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Biyodizele Katkı Maddesi Olarak Grafen Nanopartiküllerin Değerlendirilmesi: Çok Kriterli Karar Verme Yaklaşımı

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ÖZ

Sürdürülebilir enerji kaynaklarına geçiş süreci, biyodizelin fosil yakıtlara yenilenebilir bir alternatif olarak araştırılmasını hızlandırmıştır. Son dönem çalışmalar, biyodizel karışımlarının performansını ve emisyon değerlerini iyileştirmek amacıyla özellikle grafen gibi nanomalzemelerin katkı olarak kullanımını incelemiştir. Bu çalışmada, grafen katkılı biyodizel-dizel karışımları, literatürde yer alan performans ve emisyon verileri kullanılarak değerlendirilmiştir. Altı farklı Çok Kriterli Karar Verme (ÇKKV) yöntemi-TOPSIS, COPRAS, MAIRCA, MOORA, MAUT ve MOOSRA-çeşitli kriterler temelinde yakıt karışımlarını sıralamak için uygulanmış; elde edilen sıralamalar BORDA birleştirme yöntemiyle nihai hale getirilmiştir. Sonuçlara göre B20G90 karışımı çoğu yöntemde üstün performans göstererek verimlilik ve emisyonlar arasında dengeli bir çözüm sunmuştur.

Assesment of Graphene Nanoparticles as an Additive in Biodiesel: A Multi-Criteria Decision Making Approach

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ABSTRACT

The transition toward sustainable energy sources has accelerated research into biodiesel as a renewable alternative to fossil fuels. Recent studies have examined the use of nanomaterial additives—particularly graphene—to improve the performance and emissions of biodiesel blends. This study evaluates graphene-enhanced biodiesel-diesel blends using performance and emission data collected from the literature. Six Multi-Criteria Decision-Making (MCDM) methods—TOPSIS, COPRAS, MAIRCA, MOORA, MAUT, and MOOSRA—were applied to rank the blends based on various criteria. The final ranking was obtained using the BORDA aggregation method. Results indicate that the B20G90 blend consistently outperformed others, offering a favorable balance between efficiency and emissions. The study demonstrates the applicability of integrated MCDM techniques for systematic, data-driven evaluation of alternative fuel blends.

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Introduction

Energy is an indispensable element for humanity and forms the foundation of economic development. As the world's population continues to grow each year, the demand for energy also increases. However, fossil fuels can have adverse effects on both human health and the environment. Their combustion releases harmful pollutants such as hydrocarbons, carbon dioxide, carbon monoxide, sulfur dioxide, particulate matter, and nitrogen oxides, along with greenhouse gas (GHG) emissions. These pollutants have been proven to pose significant risks to human health and contribute to global warming, leading to environmental disasters such as droughts and floods. Due to the limited availability of petroleum-based fuels and their high emission levels, researchers have increasingly focused on developing alternative fuels. Considering the environmental impacts of fossil fuel consumption, scientists worldwide are striving to advance sustainable, renewable, and clean energy sources. As the world increasingly seeks alternatives to conventional energy sources, the development of sustainable fuels is becoming more critical. One such alternative is biodiesel, a renewable fuel derived from organic materials.

Biodiesel refers to renewable, oil-rich feedstocks such as animal fats, vegetable oils, and algae-derived mixtures of fatty acid methyl esters. One of the most striking advantages of biodiesel, which replaces non-renewable fuels as a renewable resource, improve engine performance. In addition, other advantages that make it attractive to use biodiesel fuel in engines are; less cost, less exhaust emissions and ease of supply of raw materials. However, most studies in the literature focus on specific types of nanoparticles (e.g., graphene or graphene oxide) and particular biodiesel sources. This makes it difficult to generalize the findings, and there is a gap in understanding how these nanoparticles perform in a wider range of biodiesel types and under varying engine conditions. It has been revealed by some studies that by using these particles, engine efficiency will increase and friction will be minimized.

Nowadays, new additives are added to biodiesel fuels used as alternative fuels to reduce emission values and increase engine performance. These additives are currently mostly nanoparticles that emerge with the development of technology. The mixture of these particles with diesel/biodiesel fuels provides better engine performance and less NOx, CO, CO_2 etc. It is thought that emission gases can be reduced. And with the continuous development of technology, studies are being carried out on these.

Nowadays, there are many studies on fuel mixtures with nanoparticles additives. One of the leading ones of these nano particles is graphene and graphene oxide. The layer of carbon atoms that has a hexagonal honeycomb-shaped carbon arrangement, is single atom high and is two-dimensional, is called graphene. Graphene additive fuel mixtures are one of them. Investigations are carried out on the engine performance and emission properties of graphene. In this section, studies on the use of nanoparticles such as graphene as additives are mentioned and theoretical studies on this are summarized.

The effects of Graphene Quantum Dot (GQD) nanoparticles in an ethanol-biodiesel blend (B10) on a diesel engine were studied by (Heidari-Maleni et al., 2020). GQD nanoparticles at 30 ppm were added to each fuel blend, tested at three different engine speeds. Despite a decrease in power and torque, the research suggested potential benefits of using GQD nanoparticles as additives in improving engine performance and emissions (Heidari-Maleni et al., 2020).

Hoseini et al studied the physicochemical properties of three biodiesel feedstocks and their performance in diesel engines when blended with GO nanoparticles. Primrose, tree of heaven fruit, and camelina were evaluated as potential biodiesel sources in Iran, finding camelina oilseeds to have superior properties such as lower viscosity. The research highlighted GO nanoparticles as beneficial additives for improving the quality of biodiesel fuels in Iran (Hoseini et al., 2020).

Rajpoot and colleagues studied a 4-stroke, single-cylinder CI engine using second-generation Jatropha biodiesel blended with 100 ppm graphene nanoparticles. Results indicated that graphene nanoparticles improved thermal efficiency, reduced fuel consumption, smoke opacity, and particulate matter emissions, enhancing overall engine efficiency (Rajpoot et al., 2023).

Sharma and et al., studied the impact of blending few-layered graphene and graphite nanoparticles with biodiesel derived from waste cooking oil. This research highlights the potential of graphene-based nanoparticle additives to improve biodiesel combustion properties and decrease NOx emissions (Sharma et al., 2022).

An experimental study conducted to investigate the effects of GO nanoparticles on a diesel engine fueled with Jatropha methyl ester (JME) by El Seesy et al. Results indicated that incorporating GO nanoparticles improved thermal efficiency by 17% and significantly reduced CO emissions by 60% and UHC emissions by 50% compared to pure JME fuel (El-Seesy et al.,2018).

Bayındırlı and colleagues investigated the effects of adding reduced graphene oxide (rGO) and graphite nanoparticles to cottonseed oil methyl ester biodiesel through transesterification. The study demonstrated that at full load, nanoparticle-enhanced fuels boosted brake thermal efficiency by up to 17.97% and lowered brake specific fuel consumption by as much as 16.28%. Additionally, increased nanoparticle concentrations correlated with higher cylinder pressures, indicating improved combustion characteristics (Bayindirli et al., 2023).

Agbulut and colleagues investigated the effects of GO nanoparticles as additives in biodiesel-diesel blends used in compression ignition (CI) engines. Results showed that blending biodiesel with diesel (B15) reduced brake thermal efficiency (BTE) by 2.67% while lowering CO and HC emissions by 7.5% and 8.53%, respectively. However, it increased brake specific fuel consumption (BSFC) by 5.54% and raised NOx emissions by 3.37% compared to pure diesel (B0) (Agbulut et al., 2022).

Hosseini and colleagues investigated the impact of GO nanoparticles on a diesel engine fueled with B20 blend of Oenothera lamarckiana biodiesel. The study found that incorporating GO nanoparticles led to increased power output and exhaust gas temperature (EGT) (Hoseini et al., 2020).

Pireh and colleagues conducted a study on the combustion characteristics, performance, and emissions of a diesel engine using graphene oxide nanoparticles (GONPs) blended with diesel and waste cooking oil (WCO) biodiesel mixtures. The findings indicated that GONPs increased NOx and CO_2 emissions while reducing CO emissions (Pireh et al., 2022).

Murugan and colleagues investigated the effects of nanographene oxide (NGO) additives on palm oil methyl ester (PME) blended with diesel fuel (B50) in a diesel engine. The results showed significant reductions in hydrocarbon, carbon monoxide, and smoke emissions, attributed to NGO's catalytic properties and increased surface area-to-volume ratio. However, there was a slight increase in nitrogen oxide emissions due to higher peak pressure and combustion heat release (Murugan et al., 2022).

Ooi et al investigates the influence of GO nanoparticles on diesel fuel combustion, showing significant improvements in combustion efficiency that could lead to cleaner emssiions and lower fuel combustion (Ooi et al., 2016).

Hosseini et al. examined the effect of graphene oxide nanoparticles on the performance and emissions of diesel engines when integrated into *Ailanthus altissima* biodiesel blends. The study revealed enhancements in engine performance and reductions in specific emissions, indicating the potential for environmentally friendly fuels (Hoseini et al., 2018).

Nair et al conducted a study on the effects of blending graphene nanoparticles with Karanja biodiesel on engine performance and emissions. The research demonstrated that blends containing nanoparticles performed comparably to diesel, while achieving reductions in emissions such as CO, HC, and NOx (Nair et al., 2021).

Bidir et al examines the influence of graphene nanoparticles on the performance and emissions of biodiesel blends, revealing enhancements in thermal efficiency and reduced NOx concentrations. However, the study also identifies negative effects on combustion rate and engine performance at higher graphene nanoparticle (GNP) proportions (Bidir et al., 2023). Despite the extensive studies on the use of graphene and other nanoparticles as additives in biodiesel and diesel fuel mixtures, there remains a notable gap in comprehensive investigations that explore the full spectrum of nanoparticle types and their effects across various biodiesel blends and engine types. The majority of studies tend to focus on specific fuel types or singular nanoparticle applications, leaving room for a broader, more integrative approach to optimizing fuel performance and emission reductions.

The integration of Multi-Criteria Decision-Making (MCDM) methods in mechanical engineering is essential for addressing the complexity and multifaceted nature of modern engineering problems. These methods offer a systematic and structured approach to decision-making, enabling engineers to evaluate multiple criteria, balance trade-offs, and make informed choices. From material selection and design optimization to supplier evaluation and project management, MCDM enhances decision-making processes across various domains in mechanical engineering. As engineering challenges continue to evolve, the significance of MCDM in achieving optimal and sustainable solutions is expected to increase further.

In the literature, there are several studies that utilize MCDM techniques to determine optimal conditions. These techniques are extensively used to address complex decisions involving conflicting criteria. In the energy and environmental sectors, they support the evaluation of renewable energy alternatives, efficiency improvements, and the selection of sustainable technologies (Rahman et al., 2022; Orozco et al., 2023). MCDM also contributes to transport planning, manufacturing optimization, and agricultural sustainability (Emovon and Oghenenyerovwho, 2020; Firuozi et al., 2021; Cai et al., 2025). Furthermore, it is applied in project risk management, including tunnel construction projects (Gogate et al., 2023). These applications highlight the versatility of MCDM techniques in addressing diverse challenges across engineering sectors. For instance, Khan et al. explored the use of biosynthesized graphene oxide nanofluids to enhance the efficiency of solar panels in photovoltaic thermal systems. Their study employed MCDM methods like AHP and TOPSIS to evaluate various nanofluids under different Direct Normal Irradiance (DNI) conditions, with graphene oxide emerging as the top performer in terms of overall efficiency, exergy loss, and surface temperature (Khan et al., 2024).

In the majority of studies in the literature, the impact of graphene blending in diesel-biodiesel fuel mixtures on engine performance and emission values has been investigated. These studies generally involve the addition of graphene additives at various concentrations (in ppm) to diesel or biodiesel fuels at 0%, 10%, and 20%, with the resulting effects on engine performance and emissions being examined. The findings of these studies indicate that graphene-enhanced fuel mixtures improve engine performance (e.g., power and torque) and reduce emissions (e.g., NOx, CO, CO_2). For this study, performance and emission data from published literature were used to assess the impact of graphene additives. The most suitable graphene concentration and biodiesel ratio were selected using a multi-criteria decision-making (MCDM) approach. The novelty of this work lies in the comprehensive application of six different MCDM methods, which were aggregated using the BORDA method, to assess graphene-enhanced biodiesel blends based on published experimental data.

Material and Methods

This study adopts a quantitative research approach to systematically evaluate the effects of graphene-doped fuel blends. The use of MCDM methods allows for the integration of multiple criteria to assess the overall impact on greenhouse gas emissions and related factors.

Standard Deviation Method

The standard deviation method is a technique used for weighting criteria. In probability and statistics, the standard deviation (σ) of a probability distribution is a measure of the dispersion of values (Demir, 2021) In the standard deviation method, it is important to normalize the criteria because of the differences in scale of the data. A prominent feature of this method is that it mitigates the effect of subjectivity from decision-makers and effectively utilizes decision information. The standard deviation method has been used in many decision-making problems in the literature (Demir, 2021)

The Standard deviation method is implemented using the equations (1)-(4) provided below (Demir, 2021)

$$A_{ij} = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \cdot & & & \cdot \\ \cdot & & & \cdot \\ a_{m1} & a_{m2} & \cdots & a_{mn} \end{bmatrix}, \quad a_{ij} = \frac{1}{a_{ji}} \tag{1}$$

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \tag{2}$$

$$\sigma_j = \sqrt{\frac{\sum_{i=1}^{m}(r_{ij}-\bar{r}_{ij})^2}{m}} \tag{3}$$

$$w_j = \frac{\sigma_j}{\sum_{i=1}^{n}\sigma_j} \tag{4}$$

TOPSIS Technique

The TOPSIS algorithm was developed by Hwang and Yoon in 1981(Abdulvahitoglu et al.2021) It is based on the total Euclidean distance between the weighted normalised elements of the decision matrix and the best and worst values for each criteria. The final ranking is determined by the ratio of the relative aggregate distance from the worst solutions to the total distances from the best and worst solutions, as well as the choice of distances from the positive and negative ideal solutions. The TOPSIS technique is used to organise options according to certain criteria (Abdulvahitoğlu et al., 2021; Abdulvahitoglu and Kilic, 2022). The TOPSIS method is implemented using the equations (5)-(12) provided below (Abdulvahitoglu and Kilic, 2022).

$$r_{ij} = \frac{a_{ij}}{\sqrt{\sum_{k=1}^{m} a_{kj}^2}}, \; i = 1, \ldots, m \; j = 1, \ldots, n \tag{5}$$

$$R_{ij} = \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1n} \\ r_{21} & r_{22} & \cdots & r_{2n} \\ \cdot & & & \cdot \\ \cdot & & & \cdot \\ r_{m1} & r_{m2} & \cdots & r_{mn} \end{bmatrix} \tag{6}$$

$$V_{ij} = \begin{bmatrix} v_{11} & v_{12} & \cdots & v_{1n} \\ v_{21} & v_{22} & \cdots & v_{2n} \\ \cdot & & & \cdot \\ \cdot & & & \cdot \\ v_{m1} & v_{m2} & \cdots & v_{mn} \end{bmatrix} = \begin{bmatrix} w_1 r_{11} & w_2 r_{12} & \cdots & w_j r_{1j} & \cdots & w_n r_{1n} \\ w_1 r_{21} & w_2 r_{22} & \cdots & & \cdots & r_{2n} \\ \cdot & & & & & \cdot \\ w_1 r_{i1} & & & w_j r_{ij} & & w_n r_{in} \\ \cdot & & & & & \cdot \\ w_1 r_{m1} & w_2 r_{m2} & \cdots & w_j r_{mj} & \cdots & w_n r_{mn} \end{bmatrix} \tag{7}$$

$$A^+ = \left\{ \max_i v_{ij} \middle| (j \in J), \quad \left(\min_i v_{ij} \right) j \in J' \right\}$$
$$A^+ = \{v_1^+, v_2^+, \ldots, v_n^+\} \tag{8}$$

$$A^- = \left\{ \min_i v_{ij} \middle| (j \in J), \quad \left(\max_i v_{ij} \right) j \in J' \right\}$$
$$A^- = \{v_1^-, v_2^-, \ldots, v_n^-\} \tag{9}$$

where

$J = \{j = 1,2, \ldots n | j \; associated \; with \; benefit \; criteria\}$

$J' = \{j = 1,2, \ldots n | j \; associated \; with \; cost \; criteria\}$

$$S_i^+ = \sqrt{\sum_{j=1}^{n}(v_{ij} - v_j^+)^2} \quad (10)$$

$$S_i^- = \sqrt{\sum_{j=1}^{n}(v_{ij} - v_j^-)^2} \quad (11)$$

$$C_i^* = \frac{S_i^-}{S_i^- + S_i^+} \quad (12)$$

COPRAS technique

Zavadskas and Kaklauskas first published the Complex Proportional Assessment method in 1996 (Demir et al., 2021). It is used to assess and rank solutions while taking into consideration the criterion's cost and benefit features (Demir, 2021). This technique compares options and reports their relative superiority as a percentage. The COPRAS method is implemented using the equations (13)-(16) provided below (Demir, 2021):

$$x_{ij}^* = \frac{a_{ij}}{\sum_{i=1}^{m} a_{ij}} \qquad (i = 1, \ldots, m \text{ and } j = 1, \ldots p) \quad (13)$$

$$n_{ij} = x_{ij}^* w_j \quad (14)$$

$$Q_i = S_i^+ + \frac{\sum_{i=1}^{m} S_i^-}{S_i^- \sum_{i=1}^{m}\left(\frac{1}{S_i^-}\right)} \quad (15)$$

$$P_i = \left(\frac{Q_i}{Q_{max}}\right) * 100 \quad (16)$$

MOOSRA Technique

In 2012, M.C. Das et al, brought MOOSRA technique to the literature as a choice ranking approach (Demir et al., 2021). MOOSRA is a method for multi-objective optimisation. The initial step is to create the problem's decision matrix, followed by normalising it. The MOOSRA approach calculates each alternative's overall performance score either by dividing the sum of the normalised performance values for advantageous criteria or by the sum of the normalised performance values for cost criteria. The MOOSRA technique is implemented using the equations (17)-(20) provided below (Demir et al., 2021)

$$X^* = \begin{bmatrix} x_{11}^* & \cdots & x_{1p}^* \\ \vdots & \ddots & \vdots \\ x_{m1}^* & \cdots & x_{mn}^* \end{bmatrix} \qquad (i = 1, \ldots, m \text{ and } j = 1, \ldots n) \quad (17)$$

$$x_{ij}^* = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}^2} \quad (18)$$

$$a_{ij} = x_{ij}^* . w_j \quad (19)$$

$$Y_i = \frac{\sum_j^g x_{ij}^{*}.w_j}{\sum_{j'=g+1}^{n} x_{ij'}^{*}.w_j} \quad , \quad j = 1,2,\dots,g \text{ for beneficial, } j' = g+1, g+2, \dots, n \quad \text{for cost} \tag{20}$$

Alternatives are ranked based on their overall performance scores, with the highest score indicating the best option. The criterion weight values w_j, determined using the standard deviation method, are used to weight the matrix values. After normalizing each criterion, the best value is set to 1, while the worst value is set to 0. The matrix is then normalized using the cost-actuated Equation 20, except when the criterion direction is advantageous, in which case Equation 19 is applied.

MAIRCA

D. Pamucar et al presented MAIRCA to the literature in 2014 as a ranking alternative. It is based on calculating the gap between theoretical and real preference levels. Unlike other MCDM approaches, it assumes that the selection probabilities of all alternatives are same. The MAIRCA technique is implemented using the equations (21-31) shown below.

$$X^* = \begin{bmatrix} x_{11}^* & \cdots & x_{1p}^* \\ \vdots & \ddots & \vdots \\ x_{m1}^* & \cdots & x_{mn}^* \end{bmatrix} \quad (i = 1, \dots, m \qquad j = 1, \dots n) \tag{21}$$

$$\text{Beneficial} \quad n_{ij} = \frac{x_{ij} - x_i^-}{x_i^+ - x_i^-} \tag{22}$$

$$\text{Cost} \quad n_{ij} = \frac{x_{ij} - x_i^+}{x_i^- - x_i^+} \tag{23}$$

$$N = \begin{bmatrix} n_{11} & \cdots & n_{1n} \\ \vdots & \ddots & \vdots \\ n_{m1} & \cdots & n_{mn} \end{bmatrix} \tag{24}$$

$$P_i = P_{i+1} = \cdots = P_m = 1/m \tag{25}$$

$$t_{ij} = P_i * w_{ij} \tag{26}$$

$$r_{ij} = t_{ij} * n_{ij} \tag{27}$$

$$R = \begin{bmatrix} t_{11}n_{11} & \cdots & t_{1n}n_{1n} \\ \vdots & \ddots & \vdots \\ t_{11}n_{m1} & \cdots & t_{mn}n_{mn} \end{bmatrix} \tag{28}$$

$$G = T - R \tag{29}$$

$$G = \begin{bmatrix} t_{11} - r_{11} & \cdots & t_{1n} - r_{1n} \\ \vdots & \ddots & \vdots \\ t_{m1} - r_{m1} & \cdots & t_{mn} - r_{mn} \end{bmatrix} \tag{30}$$

$$Q_i = \sum_j^n g_{ij} \tag{31}$$

MAUT

Keeney and Raiffa developed the MAUT technique to the literature in 1976 (Demir et al., 2021). The following formula describes the MAUT approach (Demir et al., 2021).

$$x_j(a_i) = \frac{x_i\,(a_i) - min(x)}{\max(x_i) - \min(x_i)} \quad \text{for beneficial} \tag{32}$$

$$x_j(a_i) = 1 + \frac{x_j - x_i\,(a_i)}{\max(x_i) - \min(x_i)} \quad \text{for cost} \tag{33}$$

$$r_{ij} = \frac{e^{(x_{ij})^2} - 1}{1{,}71} \tag{34}$$

$$x(a_i) = \sum_{j=1}^{q} x_j(a_i).w_j \tag{35}$$

Where $x(a_i)$ denotes the beneficial value and $x_j(a_i)$ normalized beneficial value, w_j is the weighing values which were calculated by standard deviation method.

MOORA Technique

The MOORA technique was introduced into the literature by Braures and Zavadakas in 2006. This technique is very simple and easy to apply, making it highly reliable for addressing various problems in the decision-making process. The MOORA method is implemented using the equations (36)-(38) provided below

$$x_{ij}^* = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}^2} \qquad (i = 1, \dots, m \; and \; j = 1, \dots p) \tag{36}$$

$$X^* = \begin{bmatrix} x_{11}^* & \cdots & x_{1p}^* \\ \vdots & \ddots & \vdots \\ x_{m1}^* & \cdots & x_{mn}^* \end{bmatrix}$$

$$R = \begin{bmatrix} w_1 x_{11}^* & \cdots & w_n x_{1p}^* \\ \vdots & \ddots & \vdots \\ w_1 x_{m1}^* & \cdots & w_n x_{mn}^* \end{bmatrix} = \begin{bmatrix} r_{11} & \cdots & r_{1p} \\ \vdots & \ddots & \vdots \\ r_{m1} & \cdots & r_{mp} \end{bmatrix} \tag{37}$$

$$y_j = \sum \boldsymbol{beneficial\ criteria\ values} - \sum \boldsymbol{cost\ criteria\ values} \tag{38}$$

Borda Technique

The Borda technique, developed by Jean-Charles de Borda in 1770, is a voting system used to obtain integrated solutions for multi-criteria decision problems. This method operates using a scoring system based on the rankings of alternatives.

The Borda count (B_i) is calculated as follows:

$$\boldsymbol{B_i = \sum_{k=1}^{r} m - a_{ik}} \tag{39}$$

where m is the number of alternatives.

The points for each alternative are summed up, and this total is the Borda count (Bi) for that alternative. When the Borda counts are calculated, the alternative with the highest total score is considered the best choice.

The decision matrix was constructed utilizing an experimental study contributed to the literature by Hoseini et al., in 2018.

Fuel Blend Characteristics

Symbols used in the tables are B denotes for Biodiesel and G denotes for Graphen nanoparticle. Fuel blend symbols and their meanings are shown in Table 1.

Table 1. Fuel blend symbols and their meanings (Hoseini et al., 2018)

Symbol	Meaning	Symbol	Meaning	Symbol	Meaning
B0G0	100% diesel	**B10 G0**	90% diesel 10% biodiesel	**B20G0**	80% diesel 20% biodiesel
B0G30	100% diesel 30 ppm graphen	**B10G30**	90% diesel 10% Biodiesel 30 ppm graphen	**B20G30**	80% diesel 20% Biodiesel 30 ppm graphen
B0G60	100% diesel 60 ppm graphen	**B10G60**	90% diesel 10% Biodiesel 60 ppm graphen	**B20G60**	80% diesel 20% Biodiesel 60 ppm graphen
B0G90	100% diesel 90 ppm graphen	**B10G90**	90% diesel 10% Biodiesel 90 ppm graphen	**B20G90**	80% diesel 20% Biodiesel 90 ppm graphen

Table 2. Fuel properties of blends (Hoseini et al., 2018)

Fuel Blend	Density (g/cm^3)	Kinematic Viscosity (mm^2/s)	Higher Heating Values (Mj/kg)	Cetane Number
B0G0	0.83	5.4645	45.7132	46
B0G30	0.8223	5.4423	45.8312	46.5
B0G60	0.8211	5.4091	45.8268	47
B0G90	0.8206	5.4213	45.9489	47
B10G0	0.8345	5.5338	44.1101	46.5
B10G30	0.8331	5.5103	44.6534	47
B10G60	0.8324	5.4991	44.832	47.5
B10G90	0.8327	5.5011	44.7892	47.5
B20G0	0.8381	5.564	43.6318	47
B20G30	0.837	5.5332	43.9318	47.5
B20G60	0.8364	5.5201	44.0149	48.5
B20G90	0.8369	5.5291	44.0134	48.5

Brake Power is define as the rate of work performed by the engine. Fuel properties such as heating value and viscosity have imortant effects on engine power.

Spesific fuel consumption (SFC) is a measure of the efficiency of an engine. It is typically expressed in terms of the amount of fuel consumed per unit of power produced.

Table 3, 4 and 5 is given below:

Table 3. Engine operating characteristics of blends (Hoseini et al., 2018)

Fuel Blend	Brake Power	SFC
B0G30	4.15084	404.5184
B0G60	4.35379	393.744
B0G90	4.49565	384.8
B10G0	3.97823	424
B10G30	4.191463	384.7
B10G60	4.374064	380.88
B10G90	4.607188	376.89
B20G0	3.9073	438
B20G30	4.242156	398.14
B20G60	4.39454	385.35
B20G90	4.455494	374.58

Table 4. Emissions results (Hoseini et al., 2018)

Fuel Blend	CO	CO_2	UHC	NO_x
B0G0	1.36	3.7	227.79	145.38
B0G30	1.32	3.67	211.98	146.91
B0G60	1.29	3.65	201.12	148.35
B0G90	1.27	3.65	191.94	153.11
B10G0	1.24	3.37	204.37	148.1
B10G30	1.18	3.51	185.11	149.21
B10G60	1.11	3.55	176.34	153.99
B10G90	1.01	3.61	166.7	155.96
B20G0	1.21	3.35	171.13	162.32
B20G30	1.12	3.43	148.34	167.9
B20G60	1.09	3.55	135.83	170.32
B20G90	1.11	3.77	124.12	174.32

The symbols attributed to the criterion shown in Table 5

Table 5. Criterion

Criteria	**Symbol**
Density	C1
Kinematic Viscosity	C2
Higher Heating Values	C3
Cetane Number	C4
Brake Power	C5
SFC	C6
CO	C7
CO_2	C8
UHC	C9
NO_x	C10

The blends were symbolized as alternatives as seen in the Table 6. The table illustrates different fuel blend ratios with graphene and biodiesel content. assigned with respective alternatives (A1 to A11) based on their composition.

Table 6. Symbols for alternatives of fuel blends

Fuel Blend	Alternative
B0G30	A1
B0G60	A2
B0G90	A3
B10G0	A4
B10G30	A5
B10G60	A6
B10G90	A7
B20G0	A8
B20G30	A9
B20G60	A10
B20G90	A11

The most suitable of these fuel ratios will be determined at the end with the methods to be applied.

Results and Discussion

In this study. the optimal fuel mixture alternative is identified using multi-criteria decision-making (MCDM) methods. The MCDM methods employed include Standard Deviation (for weighing the criteria), TOPSIS, COPRAS, MAUT, MAIRCA, MOORA, MOOSRA and the BORDA method. Initially, alternatives (A1 to A11) are ranked based on each fuel mixture. Subsequently, each criterion (CO, CO_2, NOx, UHC, SFC, brake power, density, kinematic viscosity, higher heating value etc.) is ranked from C1 to C10. Using these rankings, the MCDM methods generate a final ranking of the alternatives and the best alternative is selected.

In order to calculate the weight of each criteria standard deviation model was chosen. Using equation 1 the Decision matrix constructed for standard deviation model as seen in Table 7. The table presents various criteria values for biodiesel-graphene blended fuels at different ratios (30, 60 and 90 ppm grapheme, B0, B10 and B20 biodiesel) sourced from the literature. These values include density, kinematic viscosity, high-temperature stability and cetane number, resulting from the different fuel mixture ratios. Additionally, the combustion results for these fuel mixtures are provided including brake power, specific fuel consumption (SFC) and gas emission values such as CO, CO_2, UHC and NOx.

Table 7. Constructed decision matrix

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
A1	0.8223	5.4423	45.8312	46.5	4.15084	404.5184	1.32	3.67	211.98	146.91
A2	0.8211	5.4091	45.8268	47	4.35379	393.744	1.29	3.65	201.12	148.35
A3	0.8206	5.4213	45.9489	47	4.49565	384.8	1.27	3.65	191.94	153.11
A4	0.8345	5.5338	44.1101	46.5	3.97823	424	1.24	3.37	204.37	148.1
A5	0.8331	5.5103	44.6534	47	4.191463	384.7	1.18	3.51	185.11	149.21
A6	0.8324	5.4991	44.8320	47.5	4.374064	380.88	1.11	3.55	176.34	153.99
A7	0.8327	5.5011	44.7892	47.5	4.607188	376.89	1.01	3.61	166.7	155.96
A8	0.8381	5.564	43.6318	47	3.9073	438	1.21	3.35	171.13	162.32
A9	0.8370	5.5332	43.9318	47.5	4.242156	398.14	1.12	3.43	148.34	167.9
A10	0.8364	5.5201	44.0149	48.5	4.39454	385.35	1.09	3.55	135.83	170.32
A11	0.8369	5.5291	44.0134	48.5	4.455494	374.58	1.11	3.77	124.12	174.32

After constructing the decisison matrix normalisation was done using equation 2. That is, the square of each of the alternatives was taken and added. Then, the square root of this result was taken and the result was proportioned to each alternative individually. Thus, it was normalized. The normalized matrix shown in Table 8.

Table 8. Normalized matrix for standard deviation model

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
A1	0.29821	0.29852	0.30916	0.29627	0.29164	0.30837	0.33702	0.31103	0.36233	0.28107
A2	0.29778	0.29670	0.30913	0.29946	0.30590	0.30016	0.32936	0.30934	0.34376	0.28382
A3	0.29760	0.29737	0.30996	0.29946	0.31586	0.29334	0.32426	0.30934	0.32807	0.29293
A4	0.30264	0.30354	0.29755	0.29627	0.27951	0.32322	0.31660	0.28561	0.34932	0.28334
A5	0.30213	0.30225	0.30122	0.29946	0.29449	0.29326	0.30128	0.29747	0.31640	0.28547
A6	0.30187	0.30163	0.30242	0.30264	0.30732	0.29035	0.28340	0.30086	0.30141	0.29461
A7	0.30198	0.30174	0.30214	0.30264	0.32370	0.28731	0.25787	0.30595	0.28493	0.29838
A8	0.30394	0.30519	0.29433	0.29946	0.27453	0.33390	0.30894	0.28391	0.29250	0.31055
A9	0.30354	0.30350	0.29635	0.30264	0.29805	0.30351	0.28596	0.29069	0.25355	0.32123
A10	0.30333	0.30278	0.29691	0.30901	0.30876	0.29376	0.27830	0.30086	0.23217	0.32585
A11	0.30351	0.30328	0.29690	0.30901	0.31304	0.28555	0.28340	0.31950	0.21215	0.33351

Standard deviation calculated using equation 3 and result tabulated in Table 9.

Table 9. Standard deviations

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
σ1	0.00233	0.00263	0.00544	0.00414	0.01448	0.01461	0.02368	0.01067	0.04671	0.01792

Weights of each criteria calculated by using equation 4 and results tabulated in Table 10. The results show that the most important criteria is the C9 which is Unburned Hydro Carbon.

Table 10. Weights of the criterion

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
w	0.01631	0.01847	0.03815	0.02901	0.10154	0.10244	0.16604	0.07484	0.32754	0.12567

Since each MCDM method has a distinct approach to evaluating alternatives. using multiple methods helps strengthen the reliability of the final decision.

TOPSIS Technique Results

The constructed decision matrix (Table 7) was normalized by using equation 5 and in order to calculate weighted normalized matrix the weights which were calculated (Table 10) was used. Each criterion of the resulting normalized decision matrix is multiplied by its weight coefficient. Then weighted normalized matrix V was formed by using equation 7. Equation 8-12 used for calculating final ranking. Results are tabulated in Table 11.

Table 11. Final Ranking according to TOPSIS teechnique

Alternative	Symbol	C*	Rank
A1	B0G30	0.870962	11
A2	B0G60	0.789311	9
A3	B0G90	0.689010	8
A4	B10G0	0.848183	10
A5	B10G30	0.610183	7
A6	B10G60	0.512898	6
A7	B10G90	0.407043	4
A8	B20G0	0.498858	5
A9	B20G30	0.247692	3
A10	B20G60	0.145042	2
A11	B20G90	0.111837	1

According to the results summarized in Table 11, the B20G90 fuel mixture demonstrates the highest performance based on the applied evaluation criteria.

Following the results obtained through TOPSIS, the COPRAS method was utilized to assess the stability and reliability of the alternative rankings.

COPRAS Technique Results

The constructed decision matrix (Table 7) was normalized by using equation 13 and in order to calculate weighted normalized matrix the weights which were calculated (Table 10) was used. COPRAS method is implemented by using equation 13-16. Results are tabulated in Table 12.

Table 12. Results of calculations

Alternative	S_i^+	S_i^-	$1/S_i^-$	**Q**	Q_{max}
A1	0.0221	0.0765	13.0758	0.0835883	0.101146014
A2	0.0225	0.0741	13.4998	0.0860080	
A3	0.0229	0.0724	13.8145	0.0878024	
A4	0.0210	0.0747	13.3786	0.0839323	
A5	0.0218	0.0698	14.3203	0.0891573	
A6	0.0223	0.0677	14.7738	0.0918011	
A7	0.0230	0.0648	15.4302	0.0955005	
A8	0.0208	0.0701	14.2734	0.0879391	
A9	0.0218	0.0645	15.5118	0.0946874	
A10	0.0224	0.0618	16.1776	0.0984375	
A11	0.0229	0.0601	16.6362	0.1011460	

Table 13. Rankings according to COPRAS technique

Alternative	P_{index}	Rank
A1	82.64	11
A2	85.03	9
A3	86.81	8
A4	82.98	10
A5	88.15	6
A6	90.76	5
A7	94.42	3
A8	86.94	7
A9	93.61	4
A10	97.32	2
A11	100.00	1

According to the results obtained. the highest performance is observed in alternative A11 (P11). which corresponds to the B20G90 fuel mixture. indicating its superiority among the evaluated options. To validate and reinforce the findings obtained through COPRAS, the MOOSRA method was subsequently employed.

MOOSRA Technique Results

The MOOSRA technique is implemented using equation (17)-(20).The constructed decision matrix (Table 7) was normalized by using equation 18 and to calculate weighted normalized matrix the weights which were calculated (Table 10) was used. Ranking of the alternatives according to MOOSRA technique is gven in Table 14. The data in Table 14 reveal that the B20G90 fuel mixture achieves the best score among the evaluated alternatives.

Table 14. Ranking of the alternatives according to MOOSRA technique

Alternative	Result	Rank
A1	0.85905	11
A2	0.89092	10
A3	0.92732	8
A4	0.92198	9
A5	0.95293	7
A6	1.00259	6
A7	1.05609	5
A8	1.14997	4
A9	1.25325	3
A10	1.34237	2
A11	1.44787	1

To further validate the robustness of the obtained rankings, the MAIRCA method was subsequently employed.

MAIRCA Technique Results

The MAIRCA technique is implemented using equation (21)-(31).The constructed decision matrix (Table 7) was normalized by using equation 22 and to calculate weighted normalized matrix the weights which were calculated (Table 10) was used. Ranking of the alternatives according to MAIRCA technique is given in Table 15. As presented in Table 15. the criterion Q7 demonstrates the highest performance. Consequently, the optimal value is achieved with the B10G90 fuel mixture.

Table 15. Criteria function

Criteria Function Q	Result	Rank
Q1	0.0706753	11
Q2	0.0607130	9
Q3	0.0552399	7
Q4	0.0638812	10
Q5	0.0482981	6
Q6	0.0417328	5
Q7	0.0307711	1
Q8	0.0600658	8
Q9	0.0402530	4
Q10	0.0343406	3
Q11	0.0344513	2

Following the analysis with the MAIRCA method, the next step involves evaluating the alternatives using the MAUT method, which focuses on maximizing or minimizing the criteria values to determine the optimal solution.

MAUT Technique Results

MAUT technique is implemented by using equation (32)–(35). While creating the normalized decision matrix, it is created by maximizing or minimizing. The alternatives are maximized or minimized according to the desired situation. Obtained ranking is shown in Table 16.

Table 16. Final Ranking for MAUT technique

Alternative	**Final Score**	**Rank**
A1	0.2393117397	8
A2	0.2742086746	6
A3	0.2936545709	4
A4	0.1231477504	10
A5	0.2221735151	9
A6	0.2761847234	5
A7	0.4921020909	2
A8	0.0769260223	11
A9	0.2369208738	7
A10	0.4234498477	3
A11	0.6438020592	1

As evidenced in Table 16, the optimal value is achieved with the B20G90 fuel mixture. In order to compare the outcomes of different ranking techniques, the MOORA method was also applied to the same dataset.

MOORA Technique Results

The MOORA technique is implemented using equation (36)-(38).The constructed decision matrix (Table 7) was normalized by using equation 37 and in order to calculate weighted normalized matrix the weights which were calculated (Table 10) was used. Ranking of the alternatives according to MOOSRA technique is given in Table 17.

Table 17. Ranks for MOORA technique

	Results	Rank
Y1	-0.2419745	11
Y2	-0.2293383	9
Y3	-0.2206212	7
Y4	-0.2399077	10
Y5	-0.2141201	6
Y6	-0.2023479	5
Y7	-0.1866127	3
Y8	-0.2217227	8
Y9	-0.1925338	4
Y10	-0.1779156	2
Y11	-0.1680528	1

The results indicate that the optimal value is attained with the B20G90 fuel mixture. Inorder to make a decision 6 different MCDM method used and the ranks were tabulated in Table 18.

Table 18. Comparative rankings of ruel blends by applied MCDM techniques

Alternative	MAIRCA	TOPSIS	MOOSRA	COPRAS	MAUT	MOORA
A1	11	11	11	11	8	11
A2	9	9	10	9	6	9
A3	7	8	8	8	4	7
A4	10	10	9	10	10	10
A5	6	7	7	6	9	6
A6	5	6	6	5	5	5
A7	1	4	5	3	2	3
A8	8	5	4	7	11	8
A9	4	3	3	4	7	4
A10	3	2	2	2	3	2
A11	2	1	1	1	1	1

BORDA Technique Results

There are some differences in the ranks of the preferences so Borda method was used to make the decision more precise. Equation 39 is used for calculating borda number and results are tabulated in Table 19. Once the borda number calculated the ranks are decided. Final rankings were tabulated in Table 20.

Table 19. Final ranking of alternatives using the BORDA technique

Alternative	Borda Number	The Ranks
A1	3	11
A2	14	9
A3	24	7
A4	7	10
A5	25	6
A6	34	5
A7	48	3
A8	23	8
A9	41	4
A10	52	2
A11	59	1

Table 20. Overall performance ranking of Graphene-Biodiesel blends via BORDA count

Alternative	Borda Rank
A1	11
A2	9
A3	7
A4	10
A5	6
A6	5
A7	3
A8	8
A9	4
A10	2
A11	1

From the results obtained according to the BORDA method. it can be seen that the best option is A11. It can be seen from the table 20 that the best value can be obtained from the B20G90 fuel mixture. The rankings obtained from each method are presented in Figure 1. and the final result obtained using the Borda method is also provided.

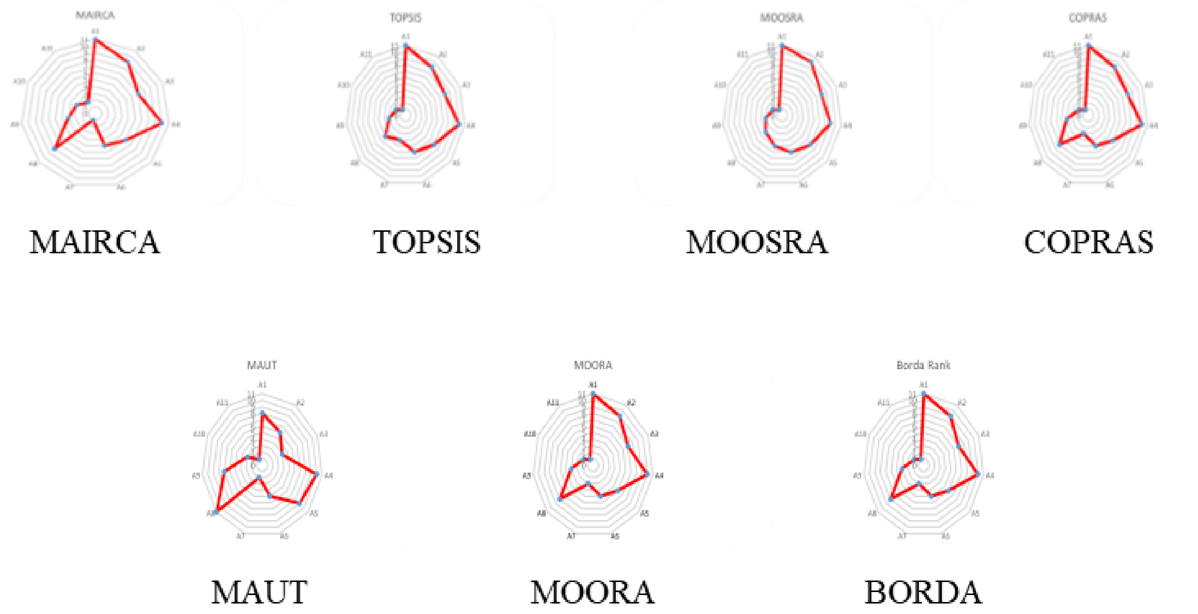

Figure 1. Graphical results of Ranks for MCDM techniques

Conclusion

The quest for sustainable energy sources has been a pressing global concern for decades. driven by the need to mitigate climate change and reduce environmental degradation. Since the Industrial Revolution. reliance on fossil fuels such as coal. oil. and natural gas has been the cornerstone of modern civilization's energy consumption. However. the combustion of these fossil fuels releases significant quantities of greenhouse gases (GHGs). primarily carbon dioxide (CO_2). methane (CH_4). and nitrous oxide (N_2O). into the atmosphere. contributing to global warming and climate change. Energy is one of the most important needs for people today. With the introduction of fossil fuels into widespread use and the recognition of their harmful effects. energy production has shifted towards new and more environmentally friendly fuel sources. One of these sources is graphene and graphene oxide. which consist of nanoparticles. Studies on these innovative graphene and graphene oxide-enhanced fuels are promising.

Studies on these innovative graphene and graphene oxide-enhanced fuels are promising. In this study. six different MCDM (Multi-Criteria Decision Making) methods were employed to evaluate various fuel blends with different graphene ratios. The aim was to identify the most suitable alternative fuel mixture based on multiple evaluation criteria. The rankings obtained from each MCDM method were then consolidated using the Borda count method to ensure a comprehensive and balanced assessment. This integrated approach helps determine the most systematic and reliable option. thereby minimizing uncertainty and risk. Ultimately. the optimal fuel blend was identified according to the given criteria through this multi-method evaluation process.

The research design provides a systematic framework to investigate the effects of graphene-doped fuel blends on greenhouse gas emissions. By applying a structured methodology. this study aims to produce reliable and comprehensive insights into the environmental and technical advantages of using graphene-doped fuels. The integration of MCDM (Multi-Criteria Decision Making) methods enables a balanced assessment of multiple performance criteria. thereby supporting informed decision-making in the field of sustainable fuel development.

Among the six MCDM methods applied. the TOPSIS. COPRAS. MOOSRA. MAUT. and MOORA methods identified A11 (B20G90) as the optimal blend. while the MAIRCA method selected A7 (B10G90). To consolidate these differing rankings and reach a final decision. the Borda count method was employed. This approach involved assigning scores to the alternatives based on their rankings in each method. leading to a unified and systematic selection process. According to the Borda method results. the most suitable option was A11. corresponding to a blend of 20% biodiesel and 90 ppm graphene oxide.

The performance metrics for B20G90 are as follows: density 0.8369 g/cm^3. kinematic viscosity 5.5291 mm^2/s. higher heating value 44.0134 MJ/kg. cetane number 48.5. brake power 4.4554. specific fuel consumption (SFC) 374.58 g/kWh. CO 1.11%. CO_2 3.77%. unburned hydrocarbons (UHC) 124.12 ppm. and NO_x 174.32 ppm. These findings indicate that applying such a multi-method decision-making strategy facilitates the identification of the most effective fuel blend among several alternatives.

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