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Optimizing Generator Selection in Industries Using Shannon Entropy and the TOPSIS Method: A New Approach for Intelligent Decision Making

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Abstract

Generator selection is a key operational task in industries, as production processes often stop during power outages, which can have significant negative effects on operations. Therefore, investment in generators is significant. Part of generator selection involves evaluating and ranking different types of generators based on multiple dimensions. The evaluation and selection of generators require consideration of multiple objectives and criteria, which necessitate Multi-Criteria Decision-Making (MCDM) methods and related analyses. In this study, an MCDM method is presented for ranking and selecting generators in the industry. In this example, the selection of a generator based on four criteria (cost, reliability, spare parts, and reparability) is examined. In this example, three generators are evaluated using Shannon entropy weighting and the TOPSIS method. The results of the Shannon entropy method show that reparability has the highest weight and reliability has the lowest weight in the generator selection problem. Additionally, using the TOPSIS technique, we selected a suitable generator for our industry.

Keywords: Multi-criteria decision making, TOPSIS, Shannon entropy.

1 | Introduction

In today's world, the proper selection of generators is recognized as a key factor in improving the efficiency and sustainability of industrial production processes. Given that power outages can halt production activities and, as a result, cause significant financial losses, investing in reliable and efficient energy supply systems is significant [1].

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The Multi-Criteria Decision-Making (MCDM) methods are frequently used to solve real-world problems with multiple, conflicting, and commensurate criteria. MCDM problems are generally categorized as continuous or discrete, depending on the domain of alternatives [2]. In many sources, MCDM is classified into two categories: Multi-Objective Decision-Making (MODM) and Multi-Attribute Decision-Making (MADM). MODM has been widely studied using mathematical programming methods within well-formulated theoretical frameworks. MODM methods have decision variables that take values in continuous or integer domains, with either an infinite or a large number of alternatives, the best of which should satisfy the DM Constraints and preference priorities [3], [4]. MADM methods, on the other hand, have been used to solve problems with discrete decision spaces and a predetermined or limited number of alternative choices. The MADM solution process requires inter- and intra-attribute comparisons and involves implicit or explicit trade-offs [5]. MADM methods are used for situations that require considering multiple options that cannot be measured on a single dimension. Each method provides a different approach for selecting the best among several pre-selected alternatives [6]. The MADM methods help DMs learn about the issues they face, the value systems of the parties involved, and the organizational values and objectives that will consequently guide them in identifying a preferred course of action.

Multi-criteria decision-making methods are a set of methods that evaluate potential solutions against several criteria to select the best solution. Decision-making involves selecting the best option from two or more options. Several criteria, which sometimes differ, are taken into account in decision-making [1]. In the 1960s, the first Multi-Criteria Decision Making (MCDM) techniques were developed to address difficulties in integrating different ideas and managing large amounts of complex information in the decision-making Process [7]. Multi-Criteria Decision making involves a multi-stage process of 1) defining objectives, 2) choosing the criteria to measure the objectives, 3) specifying alternatives, 4) assigning weights to criteria, and 5) applying an appropriate mathematical algorithm for ranking alternatives [8]. Furthermore, MCDM allows for the unbiased integration of modern planning objectives to independently identify and rank the most suitable planning solutions [9].

Selecting the right generator requires a thorough evaluation of different types of generators against multiple criteria. These criteria may include cost, reliability, availability of spare parts, and reparability [10]. For this reason, the use of MCDM methods to evaluate and rank options has become necessary. In this regard, modern methods such as Shannon entropy and TOPSIS can serve as practical tools in optimizing the generator selection process. Shannon entropy enables us to calculate the relative weights of the criteria accurately, and TOPSIS helps us make the best choice by providing a systematic framework for comparing options [11].

In the present study, a multi-criteria decision-making method is used to select a suitable generator in the industry. Generators are designed to meet industrial needs and reduce industrial costs during power outages. Given the impact of production losses, investment in a standby generator (backup) is of great importance. Generators automatically operate during power outages and stop operating once power returns. In industrial processes, generators can provide the required power for all or some selected sections. This feature of generators has led to an increasing application of them in industrial fields. Today, many hospitals, hotels, commercial centers, industries, communication centers, databases, and emergency systems require backup generators and uninterrupted power [12]. In the present study, the experience of Industry experts is used to identify the effective technical factors that affect the selection of a backup power source using multi-criteria decision-making methods.

This paper examines and analyzes these two methods in the generator selection process and, by providing a practical example, shows how they can be used to make smarter decisions in the field of generator selection across industries. The goal of this research is to provide a comprehensive and efficient framework for optimizing generator selection and improving the overall performance of production systems.

This paper is organized as follows. In Section 2, the Literature Review is presented. Research methodology is in Section 3. In this section, Shannon entropy and fuzzy TOPSIS methods are explained. Section 4 presents the numerical example. Finally, conclusions and suggestions for future studies are provided in Section 5.

2 | Literature Review

In recent decades, researchers have focused on multi-criteria decision-making models for complex decision-making. Haqshenas Kashani and Saeedi ranked the factors that affect the competitiveness in the handmade carpet industry using the Fuzzy TOPSIS method. The conceptual model of the study included 3 criteria (input resources, market position, and creativity power) and 4 sub-criteria. Finally, indicators such as market share, E-commerce, knowledge creation, Industry reputation, and Merchants' skill and expertise were found to be the most important and effective sub-criteria. In contrast, Customer satisfaction, employee training, international certifications, and fundamental studies were found to be the least effective sub-criteria [9]. Farmihani et al. identified and prioritized instructors' effective competencies from students' perspectives using the AHP and TOPSIS methods. Findings showed that students have set professional, technical, and individual competencies as their first, second, and third priorities, respectively. Moreover, the final ranking results based on 17 criteria showed that the ability to indoctrinate students with the materials and the instructor's appearance were ranked first and last, respectively, by students [10]. Miraqajani et al. used the modified version of TOPSIS to obtain the best municipal solid waste management method. This method is introduced as a means to rank the study's main factors. Moreover, the VIKOR method is used for analysis purposes [3]. Wang et al. used SAW, TOPSIS, and GRA techniques in their study. Their study is characterized by the employment of several techniques to select a decision-making option. They used a backup decision-making system in the electronic industry to rank the main factors of the study. Abdollahzade et al. employed MCDM techniques to identify the factors affecting tunneling project delays and tunnel collapse and casualties, to provide a proper basis for preventing errors, casualties, and delays [2]. Rezaeian et al. investigated the environmental impacts of the cast iron industry using the TOPSIS and Fuzzy TOPSIS techniques. In this study, the MCDM model was used to evaluate the environmental consequences [13]. Rumnten evaluated the socio-economic impacts using multi-criteria decision-making techniques. The study was conducted in an LPG recycling plant located in a deprived area of India [14]. Ong et al. investigated 10 power plants regarding their impact on the living standards of surrounding communities. This study aimed to evaluate power plants and investigate their impact on the living standards of surrounding communities, while accounting for all negative effects [15].

Tansel et al. ranked companies and industries in Turkey. They used the Fuzzy TOPSIS technique for this purpose. They used financial ratios to rank companies through Fuzzy TOPSIS. In the present study, different generators are ranked through TOPSIS and SAW MCDM techniques [16]. Kiani Mavi et al. investigated supplier selection in the context of supply chain risk management. They considered nine criteria of quality, on-time delivery, and performance history, and six supply chain risks, including supply risk, demand risk, manufacturing risk, logistics risk, information risk, and environmental risk, to evaluate suppliers. Also, Shannon entropy is used to weight the criteria, and fuzzy TOPSIS is applied to rank suppliers [10].

3 | Research Methodology

3.1 | The Shannon Entropy Weight Method

The entropy weight method was first introduced from thermodynamics to the information system [17]. The uncertainty of signals in the communication process is called information entropy. The lower the information entropy, the higher the weight. Suppose that there are m alternatives to evaluate and n evaluation criteria, $D = (X_{ij})$ where D, is a matrix with m rows and m columns, and it is the initial decision matrix of the evaluation issue [9].

The decision matrix is normalized as follows: *Eq. (1)*:

$$p_{ij} = x_{ij} / \sum_{i=1}^{m} x_{ij}. \quad (1)$$

The information entropy for each index is defined as *Eq. (2)*:

$$E_j = -(\mathrm{Ln}\ m)^{-1} \sum_{i=1}^{m} p_{ij}.\ln(p_{ij}), \quad (2)$$

and the weight obtained from information entropy is expressed as follows, *Eq. (3)*:

$$W_j = \frac{1 - E_j}{n - \sum_{j=1}^{n} E_j}, \quad (3)$$

where,

$0 \le W_j \le 1$ and $\sum_{j=1}^{n} W_j = 1$.

3.2 | TOPSIS

The TOPSIS (Technique for Order Preference by Similarity to an Ideal Solution) was first developed by Hwang and Yoon [18]. According to this technique, the best alternative is the one closest to the positive ideal solution and farthest from the negative ideal solution [5]. The ideal solution maximizes the benefit criteria and minimizes the Cost criteria. In contrast, the negative ideal solution maximizes the cost criteria and minimizes the benefit criteria [19]. In short, the positive ideal solution is composed of all best values attainable from the criteria, whereas the negative ideal solution consists of all worst values attainable from the criteria [19].

The computational steps of the TOPSIS method are presented in the following steps [10-17]:

Step 1. Establishing a performance decision matrix:

$$X_{ij} = \begin{pmatrix} x_{11} & \cdots & x_{1n} \\ \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mn} \end{pmatrix}. \quad (4)$$

Step 2. Calculating the normalized decision matrix. The normalized value p_{ij} is calculated as follows, and the normalized decision matrix is given in *Eq. (5)*:

$$p_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}};\ i = 1, \dots, m\ ;\ j = 1, \dots, n,$$

$$p_{ij} = \begin{pmatrix} p_{11} & \cdots & p_{1n} \\ \vdots & \ddots & \vdots \\ p_{m1} & \cdots & p_{mn} \end{pmatrix}. \quad (5)$$

Step 3. Calculating the weighted normalized decision matrix. The weighted normalized value V_{ij} is calculated as follows, *Eq. 6*:

$$V_{ij} = p_{ij} \times w_j = \begin{pmatrix} v_{11} & \cdots & v_{1n} \\ \vdots & \ddots & \vdots \\ v_{m1} & \cdots & v_{mn} \end{pmatrix}, \quad (6)$$

where w_j is the weight of the j^{th} criterion or attribute and, $\sum W_{x_{ij}} = 1$.

Step 4. Determining the positive ideal A_i^+ and negative ideal A_i^- solutions.

$$A_i^+ = \{(\max v_{ij} | j \in J), (\min v_{ij} | j \in J'), (i = 1, \dots, m) = \{v_1^+, \dots, v_m^+\}, \quad (6)$$

$$A_i^- = \{(\min v_{ij} | j \in J), (\max v_{ij} | j \in J'), (j = 1, \dots, n) = \{v_1^-, \dots, v_n^-\},$$

Where J and J' are the sets of criteria with positive effect and criteria with negative effect, respectively.

Step 5. Calculating the separation measures using the m-dimensional Euclidean distance. The separation measures of each alternative from the positive ideal solution and the negative ideal solution, respectively, are as follows:

$$D_i^+ = \sqrt{\sum_{j=1}^{n}(v_{ij} - v_j^+)^2}; \quad i = 1, \dots, m, \tag{7}$$

$$D_i^- = \sqrt{\sum_{j=1}^{n}(v_{ij} - v_j^-)^2}; \quad j = 1, \dots, n. \tag{8}$$

Step 6. Calculating the relative closeness to the ideal solution.

$$Cl_i = \left[\frac{D_i^-}{D_i^+ + D_i^-}\right]; 0 \leq Cl_i \leq 1; i = 1, \dots, m. \tag{9}$$

Step 7. Ranking preference orders. Choose an alternative with the maximum value of Cl_i or ranking alternatives according to CL_i value in descending order.

4 | Numerical Example

Three types of generators are considered for the supplier industry's emergency electricity, according to experts' opinions in the field who participated in this research. Based on the expert's opinion, four criteria were determined for evaluating generators. Therefore, the criteria considered for generator selection in this study are: Cost, Reliability, Spare parts, and Reparability. The decision matrix, which is the average of the experts' opinions on the scores of the alternatives in each criterion, is shown in *Table 1*. First, must calculate the criteria weights with Shannon entropy using *Eqs.* (*1*) and (*3*). Shannon entropy is shown in *Table 2*. Following the entropy steps yields the weights of the criteria shown in the last row of *Table 2*.

Table 1. Decision-making matrix.

	Cost	Reliability	Spare Parts	Reparability
Generator 1	30	0.76	9	9
Generator 2	42	0.92	7	5
Generator 3	48	0.96	5	5

Table 2. Shannon entropy steps results.

	Cost	Reliability	Spare Parts	Reparability
Generator 1	0.25	0.28	0.43	0.47
Generator 2	0.35	0.35	0.33	0.26
Generator 3	0.4	0.36	0.24	0.26
E_j	0.98	0.99	0.97	0.96
W_j	0.2	0.1	0.3	0.4

According to Shannon entropy results, reparability has the greatest weight and reliability has the least in the generator selection problem.

In the next step, the TOPSIS method is applied to rank the generators. Based on the decision matrix (*Table 1*) and the selection criteria weights (*Table 2*), the weighted normalized decision matrix and ranking generators are shown in *Tables 3* and *4,* respectively.

Table 3. TOPSIS weighted normalized decision matrix.

	Cost	Reliability	Spare Parts	Reparability
Generator 1	0.09	0.05	0.22	0.31
Generator 2	0.12	0.06	0.17	0.17
Generator 3	0.14	0.06	0.12	0.17

Table 4. TOPSIS Ranking of generators.

	D_i^-	D_i^+	CC_i^+	Rank
Generator 1	0.013	0.177	0.931	1
Generator 2	0.052	0.152	0.256	2
Generator 3	0.013	0.177	0.069	3

5 | Conclusion

In this study, the process of selecting generators in industries was examined and analyzed using two modern methods, Shannon entropy and TOPSIS. Given the importance of selecting generators correctly to improve the efficiency and sustainability of production systems, this article demonstrates how to make smarter decisions in this field using these methods. Generator selection is an essential operational task for industries. Because Companies' production processes usually come to a halt during power outages. Given the impact of production losses, investment in a generator is essential. Part of generator selection involves evaluating and ranking different types of generators across multiple dimensions. Generator evaluation and selection require consideration of multiple objectives and criteria, which call for MCDM approaches and analyses. In the present study, an MCDM method is presented for ranking and selecting generators in the industry. An example of decision-making for selecting a generator based on four criteria (cost, reliability, spare parts, and reparability) is provided. In this example, we have evaluated three generators using the Shannon entropy weight method and TOPSIS. According to Shannon entropy results, reparability has the greatest weight and reliability has the least in the generator selection problem. The results show that, according to the TOPSIS approach, generator 1 has the highest priority, while generator 3 has the lowest. Therefore, the analyses and evaluations show that the Shannon entropy method accurately calculates the relative weights of different criteria and, as a result, better enables us to understand the impact of each criterion on the final generator selection. Also, the TOPSIS method helps us to make the best choice based on the determined criteria by providing a systematic framework for comparing options. According to the practical example presented in this paper, using these two methods can improve the generator selection process and, as a result, increase the overall performance of production systems. As a comprehensive and efficient framework for optimizing generator selection in industries, this research can help managers and decision-makers to make better choices and prevent losses due to power outages by using scientific and systematic approaches. Other decision-making techniques, such as ELECTRE, are suggested for problem-solving in future studies and then compared with the technique used in the present study. Moreover, other aggregation methods, such as Copeland and Borda's methods, are suggested for selecting the highest priorities when multiple methods are used. Also, it can be devoted to fuzzy Shannon entropy.

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Data Availability

The data supporting the findings of this study are available from the corresponding author upon reasonable request.

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