Selecting a Condition Monitoring Technology to Monitor Automotive Lubrication System Using Fuzzy-TOPSIS

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Abstract

A decision on the best condition monitoring technology that fulfills the user criteria can be complicated due to the many criteria and condition monitoring alternatives. This work lists criteria filtered from an extensive literature review on the condition monitoring selection criteria then surveys experts to know the weight of each criterion when selecting a technology to monitor an automotive lubrication system. The work then applies a fuzzy-TOPSIS model to select the condition monitoring technology according to the listed criteria. The authors conclude that the performance parameters of an automotive vehicle serve as the best option to monitor the health state of the vehicle, then comes the condition monitoring technologies on the descending favourability order of oil analysis, acoustic emission, vibration, and thermography.

Keywords
Multi-Criteria Decision Making, Condition Monitoring.

1. Introduction

Light and heavy vehicles function in different environments and conditions; thus, the time of failure can vary rapidly from a vehicle to another, even for identical vehicles. One may design a preventive maintenance plan that fulfills the availability criterion of a fleet or a single vehicle (Christer and Waller, 1984; Zhao et al., 2013), but when maintenance

planners consider cost and availability trade-off in a complex system (multi-component system) as critical criteria to fulfill, condition-based maintenance becomes an attractive option that will meet this requirement (Kim et al., 2017). Condition-based maintenance is a strategy that utilizes condition monitoring (CM) tools to collect data about the machinery state. These CM tools utilize data of thermography, acoustic emission, vibration, and oil analysis to get useful information about the current state of machinery (Bingamil et al., 2018).
The technique for order of preference by similarity to ideal solution (TOPSIS) is a multi-criteria decision-making technique used in deciding among alternatives against required criteria. How each alternative fulfills each criterion can be vague as each person would have a different judgment on the matter, wherein this case fuzzy linguistics can be applied to solve this issue by assigning fuzzy numbers to a linguistic opinion that an expert state. Chu (Chu, 2002) states that the first use of fuzzy-TOPSIS was by (Chen and Hwang, 1992) and (Negi, 1989).

Analytic hierarchy process (AHP) is another MCDM technique that can be integrated with the fuzzy concept and be applied to in decision-making applications, yet the literature showed that many authors used Fuzzy-TOPSIS (Azadeh and Abdolhossein Zadeh, 2016; Chan and Prakash, 2012; Ilangkumaran and Kumanan, 2009; Momeni et al., 2011; Mousavi et al., 2009; Panchal and Kumar, 2017; Siew-Hong and Kamaruddin, 2012; Uysal and Tosun, 2012) as an MCDM tool for maintenance-related cases- like this work- compared with fewer using the Fuzzy-AHP for the same application (Firouz and Ghadimi, 2015; Ghosh and Roy, 2010; Mohamed and Saad, 2016; Wang et al., 2007). One work compared between the two techniques in a maintenance strategy selection domain and showed with results that fuzzy-TOPSIS had an advantage over Fuzzy-AHP (Ouma et al., 2015).

This work will apply a fuzzy-TOPSIS technique, which will include not only the cost and benefit criteria but also other criteria when choosing the best CM technologies. The CM selection criteria will be for an automotive lubrication system due to its criticality and lack of work on the system. The rest of the paper goes as follows: Section II is the Literature Review, section III describes the fuzzy-TOPSIS model, section IV is the Selection of the CM Technology, and finally, section V is the Conclusion.

2. Literature Review

2.1 Review of work on CM selection

Liu *et al.* (Liu et al., 2015) used an entropy-based sensor selection for aircraft CM sensors as a part of a NASA project. For the same application, a thesis by Miguez (Miguez, 2013) developed a detailed methodology to meet the goals of economic return and financial risk starting with identifying the components to be monitored, then identifying the criteria to meet and ending up with an analytical method for the decision making. Carnero (Carnero, 2008) used AHP and discrete probability distributions to rank the different CM options, and his research had its uniqueness in the fact that one CM technology may get repeated as an option but at various levels of instrumentation application. A structured approach was prepared by (Starr, 1997) for plant CM starting with plant criticality then maintenance audit, plant selection, condition-based maintenance (CBM) technique selection, and cost-effectiveness. Verma *et al.* (Verma et al., 2008) applied a more advanced method to choose CM technologies for large engineering systems, where the engineering system has been represented by a Markov process, and the problem was modeled as a multi-objective optimization model and solved using a genetic algorithm.

Utne *et al.* (Utne et al., 2012) applied another structural approach to CM technology selection for a heat exchanger, where the first step is the selection of the critical equipment through failure mode effect and criticality analysis (FMECA). The second step is the analysis and mapping of CM technologies to select the most promising ones, while the third step is the final decision making through a mathematical model that compares the cost of the different CM technologies against the cost of not using a CM technology to monitor faults. Wang & Wang (Wang and Wang, 2013) developed a cost-benefit analysis model to choose the best CM tool to use based on the detectability of the CM tool and the failure model of the monitored system. Figure 1 shows a collection of criteria considered for choosing the CM technologies from different authors and highlights the usage frequency of each listed criterion. This collection of criteria will be utilized in the decision of the best CM technology of automotive systems in this work.

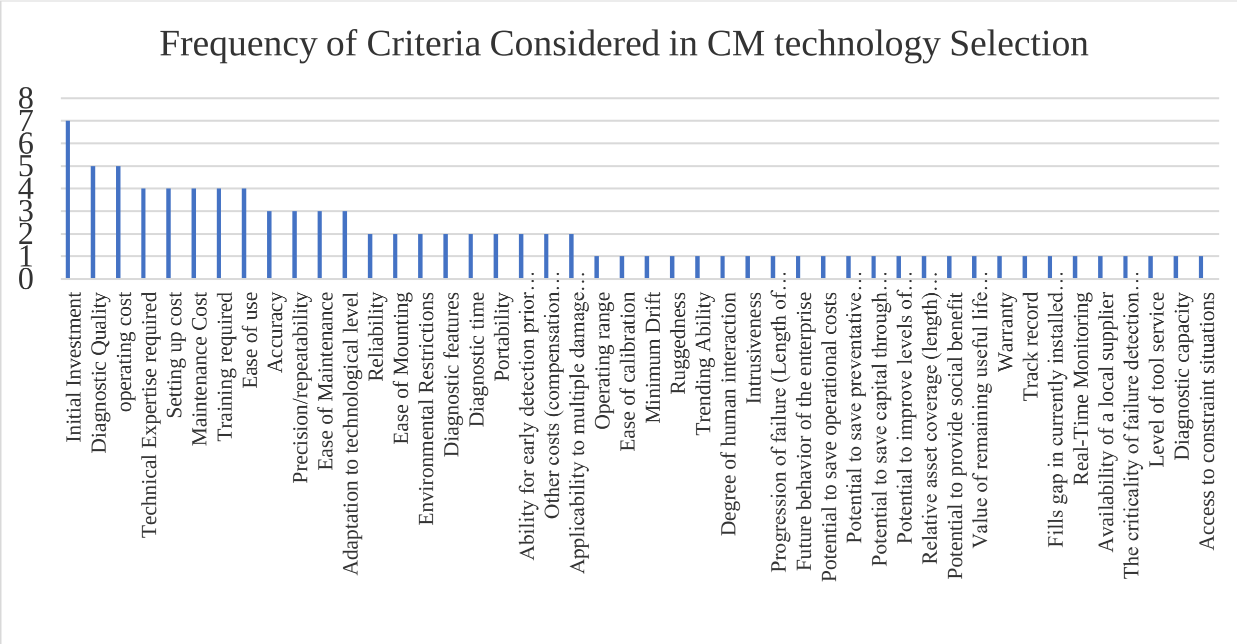

Figure 1. Frequency of Criteria Applied in Literature

2.2 Review Results

Figure 1 shows the collected criteria considered in literature when selecting a CM technology. The literature review highlights the scarcity of work on the selection of the best CM technologies using MCDM for applications in the automotive sector. Additionally, few works (Davis & Brockhurst, 2015; Davis, Sullivan, Marlow, & Marney, 2013; Miguez, 2013; Utne et al., 2012) considered criteria related to the state of the monitored asset in the bathtub curve when choosing the CM technology systematically. The importance of the consideration of the state of the monitored components lies in the concept of the bathtub or hockey-stick curve where the curve shows multiple types of systems behavior in terms of hazard rate according to time stage, and each of type of system behavior should have a different monitoring practice due to the behavior of the different systems in different regions.

3. Fuzzy TOPSIS Model

The methodology will be used of fuzzy-TOPSIS is the same as the one described in (Hamdan and Cheaitou, 2015; Mousavi et al., 2009; Torfi et al., 2010).
Step1: Define the scale that will allocate quantitative values to fuzzy variables to fill the decision matrix. An example of a scale to represent fuzzy values through TFN is shown in table 1.

Table 1. Fuzzy Linguistic Table

Linguistic variable	**TFN**
Very Low	(0, 0, 0.25)
Low	(0, 0.25, 0.50)
Medium	(0.25, 0.5, 0.75)
High	(0.5, 0.75, 1.00)
Very High	(0.75, 1.00, 1.00)

Step 2: build the fuzzy matrices of rating D and weight W as shown in equation 1.

$$\begin{array}{cc} & \begin{array}{cccc} C_1 & C_2 & \dots & C_n \end{array} \\ D = \begin{array}{c} A_1 \\ \vdots \\ A_m \end{array} & \begin{bmatrix} \bar{x}_{11} & \bar{x}_{12} & \dots & \bar{x}_{1n} \\ \vdots & \vdots & \dots & \vdots \\ \bar{x}_{m1} & \bar{x}_{m2} & \dots & \bar{x}_{mn} \end{bmatrix} \end{array} \quad (1)$$

$$W = [\bar{w}_1 \quad \bar{w}_2 \quad \dots \quad \bar{w}_n]$$

Where $\bar{x}_{ij}$, i= 1, 2, …, n; j= 1, 2, …, m; is the fuzzy value (a_{ij}, b_{ij}, c_{ij}) for CM alternative A_j according to criteria C_i. W_j is the fuzzy weight (a_{ij}, b_{ij}, c_{ij}) of criteria j. note that:

$$\bar{w}_i = 1/k\,(w_i^1 + w_i^2 + \cdots + w_i^k) \quad (2)$$

$$\bar{x}_{ij} = 1/k\,(x_{ij}^1 + x_{ij}^2 + \cdots + x_{ij}^k) \quad (3)$$

Where k is the number of decision-makers which from the data were collected, w_i^k is the value collected from decision-maker k for weight i, where these values are collected from the Delphi survey. x_{ij}^k is the fuzzy value collected from decision-maker k for CM technology alternative j according to criteria i, where these values are collected from the Delphi survey as well.

Step 3: Calculate the fuzzy value r_{ij} using equations 4 and 5 for every $\bar{x}$ and $\bar{w}$, where this step standardizes the format of all rating values.

$$r_{ij} = \left(\frac{a_{ij}}{c_j^+}, \frac{b_{ij}}{c_j^+}, \frac{c_{ij}}{c_j^+}\right) \quad (4)$$

$$r_{ij} = \left(\frac{a_j^-}{b_{ij}}, \frac{a_j^-}{c_{ij}}, \frac{a_j^-}{a_{ij}}\right) \quad (5)$$

Where $a_j^- = \min_i a_{ij}$ and $c_j^+ = \max_i c_{ij}$. Equation 4 is used when criterion i is of benefit/ positive nature, while the equation 5 is used when the criterion is cost-relevant.

Step 4: Construct a normalized fuzzy matrix V using equation 6.

$$V = \begin{bmatrix} \bar{v}_{11} & \bar{v}_{12} & \dots & \bar{v}_{1n} \\ \vdots & \vdots & \dots & \vdots \\ \bar{v}_{m1} & \bar{v}_{m2} & \dots & \bar{v}_{mn} \end{bmatrix} = \begin{bmatrix} \bar{w}_1\bar{r}_{11} & \bar{w}_2\bar{r}_{12} & \dots & \bar{w}_n\bar{r}_{1n} \\ \vdots & \vdots & \dots & \vdots \\ \bar{w}_1\bar{r}_{m1} & \bar{w}_2\bar{r}_{m2} & \dots & \bar{w}_n\bar{r}_{mn} \end{bmatrix} \quad (6)$$

Step 5: Calculate the fuzzy positive ideal number A^+ and the fuzzy negative ideal number A^- where these values are used to determine which alternative A of CM technology is the best alternative through measuring each CM technology distance from the fuzzy ideal CM technology (A^+) and the worst option of CM technology (A^-). A^+ and A^- can be found using equations 7 and 8.

$$A^+ = \{v^+_1, v^+_2, \ldots, v^+_m\} = \{(max_j\, v_{ij} \,|j=1, \ldots, m), i= 1, 2, \ldots, n\} \quad (7)$$

$$A^- = \{v^-_1, v^-_2, \ldots, v^-_m\} = \{(min_j\, v_{ij} \,|j=1, \ldots, m), i= 1, 2, \ldots, n\} \quad (8)$$

The Euclidean distance between the fuzzy alternatives and the fuzzy positive and negative ideal solutions are calculated using equations 9 and 10.

$$d^+_j = \sum_j^n d\left(v_{ij}, v_j^+\right),\ j = 1, 2, \ldots, m \quad (9)$$

$$d^-_j = \sum_j^n d\left(v_{ij}, v_j^-\right),\ j = 1, 2, \ldots, m \quad (10)$$

Where d^+_j is the distance from the positive ideal solution, and d^-_j is the distance from the negative ideal solution.

Step 6: calculate closeness coefficient CC_j, j= 1, 2, …, m to rank CM technologies alternatives according to similarities to the ideal solution using equation 11.

$$CC_j = \frac{d_j^-}{d_j^- + d_j^+} \quad (11)$$

4. Selection of CM technology

A survey was distributed among experts in the field of condition monitoring from fleet management organizations and got four responses on the importance (weight) of each criterion shown in Figure 1 when monitoring an automotive lubrication system, and how each condition monitoring technology meets the same listed criteria.
The considered condition monitoring technologies in this work are:

- *Acoustic emission:* A device that detects high-frequency noises, which is an indicator of the faults of cracks, fiber breakage, and delamination.
- *Vibration:* The movement frequency (acceleration, speed, displacement) of a component is an indicator of its health, thus measuring this parameter using vibration sensors (accelerometers) can locate faults in mechanical systems.
- *Oil analysis:* It includes measured parameter like viscosity, acid and base number, water contamination, metallic and random substances contamination added to other parameters which are used to determine the chemical state of the fluid in the applications of fuel and lubrication.
- *Thermography:* Is an infrared camera used to picture and measure the thermal state of mechanical or electrical components.
- *Performance Parameters:* Monitoring the change of efficiency in performance parameters (pressure, rotational speed, airflow) using the technologies (sensors) already installed in the vehicles.

Table 2 shows the criteria listed in figure 1, which have been grouped into ten classes according to the similarity among them, and the table also shows the fuzzy weight of each criteria resulting from the distributed survey. Hence that criteria 4 is the criteria that consider the state of the monitored system, in which few works consider it in general and non-applied it in the automotive domain, as found in the literature review. Table 3 shows the result of the fuzzy-TOPSIS methodology application using the survey answers.

Table 2. Selection Criteria

Criterion No.	**Criterion**	**Criteria Fuzzy Weight (a_{ij}, b_{ij}, c_{ij})**
1	Cost	(0.5, 0.75, 0.875)
2	Profit/benefit	(0.75, 1, 1)
3	Detectability of failures in a lubrication system	(0.75, 1, 1)
4	How early the technology can detect the system's failure	(0.5, 0.75, 0.875)
5	Ease of Handling	(0.4375, 0.6875, 0.9375)
6	Specifications	(0.6875, 0.9375, 1)
7	Conformance	(0.625, 0.875, 0.9375)
8	Serviceability	(0.6875, 0.9375, 1)
9	Diagnostic	(0.6875, 0.9375, 1)
10	Environmental Restrictions	(0.5, 0.75, 0.9375)

Table 3. Fuzzy-TOPSIS Results

Rank	**Alternatives**	**Closeness Coefficient (CC_j)**
1	Performance Parameters	0.6413
2	Oil Analysis	0.6387
3	Acoustic Emission	0.6102
4	Vibration	0.5978
5	Thermography	0.5667

5. Conclusion

With the varying alternatives of the CM technologies and the existence of many criteria to be considered when selecting a CM technology, the decision on the matter can get complicated.

This work listed out the criteria considered to select CM technologies from the literature then surveyed experts in the maintenance field to get weights of the CM selection criteria for a lubrication system in a vehicle. The work then proceeded to apply Fuzzy-TOPSIS to decide on the best CM technology to use when monitoring the lubrication system. It was concluded that the best technologies to use are the performance parameters.

The work can be extended to quantify the cost and benefit criteria according to a hazard model of the lubrication system, and then proceed with the fuzzy-TOPSIS model.

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