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Maintenance Strategy Selection using Analytic Hierarchy Process: A case study

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Abstract Maintenance of industrial equipment is faced with the challenges of lack of systematic approach in setting maintenance instructions and lack of robust maintenance decision making. A maintenance strategy is always followed, either consciously or unconsciously. When a strategy is followed unconsciously, the result is often a reactive approach. This paper describes the application of the Analytic Hierarchy Process (AHP) for selecting maintenance strategy with a case study of a Kenyan cement industry. Four maintenance strategies are considered: reactive, preventive, predictive and proactive. The research paper starts by identifying the initiators of maintenance work and then groups them into an AHP hierarchy that supports and facilitates group decision making. To do this, factors triggering maintenance work are grouped into maintenance objectives by factor analysis. The pertinent variables in the maintenance objectives are then prioritized in a hierarchical structure leading to alternative maintenance strategies being chosen. From the case study, it was found that the leading initiator of maintenance work is plant functionality measured in terms of availability and reliability. This contributes 45.0%, and is followed by plant design life at 40.4%, plant and environmental safety 10.0% and least by cost effectiveness 4.6%. It was also found that proactive maintenance with 54.58% preference is the strategy of choice in the case study industry.

Keywords Analytic Hierarchy Process (AHP), Factor analysis, Maintenance, Maintenance Strategy.

1. Introduction

The traditional perception of maintenance is to fix broken items. This view confines maintenance activities to reactive tasks of repair actions or item replacement. A recent definition of maintenance is all actions which have as an objective to retain an item in, or restore it to a state in which it can perform the required function [1].

Maintenance is one of the most crucial issues in today's competitive manufacturing environment. Machine failure may cause various business related problems such as; failure to meet delivery dates, poor product quality, loss of industrial reputation, loss of profit and opportunity. This being the case, maintenance should be carefully thought of in terms of planning, investment, and control. In planning maintenance, appropriate maintenance strategies should be selected in line with organization's global and operational objectives. However, manufacturing environment is highly dynamic with lots of technological changes and hence maintenance strategies should like-wise change with new options and practices. Maintenance selection decisions that highly impact technology should be dealt with in a technically logical manner [2].

Maintenance strategy selection is very important in manufacturing industries. This is because maintenance cost may be quite considerable in industry. Research has pointed out that as much as one third of maintenance cost is unnecessarily spent due to bad planning, overtime costs and bad use of preventive maintenance [3].

Despite this importance of maintenance, report by United Nations Industrial Development Organization (UNIDO) [4] indicates that developing countries face capacity underutilization due to prevalence of low equipment availability. Also, there is need to improve maintenance culture for higher productivity and competitiveness. This paper

proposes a model for maintenance strategy selection for robust maintenance decision making for a Kenyan cement industry. The proposed model links prioritization of maintenance objectives to maintenance strategies.

2. Review of Maintenance Strategies

Maintenance strategy is defined as a coherent, unifying and integrative pattern of maintenance decision elements in congruence with manufacturing, business and corporate level strategies, and defines the nature of economic and non-economic contributions it intends to make to the organization as a whole [5] . There are basically five maintenance strategies that can be adopted as shown in Figure 1.

Passive maintenance strategy is followed when maintenance action on a machine is carried out when there are stoppages in the production process for some reason other than breakdown [2]. The fact that production has been stopped for any reason provides an opportunity for the maintenance department to undertake maintenance activities on the machine. Passive maintenance is thus an opportunistic type of maintenance [6].

Reactive maintenance strategy is *'the run it till it breaks'* maintenance mode [7]. Maintenance in this case is in the form of repair work or replacement and is only performed when machinery has failed [8].

Preventive maintenance strategy is that maintenance performed at scheduled intervals often based on manufacturer's recommendations and past experience with the equipment [8]. The aim of preventive maintenance is to perform the work of inspection, servicing and adjustment and so prevent the failure of equipment during operation.

In predictive maintenance, measurements that detect the onset of a degradation mechanism are made on the equipment by use of sensory systems, monitoring techniques, vibration monitoring, lubrication analysis and ultrasonic testing among others [9]. Maintenance actions are therefore made to eliminate or control any significant deterioration of the equipment [7], [10]. This strategy is also known as condition-based maintenance.

Proactive maintenance takes the initiative of acting rather than reacting to failures [7]. A major part of a proactive program is root cause failure analysis. The fundamental causes of machine failures are thus eliminated, and the failure mechanisms gradually engineered out of each machine component.

Various multi-criteria decision making approaches have been proposed for maintenance strategy selection such as Analytic Hierarchy Process (AHP), Fuzzy set theory, Genetic Algorithm (GA), Mathematical programming, Factor analysis, Simple Multi-Attribute Rating Technique (SMART) and Technique for Order Preference by Similarities to Ideal Solution (TOPSIS).

AHP has been used as a multi-criteria tool by most of the authors, either independently or in combination with other approaches. Bevilacqua and Braglia [6] used Analytical Hierarchy Process (AHP) for maintenance selection in an Italian oil refinery (Integrated Gasification and Combined Cycle Plant-IGCCP). These authors classified over 200 machines in the gas plant into three homogeneous groups after critical analysis and then used AHP to analyze alternative maintenance strategies for each group. However the same authors acknowledged that the maintenance plan they had developed was faced with difficulties in data collection, large number of equipment (200 machines), large number of factors to be taken into account, and the fact that the plant was still under construction meant that the results were subjective. Bertolini and Bevilacqua [11] proposed a combined goal programming and AHP for maintenance selection of centrifugal pumps in an oil industry. They used AHP analysis to provide priority vector of possible maintenance policies for different types of failure. The global and local priorities of the AHP analysis was then used to formulate a Goal Programming (GP) objective function for the minimization of unwanted deviations from the AHP scores. The AHP-GP model that these authors developed proved to be flexible in optimizing resource allocation to different maintenance strategies. Labib et al. [12] developed an AHP model of maintenance decision making, which prioritizes criticality of machines in terms of downtime, spare parts cost and frequency of breakdowns. After this prioritization, these authors proposed a Pareto analysis to rank the machines according to their weights. The model they developed has the advantage of feedback mechanism that monitors performance. The system offers a contribution towards integrating preventive and corrective modes of maintenance, since it suggests focused actions that ought to be carried out as preventive instructions based on a real-time response to corrective modes. However these authors recommend further work on an efficient approach to specify the most appropriate maintenance action to follow based on different rules.

Arunraj and Maiti [13] used AHP and goal programming for maintenance policy selection according to risk of failure and cost of maintenance in a chemical factory. They concluded that if risk is chosen as a criterion, predictive maintenance is preferred policy over periodic maintenance. Similarly, if cost is chosen as a criterion, corrective maintenance is preferred. Nevertheless, if both risk and cost are considered, AHP-GP results show that predictive maintenance and corrective maintenance are best for high-risk equipment and low-risk equipment, respectively. Ashraf W. Labib [14] developed an AHP model for maintenance policy selection using computerized maintenance management system. This researcher observed that computerized maintenance management systems (CMMS) are information store houses that lack intelligent decision analysis tools. He then proposes a model combining AHP and fuzzy logic control to render a decision making grid which has features of fixed rules and flexible strategies. This methodology can however only work in organization with existing CMMS. HajShirmohammadi and Wedley [15] used an

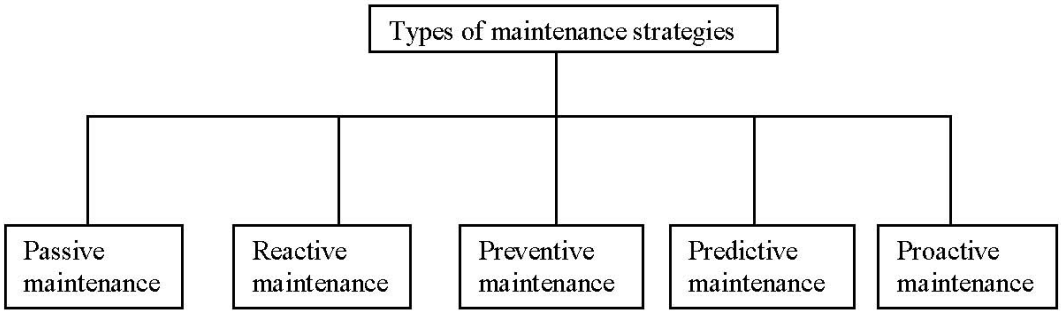

Fig. 1. Types of maintenance strategies

AHP model for maintenance management for centralization and decentralization. Centralized system means that all maintenance systems are managed from a centrally administered location. However, decentralized system implies that each production area manages its own maintenance systems. Shyjith et al. [16] developed a model using AHP and TOPSIS, for maintenance selection in textile industry.

In addition to the AHP, other tools have also been reported in evaluating and selecting maintenance strategy. For example, the use of Genetic Algorithm for different situations has been proposed to address the least-cost part replacement problem [17]. Azizollah [18] used fuzzy delphi method for selecting best maintenance strategy. Satoshi [19] used simulation approach that enabled robots to undergo preventive maintenance at optimal intervals and corrective maintenance each time they fail. Through simulation experiments, this author demonstrated effectiveness of the optimal maintenance strategy investigated. Hennequin [20] proposed a combination of simulation with fuzzy logic to optimize defective preventive maintenance and remedial steps necessary to be carried out on single equipment.

Imad Alsyouf [21] used principal component factor analysis with varimax rotation, to analyze 13 variables considered when selecting a maintenance policy. This author also analyzed 26 other variables in investigating maintenance activities performed in Swedish industry. A close look at all the variables investigated by this author points to 18 variables that trigger maintenance work. Thus this paper groups these eighteen variables by factor analysis into maintenance objectives.

The reviewed literature shows that AHP has been successful in maintenance strategy selection. However no published work accesses the influence of maintenance objectives in maintenance strategy selection. As such, AHP was selected to be the tool in this paper because it has proved useful in other researches, but has never been used to link maintenance objectives with the selection of maintenance strategies. However before being used, factor analysis is used to identify the initiators of maintenance work so as to be used in forming the AHP model.

3. Methodology for Maintenance Strategy Selection

3.1. Study Area

The paper focuses on a case study conducted in a Kenyan cement factory, where technical and economic data was collected in the maintenance department. An interview schedule containing pair-wise comparison tables was used to collect data. The maintenance department of the case study industry has a total of 25 employees, and 20 of them were identified for interview. However, responses of seven employees were dropped from analysis because the respondents were judged to be either unco-operative or biased or giving incomplete and incorrect information. Thus, case study results of 13 employees were considered in the analysis.

3.2. Proposed Methodology

The proposed methodology for maintenance strategy selection comprises of 5 steps. The method starts by identifying initiators of maintenance from literature. A data reduction multivariate analysis technique is then used to reduce the maintenance variables into maintenance objectives. Lastly, a decision tree of AHP is then used to prioritize maintenance strategies. The five steps of this methodology are;

1) From literature, variables that initiate maintenance activities are identified.
2) Since considering all the variables is not possible, a multivariate analysis technique for dimension reduction is used. In this paper factor analysis is used as the multivariate analysis technique. The factors so derived are renamed maintenance objectives. The new dimensions form the criteria level in the AHP structure.
3) With regard to each new dimension derived, pertinent measures of each dimension are used as sub-criteria.
4) The AHP hierarchical tree is then developed with maintenance strategies at the bottom level as the alternatives to choose from.

5) In order to calculate the final score of each maintenance strategy, the weight of criteria, sub-criteria and maintenance strategy is combined.

3.3. Description of Used Techniques

3.3.1. Factor Analysis

Factor analysis is a statistical approach used to analyze inter-relationships among a large number of variables and to explain these variables in terms of their common underlying dimensions (factors) [22]. It is a technique applicable when there is a systematic interdependence among a set of observed or manifest variables and the researcher is interested in finding out something more fundamental or latent which creates this communality. Factor analysis, thus, seeks to resolve a large set of measured variables in terms of relatively few categories, known as factors. This technique allows the researcher to group variables into factors (based on correlation between variables) and the factors so derived may be treated as new variables (often termed as latent variables) and their value derived by summing the values of the original variables which have been grouped into the factor. The meaning and name of such new variable is subjectively determined by the researcher. Since the factors happen to be linear combinations of data, the coordinates of each observation or variable is measured to obtain factor loadings. Such factor loadings represent the correlation between the particular variable and the factor, and are usually placed in a matrix of correlations between the variable and the factors [22].

In this paper, the 18 variables identified from literature as initiators of maintenance work were summarized by factor analysis into generalized maintenances objectives. Two tests were performed to ascertain the validity of factor analysis. These are Bartletts test of sphericity and Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy. For factor analysis to be valid, the significant level of Bartlett's test of sphericity should be <0.05 while measure of sampling adequacy values must exceed 0.50 for both the overall test and each individual variable. Principal component analysis was used as the method to extract factors since it summarizes data into composite variables. An assessment of factor loadings and communalities was then done to interpret the new factors. VARIMAX factor rotation method was selected.

3.3.2. Analytic Hierarchy Process

The AHP developed first by Saaty in 1980 [23], is a powerful and flexible multi-criteria decision-making tool that structures a complicated decision problem hierarchically at several different levels where both qualitative and quantitative aspects need to be considered. It combines both subjective and objective assessments into an integrative framework based on ratio scales from simple pairwise comparisons and helps the analyst to organize the critical aspects of a problem into a hierarchical structure. The step-by-step procedure to build and evaluate the AHP structure is as follows;

1) **Establishment of a hierarchy structure.** The hierarchy is structured on different levels from an overall objective to various criteria, sub-criteria to the lowest level (alternatives) in descending order. The basic method followed by AHP is to break down a problem into smaller and smaller components and then guide the decision maker through a series of pair-wise comparisons to obtain the relative priorities of the elements in the hierarchy.
2) **Construction of a set of pair-wise comparison matrices.** Each element in an upper level is used to compare the elements in the level immediately below with respect to it. The aim is to prioritize and convert individual comparative judgments of all elements from a level of hierarchy with respect to an element of the immediately higher level into ratio scale measurements. The preferences are quantified using nine-point scale as defined by Saaty, see Table 1 [23].

Table 1. Nine-point scale of relative importance

Intensity of Importance	Definition
1	Equal Importance
3	Moderate importance
5	Strong importance
7	Very strong importance
9	Extreme importance
2, 4, 6, 8	For compromises between the above
Reciprocals of above	In comparing elements i and j - if i is 3 compared to j - then j is 1/3 compared to i

3) **Measurement of consistency of judgments.** The goodness of judgments can be evaluated by means of consistency ratio (CR). This is an imperative aspect of the AHP technique. Before determining an inconsistency measurement, it is necessary to introduce the consistency index CI of an n $\times$ n matrix as defined by Equation 1.

$$C.I = \frac{\lambda_{max} - n}{n - 1} \tag{1}$$

Where λ_{max} is the maximum eigen value of the matrix. The consistency ratio is then calculated by Equation 2.

$$CR = \frac{CI}{RI} \tag{2}$$

Where RI is the random consistency index obtained from a large number of simulations runs and varies depending upon the order of matrix. The random consistency indexes are shown in Table 2 as derived from Saaty [23].

Table 2. Random consistency values for different matrix orders

Order of matrix	1	2	3	4	5	6	7	8
RI	0.00	0.00	0.58	0.90	1.12	1.24	1.32	1.41

The acceptable CR range varies according to the size of matrix i.e 0.05 for a 3 × 3, 0.08 for a 4 × 4 and 0.1 for all larger matrices, n≥5. If the value of CR is equal to, or less than that value, it indicates a good level of consistency in the comparative judgments represented in that matrix. In contrast, if CR is more than the acceptable value, inconsistency of judgments within that matrix has occurred and the evaluation process should therefore be reviewed, reconsidered and improved.

4) **Aggregation.** Group decision making is done by ensuring consensus of the members of a group on a decision. This consensus building can be done by aggregation of data from the members of the group. The two commonly use methods of data aggregation are aggregation of individual judgments (AIJ) and aggregation of individual priorities (AIP) [24].

Suppose at a particular hierarchy level there are n alternatives (A_i, i = 1,...,n) and r decision makers (D_k, k= 1,..., r). Let $A^{[k]}$ be the judgment matrix formed by the k-th decision maker when comparing n elements, then

$$A^{[k]} = a_{ij}^{[k]} \tag{3}$$

where a_{ij} represents the strength of element i when compared to element j and (a_{ij}) represents the matrix formed by these numbers.
Let β_k be the weight of that k^{th} decision maker (k= 1,..., r), such that

$$\beta_k \geq 0; \sum_{k=1}^{r} \beta = 1 \tag{4}$$

In AIJ, the group judgment matrix is denoted by

$$A^G = (a_{ij}^G) \tag{5}$$

This (a_{ij}^G) is created by aggregating individual judgments using the formula

$$a_{ij} = \prod {}_{k=1}^{r} (a_{ij}^k)^{\beta_k} \tag{6}$$

The priority vector $w^{G/AIJ}$ is then obtained from this aggregated matrix by using one of the prioritization methods. In AIP, the priority vector is obtained from each decision maker w^k and priority vectors are then aggregated to obtain the group priority vector.

$$w_i^{[G/AIP]} = \prod {}_{k=1}^{r} (w_{ij}^k)^{\beta_k}, i = 1, ..., n \tag{7}$$

5) **Prioritization.** The two commonly used prioritization methods are;

- *Additive normalization method (AN).* To obtain the priority vector w the elements of each column of matrix A are divided by the sum of that column (i.e. normalize the column), elements of the resulting row are then added and finally the sum is divided by the number of elements in the row [25]. This procedure is described by Equations 8 and 9.

$$a_{ij}^{'} = a_{ij} / \sum_{i=1}^{n} a_{ij}, i, j = 1, 2, .., n, \tag{8}$$

$$w_i = (1/n) \sum_{j=1}^{n} a_{ij}^{'}, i, j = 1, 2, ...n \tag{9}$$

This method of additive normalization is very popular and has a wide usage in practice due to its simplicity.

- *Eigenvector method (EV).* Saaty [23] proposes the principal eigenvector of A as the desired priority vector w. To find this vector the linear system:

$$Aw = \lambda w \tag{10}$$

is solved where λ is the principal eigenvalue of matrix A.

4. Results and Discussion

The case study was done in a cement factory between September 2013 and February 2014. Cement industries have a high degree of automation and mechanization and hence maintenance is of prime importance since any breakdown will have serious impact on production. The factory has a total of 130 employees of which 25 work in the maintenance department, representing 19% of all employees. The annual production target of the factory is 1,500,000 tonnes of cement. The annual cost of maintenance at the factory is estimated at Kenya Shillings (Kshs) 120 million, however, the factory has an average monthly down time of 13 hours. In order to help the management select the best maintenance strategy, a comprehensive study was carried out involving an analysis of the initiators of maintenance and interviews with engineers and technicians at the maintenance department. This section of the paper presents the results obtained from the case study.

4.1. Maintenance Objectives

Figure 2 shows the results of the analysis of respondent's answers on the ranking of factors initiating maintenance work on a five point likert scale. The scale used ranged from 1(= Not important) to 5(=Very important).

It was found that low availability of equipment, frequent breakdown of equipment and equipment manufacturer's recommendations, (with respondent's rating of

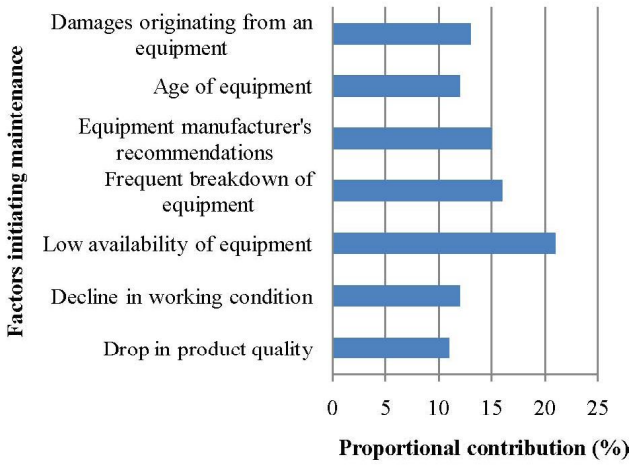

Fig. 2. Factors driving maintenance work

21%, 16% and 15% respectively), were the most important initiators of maintenance work. The other variables are also important initiators of maintenance since they were rated between 10 and 15%. This result implies that the maintenance department's work is highly influenced by continued functioning of equipment.

To further investigate the relative importance of more variables in triggering maintenance work, 18 variables, identified from literature were analyzed to determine their importance in initiating maintenance work.

Exploratory factor analysis using varimax rotation was used to analyze the 18 variables. To access if the data was suitable for factor analysis, two tests namely Kaiser-Meyer -Olkin (KMO) measure of sampling adequacy (MSA) and Bartlett's test of sphericity were carried out [23], see Table 3.

Table 3. KMO and Bartlett's test for maintenance objectives

Kaiser-Meyer -Olkin (KMO) measure of sampling adequacy (MSA)	0.812
Bartlett's test of sphericity	
Approx. Chi-square	772.125
df	81
sig.	0.000

A KMO value of 0.812 and a Chi-square value of 772.125 with significance of 0.000 were obtained. This indicates that the data is suitable for factor analysis. Also the communality values, see Table 4, range from 0.214 to 0.843 implying that no value is close to 0 or 1 hence factor analysis can be used. Furthermore, thirteen variables had a communality value greater than or equal to 0.50. Number of factors, was determined using Eigen value as an extraction criteria. Eigen value or latent root is the sum of squared values of factor loadings relating to a factor. Eigen value indicates the relative importance of each factor in accounting for the particular set of variables being analyzed. Factors with an Eigen value over one were extracted. Furthermore, Scree plot, Figure 3, of Eigen values against number of factors in their order of extraction was made and the point at which the curve starts to straighten horizontally used to determine the maximum number of factors extracted.

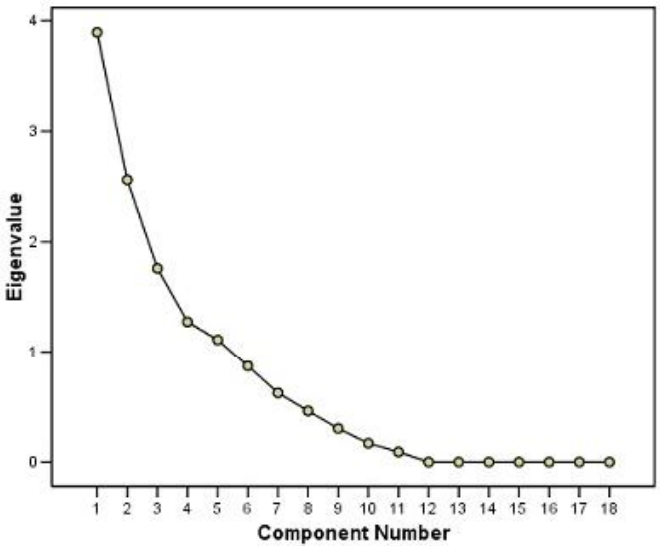

Fig. 3. Scree plot for determining the number of factors extracted as maintenance objectives

These two methods of Eigen value and Scree plot gave the number of factors extracted as four.

The four factors extracted accounted for 61% of the variation. Analyzing the factor loadings in Table 4 assisted in deriving the new constructs. Factor loadings indicate the degree of correspondence between the variable and the factor. The loadings are the means of interpreting the role each variable plays in defining each factor. It ranges from between -1 and +1; the higher loading absolute value makes the variable more representative of the factor. A loading was considered significant if it has an absolute value higher than 0.30 [22]. Since we have got a factor solution in which all the variable have at least one significant loading on a factor, the following four factors were identified, see Table 5.

Every plant is designed according to specifications which ensure timely delivery of products. The longevity of plant equipment and plant condition are both measured in terms of the age of equipment, frequency of equipment breakdown and damages from equipment. Thus, the first factor is renamed plant designed life.

The variables 'availability and reliability', determine the functionality of the plant, hence the second factor is renamed plant functionality as mentioned by Muchiri et. al [1].

Proper utilization of maintenance resources assists in reducing loss of production time and investment cost. Also maintenance department should see to it that spare parts are well utilized in accordance to the equipment manufacturer's recommendations. Therefore this third construct is renamed cost effectiveness in maintenance.

The variables in the fourth factor determine the safety

of the plant, thus its renamed plant and environmental safety.

Table 4. Rotated Component Matrix showing the Communalities, Eigenvalues and Percentage of Variance Before and After Rotation

	Factors				Communality
	Factor 1	Factor 2	Factor 3	Factor 4	
Decline in product quality	-0.259	**0.518**	0.267	0.208	0.450
To meet health and safety requirements	0.000	-0.108	0.000	**0.789**	0.634
To meet environmental requirements	0.000	-0.112	0.155	**-0.421**	0.214
To follow manufacturers recommendations	**0.795**	0.000	0.183	0.000	0.666
Reduce the aging of equipment	**-0.524**	0.372	0.425	0.187	0.629
Reducing frequent breakdown of equipment	**0.703**	-0.203	-0.110	0.000	0.548
Lowering investment cost	-0.126	0.268	**0.610**	0.000	0.459
Increasing equipment availability	0.111	**0.741**	-0.212	0.000	0.606
Increasing equipment reliability	0.000	**-0.771**	0.000	0.000	0.594
Loss of production time	-0.136	0.391	**-0.624**	0.253	0.625
Passage of time from last maintenance	**0.412**	-0.219	-0.187	0.200	0.293
Decline in equipment condition	0.164	-0.383	0.131	**0.776**	0.793
Damages originating from an equipment	**0.545**	-0.184	0.529	0.000	0.611
Budget allocated to maintenance	0.000	0.424	**0.710**	0.182	0.717
Reducing occurrence of accidents	0.000	0.254	0.000	**0.860**	0.804
Results of equipment diagnosis	-0.103	**0.566**	0.204	0.162	0.399
Smoothen production process	0.000	**0.852**	0.175	0.000	0.757
Availability of spare parts	0.502	0.246	**0.572**	0.296	0.727
Eigen values					
Before rotation	3.238	2.871	2.602	2.267	
After rotation	3.179	2.646	2.594	2.559	
% of variance					
Before rotation	17.990	15.950	14.455	12.594	
After rotation	17.660	14.698	14.414	14.216	

Note: Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.

Table 5. Extracted factors for maintenance objectives

Factor 1: Plant designed life	
Variable	Loadings
Manufacturer's recommendations	0.795
Frequent breakdown of equipment	0.703
Damages originating from an equipment	0.545
Age of equipment	0.524
Passage of time from last maintenance	0.412
Factor 2: Plant functionality	
Smoothen production process	0.852
Equipment reliability	0.771
Equipment availability	0.741
Results of equipment diagnosis	0.566
Product quality	0.518
Factor 3: Cost effectiveness	
Budget allocated to maintenance	0.710
Loss of production time	0.624
Investment cost	0.610
Availability of spare parts	0.572
Factor 4: Plant and environmental safety	
Occurrence of accidents	0.860
Health and safety requirements	0.789
Decline in equipment condition	0.776
Environmental requirements	0.421

4.2. Maintenance Strategy Selection Model

The AHP hierarchy is structured on different levels from an overall objective to various criteria, sub-criteria to the lowest level (alternatives) in descending order. The objective or the overall goal of the decision is represented at the top level of the hierarchy. The Analytic Hierarchy structure for maintenance strategy selection developed is shown in Figure 4. The priorities at different levels of the hierarchy were obtained by pair-wise comparison matrix. The pair-wise matrices were designed in the interview schedule following the methodology proposed by Saaty [23]. The individual pair-wise matrices provided by the respondents for each level of the AHP structure were aggregated using aggregation of individual judgments (AIJ) to get the group pair-wise matrix.

Prioritization of the element in each hierarchical level was done by normalization method. Consistency check was made to each pair-wise matrix before and after aggregation. Table 6 shows the aggregated pair-wise matrix for the selection of maintenance strategy. Similar aggregated matrices were developed for comparison of each criteria and sub-criteria and each sub-criteria with the alternatives (maintenance strategies).

Table 6. Aggregated pair-wise comparison for goal versus criteria (maintenance objectives)

Maintenance objectives	Plant designed life	Plant functionality	Plant and environmental safety	Cost effectiveness	Priorities (%)
Plant designed life	1.000	1.196	3.363	8.395	40.4
Plant functionality	0.836	1.000	8.057	7.808	45.0
Plant and environmental safety	0.297	0.124	1.000	2.798	10.0
Cost effectiveness	0.119	0.128	0.357	1.000	4.6
C.R = 5.3%					

Global priorities for a level in the AHP model were obtained by multiplying the local priorities for the level with the global priority for the level above.

The AHP results are shown in Figure 4. From the figure, proactive maintenance is the best suited strategy with 54.58% preference followed by preventive maintenance strategy with 22.94%. Predictive maintenance comes third with 22.65% , while reactive maintenance comes last with 10.02%.

Considering that among the tactics of proactive maintenance is total productive maintenance and business centered maintenance, the firm under study is more interested with reducing wastage and pursuing maintenance work as a business venture. However it is clear that equipment manufacturer's recommendations are given keen look and that could be why preventive maintenance comes

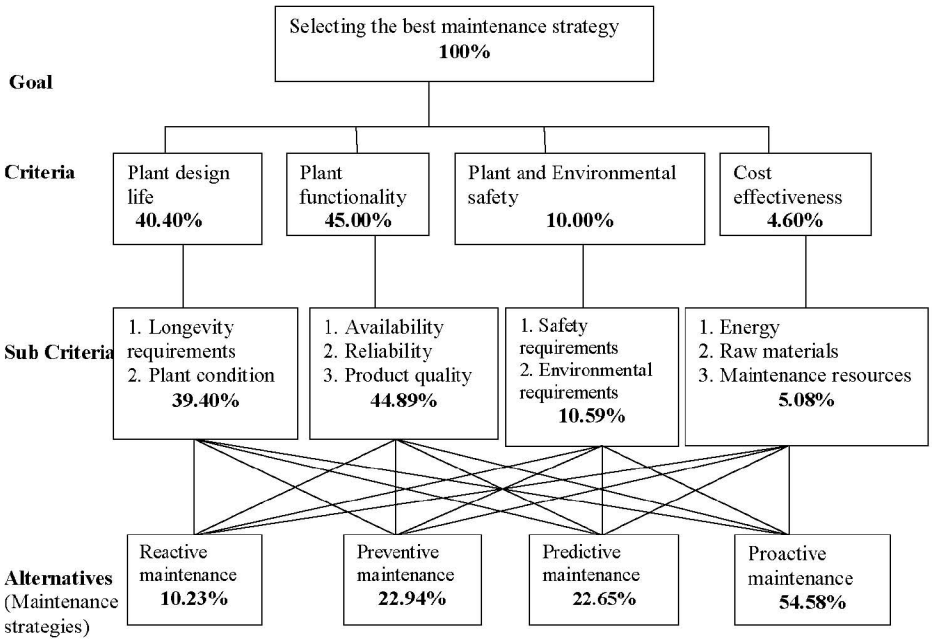

Fig. 4. Results of AHP model for maintenance strategy selection

second in priority.

5. Conclusions

The four maintenance strategies considered for selection in the cement factory are, reactive, preventive, predictive and proactive maintenance. With interview schedules from technicians and engineers, weights of the four maintenance strategies were determined. The results show that proactive maintenance is the most preferred strategy to employ in the cement industry. The advantage of the AHP model developed in this case study is a feedback mechanism that links maintenance strategy to the initiators of maintenance. The model is a structured system for group decision making, thus it can be used as a training material to enhance diagnostic skills for both operators and maintenance personnel. However other multi-criteria decision making approaches such as TOPSIS, ANP and SMART can be used in future research to compare the results of this work.

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References

[1] P. N. Muchiri, L. Pintelon, H. Martin, and A.-M. DeMeyer, "Empirical analysis of maintenance performance measurement in belgian industries," *International Journal of Production Research*, vol. 48, (20), pp. 5905 – 5924., 2010.

[2] Z. Selim, T. Ali, A. F. Mehmet, A.-T. Umar, and F. D. Omer, "Maintenance strategy selection using AHP and ANP algorithms: a case study," *Journal of Quality in Maintenance Engineering*, vol. 18(1), pp. 16–29., 2012.

[3] C. N. Madu, "Competing through maintenance strategies," *International Journal of Quality & Reliability Management*, vol. 17(9), pp. 937 – 949., 2000.

[4] W. Bank, "World development report 1995: Infrastructure for development -world development indicators," tech. rep., World Bank, 1995.

[5] W. Geert, *CIBOCOF-A Framework for Industrial Maintenance Concept Development*. PhD thesis, Katholieke Universiteit Leuven-Centre for Industrial management, 2005.

[6] M. Bevilacquaa and M. Bragliab, "The analytic hierarchy process applied to maintenance strategy selection," *Reliability Engineering and System Safety*, vol. 70, pp. 71 –83, 2000.

[7] K. Khazraei and J. Deuse, "A strategic standpoint on maintenance taxonomy," *Journal of Facilities Management*, vol. 9(2), pp. 96 – 113, 2011.

[8] M. Ben-Daya, S. O. Duffuaa, and A. Raouf, *Maintenance, Modelling and Optimization*. Kluwer Academic Publisher: Messachussets, USA, 2000.

[9] L. Wang, J. Chu, and J. Wu, "Selection of optimum maintenance strategies based on a fuzzy analytical hierarchy process," *International Journal of Production Economics*, vol. 107, pp. 151–163, 2007.

[10] A. D. Telang and A. Telang, *Comprehensive Maintenance Management Policies and Options*. PHI Learning private ltd, 2010.

[11] M. Bertolini and M. Bevilacqua, "A combined goal programming-ahp approach to maintenance selection problem," *Reliability Engineering and System Safety*, vol. 91, pp. 839 – 848, 2006.

[12] W. L. Ashraf and B. W. Richard, F OConnor andGlyn, "An effective maintenance system using the analytic hierarchy process," *Integrated Manufacturing Systems*, vol. 9(2), pp. 87– 98, 1998.

[13] N. S. Arunraj and J. Maiti, "Risk-based maintenance policy selection using ahp and goal programming," *Safety Science*, vol. 48, pp. 238–247, 2010.

[14] W. L. Ashraf, "A decision analysis model for maintenance policy selection using a cmms.," *Journal of Quality in Maintenance Engineering*, vol. 10(3), pp. 191 –202, 2012.

[15] A. HajShirmohammadi and W. C. Wedley, "Maintenance management an ahp application for centralization/decentralization," *Journal of Quality in Maintenance Engineering*, vol. 10 (1), pp. 16–25, 2004.

[16] K. Shyjith, M. Ilangkumaran, and S. Kumanan, "Multi-criteria decision-making approach to evaluate optimum maintenance strategy in textile industry," *Journal of Quality in Maintenance Engineering*, vol. 14 (4), pp. 375–386, 2008.

[17] A. S. Dragan, A. W. Godfrey, and K. Jezdimir, "Optimal, opportunistic maintenance policy using genetic algorithms, 2:analysis," *Journal of Quality in Maintenance Engineering*, vol. 1 No. 3, pp. 25–34, 1995.

[18] J. Azizollah, J. Mehdi, Z. Abalfazl, and F. Zaerpour, "Using fuzzy delphi method in maintenance strategy selection problem," *Journal of Uncertain Systems*, vol. 2, No. 4, pp. 289–298, 2008.

[19] H. Satoshi and a. J. O. Hiroya, Seki, "Optimal maintenance strategy in fault-tolerant multi-robot systems," in *2011 IEEE/RSJ International Conference on Intelligent Robots and Systems, San Francisco, CA, USA.*, September 25-30, 2011.

[20] S. Hennequin, G. Arango, and N. Rezg, "Optimization of imperfect maintenance based on fuzzy logic for a single-stage single-product production system," *Journal of Quality in Maintenance Engineering*, vol. 15, Issue: 4, pp. 412–429, 2009.

[21] A. Imad, "Maintenance practices in swedish industries: Survey results," *International Journal of Production Economics*, vol. 12, pp. 212–223, 2009.

[22] J. Hair, R. Anderson, R. Tatham, and B. William, *Multivariate data analysis, 5th edition*. USA, Prentice-Hall International, Inc, 1998.

[23] T. L. Saaty, "Decision making with the analytic hierarchy process," *Int. J. Services Sciences*, vol. 1(1), pp. 83 –98, 2008.

[24] Wen-Hsiang, Wu and Chang-tzu, Chiang and Chin-tsai Lin , "Comparing the aggregation methods in the analytic hierarchy process when uniform distribution ," *WSEAS TRANSACTIONS on BUSINESS and ECONOMICS*, vol. 5, pp. 709 –756, 2008.

[25] Bojan Srdjevic , "Combining different prioritization methods in the analytic hierarchy process synthesis ," *Computers and Operations Research*, vol. 32, pp. 1897– 1919, 2005.