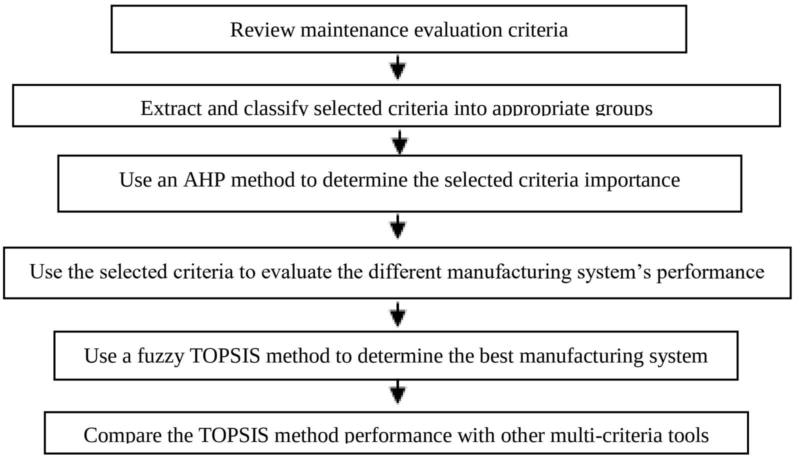

Fig. 1: Multi-attribute framework for evaluation of maintenance systems

Criteria	Sub-criteria
System safety (C_1)	Frequency of risk assessment (x_{11})
	Frequency of reporting safety problems (x_{12})
	Frequency of safety gadgets usage (x_{13})
	Frequency of hazard identification (x_{14})
	Frequency of accident investigation (x_{15})
Equipment repair (C_2)	Frequency of spare parts availability (x_{21})
	Frequency of non-approved spare parts usage (x_{22})
	Frequency of spare parts damages (x_{23})
	Frequency of availability of diagnostic equipment (x_{24})
	Frequency of availability of technical documentation on equipment (x_{25})
Human relations (C_3)	Frequency of supervision (x_{31})
	Frequency of training programmes (x_{32})
	Frequency of lack of technical knowledge during shift exchange (x_{33})
	Frequency of cooperation among maintenance crew members (x_{34})
	Frequency of disputes among maintenance crew members (x_{35})
Maintenance errors (C_4)	Frequency of improper servicing (x_{41})
	Frequency of incomplete maintenance tasks (x_{42})
	Frequency of improper faulty detection (x_{43})
	Frequency of maintenance errors (x_{44})
	Frequency of accident caused by maintenance errors (x_{45})
	Frequency of communication errors (x_{46})
Maintenance jobs Execution (C_5)	Frequency of change in job orders (x_{51})
	Frequency of violating maintenance schedules (x_{52})
	Frequency of performing tasks without checklist (x_{53})
	Frequency of omitting job steps (x_{54})
	Frequency of interruption of maintenance tasks (x_{55})

Table 1: Factors and criteria for maintenance system evaluation

In the first case of human relations, supervision is necessary. A supervisor manages the artisans and craftsmen with the demonstration of leadership attributes and affects others' tasks personally. The supervisor can do the job of the artisans and craftsmen, and of course get to the position of a supervisor from being an artisan and craftsmen for years and so has the experience and can direct the workers for results. The maintenance supervisor exhibits some hands-on effect as well as the skills in leadership in guiding people. It is expected that a rise in maintenance productivity through significant output-input relationship and increased level of job satisfaction by the maintenance employees is expected for a maintenance supervisor that is effective at work. The supervisory competence is demonstrated in the fewer times the subordinates consult the superior at the maintenance floor. Suppose excellent supervisory skills and effective skills in managing maintenance personnel are demonstrated in relationship with the workforce. In that case, the team members' performance in maintenance tasks will be high and effective in correcting faults.

The depth (quality) of workplace training, workforce competence re-evaluation and correction is also important in the maintenance workplace. Skills should be enhanced by the knowledge gained from maintenance training, and this should develop competence in the workforce. An important aspect of the human relations aspect of the maintenance workforce's current assessment criteria is how close or how wide the gap of technical knowledge of employees to take over jobs from colleagues, considering the happenings during a previous shift. Usually, historical records should reveal this. However, in many cases, though seemingly insignificant, some important technical issues may be the saving tasks to solve the maintenance problem. Hence, it is thought in developing this methodology presented here, that in handling over from one shift crew to the other, utmost knowledge of past shift events that may be useful in solving yet unresolved maintenance problem is necessary.

A good criterion in human relations measures how healthy the maintenance team is. Cooperation among maintenance crew members is most desired. If an unhealthy situation exists, there is no tendency of hiding facts about the job or breakdown from one another, knowing that it will affect the performance of concerned crew or crew members. This criterion is strongly believed to correctly assess the maintenance crew's health status and should be a key parameter in assessing the workplace crew's performance.

For this investigation, the following definitions shall apply:

- *Frequency*: Refers to the repetitions of incidences, expressed as a number
- *Spare parts* are an exchange (replacement) of a failed component being available for use in the short, medium and long term of the equipment life.
- *Risk assessment*: Refers to an orderly practice of appraising the prospective hazards that are attached to a scheme.
- *Reporting safety problems*: Feedback generation on hazard and potential risks in the manufacturing system to the designated safety officer.
- *Safety gadgets usages*: Refers to the employment of the following gadgets for intended purposes by employee ear protection devices, eyewear, face shields, breathing air systems and ventilation air systems, distress radio beacon, footwear, flame arrestors and helmets.
- *Disputes among maintenance crew members*: Disagreement among workers in maintenance often results in tension and occasionally dragging work progress. If this persists, it is a reflection of poor understanding of working relationship. It may also suggest additional training on relevant courses such as teamwork, total maintenance quality, conflict resolution, and management.
- *Improper servicing*: Refers to abuses as well as errors due to circumstances, including pressure from the internal customers (the production crew)
- *Non-approval spare parts usage*: Authorisation is a norm in maintenance service implementation as the superior approves the spares for usage in particular jobs. However, there may be instances in which the subordinates wrongfully take steps to use maintenance resources without authorisation. This maintenance system weakness and in accounted for the maintenance evaluation system being developed.
- *Spare parts damages*: Some components of expensive equipment such as compressors, vacuum pumps and blowers, may not function at the required time probably due to problems with the goods-receiving process. Such damages, for critical parts, often result in unwarranted downtime of the plant and needs to be accounted for in the framework of the model presented in this paper. The importance of this criterion in underscored in that the purchasing manufacturing company has the opportunity of benefiting from the warranty terms of the selling company but they may not fully exploit it.
- *Spare part availability*: Known by several names, such as a spare part, replacement part or simply spare, it refers to old parts interchanged with a new one, usually as a result of a failure of the old parts spare parts and their frequencies of availability are a very good criterion in the evaluation of the maintenance performance criterion, referred to as the equipment repair. The maintenance manager can take the best advantages of the spare parts provider's opportunity, which will affect his/her performance when due consideration is given to the law in association to spare parts for the various equipment and the right he/she has to warranty claims. To impact of the maintenance performance, a good distinction between functional as well as cosmetic parts, relating to those mechanical parts or electro-mechanical parts on one side and the non-functional or decorate spares must be made by the maintenance manager.

For many high-technology core engineering systems the member of the spare parts utilised are characteristically high in quality and hard-wearing in nature such that a prolonged life of the spare parts manufactures are such guarantee the use of the products for a long time, making available such spare parts to the users even after the cessation of production of such equipment. It is also a practice among the multi-national equipment producers that if the spares are not available a replacement of the equipment could be arranged with the customers such that new equipment in installed for the customer. In contrast, the payment, substantially lower than the original price of the equipment for a fresh purchase is made. Such an exchange programme encourages taking customs in a particular equipment manufacturer for decades by a purchasing form and guarantees the long-term survival of the equipment sales organisation.

3.1 AHP

The weights for safety, equipment, maintenance, human relation task, and maintenance error execution are determined based on five maintenance indices. The indices are maintenance cost, machine productivity, machine availability, machine reliability and quality rate. For different maintenance systems, the absolute weights for the criteria are expressed as (1), while the relative weights for the criteria are expressed as (2).

Equal	Moderate	Strong	Very strong	Extreme
1	3	5	7	9

Table 2: Intensity of importance

$$w_{ai} = \sum_{s=1}^{S} w_{si} \tag{1}$$

$$w_i = \frac{\sum_{s=1}^{S} w_{si}}{\sum_{i=1}^{m} \sum_{s=1}^{S} w_{si}} \tag{2}$$

$$\sum_{i=1}^{m} w_i = 1 \tag{3}$$

; where w_{ai} represents absolute weight for criterion *i*, w_{si} represents weight for criterion *i* for system *s*, and w_i is relative weight for criterion *i*.

3.2 Fuzzy Logic and Grey Relational Analysis

Each component's importance is determined using a triangular fuzzy number and fuzzy averaging approach (Equation 3 and Table 2). Consensus on the weight for a component among the different maintenance system is obtained based on the maximum operator as (4). In this study, five-scale triangular fuzzy numbers are used to convert linguistic values of responses from decision-makers into crisp values (Table 3 and Fig. 2).

Terms	Abbreviations	Membership functions
Very low	VL	(0, 0, 0.2)
Low	L	(0, 0.2, 0.4)
Moderate	M	(0.2, 0.4, 0.6)
High	H	(0.4, 0.6, 0.8)
Very high	VH	(0.6, 0.8, 1)

Table 3: Membership function for the maintenance criteria

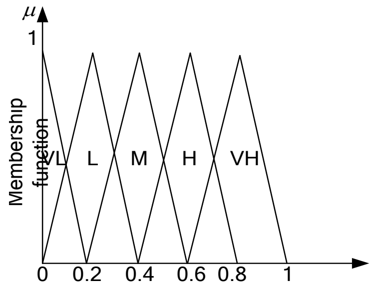

Fig. 2: Triangular membership functions for the criteria

The aggregation of the responses for a component from the decision-makers is expressed as (4). The triangular fuzzy number of a criterion is calculated based on (8). A centriod defuzzification method as (9) is used to generate the crisp values for the different criteria [18].

$$a_{ijs}, b_{ijs}, c_{ijs} = \frac{1}{K}\left(\sum_{k=1}^{K} a_{ijks}, \sum_{k=1}^{K} b_{ijks}, \sum_{k=1}^{K} c_{ijks}\right) \tag{4}$$

$$a_{is}, b_{is}, c_{is} = \sum_{j=1}^{n} w_{ij}\left(a_{ijs}, b_{ijs}, c_{ijs}\right) \tag{5}$$

$$c_{is} = \frac{1}{6}\left(a_{is} + 4b_{is} + c_{is}\right) \tag{6}$$

; where $a_{ijs}, b_{ijs}, c_{ijs}$ denote the first, second, and third numbers in fuzzy triangular numbers for sub-criterion *j* with respect to criterion *i* when rating system *s*, respectively, a_{ijks}, b_{ijks}, and c_{ijks} denote the first, second, and third numbers in fuzzy triangular numbers for sub-criterion *j* with respect to criterion *i* when rating system *s* assigned by expert *k*, respectively, c_{is} is the crisp value for criteria *i* belonging to maintenance system *s*, and w_{ij} denotes the importance of sub-criterion *j* under criterion *i*.

In order to generate a single index from the sub-criteria, GRA is considered. This process entails three stages. The required stages are explained as follows [19]:

(i.) The first stage involves the normalisation of the crisp values by considering parameters which are benefit and non-benefit based. Equation (7) is used as the normalisation scheme for benefit based parameters, while non-benefit based parameters are normalised using (8).

$$c_{is}^{*}\left(k\right)=\frac{\max c_{is}^{o}\left(k\right)-c_{is}^{o}\left(k\right)}{\max c_{is}^{o}\left(k\right)-\min c_{is}^{o}\left(k\right)} \qquad (7)$$

$$c_{is}^{*}\left(k\right)=\frac{c_{is}^{o}\left(k\right)-\min c_{is}^{o}\left(k\right)}{\max c_{is}^{o}\left(k\right)-\min c_{is}^{o}\left(k\right)} \qquad (8)$$

(ii.) The second stage is used to generate the grey relation coefficient (GRC) for the normalised parameters. To obtain the GRC for the parameters, a parameter which is known as identification coefficient is considered as (9).

$$\zeta_{ij}\left(k\right)=\frac{\Delta\min+\zeta\Delta\max}{\Delta_{o,i}\left(k\right)+\zeta\Delta\max} \qquad (9)$$

$$\Delta\min=\min_{\forall j\in i}\min_{\forall k}\left\|x_{o}^{*}(k)-x_{i}^{*}(k)\right\| \qquad (10)$$

$$\Delta\max=\max_{\forall j\in i}\max_{\forall k}\left\|x_{o}^{*}(k)-x_{i}^{*}(k)\right\| \qquad (11)$$

where $x_{o}^{*}(k)$ represents reference sequence, $x_{i}^{*}(k)$ represents comparative sequence ζ is called identification coefficient and its values lies between (0,1).

(iii.) The last stage is used to compute the grey relational grade represents. This is achieved using the weights for the parameters that are considered. For the current study, the sub-criteria's weights are assumed to be equal (12); where $\tilde{w}_{ij}$ represents the weight for sub-criterion *i* belonging to criterion *j*.

$$c_{is}=\frac{1}{n}\sum_{j=1}^{n}\tilde{w}_{ij}\zeta_{ij}\left(s\right) \qquad (12)$$

3.3 TOPSIS

The outputs from the aggregated components for the criteria are used to rank the maintenance systems based on TOPSIS. The implementation of TOPSIS involves five steps. These steps are outlined as follows [20]-[21]:

Step 1: Normalisation of the various performance indices in a decision matrix as (13).

$$r_{is}=\frac{c_{is}}{\sqrt{\sum_{i=1}^{m}c_{is}^{2}}} \quad \forall i\in m;\forall s\in S \qquad (13)$$

; where r_{is} denotes the normalised value of criterion *i* for system *s*.

Step 2: Design of weighted normalised decision matrix. The weighted decision matrix for the maintenance system is generated using the weights obtained from AHP and the GRA results for each of the criteria as (14).

$$V_{is}=w_{i}r_{is} \quad \forall i\in m;\forall s\in S \qquad (14)$$

; where V_{is} denotes the weighted normalised value of criterion *i* for system *s*, and w_i denotes the importance of criterion *i*.

Step 3: Determination of the positive and negative ideal solutions

The values of positive and negative ideal solutions depend on the preferred direction of each of the criteria. The value of a positive ideal solution is expressed as (15), while (16) is used to express the value of the negative ideal solution (15).

$$D^{+}=\left\{v_{1}^{+},\cdots,v_{i}^{+}\right\}=\left\{\left(\max v_{is}\middle|i\in I'\right),\left(\min_{s}v_{is}\middle|i\in I''\right)\right\} \qquad (15)$$

$$D^{-}=\left\{v_{1}^{-},\cdots,v_{i}^{-}\right\}=\left\{\left(\min v_{is}\middle|i\in I'\right),\left(\max_{s}v_{is}\middle|i\in I''\right)\right\} \qquad (16)$$

; where I' is the maximum performance index value, I'' is the minimum performance index value, v_i^{+} denotes the positive ideal solution for criterion *i*, and v_i^{-} denotes the negative ideal solution for criterion *i*.

<u>Step 4:</u> Evaluation of the distance of the negative and positive ideal solutions

Based on the criteria' weights, the negative ideal solution distance for each of the maintenance system is determined using (17). The value of positive ideal solution distance for each maintenance system is expressed as (18).

$$D_s^+ = \sqrt{\sum_{i=1}^{m}\left(v_{is} - v_i^+\right)^2} \qquad \forall s \in S \qquad (17)$$

$$D_s^- = \sqrt{\sum_{i=1}^{m}\left(v_{is} - v_i^-\right)^2} \qquad \forall s \in S \qquad (18)$$

; where D_s^+ denote the positive ideal distance of system *s*, and D_s^+ denote the negative ideal distance of system *s*.

<u>Step 5:</u> Maintenance system ranks

The ranking of the maintenance systems is based on their negative ideal solution for the sum of their positive and negative ideal solutions (19). The maintenance system with the highest rank (R_s) is taken as the best maintenance system.

$$R_s = \frac{D_s^-}{D_s^+ + D_s^-} \qquad (19)$$

; where R_s denotes closeness coefficient of system *s*.

3.3 ARAS method

This methods use the relationship between a criterion weight and its rating to determine the best alternative for a decision-making problem (Jovčić et al., 2020). Before this process can be achieved, pre-data processing are carried out. First, the rating of alternatives is determined using either crisp or fuzzy values.

The relationship between the criteria weights and their normalised values are used to determine an alternative weighted normalised value as (20).

$$\tilde{V}_{is} = w_i r_{is} \qquad \forall i \in m; \forall s \in S \qquad (20)$$

; where $\tilde{V}_{is}$ denotes the weighted normalised value for criterion *i* for alternative *s*.

The summation of an alternative's weighted normalised values give its performance rating (21).

$$\tilde{S}_s = \sum_{i=0}^{n}\tilde{V}_{is} \qquad \forall i \in m; \forall s \in S \qquad (21)$$

; where $\tilde{S}_s$ denotes the performance rating for alternative *s*.

The alternative performance ratings are used to generate their degree of utility as expressed by (22).

$$Q_s = \frac{\tilde{S}_i}{S_0} \qquad \forall i \in m; \forall s \in S \qquad (22)$$

; where Q_s denotes the degree of utility for alternative *s*.

4. Model Application and Discussion of Results

The proposed framework was applied in four manufacturing systems in Nigeria. The first (M_1) and second (M_2) manufacturing systems are pharmaceutical industries. The third (M_3) manufacturing system specialises in the production of dairy foods. The last manufacturing system deals with the production of cement (M_4). Two maintenance experts each of the manufacturing system considered during the administering of a structured questionnaire. The proposed framework was used to analysed the information obtained from the experts.

Based on the AHP in Section 3.1, we generated numeric weights for the criteria – see Table 4 for more details. From this table, the most important criterion is c1, while c3 is the least important criterion. Among the various maintenance systems that were considered, human relation is the least important criterion (Table 4). For the maintenance system (M1), the most important criteria for their maintenance system were maintenance jobs execution, and system safety is the most important criterion for the maintenance system (M2). For maintenance system (M3), the most important criterion was maintenance error, while the most important criterion for the maintenance system (M4) was maintenance errors (Table 4).

Case studies	c_1	c_2	c_3	c_4	c_5
M_1	0.1805	0.2233	0.1188	0.2068	0.2706
M_2	0.3483	0.1705	0.1038	0.1610	0.2164
M_3	0.2676	0.1596	0.1392	0.2821	0.1561
M_4	0.2027	0.2027	0.1370	0.2614	0.1720
Relative weights	0.2510	0.1900	0.1253	0.2289	0.2048

Table 4: Weights for the criteria

This study used the fuzzy triangular numbers in Fig. 2 to convert the selected systems' linguistic assessment during the proposed model application. Table 5 shows the numeric information obtained from the experts.

	M_1			M_2			M_3			M_4		
x_{11}	0.20	0.30	0.50	0.10	0.20	0.40	0.20	0.40	0.60	0.50	0.70	0.90
x_{12}	0.00	0.10	0.30	0.50	0.70	0.90	0.20	0.40	0.60	0.60	0.80	1.00
x_{13}	0.20	0.40	0.60	0.50	0.70	0.90	0.00	0.20	0.40	0.60	0.80	1.00
x_{14}	0.00	0.20	0.40	0.50	0.70	0.90	0.20	0.40	0.60	0.50	0.70	0.90
x_{15}	0.00	0.00	0.20	0.40	0.60	0.80	0.00	0.00	0.20	0.50	0.70	0.90
x_{21}	0.20	0.40	0.60	0.30	0.50	0.70	0.20	0.40	0.60	0.50	0.70	0.90
x_{22}	0.00	0.00	0.20	0.30	0.50	0.70	0.00	0.00	0.20	0.50	0.70	0.90
x_{23}	0.00	0.00	0.20	0.10	0.20	0.40	0.00	0.20	0.40	0.40	0.60	0.80
x_{24}	0.00	0.10	0.30	0.10	0.20	0.40	0.00	0.20	0.40	0.50	0.70	0.90
x_{25}	0.40	0.60	0.80	0.30	0.50	0.75	0.40	0.60	0.80	0.50	0.70	0.90
x_{31}	0.30	0.50	0.70	0.60	0.80	1.00	0.40	0.60	0.80	0.50	0.70	0.90
x_{32}	0.30	0.50	0.70	0.30	0.50	0.70	0.40	0.60	0.80	0.40	0.60	0.80
x_{33}	0.00	0.10	0.30	0.10	0.30	0.50	0.60	0.80	1.00	0.30	0.50	0.70
x_{34}	0.40	0.60	0.80	0.40	0.60	0.80	0.40	0.60	0.80	0.40	0.60	0.80
x_{35}	0.00	0.10	0.30	0.10	0.30	0.50	0.00	0.20	0.40	0.20	0.40	0.60
x_{41}	0.00	0.00	0.20	0.10	0.30	0.50	0.00	0.20	0.40	0.50	0.70	0.90
x_{42}	0.00	0.00	0.20	0.00	0.20	0.40	0.00	0.20	0.40	0.30	0.50	0.70
x_{43}	0.00	0.00	0.20	0.00	0.10	0.30	0.00	0.20	0.40	0.50	0.70	0.90
x_{44}	0.00	0.00	0.20	0.20	0.40	0.60	0.00	0.20	0.40	0.30	0.50	0.70
x_{45}	0.00	0.00	0.20	0.00	0.10	0.30	0.00	0.20	0.40	0.20	0.30	0.50
x_{46}	0.00	0.00	0.20	0.00	0.20	0.40	0.00	0.20	0.40	0.20	0.30	0.50
x_{51}	0.00	0.00	0.20	0.00	0.20	0.40	0.00	0.20	0.40	0.30	0.50	0.70
x_{52}	0.00	0.00	0.20	0.00	0.20	0.40	0.00	0.20	0.40	0.30	0.40	0.60
x_{53}	0.00	0.00	0.20	0.00	0.10	0.30	0.00	0.00	0.20	0.20	0.30	0.50
x_{54}	0.00	0.00	0.20	0.10	0.30	0.50	0.00	0.00	0.20	0.20	0.30	0.50
x_{55}	0.00	0.00	0.20	0.00	0.20	0.40	0.00	0.00	0.20	0.20	0.40	0.60

Table 5: Fuzzy triangular number for the sub-criteria

The information in Table 5 was converted into crisp values. This convention is to enable us to proceed with the application of the GRA method. Table 6 presents the generated crisp values for the system.

	M_1	M_2	M_3	M_4
x_{11}	0.3167	0.2167	0.4000	0.7000
x_{12}	0.1167	0.7000	0.4000	0.8000
x_{13}	0.4000	0.7000	0.2000	0.8000
x_{14}	0.2000	0.7000	0.4000	0.7000
x_{15}	0.0333	0.6000	0.0333	0.7000
x_{21}	0.4000	0.5000	0.4000	0.7000
x_{22}	0.0333	0.5000	0.0333	0.7000
x_{23}	0.0333	0.2167	0.2000	0.6000
x_{24}	0.1167	0.2167	0.2000	0.7000
x_{25}	0.6000	0.5075	0.6000	0.7000
x_{31}	0.5000	0.8000	0.6000	0.7000
x_{32}	0.5000	0.5000	0.6000	0.6000
x_{33}	0.1167	0.3000	0.8000	0.5000
x_{34}	0.6000	0.6000	0.6000	0.6000
x_{35}	0.1167	0.3000	0.2000	0.4000
x_{41}	0.0333	0.3000	0.2000	0.7000
x_{42}	0.0333	0.2000	0.2000	0.5000
x_{43}	0.0333	0.1167	0.2000	0.7000
x_{44}	0.0333	0.4000	0.2000	0.5000
x_{45}	0.0333	0.1167	0.2000	0.3167
x_{46}	0.0333	0.2000	0.2000	0.3167
x_{51}	0.0333	0.2000	0.2000	0.5000
x_{52}	0.0333	0.2000	0.2000	0.4167
x_{53}	0.0333	0.1167	0.0333	0.3167
x_{54}	0.0333	0.3000	0.0333	0.3167
x_{55}	0.0333	0.2000	0.0333	0.4000

Table 6: Crisp sub-criteria values

	M_1	M_2	M_3	M_4
x_{11}	0.4545	1.0000	0.0000	0.8333
x_{12}	1.0000	0.0000	0.5143	0.8667
x_{13}	0.6000	0.0000	1.0000	0.6333
x_{14}	1.0000	0.0000	0.6000	0.9000
x_{15}	1.0000	0.0000	1.0000	0.8431
x_{21}	0.6667	0.0000	0.6667	1.0000
x_{22}	1.0000	0.0000	1.0000	0.8452
x_{23}	1.0000	0.0000	0.0909	0.8636
x_{24}	0.9730	0.0000	0.1622	1.0000
x_{25}	0.0000	0.8014	0.0000	1.0000
x_{31}	0.9000	0.0000	0.6000	1.0000
x_{32}	0.5455	0.5455	0.0000	1.0000
x_{33}	1.0000	0.7317	0.0000	0.9837
x_{34}	0.0000	0.0000	0.0000	1.0000
x_{35}	1.0000	0.0000	0.5455	0.9394
x_{41}	1.0000	0.0000	0.3750	0.8542
x_{42}	1.0000	0.0000	0.0000	0.8667
x_{43}	1.0000	0.5000	0.0000	0.9500
x_{44}	1.0000	0.0000	0.5455	0.8485
x_{45}	1.0000	0.5000	0.0000	0.9500
x_{46}	1.0000	0.0000	0.0000	0.8667
x_{51}	1.0000	0.0000	0.0000	0.8667
x_{52}	1.0000	0.0000	0.0000	0.8667
x_{53}	1.0000	0.0000	1.0000	0.9000
x_{54}	1.0000	0.0000	1.0000	0.8542
x_{55}	1.0000	0.0000	1.0000	0.8667

Table 7: Normalised crisp sub-criteria values

Normalisation operation was carried out on the information presented in Table 6. This operation serves as a data pre-processing for the GRA method. Table 7 presents the processed information.

Using the GRA method, we generated the systems' GRG. The generated information is used as the original decision matrix for the TOPSIS implementation. Table 8 shows the pair-wise results for the criteria and the systems.

Criterion	M_1	M_2	M_3	M_4
c_1	0.8109	0.2000	0.6229	0.8153
c_2	0.7279	0.1603	0.3839	0.9418
c_3	0.6891	0.2554	0.2291	0.9846
c_4	1.0000	0.1667	0.1534	0.8893
c_5	1.0000	0.0000	0.6000	0.8708

Table 8: GRG for the criteria

To apply the TOPSIS method, we normalised the information in Table 8 and the results obtained are presented in Table 9.

Case study	c_1	c_2	c_3	c_4	c_5
M_1	0.6129	0.5773	0.5513	0.7368	0.6871
M_2	0.1512	0.1271	0.2044	0.1228	0.0000
M_3	0.4708	0.3045	0.1833	0.1130	0.4122
M_4	0.6163	0.7469	0.7878	0.6552	0.5983

Table 9: Normalised decision matrix for the criteria

To generate the normalised weighted values for the case study, we combined Tables 4 and 9. This combination generated the results in Table 10.

Case study	c_1	c_2	c_3	c_4	c_5
M_1	0.1539	0.1449	0.1384	0.1849	0.1725
M_2	0.0233	0.0196	0.0314	0.0189	0.0000
M_3	0.0110	0.0071	0.0043	0.0026	0.0096
M_4	0.0067	0.0082	0.0086	0.0072	0.0066

Table 10: Normalised weight matrix for the criteria

The normalised values in Table 10 were used to generate a fuzzy position and negative solutions for the criteria. Table 10 shows that c_4 had the highest positive ideal solution, while c_3 had the lowest positive ideal solution. On the other hand, c_2 had the highest negative ideal solution, while c_5 had the lowest ideal solution.

Criteria	c_1	c_2	c_3	c_4	c_5
A_i^+	0.1539	0.1449	0.1384	0.1849	0.1725
A_i^-	0.0067	0.0071	0.0043	0.0026	0.0000

Table 11: Fuzzy positive and negative ideal solutions

Using the information in Table 11, we determined the systems' closeness coefficients shown in Table 12. This information indicates that the best manufacturing system is M_4, while M_2 is the worst manufacturing system.

Case study	D_i^+	D_i^-	CC	Ranks
M_1	0.0000	0.1137	0.0000	4
M_2	0.1016	0.0013	0.9874	3
M_3	0.1171	0.0006	0.9949	2
M_4	0.1163	0.0004	0.9966	1

Table 12: Closeness coefficient of the case studies

This study uses ARAS (Additive Ratio Assessment) to evaluate the proposed model's ability to identify the best manufacturing system. Section 3.4 contains details of this method. Using the information in Table 10, we determined the systems' utility degree values – see Table 13 for more details.

System	Utility degree	Relative efficiency	Rank
M_1	0.6420	0.9613	2
M_2	0.1158	0.1734	4
M_3	0.3093	0.4631	3
M_4	0.6678	1.0000	1

Table 13: Summary of the ARAS results

Table 13 shows that the systems' relative efficiency shows that the best manufacturing system is M_4, while the worst manufacturing system is M_2. From these results, we can deduce that the proposed methodology can identify the best manufacturing system. This is because both methods identified M4 as the best system – see Tables 12 and 13 for more details.

5. Conclusions

The use of fuzzy logic, AHP, GRA, and TOPSIS to evaluate a maintenance system's performance based on key maintenance performance indices has been successfully demonstrated in this study. The proposed framework was tested using information that was obtained from four production systems. The results obtained showed that production system 4 had the best maintenance system. Maintenance system for production system 1 was ranked the lowest maintenance system. This study has contributed to maintenance system evaluation by integrating safety, maintenance task and errors with human relation and equipment factors using a fuzzy multi-criteria approach.

In a future study, the use of other ranking tools such as VIKOR and ELECTRE will be investigated. Also, the number of factors will be extended to include maintenance sustainability factors. Finally, a study that uses the proposed model's outputs to predict a maintenance system's performance that uses the outputs of the proposed model to predict a maintenance system's performance could be considered a further study. Furthermore, a maintenance department's evaluation of safety violation level could be pursued as a further study.

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