A Multi-Criteria Approach to Maintenance Performance Assessment in a Manufacturing System

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Abstract. *Nowadays, intensive maintenance research has established procedures for evaluating the performance of industries for control and organisational planning purposes (decision making). However, decisions must be carried out in an accurate, fast and cost-effective manner in compliance with the dynamics of today's industrial activities. This brings the need for intelligent systems for control. Maintenance performance has huge metrics, and the question of how to track these measures in the circumstance of interwoven indices is an urgent problem for all maintenance systems. A novel intelligent approach was developed using the Taguchi method and grey relational analysis for the multi-response optimisation problem to cope with the demand. The key performance indicators used to achieve the optimum response characteristics were the grey-relational grade and the Taguchi's orthogonal array. A comprehensive framework that utilises TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution), fuzzy logic, and ANN, respectively, in ranking, quantifying uncertainties and predicting performance is proposed. In achieving optimal global results, differential evolution (DE), big-bang big-crunch (BB-BC) algorithm and harmony search algorithm (HAS) are introduced, fused with ANN in all cases, and the comparison of the hybrids is reported. We found that the differential evolution algorithm performed better than BB-BC and HSA. The principal novelty of the paper is the unique introduction of Taguchi's approach and grey-relational analysis in performance analysis. In the current perspective, the applications of TOPSIS, fuzzy logic, and ANN are also novel. A third novel contribution is the introduction of optimisers in the model framework. It is concluded that this intelligent maintenance performance approach is applicable in industrial environments. The conclusion is supported by the results obtained from real-life manufacturing companies operating in Nigeria, utilised to validate the approach.*

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1.Introduction

During this century, several important phenomena have characterised the business scene worldwide, including in developing countries. There is intensive competition prevailing in industries amidst stiff and harsh business environmental factors, dwelling economic fortunes, and a need to meet and exceed customers' expectations satisfactorily. Organisations have commenced heavy investments in human capital and initiated short and long-term relationships with social stakeholders, striving to meet and exceed the demands set by law [1]. The high competitiveness of contemporary manufacturing industries has been moulded by the influence of high quality, low price, and the first-to-market drive of organisations, leading to organisational issues [2]. Most manufacturing systems survive under the circumstance described above by implementing performance enhancement schemes initiated by them or imposed on them by regulatory agencies, governments or customers' demands. Such schemes, as reported in the literature, include service quality standardisation [3-4], health and safety improvement drive [1], world-class maintenance system attainment drive [5], profitability campaign drive [6-7] and the total productive maintenance schemes [8-9]. A well-organised performance measurement system has to be installed to monitor these schemes. Maintenance has been regarded as a critical function in manufacturing whose performance should be measured from time to time.

With the significant number of maintenance performance measures, the issue of tracking maintenance performance in the circumstance of complex computations of interwoven indices is challenging. It should be noted that the indices are meant to regulate the health status of the maintenance system and should therefore be used effectively and efficiently. In earnest, the maintenance system needs a practical approach and tool to track maintenance performance within the constraints of computational times and depth of analysis to accomplish this goal. The main objective of this paper is to develop a novel, intelligent approach using the Taguchi method with grey-relational analysis for multi-response optimisation problems with the grey-relational analysis and The Taguchi's orthogonal array as key performance indicators to achieve optimum response characteristics.

A comprehensive framework that utilises TOPSIS, fuzzy logic and ANN is presented. TOPSIS has been used to determine the rank of the different outcomes based on the concept of a proportional distance between each option and the ideal solution [10]. Fuzzy logic has been used to establish a capturing mechanism for the uncertainties in the system [11]. ANN's contribution is in the prediction of the performance indices.

The Taguchi method has gained widespread usage in quantitative research in the past several years. In this study, a Taguchi-grey relational analysis framework is proposed based on the advantages of the Taguchi technique and the merits of grey relational analysis. The reasons for using the Taguchi method in the current investigation are that it serves as: (1) a method based on statistical principles to improve the quality of manufacturing goods and, by extension, service improvement [12]; (2) a predictor that makes huge percentage reduction in experimental times [13]; (3) predictive tool for understanding the effects of various maintenance factors on the overall maintenance performance; (4) a tool for cost reduction in experiments.

The integration of the Taguchi method with grey relational analysis is pursued in the current research for the following reasons. First, several successful documentation on the applications of Taguchi and grey relational analysis exist in literature - for example, to turning [14]. Second, there are great benefits if Taguchi is added to the grey relational analysis: it works effectively in situations where incomplete data exists. A significant novelty demonstrated in the current work is its focus on maintenance performance evaluation; previous studies on the Taguchi technique have been limited to composite fabrications. For instance, Subbaya et al. [15] worked on the wear assessment of composite. A prior investigation by Natarajan and Arunachalam [16] was to non-conventional machining. According to Yang [17], the application was to the cutting process in composite fabrication. Other previous applications of grey relational analysis have been made in various studies on the optimisation of boilers parameters [18], parametric welding optimisation [19], general optimisation [20], and wear property optimisation [21]. Ottosson et al. [7] investigated the productivity of stators production lines for electric motor manufacturing by measuring the overall equipment effectiveness of the machines. This showed that while availability was high, the performance efficiency was low. Hagg [6] revealed the potential of profitability for the Swedish industry, emphasising the connection between maintenance activities and profitability [22].

From the literature discussed in the previous lines, it could be observed that considerable research has been done on the issue of maintenance performance. Unfortunately, an explicit limitation of most studies is the limited data available for making decisions on maintenance. While some data may be available, they are either scanty, not involve depth in terms of coverage of years or plan period for analysis. Other data are of minimal scope. Nevertheless, decisions must be made, and the performance of systems evaluated for monitoring and control proposed. A model, which could adequately work in circumstances of minimal information, the grey model, is then the best suited for this purpose. Parida et al. [23] introduced the concept of a balanced scorecard in maintenance as an efficient management process.

The motivation for this study is the quest for a scientific-based methodology that can be used to determine the optimal value for key performance indicators (KPIs) of maintenance systems [24]. Thus, the objective of this study is to develop a single multi-attribute index model based on different KPIs. The benefit of grey-relational analysis in identifying the best combination of different factors for the problem of interest is brought into the maintenance performance selection domain. Furthermore, the rich ability of Taguchi methods in generating different combinations of system factors is used to design a factor matrix upon which the Grey Relational Analysis (GRA) is carried out in Sibalija et al. [25]. A manufacturing system with the right combination of maintenance performance indicators will experience a higher level of organisational goals attainment when compared with an instance with inappropriate performance level combinations.

In section 2, a review of performance measures in maintenance systems is presented. The research methodology of this study is in section 3, while testing of applicability of the proposed model and the discussion of results obtained are presented in section 4. The conclusions of this article are in section 5.

2.Literature Review

2.1 General Review

There have been classic contributions to developing maintenance performances for more than twenty years. The novel contributions of [22-24], [26], [27] seem to emphasise the important need of having a comprehensive platform upon which quick decisions can be made.

Some years ago, Fritzsche et al. [28] evaluated the total maintenance cost to optimise it. To minimise the total maintenance cost, the authors found an optimal length of the prognostic distance for the prognostic health management (PHM) system. It was concluded that the approach led to a better interpretation of PHM results and helped interpret PHM information for maintenance actions and policies. Maintenance performance is a crucial avenue through which the progress of the maintenance systems could be ascertained and controlled compared to the standard or targeted results. Performance is being given importance in maintenance. Therefore, performance occupies the epicentre and is central to the advancement of maintenance systems.

Maintenance measures such as Mean Time to Repair (MTTR), Mean Time Between Failure (MTBF), Meantime Between Repairs (MTBR) and Overall Equipment Effectiveness (OEE) are commonly used for assessment. Others are Productivity (P), efficiency (E), reliability (R), and Maintenance Workforce Cost (MWC). Still, others are Maintenance Cost/hour (MC), Total Material Cost (TMC), Unscheduled Downtime (UD) as a ratio of Scheduled Downtime (SD) and Shutdown Overrun (SO).

These measurements are applied in maintenance practice on an individual basis or infusion with one another. The present situation warranted asking whether these measures should be applied in practice as a single index or in combined form so that the synergic characteristics of the measures could be benefited. The response to the first question was that maintenance organisations would like to adopt the combined approach, hence the motivation for the integrated KPIs, the framework proposed in the current study. The second question is that since all activities related to maintenance are known to be done in a fast manner and maintenance itself should be done very fast [29], will the intelligent maintenance performance assessment tool not be the best fit for today's industry? The response to the second question is that since technological sophistication and the increased demand for maintenance performance have characterised today's industry, an intelligent maintenance performance system would yield optimum results for the maintenance system. Therefore, desirable for investigations and implementations in the current manufacturing practices.

The current researchers made efforts to fuse the existing performance measures in maintenance and compile a framework as an integrated maintenance performance system in which Taguchi's orthogonal array is being fused with grey-relational analysis to produce a model benefiting from the concepts. In this work, the fusion level is done in the following paths. MTTR, MTBF, MTBR, and OEE as the total productive maintenance index (TPMI), productivity, efficiency, and reliability are fuzzy into Human Factor Performance Index (HFPI). Furthermore, MWC, MAC, and TMC are fused into the maintenance cost management index (MCMI), while UD, SD, etc., are fused into the Downtime Performance Index (DPI). The four indices, viz, TPMI, HFPI, MCMI, and DPI, are fused into a unit index, reference to as a single multi-attribute index (Fig. 1).

From the preceding discussions, the current work appears to be a maiden attempt to use the Taguchi's orthogonal arrays' powerful attribute infusion with the grey relational analysis that has dominated the manufacturing scene in maintenance. It is noted that practising performance measurement in maintenance is not alone; maintenance practitioners and researchers are looking for measures that will optimise their variables, hence the motivation to utilise Taguchi's orthogonal array in contribution with grey relational analysis for optimisation.

To tackle the problem of the non-clarity of maintenance goals concerning profit enhancement, the most suitable solution would be to use performance measures that emanate from a set of structured industries such as productivity-related, efficiency-based, etc. Nowadays, the challenge has been using intuition to manage the maintenance function since minimal data are often available. Intuition is based on experience and, therefore, would be a problem when a new manager without experience in a specific maintenance function is asked to manage such a function; intuition may fail in this instance. Performance measurement in maintenance has several merits over intuition, including improvement in maintenance function; with measurements, improvements are possible. However, improvements are difficult to achieve with intuition.

Keeping in mind the foregoing discussions, the following summary is obtained. Firstly, from the literature review, it was noted that many investigations dealt with single performance measures such as productivity, efficiency and service quality for the maintenance situation. Limited studies have been carried out with more than one index. Time and cost are two parameters that were varied during investigations. Second, the balanced scorecard approach and benchmarking have been widely used in industrial applications. Third, Taguchi's orthogonal arrays have not been previously applied in the maintenance performance literature. Fourth, grey relational analysis as a technique seems absent in the literature concerning performance measurement in maintenance. Fifth, the synergic benefits of Taguchi's orthogonal array and grey relational analysis in multi-response capture for maintenance performance measurement have not been enjoyed for model robustness. Sixth, there seems to be a limited ranking of performance measures in maintenance and a composite absence in TOPSIS specifically. Seventh, to date, limited interest has been shown in the uncertainties in measurements. Detailed treatment of fuzzy logic, which could help manage uncertainties in maintenance performance measurement, is not yet reported in the literature.

2.2 Maintenance Performance Indicators

In this study, maintenance performance indicators are grouped into four groups. The grouping is based on the key factors that can be used to evaluate maintenance systems' performance (human, machine, cost, and maintenance practice). The description of maintenance system performance indices with linguistic terms is expected to be based on the industry’s best practices (Benchmark). The importance of describing maintenance performance indices in linguistic terms is that it will help non-maintenance personnel to have a general knowledge of how well a maintenance department is performing. A brief discussion on the computation of maintenance performance indices is presented as follows:

Total productive maintenance index

The main performance measure under TPM is overall equipment effectiveness (OEE), which considers the availability, efficiency and quality of products from a plant [30-31]. For a maintenance system to be considered world-class, the value of overall equipment availability (OEE) must be at least 85 % [8-9], [30].

The quality rate is measured as a function of the total amount of products produced and the total number of defective products at a particular time [32]. The amount of products produced is influenced by operating time and the number of breakdowns during a particular period. [30] pointed out that the values of MTBF and OEE can be selected based on the larger-the-better criterion, while MTTR and MTTF may be chosen based on the smaller-the-better criterion.

The quality of maintenance technician’s work is among the key factors which affect the MTBF of machines. It reflects the number of breakdowns expected in a period. To improve the quality of technicians, they are usually given training on how to carry out maintenance of machines effectively. Also, the age of machines and the machine's production period are other factors that affect the value of machine MTBF. According to [32], MTBF is a function of several operating periods and the number of breakdowns. The size of maintenance technicians determines the MTTR of a breakdown machine to a large extent. Also, the skills of the maintenance technician contribute significantly to the rate at which the fault on a broken-down machine will be identified, and this has a direct effect on maintenance systems. Thus, technicians and their skillsets need to be integrated into designing an efficient maintenance department. One such way is the use of system dynamics in analysing the effects of training on technicians' performance.

By computing the rate at which technicians are expected to work in maintenance systems, each technician's workload in a period can be approximate [33]. In the long run, all the technicians' average service rates constitute the value of MTTR of maintenance systems. Meantime between repairs (MTBR) measures the difference between a system MTBF and MTTR, as direct relationships with the size of technicians in maintenance systems. Given that a large percentage of the technicians are qualified workers, it may be inferred that the larger the technicians' size, the smaller the value of MTBR. However, the need to reduce labour costs in manufacturing systems does not encourage retaining a large number of technicians. To generate a compromise solution for the technician's size, their performance may be measured alongside other maintenance performance indices.

Human Factor Performance Index

The deployment of technicians to execute maintenance tasks is pivotal to the level of plant availability. Thus, there is a need to monitor technicians' performance for effective resource planning. To evaluate the performance of technicians, different performance indices are used. Common human performance indices are productivity, effectiveness, reliability, and maintenance improvement.

Technicians' productivity is used to measure the interrelationships between the cost of production or service and the cost of maintenance technicians. Technician's costs include the salary, severity allowance, bonuses and training expenses [34]. Maintenance technician effectiveness measures the ratio of time used in executing assigned maintenance activities to the actual time allocated for the maintenance activities [32]. A maintenance system is said to be effective when the value of maintenance technicians is less than unity. A maintenance system with technicians' effectiveness that is more than unity will experience a change in the production scheme as the due date of machines under maintenance will not be met. The technicians will have to be trained to address this problem, or more technicians will be employed. Under this situation, if there is no corresponding increase in the value of goods produced, the productivity of the maintenance system will decrease.

Technicians' reliability measures the degree to which technicians will satisfactorily carry out assigned maintenance tasks [33]. The need for technicians' reliability consideration during maintenance planning is that it helps ascertain the quality of maintenance work that will be carried out. However, the time used in carrying out any maintenance activities must be considered alongside technicians' reliability. For example, the relationship between the total man-hour used in carrying out preventive maintenance tasks and the budgeted total man-hour for preventive maintenance tasks is used in defining maintenance improvement [32]. A smaller value of maintenance improvement is desired by management; this implies that the actual time used to complete a schedule of maintenance tasks will be less than the amount of time allocated for the maintenance time (i.e., high technicians' efficiency).

Maintenance Cost

One benefit of maintenance cost control is to reduce the cost of goods produced by reducing the cost of maintenance materials and the cost of maintenance technicians. The cost of maintenance materials covers the purchase costs of spare parts, spare parts inventory, and maintenance consumables. To provide more detailed monitoring of maintenance materials costs, decision-makers often design the expected maintenance cost that may be incurred per period [32].

Maintaining the workforce covers their salaries, and other costs will be incurred due to motivating and improving technicians' skills. The full benefits from the technicians in maintenance systems to be derived, there is the need to optimise the number of technicians and workload in the different maintenance sections [34-35].

Apart from the direct cost of in-hose maintenance technicians, the cost of maintenance tasks that are outsourced must be considered when estimating maintenance workers' costs. The cost of maintenance technicians for outsourced maintenance tasks may be taken total cost of outsourced maintenance tasks less the total cost of materials used for maintenance activities.

Downtime Performance Index

The provision of the required maintenance materials and technicians plays an important role in determining the uptime of production facilities. However, the problem of downtime of the production facility persists. In some cases, the decision-makers usually determine the duration in which production facilities will not be available for production activities—this helps minimise unscheduled downtime. The problem of unscheduled downtime may be machine-based, human-based or management-based. Machine-based unscheduled downtime may result from ageing production facilities whose mean time to failure is stochastic, and it becomes difficult to predict which machine parts will cause a breakdown.

When such a machine fails, the problem of spare parts unavailability may increase the downtime of the production facility. Another problem is the unavailable of skilled technicians to restore the machine to an acceptable functional state. This problem is more challenging when the maintenance of such a machine is outsourced; it may take longer than expected for the company in charge of the machine to be responsible to call to come for the maintenance of such facility. By outsourcing maintenance activities, the management of such systems is indirectly cutting down the number of maintenance technicians in their systems. In a developing economy, tuition and direct monetary benefits often decide to outsource maintenance activities.

For new production systems, the problem of importing special spare parts for machines may result in long periods of shutdown overrun due to the lack of required spare parts in their engineering stores. In some cases, diagnosis of machine breakdown may be required by the engineers (experts) from the company that manufactured the machine. This problem becomes more challenging when the experts require a work permit before visiting the broken-down machine's site.

3.Methodology

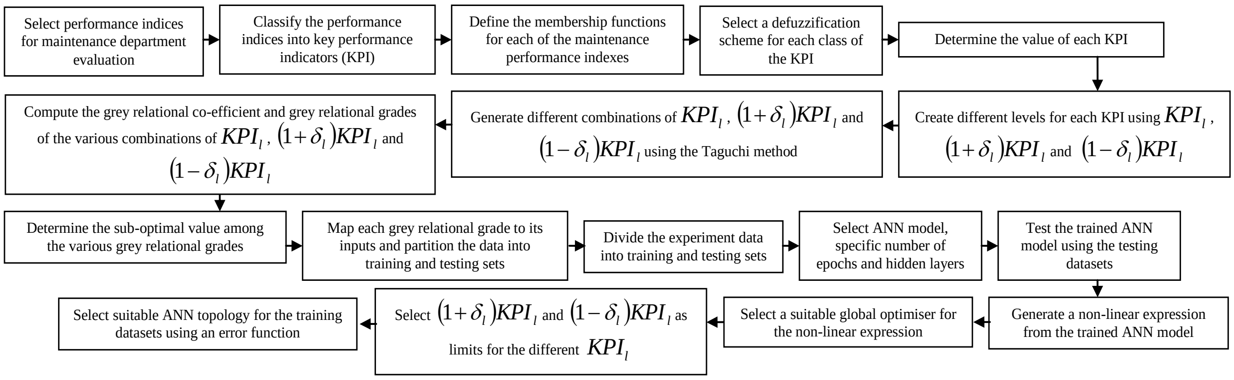
Given the strategy impacts of maintenance activities on business competitiveness [36], there is the need to develop a framework that can identify the right combinations of maintenance systems variables. Such selection is faced with the problem of multiple input and multiple output relationships [37]. Another challenge is the qualitative nature of some maintenance performance evaluation variables (worker morale, customer satisfaction and employee satisfaction). To resolve these challenges, fuzzy logic theory, grey relational analysis and the Taguchi method are employed in this study. This study adopts the proposed methodology because of the following reasons:

- It generates optimal values for system parameters.
- It allows stakeholders to moderate potential solutions for operational parameters.
- It harnesses the unique properties of different operational research tools, such as ANN, Taguchi and grey relational analysis.

The selection of appropriate tools for combining different *KPIs* is significant in addressing the problem of the incorrect combination of *KPIs*, which may result in bad management decisions [31]. To justify the use of the various tools used in this study, the unique features of each of the selected scientific tools are discussed as follows:

- Taguchi method provides a means for combining different levels of *KPIs* that are desired by decision-makers in maintenance systems;
- Fuzzy logic provides means for converting linguistic terms used in describing the performance of maintenance systems. By considering linguistic terms, the difficulty of using numeric values to describe maintenance performance will be addressed numeric data from industries;
- Grey relation analysis provides a means for combining the values of different *KPIs* by considering the direction of each *KPI*;
- ANN provides a means of predicting the outcome of combining different *KPIs* values, and it is used in generating an expression that needs to be optimised;
- Meta-heuristics generate optimal values for the *KPIs* based on their minimum and maximum levels.

The flowchart that shows the integration of the stage at which each of the selected tools is used in this study is presented in Fig. 1. The proposed framework for evaluating the performance of the maintenance department is presented in Fig. 2. The information in Fig. 2 is based on the knowledge gained from the works of [23] [31], [33].



where, KPI_l is the calculated *KPI* for KPI_l, δ_l is the deviational variables for KPI_l

Fig. 1 A framework for Maintenance Performance Evaluation (MPE) using AI tools

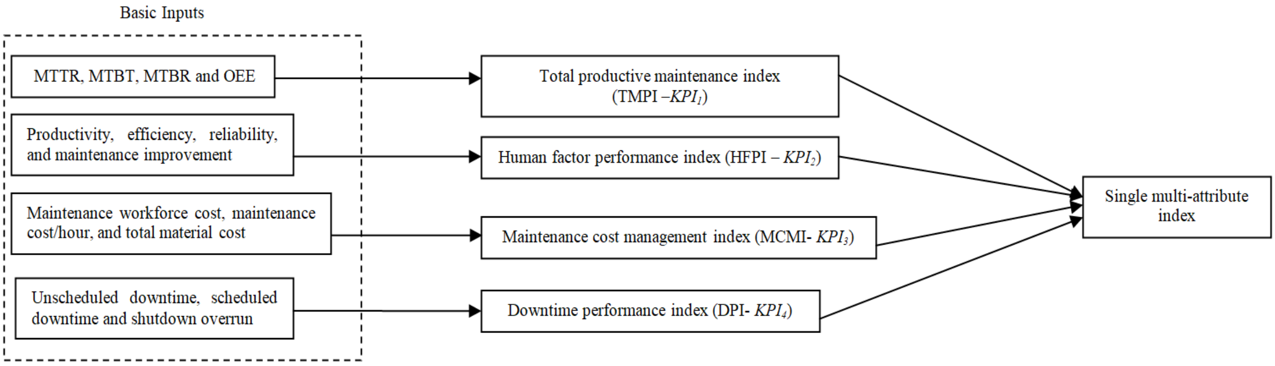


Fig. 2 A single multi-attribute index for the maintenance department's performance evaluation

3.1 Maintenance KPI Fuzzy System

The presence of vagueness in qualitative information used in analysing the performance of maintenance systems does not always present the true state of a maintenance system. The vague information may be attributed to the subjective information provided by the maintenance supervisors or the maintenance foremen and managers. In addressing this problem of vague information, a fuzzy logic theory generates crisp values that can be used for empirical analysis of maintenance performance. In this article, the triangular membership function is selected to generate membership functions for the performance as mentioned earlier indices presented in Fig. 2 [3].

To convert the responses from a questionnaire that is administered into a triangular fuzzy number (TFN), Equation (1) is used [4]. Fig. 3 shows a triangular function membership diagram, and Fig. 4 depicts the distribution of the normalised scale for the input indices.

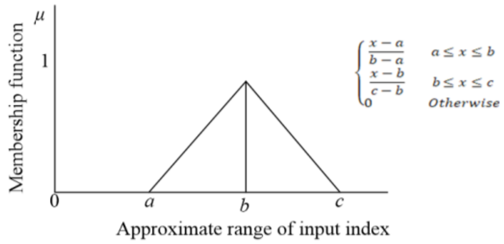


Fig. 3 Triangular membership function

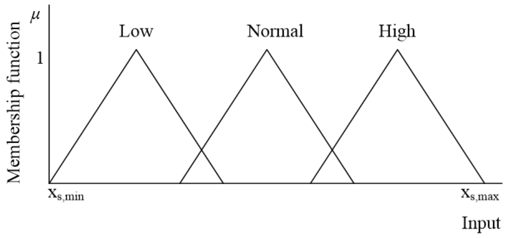


Fig. 4 Distribution of the normalised scale for the input indices

where, $x_{s,\min}$ and $x_{s,\max}$ are the expected minimum and maximum normalised values of the inputs, respectively.

With Fig. 4, the range of *a*, *b*, and *c* is expressed as $x_{s,\min} \le a \le b \le c \le x_{s,\max}$. Given that $x_{s,\min}$ and $x_{s,\max}$ are 0 and 100, respectively, the fuzzy number set for the linguistic terms in Fig. 4 is presented in Table 1. Equation (1) computes the overall judgement of decision-makers in the maintenance system [4].

$$A_{ij} = \frac{1}{m} \otimes \left(A_{ij}^{1} \oplus, \ldots, \oplus A_{ij}^{m} \right) \tag{1}$$

where, A_{ij} is input index i for KPI j and A_{ij}^{m} is the response of decision-maker m to A_{ij}, $\otimes$ and $\oplus$ are multiplication and addition, operations, respectively of fuzzy numbers

Linguistic terms	TFN
Low	(0, 20, 40)
Normal	(30, 50, 70)
High	(60, 80, 100)

Table 1 Triangular fuzzy number (TFN)

Equation (2) is used to convert the fuzzy number to a non-fuzzy (*NF*) number (Wang *et al*., 2012).

$$NF = (a + b + c)/3 \tag{2}$$

Since the dimensions of some of the inputs are not the same, the work proceeds to the fuzzification of the values generated from Equation (2). This allows us to apply the weighted average formula to generate the actual value of each of the performance indicators [38].To achieve this task, Fig. 4 generates the membership functions of the various inputs in Fig. 2. The values of TMPI, HFPI, MCMI, and DPI are expressed with Equations (3) to (6).

$$KPI_1 = \frac{\mu_{MTTR}(x_{MTTR})x_{MTTR} + \mu_{MTBR}(x_{MTBR})x_{MTBR} + \mu_{MTBF}(x_{MTBF})x_{MTBF} + \mu_{OEE}(x_{OEE})x_{OEE}}{\mu_{MTTR}(x_{MTTR}) + \mu_{MTBR}(x_{MTBR}) + \mu_{MTBF}(x_{MTBF}) + \mu_{OEE}(x_{OEE})} \tag{3}$$

Where, MTTF = mean time to repair, MTBR = mean time between repair, OEE = overall equipment effectiveness, MTBF = mean time between failure.

$$KPI_2 = \frac{\mu_{PROD}(x_{PROD})x_{PROD} + \mu_{REL}(x_{REL})x_{REL} + \mu_{MI}(x_{MI})x_{MI} + \mu_{EFF}(x_{EFF})x_{EFF}}{\mu_{PROD}(x_{PROD}) + \mu_{REL}(x_{REL}) + \mu_{MI}(x_{MI}) + \mu_{EFF}(x_{EFF})} \tag{4}$$

Where, PROD = Productivity, EFF = efficiency, REL = reliability, and MI = maintenance improvement

$$KPI_3 = \frac{\mu_{MWC}(x_{MWC})x_{MWC} + \mu_{MC}(x_{MC})x_{MC} + \mu_{TMC}(x_{TMC})x_{TMC}}{\mu_{MWC}(x_{MWC}) + \mu_{MC}(x_{MC}) + \mu_{TMC}(x_{TMC})} \tag{5}$$

Where, MWC = Maintenance workforce cost, MC = maintenance cost/hour, and TMC = total material cost

$$KPI_4 = \frac{\mu_{UD}(x_{UD})x_{UD} + \mu_{SD}(x_{SD})x_{SD} + \mu_{SO}(x_{SO})x_{SO}}{\mu_{UD}(x_{UD}) + \mu_{SD}(x_{SD}) + \mu_{SO}(x_{SO})} \tag{6}$$

Where, UD =Unscheduled downtime, SD = scheduled downtime and SO = shutdown overrun

3.2 Design of Experiments (DOE)

The right combination of maintenance performance indicators can be determined experimentally by studying the different performance indices' different combinations at varying levels. To achieve this, this study investigated the combination of four *KPIs* at three different levels. The experimental layout for the maintenance performance selection is presented in Table 2.

Parameters	Notations	Level 1 (1)	Level 2 (2)	Level 3 (3)
Total productive maintenance index (TPMI)	x_1	$(1-\delta_1)KPI_1$	KPI_1	$(1+\delta_1)KPI_1$
Human factor performance index (HFPI)	x_2	$(1-\delta_2)KPI_2$	KPI_2	$(1+\delta_2)KPI_2$
Maintenance cost management index (MCMI)	x_3	$(1-\delta_3)KPI_3$	KPI_3	$(1+\delta_3)KPI_3$
Downtime performance index (DPI)	x_4	$(1-\delta_4)KPI_4$	KPI_4	$(1+\delta_4)KPI_4$

Table 2 Maintenance *KPIs* and their levels

Based on the concept of Taguchi orthogonal array, the performance of each experiment may be computed by considering Equation (7). Two possible ways of determining the values of p_i is to use signal-noise ratio or grey relational analysis. By definition, the values of the different p_i and intelligent systems can be developed that can utilise the input-output relationships in Equation (7). When the values of $p_i{}'s$ are defined, an intelligent system can be created based on the concept of supervised learning.

$$\begin{bmatrix} x_{1,1} & x_{1,2} & x_{1,3} & x_{1,4} \\ \vdots & \vdots & \vdots & \vdots \\ x_{27,1} & x_{27,2} & x_{27,3} & x_{27,4} \end{bmatrix} = \begin{bmatrix} p_1 \\ \vdots \\ p_{27} \end{bmatrix} \tag{7}$$

where, $x_{l,j}$ is the aggregated values of x_i at experiment number *j*

By using the Quality Loss (QL_i) function, the desired value of the experimental output is nominal-the-best and it is expressed as Equation (8). The decision to select nominal-the-better is based on the fact that the performance indices that are considered in Fig. (2) are of maximum and minimum desired value types.

$$QL_i = \frac{1}{n}\sum_{j=1}^{n}(y_j - m)^2 \tag{8}$$

3.3 Grey Relational Analysis

To verify the decision of using the normal-the-best QL_i, this study also used GRA to compute the different experimental outcomes' values. The desired direction for each performance index will be defined to apply GRA in maintenance performance indices selection. For a maintenance system, there exist two possible outcomes. The first outcome is Nominal-the-Better (Equation 9); machine availability and utilisation follow under this category. The second outcome is lower-the-better (Equation 10); maintenance costs, accidents and delays in machine release time are subsets of this outcome. The combination of the values that will be obtained from Equations (9) and (10) will help in addressing the complex interrelationships among performance indices of a higher-the-better and lower-the-better nature in maintenance systems [39].

$$x^*(k) = \frac{\max x_i^o(k) - x_i^o(k)}{\max x_i^o(k) - \min x_i^o(k)} \tag{9}$$

$$x^*(k) = \frac{x_i^o(k) - \min x_i^o(k)}{\max x_i^o(k) - \min x_i^o(k)} \tag{10}$$

where, $x_i^o(k)$ is the original sequence and $x_i^*(k)$ is the sequence after data pre-processing, $\min x_i^o(k)$ $\max x_i^o(k)$ and are the minimum and maximum values, respectively, of $x_i^o(k)$.

The importance of Equations (9) and (10) is to generate normalised data that will be used in defining the grey relation coefficient [40] for each of the performance indexes. The expression for computing the grey relation coefficient for each performance index is given as Equation (11); this is the second stage in GRA.

$$\zeta_i(k) = \frac{\Delta\min + \zeta\Delta\max}{\Delta_{o,i}(k) + \zeta\Delta\max} \quad (11)$$

$$\Delta\min = \min_{\forall j \in i}\min_{\forall k}\left\| x_o^*(k) - x_i^*(k) \right\| \quad (12)$$

$$\Delta\max = \max_{\forall j \in i}\max_{\forall k}\left\| x_o^*(k) - x_i^*(k) \right\| \quad (13)$$

where, $x_o^*(k)$ and $x_i^*(k)$ are the reference sequence and comparative sequence, ζ is called identification coefficient and its values lie between (0,1).

The last stage of GRA is the computation of grey relational grade (Equation 14) for each experiment [40].

$$\gamma_i = \frac{1}{n}\sum_{k=1}^{n}\zeta_i(k) \quad (14)$$

3.4 ANN-HSA Based Method

ANN is a predictive tool used to study relationships among systems' inputs and outputs by different researchers and practitioners. In this study, a forward multilayer ANN model (Fig. 5) is used in predicting the value of each grey relational grade of the experiment. The input to the ANN model is taken as the value of each experiment input. A gradient descent algorithm is taken as the training algorithm for the ANN model [33], and the hidden and output layer transfer functions are sigmoid and linear, respectively. The performance monitoring of the ANN model is based on Mean Square Error (MSE).

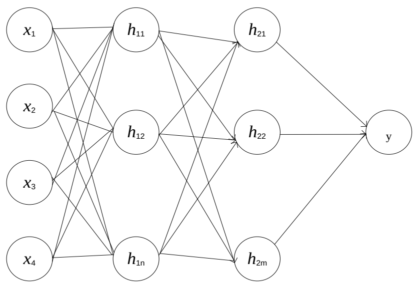


Fig. 5 A 4-n-m-1 ANN architecture

The objective function which is used for the determination of optimal values for the *KPIs* is taken as the value of the single multi-attribute index generated from the combination of the optimal values of the *KPIs* using the expression generated by the trained ANN model (Equation). In Equation (15), *Net* is the value of net signal in the output layout in Fig. (5).

$$\text{Max } Z = 1/\left(1 + e^{-Net+\theta}\right) \quad (15)$$

where, θ is known as bias

The expected value of the grey relational grade is taken as a constraint for the optimisation model (Equation 16). For the current study, nominal-the-better is desired. The bounds for each of the *KPIs* are also used in constraining the optimal value of Equation (17).

$$\frac{1}{n}\left(\sum_{i=1}^{n}\frac{\Delta\min,i + \zeta\Delta\max,i}{\Delta_{o,i} + \zeta\Delta\max,i}\right) \geq \gamma_{\min} \quad (16)$$

$$X_l^j \leq x_j \leq X_u^j \qquad \forall j \in n \quad (17)$$

$$x_j > 0 \qquad \forall j \in n \quad (18)$$

where, n is the total number of input data and x_j is the value of an input; S_L and S_U are the minimum and maximum values, respectively, of the signal-noise ratio of the systems; X_l^j and X_u^j are the minimum and maximum values, respectively, of *KPIj*

i. The Structure of HSA

The structure of HSA used for generating the optimal values for the *KPIs* is described as follows [41]:

These initial values for each decision variable are generated using the minimum and maximum values of the decision variables and a random number that lies between (0, 1), Equation (19).

$$x_j = x_l^j + Rnd(x_u^j - x_l^j) \quad (19)$$

The quality of each solution is evaluated and stored as harmony memory. New values of the decision variables are created using the data in the harmony memory, and HMCR is Harmony Memory Considering Rate (HMCR), whose a value is between (0, 1), and Equation (20).

$$x_{ij}^{'} = \begin{cases} x_{ij}^{'} \in \left\{x_{ij}^1, x_{ij}^2, x_{ij}^3, \ldots, x_{ij}^n\right\} & \text{with probability of HMCR} \\ x_{ij}^{'} \in X^{'} & \text{Otherwise} \end{cases} \quad (20)$$

where, $X^{'}$ represents new value selected from a possible solution range.

The newly variables are fined tuned using pitch adjustment rate (PAR) and bandwidth, Equation (21). The value may be used as a constant or variable. When considered as a variable, its value decreases exponentially from one epoch to another [42]. Also, when training the ANN, the estimation of the number of epochs is important because choosing an extremely high number of epochs triggers the overfitting of the training data from the model. An epoch shows the number of passes that the whole training dataset completes during the implementation of an ANN model. From the foregoing, by experiment, the error rates are the best determinants of the number of epochs. Equation (22) generates a new value for bw_t at each epoch. [42] reported that the value of $bw_{\max}$ for each variable can be estimated by considering their minimum and maximum values.

$$x_{ij}^{'} = \begin{cases} x_{ij}^{'} \pm rnd * bw_t & \text{with probability of PAR} \\ x_{ij}^{'} & \text{Otherwise} \end{cases} \tag{21}$$

$$bw_t = bw_{\min} + \frac{bw_{\max} - bw_{\min}}{t_{\max}} t \tag{22}$$

Adjustment of the solution quality in the harmony memory is carried out by comparing the worst solution in the harmony memory with the best solution generated at each epoch (Equation 23).

$$sol = \begin{cases} f\left(x_{ijt}^{k}\right) & \text{If } f\left(x_{ijt}^{k}\right) \le f\left(x_{ij,worst}^{k}\right) \\ f\left(x_{ij,t-1}^{k}\right) & \text{Otherwise} \end{cases} \tag{23}$$

The performance of the HSA is compared with genetic GA [43] and a big-bang big-crunch (BB-BC) algorithm [33], which has been used in generating optimal values for different parameters by integrating these algorithms with the ANN model.

ii. Differential Evolution

Differential Evolution (DE) belongs to the family of meta-heuristics known as evolutionary algorithms. The characteristic of an evolutionary algorithm is applying mutation and reproduction operations in tuning the values of decision variables in a problem from one generation to another [44 -45].

(a) Mutation operation: This operation involves a random selection of variables in a current reproduction pool, such that none of the variables is from that same individual in a population. Equation (24) presents the expression for mutation operation in DE.

$$v_{i,j,g+1} = x_{i,j,g}^{1} + MR\left(x_{i,j,g}^{2} - x_{i,j,g}^{3}\right) \tag{24}$$

where, $x_{i,j,g} \ne x_{i,j,g}^{1} \ne x_{i,j,g}^{2} \ne x_{i,j,g}^{3}$

(b) Crossover operation: This operation is used to decide whether to accept the newly generated off-spring or the current value of a decision variable. A decision is taken based on crossover probability. Equation (25) presents the expression for crossover operation.

$$u_{i,j,g+1} = \begin{cases} u_{i,j,g+1} & Rnd \le CR \text{ or } j = I_{Rnd} \\ x_{i,j,g} & Rnd \ge CR \text{ and } j \ne I_{Rnd} \end{cases} \tag{25}$$

where, the value of CR lies between (0, 1). *Rnd* is a uniformly distributed random number between (0, 1) and I_{Rnd} is an integer value selected randomly from the problem dimension (j = 1, . . . D).

(c) Selection operation: This operation is used in deciding among off-springs and parents that will survive to the next generation, Equation (26)

$$x_{i,j,g+1} = \begin{cases} u_{i,j,g+1} & \text{If } f\left(u_{i,j,g+1}\right) \le f\left(x_{i,j,g}\right) \\ x_{i,j,g} & \text{Otherwise} \end{cases} \tag{26}$$

iii. BB-BC Algorithm

The BB-BC algorithm has been applied in as a solution method for different optimisation problems since its development by [46]. Implementing the BB-BC algorithm involves the generation of centre-of-mass (big-bang phase) and a new position for decision variables (Big-crunch phase). The BB-BC algorithm has a low computation time and can compete with existing meta-heuristics [33]. The procedure for BB-BC algorithm implementation is given as follows [46]:

Step 1: Select the population size and stoppage criterion
Step 2: Create initial values for each of the decision variables
Step 3: Evaluate the quality of particle
Step 4: Compute the centre of mass for the different decision variables (x_i^c) using Equation (27)

$$x_i^c = \frac{\sum_{k=}^{K} x_{ik} / f_k}{\sum_{k=1}^{K} 1/ f_k} \tag{27}$$

Step 5: Generate a new position of each particle in the population using Equations (28)

$$x_i^{t+1} = x_i^c + \frac{Rnd_i\left(x_{i,\max} - x_{i,\min}\right)\alpha}{t+1} \tag{28}$$

where, $\widehat{\alpha}$ is a constant parameter that controls the search capacity of the algorithm, and Rnd_i is a uniform random number that is between (-1,1).

Step 6: Check the stoppage criterion

4. Model Application and Discussion of Results

The applicability of the proposed model performance is carried out using data obtained from a manufacturing system. The value of the fuzzy calculations of the inputs in Fig. 2 is presented in Table 3. These values were obtained by analysing the questionnaires circulated using Equations (1) and (2). The Taguchi method presented in Table 2 was used to generate the experiments levels in Table 3. The fuzzy calculated values for *A*, *B*, and *C* are presented in Table 4. Using the information in Table 4 and Equations (3) to (6), 95, 97.5, 80, and 80 were obtained as the values of x_1, x_2, x_3 and x_4, respectively. The value of *A* for input 12 is zero because the responses from all the questionnaires administered for input 12 are low. The maintenance KPIs are evaluated by considering 4, 2, 10, and 5 as the deviational variables for x_1, x_2, x_3 and x_4, respectively. The outcomes from each combination of the different performance indices based on *QL* and *GRA* are presented in Table 5. From the results in Table 4, it can be inferred that the optimal local combination of the performance indices is 99, 95, 70, and 75 for x_1, x_2, x_3 and x_4, respectively. The worst combination of the performance indices is 91, 97.5, 90, and 85 for x_1, x_2, x_3 and x_4, respectively.

Parameters	Inputs													
	1	2	3	4	5	6	7	8	9	10	11	12	13	14
A	40	30	40	60	30	60	50	40	30	20	30	0	20	60
B	60	50	60	80	50	80	70	60	50	40	50	20	40	80
C	80	70	80	100	70	100	90	80	70	60	70	40	60	100
Crisp value	60	50	60	80	50	80	70	60	50	40	50	20	40	80

Table 3 Fuzzy calculations and crisp values for each input parameter

S/N	x_1	x_2	x_3	x_4	*GRA*	*QL*	S/N	x_1	x_2	x_3	x_4	*GRA*	*QL*
1	1	1	1	1	0.75	110.19	15	2	3	2	3	0.71	60.05
2	1	1	1	2	0.67	95.50	16	2	3	3	1	0.79	85.05
3	1	1	1	3	0.63	90.19	17	2	3	3	2	0.71	52.55
4	1	1	2	1	0.67	65.19	18	2	3	3	3	0.67	29.42
5	1	1	2	2	0.58	44.25	19	3	1	1	1	0.88	155.19
6	1	1	2	3	0.54	32.69	20	3	1	1	2	0.79	135.50
7	1	2	3	1	0.67	67.92	21	3	1	1	3	0.75	125.19
8	1	2	3	2	0.59	39.17	22	3	1	2	1	0.79	100.19
9	1	2	3	3	0.55	19.80	23	3	1	2	2	0.71	74.25
10	2	2	1	1	0.84	144.92	24	3	1	2	3	0.67	57.69
11	2	2	1	2	0.76	126.17	25	3	2	3	1	0.80	90.42
12	2	2	1	3	0.71	116.8	26	3	2	3	2	0.71	56.67
13	2	3	2	1	0.83	103.17	27	3	2	3	3	0.67	32.30
14	2	3	2	2	0.75	76.92							

Table 4 GRA and Quality loss values of each experiment

Using the quality loss as output for each of the experiments in Table 3, an investigation of suitable ANN topology was carried out by varying the number of nodes in each of the hidden layers in the ANN architecture. The total number of epochs for each ANN topology is the same (i.e., 2000 epochs). Six different ANN topologies were considered during the ANN model training, and the results are presented in Table 4. It can be inferred that the most suitable ANN topology for the data sets in Table 5 is the 4-5-8-1 architecture.

In the ANN topology discussed in this article, the selection of the number of nodes for each hidden layer is an important consideration to obtain a superior decision boundary. Moreover, the hidden layers are in-between the output and input layers with the function of permitting the artificial neuron to receive groups of weighted inputs to generate output(s) during the active service of an activation function. Besides, in this article, the great advantage of the hidden layers is exploited, which is the ability to confine small details to determine several associations between the inputs. This is possible as the hidden layers obtain data from particular neuron sets and offer other neuron sets the output while maintaining their hidden status. However, the choice of the number of nodes that each hidden layer possesses depends on the complexity of the data. In the present article, two hidden layers were assumed since the data could be well managed and less complicated than some heavily demanding maintenance data. On this basis, the data is known to exhibit fewer dimensions. Nonetheless, the input layer's size and that of the output layer generally determine the number of hidden layers used in a scheme. Furthermore, some researchers recommend 2 to 3 the size of the input layer together with the output layer's size as the ideal number of hidden neurons.

S/n	ANN topology	MSE
1	4-4-8-1	0.00013
2	4-5-8-1	0.00011
3	4-5-5-1	0.00080
4	4-5-6-1	0.00089
5	4-6-8-1	0.00098
6	4-6-9-1	0.00126
7	4-6-10-1	0.00126

Table 5 Training results of different ANN topologies

Based on the information from the best and worst performance indices combinations in Table 4, the bounds for each of the *KPIs* are fixed, and the sample of the optimisation model is presented as follows:

$$\text{Max } Z = 1/\left(1+e^{-Net+\theta}\right)$$

$$0.55 \le \frac{1}{n}\left(\sum_{i=1}^{n}\frac{\Delta\min,i+\zeta\Delta\max,i}{\Delta_{o,i}+\zeta\Delta\max,i}\right) \le 0.88$$

$$91 \le x_1 \le 99$$

$$95 \le x_2 \le 99.5$$

$$70 \le x_3 \le 90$$

$$75 \le x_4 \le 85$$

$$x_j > 0 \qquad \forall j \in n$$

The work proceeds to generate optimal value for the optimisation model using HSA, DE, and BB-BC. To compare the performance of these meta-heuristics, each of the algorithms was run 50 times, and the optimal value for the objective function is presented in Fig. 6. The best algorithm is selected based on possible solutions for the optimisation model. The results for the different range of the solutions in Fig. 6 are shown in Table 5.

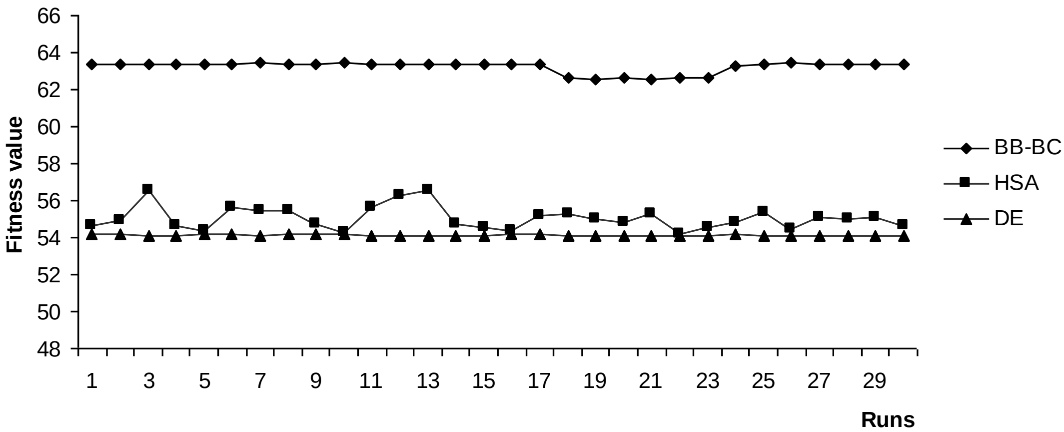


Fig. 6 Optimal values for each of the meta-heuristic at different runs

Measures	BB-BC	HAS	DE
Best	62.55	54.19	54.11
Worst	63.42	56.59	54.19
Average	63.21	55.05	54.13

Table 6 Analysis of meta-heuristic solutions

Based on the results presented in Table 6, the most suitable solution method for the developed model is DE. By using DE as a solution method for the developed model, a sample of what the different *KPIs* values should be is presented in Table 7. The results in Table 7 show that the single multi-attribute results from the intelligent method are very close to the *GRA/QL* optimal results. Furthermore, the HSA performed better than the BB-BC algorithm.

Parameters	*GRA/QL*	DE
x_i	99	98
x_2	95	98
x_3	70	78
x_4	75	79
Optimal value	0.88	0.86

Table 7 Comparison of TOPSIS and optimisation model results

5.Conclusions

The report presented in this study demonstrated how different *KPIs* for maintenance systems could be combined scientifically and used for maintenance systems evaluation, *KPIs* prediction and *KPIs* optimisation. The methodology presented is based on integrating different research techniques like fuzzy logic theory, Taguchi method, GRA, ANN and HSA. This allowed us to address two common problems when combining different *KPIs* units and the problem of different desirability functions of *KPIs*. The combination of the different KPIs was carried out using fuzzy logic theory and grey relational analysis. This provides the opportunity to determine the best and worst combinations of different *KPIs* based on a single multi-attribute index from the grey relational analysis results. The result from the different combinations of the *KPIs* was used in developing a non-linear prediction model based on ANN application. A suitable ANN topology was selected by considering the effects of a different number of nodes in the ANN hidden layers on prediction error.

An optimisation model is presented for determining the optimal values of each *KPI* based on the generated non-linear expression for the single multi-attribute index and the grey relational grade equation. The non-linear optimisation model was solved using different meta-heuristics (HSA, DE and BB-BC). The results from the different meta-heuristics showed that DE is more suitable for solving the presented optimisation model. This paper did not discuss the implementation of the single multi-attribute index but instead focused only on how the single multi-attribute index is developed. The model presented can be extended to integrate *KPIs* from other departments, such as production and marking, with maintenance *KPIs*. One benefit of the proposed model is that performance measures that are not relevant to a system can be removed, and the actual single multi-response performance can be computed without much difficulty.

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