Original Research Article:
full paper

(2024), «EUREKA: Physics and Engineering»
Number 3

SELECTING LUBRICATING OIL FOR TWO-STROKE GASOLINE ENGINES: A MULTI-CRITERIA DECISION-MAKING APPROACH

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Abstract

The two-stroke engine boasts advantages in terms of simpler manufacturing and a smaller size when compared to the four-stroke engine. Vehicles powered by two-stroke engines can thus effortlessly overcome road obstacles compared to their four-stroke counterparts. However, the use of a two-stroke engine results in higher carbon monoxide and hydrocarbon emissions than that of a four-stroke engine. This discrepancy places greater demands on the selection of lubricating oil for two-stroke engines compared to four-stroke engines. In market, there exists a multitude of lubricating oil options tailored for two-stroke engines, each characterized by varying technical parameters. These disparities are expressed through factors such as density, viscosity index, viscosity, and combustion temperature, among others. Consequently, the task of choosing the optimal lubricant becomes a complex endeavor for consumers. In this study, an examination of lubricant selection is presented using a Multi-Criteria Decision-Making (MCDM) approach. The MCDM method employed in this article is the Combined Compromise Solution (COCOSO) method. The selection of the best lubricant is based on an evaluation of four distinct types. Each type of oil is described by four key parameters (criteria): density, viscosity index, viscosity at 100 °C, and viscosity at 40 °C. The weights for these four criteria are determined through three different methods, including the Entropy method, Criteria Importance Through Intercriteria Correlation (CRITIC) method, and Standard Deviation (SD) method. Thus, the ranking of lubricants is conducted three times, corresponding to these three weighting methods. The results indicate that the best oil choice remains consistent regardless of the weighting method applied.

Keywords: lubricant selection, COCOSO method, entropy method, CRITIC method, SD method.

DOI: 10.21303/2461-4262.2024.003264

1. Introduction

During engine operation, approximately one-third of energy loss is attributed to friction. Proper lubrication of machine parts is essential to minimize this level of loss. Lubricant is a crucial component, often likened to the circulatory system's blood in an engine [1]. Each type of lubricant exhibits unique characteristics; some excel in lubricating properties, while others are known for their anti-clogging capabilities in pipes or their high combustion temperature resistance, or excellent rust protection, among other features [2]. In general, the properties of each lubricant type differ and may even be contradictory [2]. This complexity makes the selection of the appropriate lubricant a demanding and intricate task.

For a two-stroke engine, lubricant must be mixed with gasoline during operation, creating a mixture that acts as a bloodstream, circulating through all engine parts to perform its critical function: reducing friction between contact surfaces. The effectiveness of the gasoline and lubricant mixture in minimizing surface friction depends on the lubricant's properties. Currently, the market offers a wide variety of lubricant types for use in two-stroke engines. However, no documentation exists that compares these types of lubricants, emphasizing the necessity for a well-informed selection of the right lubricant.

Several recent studies on lubricant selection have been published. In [3], lubricant classification was conducted using spectral analysis, involving the use of infrared rays to examine lubricant surfaces. Complex algorithms like Support Vector Machine (SVM) and Kennard-Stone (K/S) were employed to interpret the received signals, a task demanding a high level of expertise and modern equipment. In [4], lubricant selection was accomplished through experimental activities. The process involved a series of experiments to measure fluidity, viscosity, sensitivity to working conditions, oxidation levels, conductivity, and other factors. This is a complex and specialized task requiring highly qualified individuals. Thus, it is clear that these approaches face substantial challenges. In [5], lubricant types were selected based on their friction properties. This involved the use of a tribometer, mounted on a rotating disk to measure lubricant friction coefficients. However, this phase constitutes post-purchase testing, not the initial selection process. In [6], the selection of the best lubricant among four available types was based on experiments measuring friction coefficients, defect types, and product roughness when using each lubricant. This too happens after purchasing all four types of lubricants. In [7], used lubricant classification was conducted, comparing the ability to regenerate used lubricants, a distinct task from selecting a new lubricant. In [8], the analysis of in-use lubricant quality was performed, involving measurements of indicators such as water content, viscosity, solid particle content, and acid index. This task also differs from selecting a new lubricant (unused lubricant). In [9], lubricant selection was based on its corrosion resistance to metal surfaces, an approach flawed because various parameters must be considered when selecting a lubricant. In [10], lubricant selection centered on lubricating properties alone, which is an incomplete method, as several factors must be considered when making a selection.

Through the analysis of the above studies, it becomes evident that evaluations and selections of lubricants have been conducted in several studies. However, in all these cases, lubricant evaluations were performed after purchasing the lubricants. The initial ranking of brand-new lubricants (unused lubricants) for purchase remains unaddressed in existing publications. This gap necessitates the ranking of lubricants for purchase, a Multi-Criteria Decision Making (MCDM) process. COCOSO is a commonly used MCDM method today, and it is employed in this study to rank lubricating oil types. However, the choice of the best type can vary based on the method used to determine criteria weights. Therefore, it is crucial to rank lubricating oils using different methods to assign criteria weights. The Entropy, SD, and CRITIC methods represent three distinct approaches for calculating criteria weights, with potentially significant variations in the weights they assign. Surprisingly, no existing documentation combines all three methods to determine criteria weights for a specific case. This study seeks to fill this void.

The study's purpose is to compare the rankings of lubricating oils using the COCOSO method with various sets of criteria weights. This is achieved through the following objectives: calculating criteria weights using the Entropy method, calculating criteria weights using the CRITIC method, calculating criteria weights using the SD method, and ranking various types of lubricating oils using the COCOSO method with criteria weights determined through these three different methods.

2. Materials and methods

2. 1. Entropy method

Suppose there are m alternatives, each alternative includes n criteria, the value of the criterion j in the alternative i is x_{ij}. Use the Entropy method to calculate the weights of the criteria following the steps below [11]:

Step 1. Calculate the normalized value for the criteria:

$$n_{ij} = \frac{x_{ij}}{m + \sum_{i=1}^{m} x_{ij}^{2}}. \tag{1}$$

Step 2. Calculate the value of the Entropy measure for each criterion:

$$e_j = \sum_{i=1}^{m} \left[n_{ij} \cdot Ln(n_{ij}) \right] - \left(1 - \sum_{i=1}^{m} n_{ij} \right) \cdot Ln\left(1 - \sum_{i=1}^{m} n_{ij} \right). \tag{2}$$

Step 3. Calculate the weight for each criterion, where *n* is the number of criteria:

$$w_j = \frac{1-e_j}{\sum_{j=1}^{n}(1-e_j)}. \quad (3)$$

The above three formulas will be used to calculate the weights of the criteria of lubricant types in the next part of this article.

2. 2. CRiteria Importance Through Intercriteria Correlation method

The sequence for determining the weights for criteria using the CRITIC method is by applying the (4) and (5) [12]:

$$C_j = \sigma_j \sum_{j=1}^{n}(1-r_{ij}), \quad (4)$$

$$w_j = \frac{C_j}{\sum_{j=1}^{n} C_j}. \quad (5)$$

In which σ_j is the standard deviation of the dataset for criterion *j*, r_{ij} is the correlation coefficient between the two criteria.

2. 3. Standard Deviation method

The weight of the j^{th} criterion is calculated in accordance with the (6) [13]:

$$w_j = \frac{\delta_j}{\sum_{j=1}^{n} \delta_j}. \quad (6)$$

In which σ_j is the standard deviation of the dataset for criterion *j.*

2. 4. COmbined COmpromise SOlution method

In order to select the best alternative among the available ones, the application of COCOSO method is carried out in the following sequence [14]:

Step 1. Normalize the data in accordance with the (7) and (8). The (7) is applied to the as-large-as-possible criteria, and the (8) is applied to the as-small-as-possible criteria:

$$n_{ij} = \frac{x_{ij} - \min x_{ij}}{\max x_{ij} - \min x_{ij}}; \quad (7)$$

$$n_{ij} = \frac{x_{ij} - \max x_{ij}}{\min x_{ij} - \max x_{ij}}. \quad (8)$$

Step 2. The two quantities S_i and P_i are calculated in accordance with the (9) and (10). In which, w_j is the weight of the j^{th} criterion:

$$S_{ij} = \sum_{j=1}^{n}\left(w_j \cdot n_{ij}\right), \quad (9)$$

$$P_i = \sum_{j=1}^{n}\left(n_{ij}\right)^{w_j}. \quad (10)$$

Step 3. The values k_{ia}, k_{ib}, and k_{ic} are calculated in accordance with the (11)–(13):

$$k_{ia} = \frac{P_i + S_i}{\sum_{j=1}^{n}(P_i + S_i)}, \quad (11)$$

$$k_{ib} = \frac{S_i}{\min S_i} + \frac{P_i}{\min S_i}, \quad (12)$$

$$k_{ic} = \frac{\lambda S_i + (1-\lambda)P_i}{\lambda \max S_i + (1-\lambda)\max P_i}. \quad (13)$$

In (8), λ is a coefficient, usually chosen to be 0.5 [14].

Step 4. Calculate the k_i values in accordance with the formula:

$$k_i = (k_{ia}k_{ib}k_{ic})^{1/3} + \frac{1}{3}(k_{ia} + k_{ib} + k_{ic}). \quad (14)$$

Step 5. The best alternative is the one with the largest k_i value.

3. Results of lubricant selection for two-stroke engines

3. 1. Calculation of weights for criteria using the Entropy method

Four types of lubricating oils commonly used for two-stroke engines are as follows: conventional two-stroke engine oil (*L*1), Castor oil-based Biolubricant (*L*2), Palm oil-based Biolubricant (*L*3), and Waste cooking oil biolubricant (*L*4). These lubricating oil types are typically employed in small two-stroke engines found in various vehicles and equipment, such as motorcycles, water pumps, and grass trimmers, among others. The technical specifications for these four types of lubricating oils are provided in **Table 1** [15], including data on density, viscosity index, viscosity at 100 °C, and viscosity at 40 °C. These four criteria are denoted as *C*1, *C*2, *C*3, and *C*4. Lower density is desirable for lubricants, making *C*1 the «as-small-as-possible» criterion, while the opposite is true for *C*2, *C*3, and *C*4, which are in the «as-large-as-possible» form. The viscosity index (*C*2) is a dimensionless number used to assess the variation of the viscosity of lubricating oil with temperature. A higher viscosity index indicates that the lubricating oil maintains viscosity better as temperature changes. This makes oils with a high viscosity index suitable for use in environments with significant temperature fluctuations. The units of the other three parameters (*C*1, *C*3, and *C*4) are listed at the bottom of **Table 1**. CST is an abbreviation for «CentiSTokes», a unit measuring the viscosity of oil and liquids in the centimeter-gram-second system. It measures the fluid's ability to flow through a tube or its resistance to movement.

Table 1
Types of lubricants

Type	*C*1	*C*2	*C*3	*C*4
	min	max	max	max
*L*1	0.883	95	9	71.73
*L*2	0.953	82	8.67	75.82
*L*3	0.9058	390	4.9	12.67
*L*4	0.8316	166	2.67	8.04
Unit	gr/cm^3	–	CST	CST

Applying (1), the normalized values were calculated as shown in **Table 2**.

Applying (2), the e_j values were calculated, the results are shown in **Table 3**.

The (3) was used to calculate the weights for the criteria. Accordingly, the weights of *C*1, *C*2, *C*3 and *C*4 are 0.33193, 0.20070, 0.25826 and 0.20911, respectively.

Table 2

Normalized values in the Entropy method

Type	*C*1	*C*2	*C*3	*C*4
*L*1	0.12264	0.00049	0.04704	0.00645
*L*2	0.13236	0.00042	0.04532	0.00682
*L*3	0.12581	0.00200	0.02561	0.00114
*L*4	0.11550	0.00085	0.01396	0.00072

Table 3

e_j value in the Entropy method

*C*1	*C*2	*C*3	*C*4
–0.6897	–0.0216	–0.3147	–0.0645

3. 2. Calculation of weights for criteria using the CRiteria Importance Through Inter-criteria Correlation method

The correlation coefficient between the criteria (r_{ij}) was calculated online, the results have been summarized in **Table 4** [16].

The standard deviation (σ_j) was calculated. The C_j coefficients were also calculated in accordance with the (4). All calculated values have been summarized in **Table 5**.

Table 4

Correlation coefficient between criteria

Criteria \ Criteria	*C*1	*C*2	*C*3	*C*4
*C*1	1.00000	–0.06880	0.69190	0.61960
*C*2	–0.06880	1.00000	–0.53870	–0.73360
*C*3	0.69190	–0.53870	1.00000	0.96460
*C*4	0.61960	–0.73360	0.96460	1.00000

Table 5

Standard deviation and C_j coefficients in the CRITIC method

Criteria	*C*1	*C*2	*C*3	*C*4
σ_j	0.49965	0.00565	0.18090	0.06735
C_j	0.87803	0.02453	0.34049	0.14476

The weights of criteria *C*1, *C*2, *C*3 and *C*4 were calculated in accordance with (5), with the corresponding values of 0.63267, 0.01767, 0.24534, and 0.10431.

3. 3. Calculation of weights for criteria using the Standard Deviation method

The quantities δ_j in (6) have been calculated, the values are summarized in the **Table 6**.

Table 6

δ_j values in the SD method

*C*1	*C*2	*C*3	*C*4
0.4327	0.0049	0.1567	0.0583

The (6) was used to calculate the weights of the criteria. Accordingly, the weight of *C*1 is 0.66306, the weight of *C*2 is 0.00750, the weight of *C*3 is 0.24007, and the weight of *C*4 is 0.08938.

3. 4. Selection of lubricant type using the COmbined COmpromise Solution method

The (7) and (8) were applied to calculate the normalized values, the results have been summarized in **Table 7**.

The (9) and (10) were applied to calculate the values S_i and P_i. This was carried out for the three different cases corresponding to the three weighting methods used. The results have been summarized in **Table 8**.

The coefficients k_{ia}, k_{ib}, and k_{ic} were calculated in accordance with the corresponding (11)–(13). This was also carried out three times corresponding to the three different weighting methods, the results have been summarized in **Table 9**.

Table 7

Normalized values in the COCOSO method

Type	*C*1	*C*2	*C*3	*C*4
*L*1	0.57661	0.42339	0.04221	1.00000
*L*2	0.00000	1.00000	0.00000	0.94787
*L*3	0.38880	0.61120	1.00000	0.35229
*L*4	1.00000	0.00000	0.27273	0.00000

Table 8

S_i and P_i values

Type	Entropy weight		CRITIC weight		SD weight	
	S_i	P_i	S_i	P_i	S_i	P_i
*L*1	0.49638	3.11610	0.48695	3.15077	0.48501	3.15546
*L*2	0.39890	1.98887	0.11654	1.99443	0.09222	1.99523
*L*3	0.58365	3.44074	0.53888	3.43831	0.53393	3.44180
*L*4	0.40237	1.71494	0.69959	1.72704	0.72853	1.73205

Table 9

k_{ia}, k_{ib}, and k_{ic} coefficents

Type	Entropy weight			CRITIC weight			SD weight		
	k_{ia}	k_{ib}	k_{ic}	k_{ia}	k_{ib}	k_{ic}	k_{ia}	k_{ib}	k_{ic}
*L*1	0.2975	3.0614	0.8976	0.2993	6.0026	0.8791	0.2993	7.0813	0.8729
*L*2	0.1967	2.1597	0.5933	0.1737	2.1548	0.5102	0.1716	2.1519	0.5005
*L*3	0.3314	3.4695	1.0000	0.3273	6.6146	0.9612	0.3268	7.7772	0.9533
*L*4	0.1744	2.0087	0.5261	0.1997	7.0027	0.5864	0.2023	8.9004	0.5900

The k_i scores of the lubricants were calculated in accordance with the (14). The ranking of lubricants has also been determined in accordance with the value of their scores. This task was also carried out three times corresponding to the three weighting methods, the results have been summarized in **Table 10**.

Table 10

Scores and rankings of lubricant types

Type	Entropy weight		CRITIC weight		SD weight	
	k_i	Rank	k_i	Rank	k_i	Rank
*L*1	2.35392	2	3.55832	2	3.97879	3
*L*2	1.61487	3	1.52208	4	1.51101	4
*L*3	2.64798	1	3.91101	1	4.36230	1
*L*4	1.47213	4	3.53229	3	4.25122	2

In **Fig. 1**, it is a chart showing the ranking results of lubricant types corresponding to the three different weighting methods.

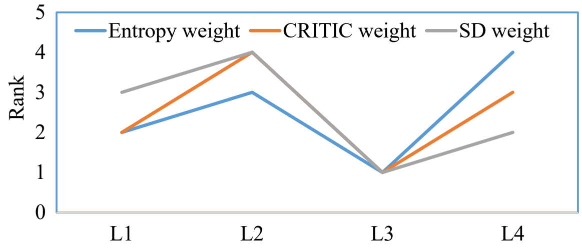

Fig. 1. Ranking of lubricant types

Analysis of the chart in **Fig. 1** reveals that, in all surveyed cases, *L*3 consistently emerges as the optimal lubricant type. In other words, the palm oil-based biolubricant (*L*3) proves to be the superior choice among the four oils analyzed in this study. As a result, the COCOSO method consistently identifies *L*3 as the best solution, regardless of the criteria weights used, underscoring the method's effectiveness and robustness [14]. The ranking results for lubricant types may differ when using different weighting methods, a phenomenon also discussed in numerous previous documents [17–19]. A limitation of this method is its lack of consideration for environmental factors in the use or recycling of lubricating oils. A drawback of this study is that it focuses solely on selecting lubricating oil based on its characteristics. After identifying the best type of lubricant, experimental studies are needed to validate the results. Verification will involve assessing torque, capacity, fuel consumption, exhaust pollution levels, and other engine-related factors. To make lubricant selection more comprehensive, additional criteria should be considered for each product type. If the number of criteria for describing each type of lubricant changes, re-weighting the criteria becomes necessary. When qualitative criteria are introduced, calculating weights for these criteria using the Entropy, CRITIC, and SD methods can be challenging. In such cases, the PIPRECIA (PIvot Pairwise RElative Criteria Importance Assessment) method can be a viable alternative [20]. In the case where the number of lubricant types needs to be ranked either increased or decreased, combining the Design of Experiments (DOE) method with the COCOSO method can be applied to quickly rank the lubricant types without the need to redo the entire calculation process [21–23].

4. Conclusions

When employing the Entropy method, the weights for the criteria of density, viscosity index, viscosity at 100 °C, and viscosity at 40 °C were determined as 0.33193, 0.20070, 0.25826, and 0.20911, respectively.

In the case of the CRITIC method, the weight assigned to density was calculated as 0.63267, while viscosity received a weight of 0.01767, viscosity at 100 °C was assigned 0.24534, and viscosity at 40 °C received a weight of 0.10431.

Utilizing the SD method, the weights for the criteria, including density, viscosity index, viscosity at 100 °C, and viscosity at 40 °C, were determined as 0.66306, 0.00750, 0.24007, and 0.08938, respectively.

Despite using different methods to determine criteria weights (Entropy, SD, and CRITIC), the COCOSO method consistently identifies a single best type of lubricant. The Palm oil-based Biolubricant stands out as the superior lubricating oil, boasting a density of 0.9058 g/cm^3, a viscosity index of 390, a viscosity at 100 °C of 4.9 cSt, and a viscosity at 40 °C of 12.67 cSt.

Conflict of interest

The authors declare that there is no conflict of interest in relation to this paper, as well as the published research results, including the financial aspects of conducting the research, obtaining and using its results, as well as any non-financial personal relationships.

Financing

The study was performed without financial support.

Data availability

Manuscript has data included as electronic supplementary material.

Use of artificial intelligence

The authors confirm that they did not use artificial intelligence technologies when creating the current work.

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Received date 08.11.2023
Accepted date 04.02.2024
Published date 27.05.2024

How to cite: *Mai, N. T., Thinh, H. X. (2024). Selecting lubricating oil for two-stroke gasoline engines: a multi-criteria decision-making approach. EUREKA: Physics and Engineering, 3, 81–89. https://doi.org/10.21303/2461-4262.2024.003264*