Application of Topsis in Selection of Maintenance Model for Gas a Processing Plant

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Abstract:- The importance of day-to-day maintenance has increased because it plays a vital role in maintaining and improving the availability, product quality, safety requirements, and low costs for organizations. There are numerous ways to plan and decide on the maintenance problems, where multi-criteria decision making is one of the fundamental tools. However, in many organizations, especially where information about the likelihood of equipment failure is low, the use of quantitative models is not feasible. The goal of the study is to select a maintenance model for a gas processing plant taking into account the following criteria: availability of input data, reliability of the input data, ease of computation, level of usage, reliability of the results. Delay time degradation model and Markovian degradation model were considered. TOPSIS was applied to the two models using five criteria to select the most suitable model for maintenance schedule optimization. The delay time degradation model was selected ahead of the Markovian model and used for further analysis in this study.

***Keywords**:- Multicriteria Decision Making, TOPSIS, Delay Time Degradation Model, Maintenance, Markovian Degradation Model.*

I. INTRODUCTION

The practice of preventive maintenance has transformed into one of the oldest and most significant sections of the petroleum and natural gas sector. The rise of global competitiveness has resulted in significant shifts in the manner in which production and petroleum and gas businesses operate. These changes have impacted maintenance, making its function even more critical to corporate success. Developing an effective preventative maintenance plan constitutes one of the most critical developments within manufacturing and petroleum and natural gas production firms.

Maintenance is a critical idea that, when implemented on a regular basis, brings about survival, manufacturing process continuity, as well as reduced expenses. In an environment of competition, firms operate on the basis of their competencies (Zaim et al. 2012). As a result, implementing an effective maintenance program can help to significantly reduce the finished product's cost. The consequences, nevertheless, extend beyond just to cost; they also affect the speed of delivery of products along the value chain, the quality of the product, consistency, agility of organization, and other comparable characteristics. In various manufacturing facilities, repair and maintenance expenses contribute from 15% - 70% of the cost of manufacturing, varying according to the type of business (Bevilacqua & Braglia, 2000).

There are numerous types of maintenance plans in the industry. A particularly essential strategy is preventive maintenance (PM), more precisely time-based maintenance (TBM). PM has its foundation around the lifetime of components and is designed to limit the possibility of breakdown. It is performed at preset times or according to mandated criteria (de Almeida et al., 2016) in advance of a machine malfunction with the objective to sustain the machines functioning in the desired state, by means of a process that involve routine checks, recognition, and mitigation of prospective failures (Moghaddam and Usher, 2011). As a result, this method has been successful in addressing the issues related with components aging. Choosing appropriate PM action periods on the basis of unit rates of failure is crucial in project management decision-making (Ben-Daya et al., 2016).

There are various approaches for organizing and executing decisions in project management. Amongst them, the multi-criteria decision-making (MCDM) process is an important instrument for arriving at decisions and establishing frequencies for component replacement (de Almeida et al., 2015). The right replacement periods ought to be stated as decision-making options, while additional factors such as optimal safety, reliability, and environmental impact might be viewed as maintenance goals.

Several research have been employing MCDM techniques to identify distinct decision factors in maintenance; for instance, Monte and de Almeida-Filho (2016) developed a framework of PM scheduling in a system that supplies water using the multi-attribute utility theory (MAUT) approach. This framework was utilized in conjunction with the Weibull distribution as a means to estimate the failure of the system over time. In another work, da Silva Monte et al. (2015) suggested a MCDM model of PM scheduling for an irrigation

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system that used the preference ranking organization method for enrichment evaluation 2 (PROMETHEE 2) method. Emovon et al. (2016) created a MCDM framework to determine maintenance intervals for maritime equipment systems. Following this research, the AHP approach was utilized for weighing the choice factors, which included cost, interruption, and credibility, as well as the delay time model paired alongside ELECTRE. Furthermore, MAUT was used to determine the optimal interval.

da Silva and Lopes (2018) developed a novel scheme for identifying appropriate maintenance times for the examined failure mechanisms by combining different types of failure, delay time, and MCDM. An investigation at a hydroelectric plant demonstrated the suggested framework's effectiveness. Allah et al. (2018) suggested an innovative strategy for determining network-level bridge priority for scheduled maintenance operations utilizing the MAUT technique. In this investigation, selection factors included the state index, ownership cost, environment cost, and client tardiness cost. The resulting model was put to the test on twenty-two bridges from the Netherlands' traffic network. In a detailed review, Garmabaki et al. (2016) investigated MAUT approach in condition assessment and optimization.

Several investigations have been carried out in order to enhance TOPSIS methodology for various uncertainties and new applications. Yoon and Kim (2017) suggested an enhanced the TOPSIS technique called the psychological TOPSIS method. In this work, the psychological component of decision makers (DM) and the concept of loss aversion notion were incorporated to traditional TOPSIS relationships. Two examples from a power plant's electrical system and selection of security were provided to demonstrate the suggested approach's capabilities. Dwivedi et al. (2018) suggested a broader FTOPSIS architecture for tackling a variety of MCDM challenges. The proposed solution was suitable to many forms of fuzzy numbers regardless of the necessity for specialists to determine the relative importance of attributes. It also increased the proximity score of conventional TOPSIS. The practicality of the created approach was tested using two separate cases.

Pei et al. (2019) introduced FLM-TOPSIS, an entirely novel TOPSIS approach for fuzzy linguistic multisets. In this framework, they proposed several relations for producing positive and negative ideal solutions, as well as a false distance that links two fuzzy linguistic multisets and an improved proximity metric derived from it. The practicality of the suggested model was examined using two separate examples. Dong et al. (2016) created an adaptive cooperative MCDM model for complicated decision-making issues that takes into account collaboration, diversity characteristics, and rapid evolution of attributes and options. According to the suggested framework, an expanded TOPSIS was created for the heterogeneity attributes. A real-world instance in an electronics production firm demonstrated the efficiency and robustness of this novel approach.

II. METHODOLOGY

The basic steps and the mathematical formulations of the TOPSIS method applied in this work are highlighted below.

Step 1: Formulation of decision matrix

The decision matrix is formed by identifying alternatives, the attributes or criteria for judging their levels of relevance and providing values for each attribute against each criterion. The required values are obtained as input data.

Step 2: Assigning weights to each criterion

The second step in the TOPSIS methodology is to assign weights to the different criteria to indicate their level of importance.

Step 3: Formulation of normalized decision matrix

The mathematical formulations in the TOPSIS algorithm start here. For single value inputs in the decision matrix denoted as $D_{i,j}$ where $i = 1, 2, \ldots, n$ are the number of criteria and $j = 1, 2, \ldots, m$ are the number of alternatives, the norm of the row vector applicable to each criterion for the different alternatives is given as,

$$norm = \left\{\sum_{j=1}^{m}\left(D_{i,j}\right)^2\right\}^{0.5} \tag{1}$$

The normalized entry in the normalized decision matrix is obtained by diving the respective entry in the decision matrix with the norm of the row vector as in Equation (2),

$$n_{i,j} = \frac{D_{i,j}}{norm} \tag{2}$$

where $n_{i,j}$ is the normalized value.

Step 4: Formulation of weighted normalized decision matrix

A weighted normalized decision matrix is formed by multiplying each row of elements in the normalized decision matrix with the weight of the criteria. The elements in the weighted normalized decision matrix are thus given as,

$$N_{i,j} = w_i n_{i,j} \tag{3}$$

where w_i is the weight of the ith criterion; $i = 1, 2, \ldots, n$.

Step 5: Evaluation of PIS and NIS

The PIS is an indication of the highest performance of the alternatives with respect to each criterion. The NIS on the other hand represents the worst performance of the alternatives on each criterion. The PIS, denoted as S^+ is given as,

$$S^{+} = N_1^{+}, N_2^{+}, \ldots, N_n^{+} = \left(\max N_{i,j} \left| i = 1, 2, \ldots, n;\ N_{i,j} \in B\right.\right) \quad (4)$$

where $N_1^{+}, N_2^{+}, \ldots, N_n^{+}$ represents the maximum weighted normalized entry in each row in the weighted normalized decision matrix, and B represents the benefit matrix. The NIS on the other hand is given as,

$$S^{-} = N_1^{-}, N_2^{-}, \ldots, N_n^{-} = \left(\min N_{i,j} \left| i = 1, 2, \ldots, n;\ N_{ij} \in B\right.\right) \quad (5)$$

where $N_1^{-}, N_2^{-}, \ldots, N_n^{-}$ represents the minimum weighted normalized entry in each row in the weighted normalized decision matrix,

Step 6: Determination of the Euclidean distance from each alternative from the PIS and the NIS respectively

The distance of each alternative from the PIS denoted D^{+} is given as,

$$D^{+} = \left\{\sum_{i=1}^{n}\left(N_i^{+} - N_{i,j}\right)^2\right\}^{\frac{1}{2}} \quad (6)$$

The distance of each alternative from the NIS, denoted as D^{-} is given by Equation (7)

$$D^{-} = \left\{\sum_{i=1}^{n}\left(N_j^{-} - N_{i,j}\right)^2\right\}^{\frac{1}{2}} \quad (7)$$

Step 7: Closeness Coefficient Matrix Computation

The closeness coefficient matrix is given as,

$$C^{\wedge} = \frac{D^{-}}{(D^{-} + D^{+})} \quad (8)$$

where $C^{\wedge}$ is the closeness coefficient matrix.

Step 8: Selection of the best alternative

In working with the benefit criteria, the alternative that has the highest value of closeness coefficient matrix is chosen as the best alternative.

III. RESULTS AND DISCUSION

The results of the application of TOPSIS methodology in the selection of maintenance model are presented in this section. Table 1 shows the decision matrix whose entries were obtained from the field. The data was obtained from experts from the field of maintenance who have done different works relating to maintenance modelling. Data was collected from 30 professionals and the average values are presented in Table 1. The weights of the different criteria were also obtained from same professionals are presented in Table 2. Here again, the average values are presented.

Table 1: Decision matrix with alternative ratings obtained from the field

Criteria	Alternatives						
	Delay time degradation model			Markovian degradation model			
Availability of input data	8			6.5			
Reliability of the input data	8			8			
Ease of computation	9			7			
Level of usage	7			9			
Reliability of the results	9			9			

Table 2: The weights of the different criteria

Criteria	Weights
Availability of input data	0.95
Reliability of the input data	0.95
Ease of computation	0.7
Level of usage	0.55
Reliability of the results	0.95

Looking at the decision matrix critically, both models performed well in all the criteria used for the analysis. On a scale of 1 to 10, both models scored up to 7 in all the criteria except in availability of input data where the Markovian degradation model scored 6.5. This most likely influenced the TOPSIS scores of the two models. The availability of input data, reliability of input data and the reliability of the results are of higher weights compared to the other two criteria employed (ease of computation ad level of usage). Level of usage has the lowest weight. The ease of computation is very important as it affects the implementation time and may also prevent many from using the method.

The normalized decision matrix is shown in Figure 2. Here, each of the entries in each row, D_{ij} is divided by $\left(\Sigma D_{ij}^2\right)^{\frac{1}{2}}$. The weighted normalized decision matrix which is the next step in the TOPSIS implementation is shown in Table 4.

Table 3: The normalized decision matrix

Criteria	Alternatives	
	Delay time degradation model	**Markovian degradation model**
Availability of input data	0.7761	0.6306
Reliability of the input data	0.7071	0.7071
Ease of computation	0.7894	0.6139
Level of usage	0.6139	0.7894
Reliability of the results	0.7071	0.7071

Table 4: The weighted normalized decision matrix

Criteria	Alternatives	
	Delay time degradation model	**Markovian degradation model**
Availability of input data	0.7373	0.5991
Reliability of the input data	0.6718	0.6718
Ease of computation	0.5525	0.4298
Level of usage	0.3377	0.4341
Reliability of the results	0.6718	0.6718

Obtaining the PIS and the NIS is the next step in TOPSIS analysis. The PIS consists of the highest values in each row of the weighted normalized decision matrix while the NIS comprises the lowest values in each row of same matrix. Whenever all the values in each row are the same, the PIS and NIS are the same too. Both the PIS and the NIS form column matrices and they are shown below:

$$PIS = \begin{bmatrix} 0.7373 \\ 0.6718 \\ 0.5525 \\ 0.4341 \\ 0.6718 \end{bmatrix} \qquad NIS = \begin{bmatrix} 0.5991 \\ 0.6718 \\ 0.4298 \\ 0.3377 \\ 0.6718 \end{bmatrix}$$

The second and last elements in the PIS and the NIS are the same as the ratings are the same as in Table 1. Tables 5 and 6 show respectively the distance of each alternative from the PIS and the NIS.

Table 5 The distance of each alternative from the PIS

Criteria	Alternatives	
	Delay time degradation model	**Markovian degradation model**
Availability of input data	0	0.019112
Reliability of the input data	0	0
Ease of computation	0	0.015077
Level of usage	0.009308	0
Reliability of the results	0	0
$\sum_{i=1}^{n}\left(D_i^+ - D_{i,j}\right)^2$	0.009308	0.034189
$D^+ = \left\{\sum_{i=1}^{n}\left(D_i^+ - D_{i,j}\right)^2\right\}^{\frac{1}{2}}$	0.09648	0.184902

Table 6 The distance of each alternative from the PIS

Criteria	Alternatives	
	Delay time degradation model	**Markovian degradation model**
Availability of input data	0.019112	0
Reliability of the input data	0	0
Ease of computation	0.015077	0
Level of usage	0	0.009308
Reliability of the results	0	0
$\sum_{i=1}^{n}\left(D_i^- - D_{i,j}\right)^2$	0.034189	0.009308
$D^- = \left\{\sum_{i=1}^{n}\left(D_i^- - D_{i,j}\right)^2\right\}^{\frac{1}{2}}$	0.184902	0.096476

The closeness coefficients which indicate the level of importance of the different alternatives with respect to the different criteria employed in judging the importance of the alternatives are shown in Figure 1.

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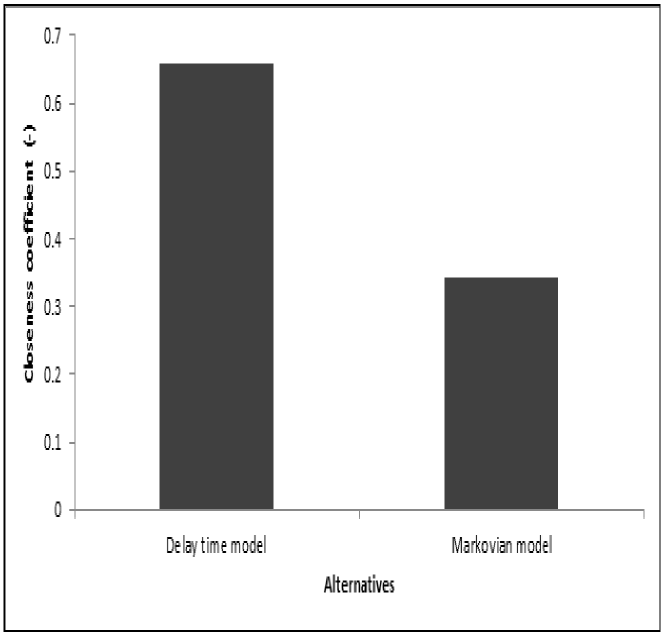

Fig 1: Closeness coefficients of the two maintenance models

From Figure 1, the delay time degradation model performs far better than the Markovian model. This is attributable to the two criteria where the delay time degradation model performed better than the Markovian degradation model. The delay time degradation model was better than the Markovian degradation model in availability of input data and ease of computation which weights are 0.95 and 0.7 respectively. The Markovian degradation, on the other hand, was better than the delay time degradation model in the criterion of level of usage. But this criterion has a much lower weight (0.55). Both models have same weight in the other two criteria (reliability of the input data and reliability of the results), suggesting that any of the models can be applied to obtain reliable results. The delay time degradation model was chosen and applied in this study not only because it performed better in the TOPSIS analysis but there was difficulty in obtaining input data in the Markovian degradation model. The delay time degradation model was thus adopted in this work and used for further analysis.

IV. CONCLUSION

Delay time degradation model and Markovian degradation model were considered in this study. Five criteria were identified for the selection of any of the two models. The criteria are availability of input data, reliability of the input data, ease of computation, level of usage, and reliability of the results. On the basis of the criteria used, the delay time degradation model performed better in terms of availability of input data and ease of computation while the Markovian degradation model performed better in terms of level of usage. Generally, the delay time degradation model performed much better than the Markovian degradation model. The delay time degradation model was selected ahead of the Markovian model. It is recommended to utilize the delay time degradation model were there are insufficient data for running the Markovian degradation model.

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