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Optimizing Electric Mobility: A Multi-Criteria Decision-Making Approach for Sustainable Future of Electric Vehicles Through Smart Motor Choices

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ABSTRACT

To decrease reliance on fossil fuels and carbon emissions, electric vehicles (EVs) have emerged as indispensable instruments in the automotive industry's shift toward more sustainable methods. The achievement of peak efficiency in EVs is contingent upon the appropriate selection of motors and batteries; therefore, exploring methods that ensure sustainable decisions is imperative. The article employs Multi-Criteria Decision-Making (MCDM) techniques to assess and propose the most environmentally friendly amalgamation of batteries and motors for EVs. The research investigates many sustainability-related factors, encompassing energy density, power density, cost, longevity, and environmental impact. By employing MCDM methodologies, including the Analytic Hierarchy Process (AHP), Simple Additive Weighting (SAW), and the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), a comprehensive decision framework is developed with an emphasis on sustainability. The research outcomes provide a thorough understanding of the trade-offs between battery life and motor efficiency, which holds significance for policymakers, academics, and manufacturers dedicated to endorsing sustainable energy practices. The suggested methodology not only streamlines the decision-making process but also promotes the development of environmentally sustainable and highly efficient EVs.

1. INTRODUCTION

Over the past few decades, there has been a heightened scientific consciousness regarding the critical importance of developing sustainable, environmentally friendly alternatives to conventional solutions. This was prompted by issues such as air pollution, air resource depletion, and the search for a pollution-free, healthy environment. Human health in developing countries, particularly in major cities, can be adversely affected by several significant contributors to the increase in harmful exhaust emissions into the atmosphere, such as sulfur dioxide (CO), nitrogen oxides with particulate matter (NO_X), and sulfur dioxide (PM). There is a prevalent belief among many individuals that powertrains represent a viable approach to optimize unleaded emissions and enhance fuel economy within the automotive industry [1]. EV technology is classified as operating on the principle of electric force. It is then transferred to the vehicle's axles via the most efficient gearbox configuration possible after being converted to mechanical energy by the motor. Reversible and highly efficient, this mechanism must provide the wheels with the necessary torque and speed. A hybrid storage system is typically utilized to store the energy. Single-speed gear ratios are the prevailing transmission mechanism chosen for electric powertrains. The electric motor must provide the requisite energy for the EV to advance. Selecting the proper electric motor for a chassis could be difficult [2]. Currently, a wide variety of EVs are available for purchase. Numerous engines in these automobiles perform a variety of functions. Depending on their configuration or intended function, EVs may employ direct (DC) or alternating (AC) motors. Considerable research has been devoted to electric motors, resulting in the creation of numerous varieties. EV manufacturers can select from various electric motors following their unique requirements. The motor's characteristics impact the vehicle's overall performance, so care should be taken when choosing a particular EV motor type [3]. Several considerations must be considered, including management, efficacy, cost-effectiveness, and reliability. In addition to industrial applications and EV usage, additional factors must be considered [4]. The most widely recognized EV motors include induction motors (IM), permanent magnet synchronous motors (PMSM), and brushless DC motors. The traction motor candidates for the electric traction system should supply an economical solution for high-performance, speed sensor-free control and be dependable and effective. They should also possess an extended point of stability at varying velocities [5].

In addition to analyzing electric motors and their interactions, this article provides a synopsis of current market trends in the design of electric motors. In addition, a multi-criteria evaluation of the use of electric motors in EV applications is provided. Figure 1 illustrates many types of electric motors. EVs require appropriate electric machinery to power their propulsion systems efficiently. According to literature analysis, academics are increasingly interested in applying the MCDM theory to selecting electric motors for EVs. This approach facilitates a methodical and unbiased evaluation of diverse motor solutions by considering a range of criteria, such as energy efficiency, cost, performance, and dependability. An assortment of electric devices is utilized to power EVs. A frequently employed variety is the induction motor, renowned for its exceptional reliability, minimal upkeep requirements, and economical nature [6]. Another type is the PMSM, which offers a high power density and efficiency. The SRM is also gaining popularity due to its straightforward design, robustness, and cost-effectiveness. Each form of electric machine has both advantages and downsides. Induction motors, for example, may be less efficient than PMSM or SRM, despite their dependability and inexpensive cost. PMSM provides excellent power density and efficiency but may be more expensive [7].

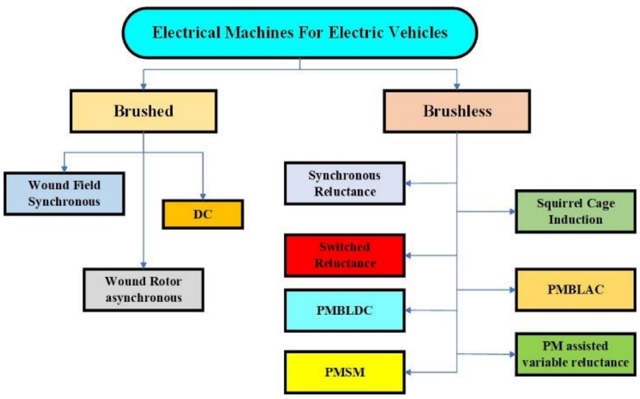


Figure 1. Types of electric motors/machines for EVs

In contrast, SRM has a basic structure and is less expensive but may cause more noise and vibration. The right electric machine is selected based on the EV application's requirements and limits. Factors such as driving range, vehicle weight, power requirements, and pricing must be considered during decision-making. MCDM theory promotes the development of efficient and sustainable EVs by identifying the most appropriate electric motor for specific EV applications, considering both qualitative and quantitative parameters [8].

Selecting proper electric motors for EVs is critical to advancing efficient and sustainable transportation. Recent years have witnessed a surge in interest regarding the application of MCDM theory to the selection procedure [9]. Researchers have acknowledged the importance of considering numerous factors when selecting electric motors for EVs, including performance, affordability, dependability, and energy efficiency [10]. The MCDM theory allows for a systematic and objective evaluation of various electric motor solutions, considering qualitative and quantitative parameters. The MCDM theory provides a framework for decision-making procedures with numerous criteria and competing goals. When applied to electric motor selection for EVs, this theory allows for the simultaneous examination of several parameters, allowing for a thorough study of alternative motor possibilities. This comprehensive approach helps determine the most suitable electric motor for individual EV applications, considering the vehicle's unique requirements and limits [11]. One of the primary advantages of selecting electric motors using MCDM theory is the capacity to consider qualitative and quantitative factors. Subjective qualitative factors, including customer satisfaction and dependability, can be challenging to integrate into conventional decision-making processes [12]. However, MCDM theory provides a structured approach to quantifying and comparing these qualitative factors, enabling a more comprehensive evaluation.

On the other hand, quantitative factors, such as performance metrics (e.g., torque, power, and efficiency) and cost considerations, can be easily measured and compared. MCDM theory allows for integrating these quantitative factors into the decision-making process, providing a robust basis for evaluating different electric motor options [13]. Choosing the most suitable electric motor for an EV is contingent upon many application-specific factors. The elements above encompass traveling range, vehicle mass, power demands, and financial implications [14]. An assortment of electric machine varieties, including induction motors, PMSM, and SRM, present a range of benefits and drawbacks. Due to their straightforwardness, durability, and economical nature, induction motors are extensively employed in EVs. However, their efficiency may be inferior to other motor varieties [15].

In contrast, PMSMs provide superior power density and efficiency but are more complicated and costly. Although SRMs offer benefits like increased torque density and defect tolerance, they may produce more acoustic noise and vibration. Future research and development will enhance the dependability, performance, and efficiency of electric apparatus for EVs [16]. This includes advancements in motor design, materials, control strategies, and power electronics. Additionally, efforts will be made to develop innovative motor technologies that address the specific requirements of EV applications, such as high power-to-weight ratio, compact size, and improved thermal management [17].

In the fast-changing environment of EVs, the search for sustainable energy solutions in electric motors has become increasingly important. MCDM approaches are a powerful tool in the decision sciences and are critical in navigating the complicated trade-offs connected with electric motors for EVs. With numerous elements to consider, ranging from energy efficiency and environmental impact to cost-effectiveness and technological feasibility, MCDM offers a structured strategy for evaluating and prioritizing these criteria. In the context of electric cars, where the transition to sustainability is a major priority, MCDM guides stakeholders in selecting electric motors that meet the broad goals of eco-friendliness and efficiency. As the automotive industry accelerates its transition to electrification, MCDM emerges as a key driver in steering decision-makers towards electric motor options that meet performance requirements and contribute significantly to the larger agenda of creating a greener and more sustainable future for EVs. In this delicate dance of criteria and considerations, MCDM stands as a beacon, guiding the automobile industry into choices that harmonize technological progress with environmental responsibility to create a cleaner and more energy-efficient transportation ecosystem.

In response to the critical conditions of global climate change and the exhaustion of fossil fuel reserves, there has been a surge in both investment and demand for EVs. It is crucial to shift towards transportation alternatives that are more environmentally sustainable, as conventional internal combustion engine vehicles significantly contribute to air pollution and greenhouse gas emissions. Powered by batteries built into the vehicle, EVs present an enticing remedy to these ecological issues. Despite the undeniable environmental advantages of EVs, their extensive adoption is contingent upon resolving several technological challenges, with energy storage systems and propulsion mechanism optimization being the most critical. Electric vehicles rely on propulsion batteries to supply the necessary energy to operate the electric motor. The electric engine propels the automobile concurrently, transforming electrical energy into mechanical energy. Overall efficacy and success of EVs depend heavily on the interplay between these two components.

This study aims to investigate and implement MCDM techniques to optimize the selection of batteries and actuators for EVs. Key Objectives of this study are:

• The study emphasizes the importance of MCDM in guiding electric motor selection, recognizing the complexity and interdependence of parameters such as torque, power, efficiency, weight, cost, and environmental impact.

• Validating the MCDM-based method using real-world electric motor data for EVs adds a practical layer. This case study provides real-world evidence to back up the suggested method.

• The research enhances scholarly comprehension of the automotive sector and actively promotes the widespread implementation of intelligent and eco-friendly EVs. These vehicles are marketed as potential resolutions to urgent environmental issues.

The findings of this research article are presented clearly and coherently by division into sections. After this introductory segment, the second section investigates into significant scholarly works on the present condition of EVs, advancements in battery and motor technologies, and established methodologies for their selection. The third section details the research methodology, including the process of identifying criteria, developing the decision framework, and applying MCDM methods. The analysis results, presented in the fourth component, offer valuable insights regarding the prioritization of criteria and the assessment of different combinations of batteries and motors. In the fifth segment, recommendations for stakeholders in the EV industry are provided in light of the findings. In summary, the conclusion elucidates the significant contributions of the research, underscores its constraints, and proposes avenues for future investigation in the perpetually evolving and dynamic domain of EV technology. The primary objective of this study is to enhance comprehension of the decision-making process involved in EV design. Additionally, it offers a pragmatic and executable framework for stakeholders interested in optimizing the choice of batteries and motors to promote efficient and sustainable electric mobility.

2. LITERATURE REVIEW

Zhu et al. [18] presented a modified particle filter method for reliably and robustly estimating vehicle states and parameters in complex disturbances and sensor fault circumstances. The efficacy of the proposed estimation scheme is validated by utilizing Carmaker-Simulink joint simulations of typical maneuverers subjected to stochastic as well as needling noises, accelerating sensor errors, and unscented Kalman filter (UKF) scenarios. The suggested estimating approach beats the unscented particle filter (UPF) and the unscented Kalman filter (UKF), two popular vehicle state estimators. To assist and augment this process, EVs must be given precedence over traditional motor vehicles. Kaya et al. [19] had investigated MCDM and GIS-based site selection for EVCs in Istanbul. The parameters that influence the locations of EVCS have been identified for this objective. Once more, as contemporary drive technologies continue to advance in diverse electric propulsion applications, a thorough comprehension of appropriate motor selection is gaining significant importance.

A comparison was made between IM, BLDC, and PMSM in the study [20]. The rationale behind choosing an ANN-based controller for EV propulsion applications is its precise control, rapid dynamic response, and simplicity in speed and torque modulation. The 5-phase PMSM is a prime candidate material for EVs because the selection process is predicated primarily on dependability, efficiency, and robustness. Hezzi et al. [21] examined the Linear Active Disturbance Rejection Controller (LADRC) and an Active Disturbance Rejection Controller (ADRC) in their study. To stabilize the system when anticipated internal and external disturbances occur, the ADRC employs online dynamic correction. Aliasand and Josh [22] investigated the process of selecting an EV motor. The article describes five different types of EV motor drive train systems. A comparison is made between axial flux permanent magnet brushless DC motors, switching reluctance motors, induction motors, permanent magnet motors, and DC motors concerning their dependability, price, efficiency, and maximal speed. The objective is to determine which electric motor drives are most suitable for EV applications. Alosaimi et al. [23] described the various categories of EVs, including BEVs, FCEVs, HEVs, PHEVs, and REHEVs. Despite significant advancements in recent years in the powertrain capabilities of numerous EV models, certain obstacles continue to impede the choices of several consumers. The dynamic performance and energy efficiency improvements of an EV powertrain featuring dual motors and multiple gear ratios were examined by Nguyen et al. [24]. Significant electricity consumption reductions of 4.82–5.08% are observed when a single-motor powertrain is compared to one with an optimal motor size greater than 0.42 and matching gear ratios.

Chahba et al. [25] compared the flying times of electric multirotor propulsion chains powered by fuel cells and batteries. To develop and validate a method for sizing and selecting the propulsion chain components of an E-VTOL air vehicle, Espino-Salinas et al. [26] conducted a survey. The ultimate phase involves employing regression techniques and data from the propulsion chain supplier to compute the propulsion chain's optimized gross take-off weight (GTOW), which was acquired through the sizing methodology. Motorist authentication is the process of determining the identity of a driver through the collection of pertinent information. This information is utilized to ascertain the identity of the vehicle's operator. For driver identification, Li et al. [27] suggested the use of genetic algorithms. The proposed method, which is more recent than those currently in use, attempts to analytically and objectively identify the most significant statistical characteristics of the motor activity produced by the primary components of the vehicle. To reduce the capacity of hard-wired batteries to subunits, the authors suggest a drive train configuration that utilises a dynamically reconfigurable DC battery. By improving voltage output and reducing losses in EV propulsion systems, the proposed method makes use of recent developments in 48 V power electronics, low-voltage transistors, and modular circuit topologies. Zhang et al. [28] introduced a hybrid methodology for approaching PHEB that combines model predictive control (MPC) with an equivalent consumption minimization strategy (ECMS). The plug-in hybrid electric bus (PHEB) faces considerable requirements for vehicle capacity during periods of high demand and when navigating steep inclines due to its operation in urban settings. The following measures should be taken to address the difficulty of reconciling excessive motor temperature reduction with fuel efficiency

As a technique for determining which smart sensors should be installed in the escalator of a metro station, AHP-Gaussian was proposed by Pereira et al. [29]. Through its implementation in the choice of a smart sensor for an electric motor located in an escalator at a metro station, the proposed AHP-Gaussian method was shown to be effective. Shu et al. [30] addressed an approach to address the issue where the current capacity setting for highway charging stations fails to account for user charging preferences adequately. This method involves implementing a charging guidance mechanism consisting of two stages and is designed to optimize the setting of highway charging stations during peak charging periods. Yu and Chang [31] proposed a method to suppress excessive common mode voltage at the output of PMSM for new energy vehicles operating on high-voltage platforms. This voltage is likely to cause electromagnetic interference with other electronic devices. While minimizing the common-mode voltage suppression to virtually zero, the control is simplified through vector selection optimization. Users of EVs are guided through the charging selection process in the second stage, which is determined by a constant capacity. By utilizing model predictive current control on the inverter circuit of four legs.

Zhou et al. [32] proposed a pragmatic framework for determining the location of photovoltaic charging stations (PVCS) by combining geographic information system (GIS) techniques with MCDM methodologies. Numerous factors must be thoughtfully considered to increase the number of people who purchase EVs, including installing charging stations. Guler and Yomralioglu [33] established a system combining MCDM and Geographic Information System (GIS) methodologies to discover the best places for EV charging stations. In the context of EV charging station location selection, Ghosh et al. [34] examined the application of hexagonal fuzzy MCDM. A novel MCDM approach was introduced by Feng et al. [35] to ascertain the most environmentally sustainable location for an EV charging station. Additionally, other emerging or rapidly expanding economies can utilize the proposed evaluation criteria and method. Innumerable research studies emphasize the absence of charging station data required to develop realistic models. Awasthi et al. [36] investigated the use of fuzzy TOPSIS, fuzzy VIKOR, and fuzzy GRA, three ideal solution-based MCDM methodologies, to assess the sustainability of urban mobility programs. In their study, Gholinejad et al. [37] introduced a sophisticated charging methodology for off-board EV devices utilized in home-energy hub (HEH) scenarios when coupled with DC power sources like battery storage and photovoltaic systems. A comprehensive model was developed by Lu et al. [38] to estimate the energy consumption of EVs. An extensive examination was conducted by the authors into the effects of traffic flow on driving resistances and motor efficacy. Wei et al. [39] modified an advanced deep reinforcement learning (DRL) framework to propose an online battery anti-aging energy management approach for the energy-transportation nexus. Bongiovanni et al. [40] suggested an updated machine learning (ML) approach that utilizes the differential search optimized random forest regression (RFR) algorithm to precisely and robustly determine the state of charge (SOC) of EV batteries. Lipu et al. [41] offered regulatory options for recycling retired EV batteries. A bottom-up, technology-rich model was devised by Lin et al. [42] to assess the overall cost of ownership (TCO), performance, and economy of battery electric vehicles (BEVs). This study underscores the criticality of developing BEVs with exceptionally extended driving ranges. Liu et al. [43] determined the most appropriate number of charging stations and EV costs for each scenario. Utilizing the MCDM method, Wang et al. [44] introduced a paradigm for the sustainable supplier selection of batteries for BSS. The criteria weights are concurrently established by implementing the Maximizing Deviation technique.

2.1 Electric vehicle motors

Climate change's critical consequences and the imperative to mitigate carbon emissions propel the global transition towards sustainable transportation. In this regard, EV propulsion systems play a pivotal role. The progressions in automotive technology since the early 19th century can be ascribed to the revolutionary contributions of scientists exploring electromagnetic phenomena, including Nikola Tesla and Michael Faraday [45]. An increased focus on electric propulsion emerged at the turn of the 21st century, spurred by concerns over dependence on fossil fuels, environmental degradation, and the need to diversify energy sources. The operating mechanism of EV motors relies on electromagnetic induction to convert electrical energy stored in batteries to mechanical energy. The predominant motor types within the domain of EVs are BLDC and IM. BLDC motors have gained significant recognition due to their exceptional efficiency, reliability, and reduced maintenance needs compared to alternative motor varieties. By minimizing wear and strain, the lack of brushes in these motors effectively prolongs their operational lifespan [46]. EV propulsion motors are at the forefront of environmentally sustainable vehicle propulsion technology and signify a significant paradigm shift within the automotive sector. Unlike conventional internal combustion engines, EV motors operate via electromagnetic induction. This mechanism transforms electrical energy in the vehicle's batteries into rotational motion [47].

2.1.1 Permanent magnet synchronous motors (PMSM)

PMSM is frequently employed in EVs owing to their manifold advantages. Due to their exceptional power density and efficiency, these motors are ideally suited for EV traction applications. PMSM leverage permanent magnets housed within their rotors to produce a robust magnetic field and facilitate efficient power conversion. This configuration facilitates increased torque generation and overall motor efficiency [48].

PMSM has higher efficiency, which reduces EV energy utilization and increases driving range, which is one of their primary advantages. Furthermore, their reduced dimensions and light weight contribute to an increased power density, facilitating enhanced acceleration and overall performance. Nonetheless, PMSM is not without its limitations. Permanent magnets can be comparatively expensive, which impacts the motor's total cost. In addition, temperature fluctuations can impact PMSM's performance, necessitating effective thermal management systems to guarantee optimal operation. PMSM is currently engaged in continuous research and development efforts to enhance its performance and cost-effectiveness to overcome these limitations. The aforementioned comprise advancements in thermal management techniques, motor control algorithms, and magnet materials [49].

$$\text{Synchronous Speed (Ns)} = \frac{120f}{P} \tag{1}$$

where, P represents the number of poles, f is the electrical frequency of the system in Hertz (Hz), and Ns represents the synchronous speed in revolutions per minute (RPM).

2.1.2 Induction motors (IM)

Due to their low cost and dependability, IMs, known as asynchronous motors, are utilized in various industrial and commercial applications. These motors generate torque by interacting with a rotating magnetic field in the stator and the rotor. Durability is a key advantage of IMs, enabling them to operate effectively in hostile environments. Additionally, their design is relatively uncomplicated, necessitating only a minimal amount of maintenance compared to alternative motor varieties [50].

However, IMs have some limitations. They generally have lower efficiency than permanent magnet motors, resulting in higher energy consumption and operating costs. Additionally, IMs have poor starting torque, which can be a drawback in certain applications. They also tend to have a lagging power factor, leading to lower power quality and potential issues with power distribution systems. To address these limitations, ongoing research efforts focus on improving IMs' efficiency and power density [51]. This includes advancements in materials, such as using amorphous alloys to reduce losses and improve motor performance. Design strategies and control algorithms are also being developed to improve motor performance and energy economy. IM provides cost-effective and dependable solutions for a variety of applications. Induction motors have constraints regarding efficiency, starting torque, and power factor, but continuing research and development efforts attempt to overcome these problems and increase their performance [52].

$$\text{Slip (s)} = \frac{N_s - N}{N_s} \tag{2}$$

where, N represents the actual rotor speed, while N_s denotes the synchronous speed.

2.1.3 Permanent magnet brushless DC (PMBLDC)

PMBLDC motors are a subtype of electric motors in which the rotor is composed of permanent magnets instead of electromagnets. The motors possess many advantages, such as optimal performance, minimal upkeep, compact dimensions, silent functioning, and dependability. PMBLDC motors achieve rapid dynamic performance and enhanced efficiency by using permanent magnets. They are utilized extensively in numerous contexts, such as vehicles, EVs, robotics, automation, and power generation on aircraft and ships [53]. Since regulating the winding currents of PMBLDC motors necessitates rotor-position sensing, sensor-less control strategies are frequently implemented. The selection of permanent magnet materials, including Nd-Fe-B rare earth magnets, is application-specific and contingent upon the intended energy density. The current investigation aims to enhance the efficiency and economic viability of PMBLDC motors by employing advancements in control algorithms, construction methodologies, materials, and additional aspects [54].

2.1.4 Switched reluctance motors (SRMs)

Utilizing magnetic reluctance as their driving force, SRMs are electric motors. SRMs have salient poles on the rotor and stator but lack windings or magnets, in contrast to conventional motors, which employ permanent magnets or electromagnets on the rotor and stator. Motivated by magnetic attraction and repulsion, the energized rotor generates torque as its salient poles align with those of the stator [55].

The fundamental advantages of SRMs are their simple and strong design, making them cost-effective and reliable. They require fewer components because of their intrinsic simplicity, making production and maintenance easier. Furthermore, SRMs can survive difficult working conditions and tolerate high temperatures, making them useful for various applications, including EVs, industrial motors, and appliances [56]. SRMs have advantages, including high torque density, a broad speed range, and increased efficiency under partial loads. Their speed and torque control may be performed by properly switching the stator phases, providing versatility in various applications. Furthermore, the absence of rotor windings and magnets decreases the possibility of demagnetization, adding to the motor's long-term reliability [57].

$$\text{Torque Equation (T)} = \frac{1}{2}\frac{L_d - L_q}{L_d L_q} i^2 \tag{3}$$

where, T is the torque, L_d and L_q are the direct and quadrature inductances, and i is the current.

2.1.5 Direct current (DC) motors

DC motors are electrical devices utilized to transform electrical energy into mechanical energy. These entities are widely utilized across various domains due to their simplicity, dependability, and capacity for regulation. DC motors function according to the Lorentz force principle, which posits that the presence of a magnetic field induces force on a current-carrying conductor. Although there are numerous types of DC motors, the two most prevalent are:

Brushed DC motors

At specific locations, the commutator, which is a rotary switch, reverses the direction of current in the coils when connected to the rotor (armature) of a brushed DC motor. Carbon brushes influence rotor rotation by establishing physical contact with the commutator and allowing current to flow through the coils, generating a magnetic field that interacts with the stator's magnetic field. Due to brush wear and tear, regular maintenance is required for brushed DC motors, notwithstanding their affordability and simplicity [58].

$$\text{Back EMF (E)} = K\omega \tag{4}$$

where, ω represents the angular velocity, K denotes the motor constant, and E signifies the reverse electromotive force.

Brushless DC motors (BLDC)

BLDC motors have gained favor over brushed DC motors due to their higher efficiency and lower maintenance requirements. They don't use brushes or commutators. Instead, they use a permanent magnet rotor and a stator with electronically controlled coils. The current in the coils is switched electronically via a controller, which affects the motor's rotation. BLDC motors are widely utilized in various applications, including consumer electronics and EVs. DC motors originate in various dimensions and designs, and their performance may be regulated by varying the voltage applied to the motor. Lower voltage usually results in slower speeds and reduced torque, whereas higher voltage delivers higher speeds and greater torque [59].

$$\text{Back EMF (E)} = K_b\omega \tag{5}$$

Motor equation

$$V = I_a R_a + \text{E} \tag{6}$$

where, V is the applied voltage, I_a is the armature current, R_a is the armature resistance, E is the back electromotive force, K is the motor constant, and ω is the angular velocity. K_b is the back EMF constant.

3. METHODOLOGY

Established in the middle of the 20th century, MCDM is a multidisciplinary domain originating in operations research and decision analysis. It tackles decision problems that involve the consideration of multiple criteria, frequently with competing priorities. Herbert A. Simon and Ronald A. Howard, among others, contributed significantly to its foundational concepts. Common approaches in MCDM include ELECTRE and TOPSIS [60, 61].

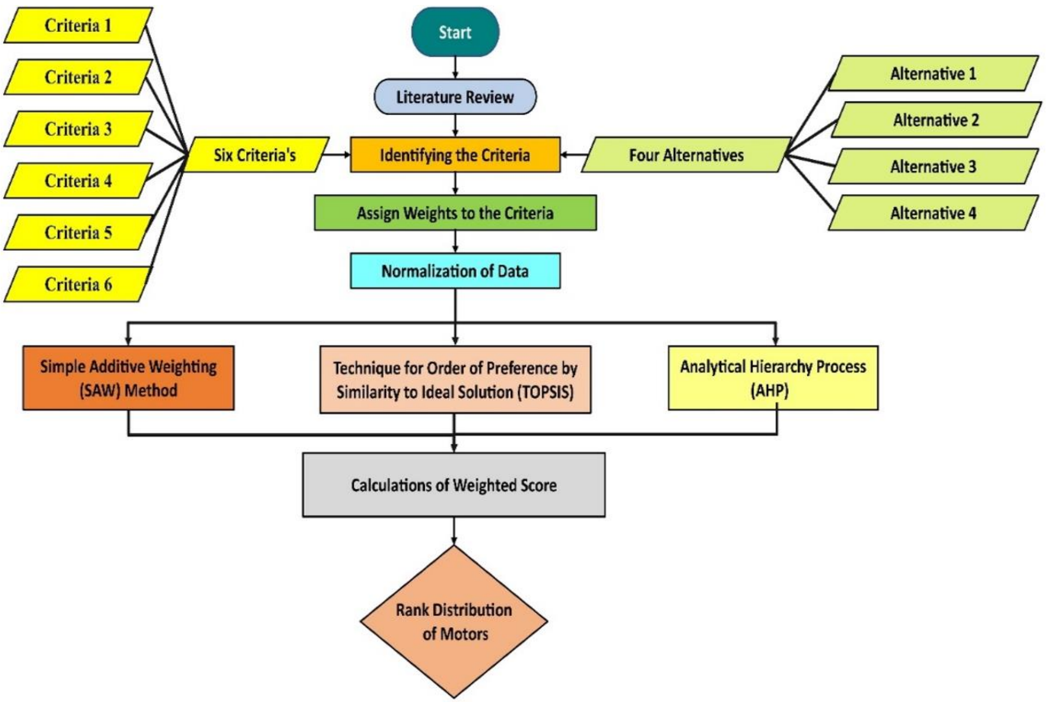


Figure 2. Flowchart of methodology

On the other hand, ELECTRE prioritizes the outranking of alternatives. In contrast, TOPSIS evaluates alternatives according to their proximity to an ideal solution, as opposed to AHP's hierarchical approach to problem organization. Fuzzy logic is employed to reduce uncertainties, whereas Data Envelopment Analysis (DEA) is utilized to assess the performance of decision-making appliances. Contemporary progressions in computational techniques and Artificial Intelligence (AI) have significantly broadened the functionalities of MCDM, furnishing decision-makers with sophisticated instruments to navigate intricate, multifaceted dilemmas in various domains, including business, engineering, and environmental management. Maintaining its status as a dynamic and developing field, MCDM is essential for traversing the complexities of decision landscapes in an ever more complex world [62]. Figure 2 shows the methodology flow chart of different MCDM techniques implemented in this article and other important parameters. The significance of MCDM resides in its capacity to methodically tackle decision-making scenarios that involve numerous, frequently contradictory objectives. By employing decision matrices and methodologies such as AHP, TOPSIS, and ELECTRE, decision-makers can navigate the intricacies of assessing alternatives based on various criteria using a structured approach. Fuzzy logic is a method that can be applied to real-world decision problems to account for uncertainties, and recognizing the intrinsic ambiguity of preferences. Furthermore, the integration of DEA enables the evaluation of efficacy in the management of numerous decision-making entities [63]. Incorporating sophisticated AI and advanced computational methods signifies the ongoing development of MCDM, which facilitates the implementation of more sophisticated analyses and adaptive decision support systems. This interdisciplinary domain has become essential in contemporary decision-making procedures, as it offers a structured approach to tackle the intricate difficulties presented by conflicting goals and unpredictable contexts. In an increasingly linked and complex global world, MCDM is a leading framework that enables industry-spanning decision-makers to create well-informed and strategic judgements that harmonise with various, frequently competing objectives [64].

There are a few crucial phases or steps in the MCDM process for choosing appropriate electric motors for application in EVs with certain parameters that are included in this study, such as efficiency, power density, reliability, controllability, cost, and technical maturity. The AHP method has different steps for getting the results for selecting appropriate motors. In contrast, the SAW and TOPSIS are the MCDM techniques that are implemented for EV motors using the below steps [65]:

Identification of criteria: The initial phase is establishing the essential criteria for selecting a suitable electric car motor. The criteria above may comprise motor horsepower, efficiency, cost, and mass.

Assign weights to the criteria: Once the criteria have been defined, each criterion is weighted according to its relative value. Weights can be allotted in various ways, including pairwise comparison or expert judgment.

Normalize the data: Normalization should be performed on the data for each criterion to ensure that they all fall on the same scale. Several approaches to accomplish this include min-max normalization and z-score normalization.

Calculate the weighted score: To compute the weighted score for each motor, multiply the normalized value for each criterion by its associated weight and then sum the results.

Rank the motors: Finally, the motors can be evaluated based on their weighted scores, and the motor with the greatest score is the most appropriate choice [66].

3.1 SAW method

The most prevalent and uncomplicated MCDM method is weighted sum. Considering this attribute, the overall significance of the system must be equal to one. Every potential option is considered for a given attribute. The subsequent measurements employ this methodology:

• Decide on the objective and have an understanding of the relevant evaluation criteria for this objective.

• A choice matrix can be obtained from Eq. (1). Every row in this matrix represents a different option or alternative, which in this case is motors, and every column represents a different characteristic, which includes power density, efficiency, controllability, dependability, technological maturity, and cost [32]. As an outcome, an element E_{ij} is utilized as an input from the decision matrix 'DM' [E_{ij}; i = 1, 2,..., the number of alternatives (n); j = 1,2,..., number of attributes (m)] [67].

$$DM=\begin{bmatrix} E_{11} & E_{12} & \_\_ & E_{1j} & \_\_ & E_{1m} \\ E_{21} & E_{22} & \_\_ & E_{2j} & \_\_ & E_{2m} \\ \_\_ & \_\_ & \_\_ & \_\_ & \_\_ & \_\_ \\ E_{i1} & E_{i2} & \_\_ & E_{ij} & \_\_ & E_{im} \\ \_\_ & \_\_ & \_\_ & \_\_ & \_\_ & \_\_ \\ E_{n1} & E_{n2} & \_\_ & E_{nj} & \_\_ & E_{nm} \end{bmatrix} \tag{7}$$

• In order to construct the normalized decision matrix, the linear normalization approach is utilized, NDM_{ij}, for favourable conditions (profit) and non-en.

$$NDM_{ij} = \frac{E_{ij}}{Max\ E_{ij}} \tag{8}$$

For advantageous criteria, j = 1, 2, …, m

$$NDM_{ij} = \frac{Min\ E_{ij}}{E_{ij}} \tag{9}$$

For non-advantageous criteria, j = 1, 2, …, m

• Make your selection based on the relative importance of a multitude of objective criteria. Assign importance weights (w_j) to attributes so that $\sum w_j = 1$. The present investigation employs the Equal weights method to assign weights to attributes [68].

3.1.1 Equal weights method

Eq. (10) calculates the weight of each attribute (m) by dividing 1 by the total amount of attributes (using the equal weight technique).

$$w_j = 1/m \text{ for } j = 1, 2, \ldots, m \tag{10}$$

The result of multiplying each column aspect of NDM_{ij} by w_j is the weighted and normalized matrix WZ_{ij}. Eq. (11) displays the components of the weighted, normalized matrix WZ_{ij} [69].

$$WZ_{ij} = [w_j NDM_{ij}] \tag{11}$$

Eq. (12) gives an alternative composite performance score (CPS).

$$CPS_{SAW} = \sum_{j=1}^{m} WZ_{ij} \tag{12}$$

The technique generates alternatives based on CPS value, identifying the most and least superior solutions [70].

3.2 TOPSIS method

Throughout the 1980s, TOPSIS emerged as an MCDM methodology. When determining the optimal or negative ideal solution, TOPSIS selects the option that is the greatest Euclidean distance from either. A methodology for selecting the most effective motors for EVs is utilized in this investigation. The factors above comprise technological maturity, power density, efficiency, dependability, controllability, and cost [68].

Step 1: Calculate the normalised matrix and weighted normalized matrix

Weighted Normalised Matrix and Normalised Matrix Calculations. Each value is normalized as follows: where n is the number of columns and m is the number of rows in the dataset. While j varies along the columns, I fluctuate along the rows.

$$\bar{X}_{ij} = \frac{X_{ij}}{\sqrt{\sum_{i=1}^{n} X_{ij}^2}} \tag{13}$$

$$V_{ij} = \bar{X}_{ij} \times W_j \tag{14}$$

Step 2: Calculate the ideal best and ideal worst value

The calculations to determine the ideal best and ideal worst values for our scenario are currently underway. The minimum allowable value and maximum acceptable value of the cost factor also referred to as criterion C1, are in opposition to being beneficial. Similar to how the minimum value represents the optimal worst-case scenario, the maximum value corresponds to the optimal best-case scenario concerning each Beneficial Criteria (C2, C3, C4, and C5). The ideal best and worst values must be determined to initiate the process. Here, it is necessary to ascertain the direction of the influence ('+' or '-'). The "+" impact denotes the condition that the minimum and maximum values of the column are ideal worst and ideal best, respectively. The "-" impact signifies the contrary [69].

Step 3: Calculate the Euclidean distance from the ideal best and ideal worst

At this point, calculate the Euclidean distance between each row element and the ideal worst. The ideal best Euclidean distance for the ith row is S_i^+, where $V_{i,j}$ is the element value, and V_j^+ is the ideal worst for that column. Similarly, the worst Euclidian distance on the ith row is S_i^-. Eq. (15) calculates the ideal best-case Euclidean distance, whereas Eq. (16) computes the ideal worst-case [70].

$$S_i^+ = \left[\sum_{j=1}^{M} \left(V_{IJ} - V_J^+\right)^2\right]^{0.5} \tag{15}$$

$$S_i^- = \left[\sum_{j=1}^{M} \left(V_{IJ} - V_J^-\right)^2\right]^{0.5} \tag{16}$$

Step 4: Calculation of performance score and distribution of ranks

The TOPSIS Score is computed. Let us compute the TOPSIS score for each row using the Euclidean distances for the Ideal Best and Ideal Worst cases, which are now in our possession.

$$P_i = \frac{S_i^-}{S_i^+ + S_i^-} \tag{17}$$

The alternatives are subsequently ranked following their relative proximity; the option receiving the highest recommendation is the one farthest from the anti-ideal solution and closest to the ideal solution [71].

3.3 Analytical hierarchy process (AHP)

In 1980, Saaty introduced a practicable and resilient instrument designed to supervise quantitative and qualitative multi-criteria factors influencing the decision-making process. The AHP paradigm is constructed hierarchically. AHP is a highly inclusive system for evaluating judgments by considering multiple factors. Its distinctive feature is its belief in combining qualitative and quantitative parameters and its ability to facilitate hierarchical problem descriptions. To commence, the problem must be arranged hierarchically. Assigning a nominal value to each level of the hierarchy and constructing a matrix of pairwise comparison judgments comprise the second stage [72]. Figure 3 shows the hierarchal structure of AHP for motor selection.

Utilizing a step-by-step process, the relative weights of criteria were determined. Those above are the stages comprised of AHP.

Step 1: Determination of the issue about decision-making.

Step 2: Establishment of the bilateral comparison matrix.

Step 3: Construct the normalized matrix through calculation.

Step 4: Establish the coefficient of weight for each criterion.

Step 5: Determining the ratio of consistency.

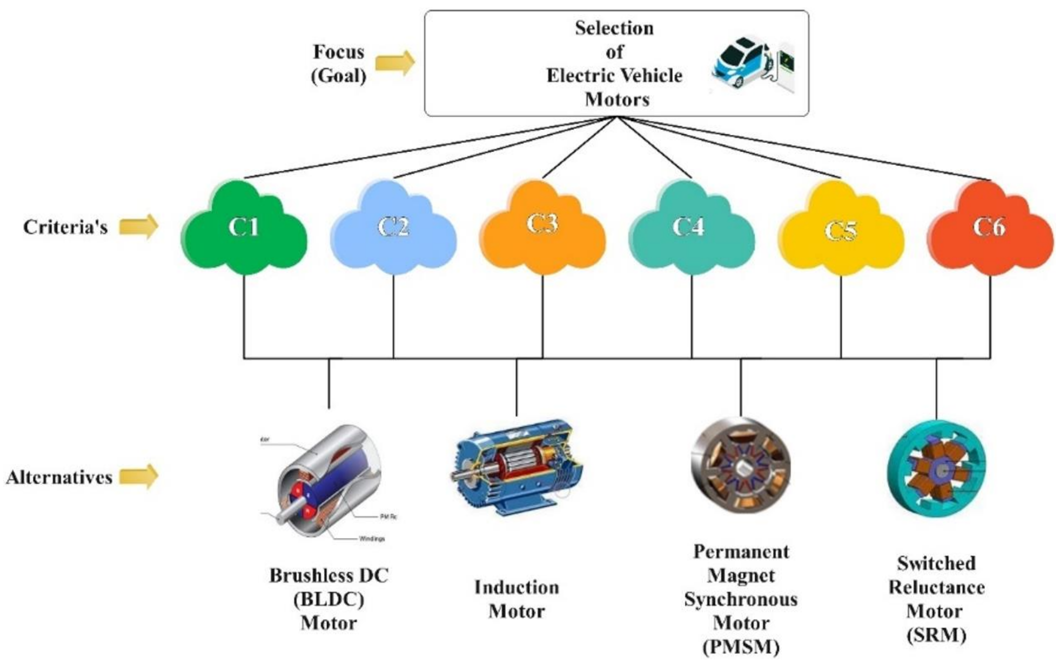


Figure 3. Model of motor selection in AHP

Table 1. Different scales used for the AHP analysis

Intensity on Scale Based on Absolute Importance	Definition	Explanation
1	Equally important	Two criteria equally contribute to the objectives
3	Moderately important to one over another	Experience and judgement strongly slightly favour one activity over another
5	Strongly essential and important	Experience and judgment clearly indicate a strong preference for one activity
7	Very strongly important	An activity is favoured heavily and its dominance is demonstrated in practice
9	Extremely important	The evidence supporting a particular course of action has the greatest degree of confirmation attainable
2,4,6,8	Intermediate values between the two adjacent values	Prerequisites for compromise

As shown in Table 1, each of these evaluations is designated a numerical value ranging from one to nine. The consistency of decisions executed in AHP is denoted by the consistency ratio (CR) [73]. The CR is calculated using the following formula:

$$CR = \frac{Consistency\ Index\ (CI)}{Random\ Index\ (RI)} \quad (18)$$

The N-order matrix is computed through the implementation of the given formula.

$$CI = \frac{\lambda_{Max-N}}{N-1} \quad (19)$$

In this context, λ_{Max} represents the highest eigenvalue, while N signifies the Random Index (RI) or criteria (CN) for the matrix order specified in Figure 4. When dealing with matrices of greater scale, a CR below 0.1 is considered acceptable. An evaluation is considered suitable and maintains an adequate level of consistency when the observed value is equal to or lower than the predetermined value [74].

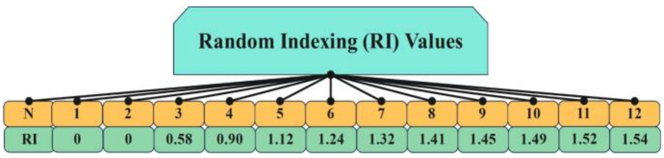


Figure 4. RI values for matrix order preferences

4. RESULTS AND DISCUSSION

We employed an extensive array of decision-making methodologies in our comprehensive investigation into the optimal battery selection for EVs, recognizing the diverse characteristics of the parameters at play. By assigning criteria weights and calculating the mean of their outcomes, the SAW method enabled us to ascertain the overall desirability of each alternative. As an adjunct to AHP, the TOPSIS conducted a comparative analysis of various battery alternatives, identifying the greatest benefits. The AHP facilitated the systematic organization of the decision hierarchy by assigning relative importance to various factors. The capability above enabled a more thorough assessment of various aspects, including but not limited to environmental impact, cost, energy density, and lifespan. By integrating these disparate methodologies, we aimed to illustrate the complexities and trade-offs associated with the critical decision of motor selection for EVs. By utilizing this all-encompassing approach, stakeholders are guaranteed a rigorous evaluation procedure and are provided with a holistic comprehension of the optimal battery selections; this contributes to the advancement of electric mobility.

Table 2. Assignment of weights in %

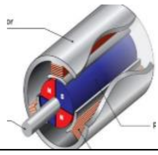
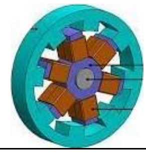
Attributes	C1	C2	C3	C4	C5	C6
Weightage	16.67	16.67	16.67	16.67	16.67	16.67

Table 2 shows the weight allocation, stated as a percentage, for the features or criteria (C-1 to C-6) in the decision-making process. The phrase "Weightage" in each row denotes the degree of relevance assigned to the relevant criterion. In this case, each criterion is allocated the same weight of 16.67%, indicating that decision-makers believe all factors have similar importance in influencing the ultimate decision. Employing the equal-weighting technique ensures that all factors are accorded equal weight in the decision-making process and that no single criterion is considered more significant than others. In this instance, the weightage allocated to each criterion is calculated to guarantee an impartial and symmetrical evaluation of its contribution to the comprehensive assessment of alternatives, including EV motors. The aggregate weighting assigned to each criterion is one hundred percent. The weight allocation is crucial for the final phases of the decision-making process, specifically when calculating the weighted scores for each alternative according to their performance in the Normalized Decision Matrix.

4.1 Validation using SAW

Table 3 describes the experimental setup in detail, including comparing four distinct types of EV motors: BLDC, IM, PMSM, and SRM. Each motor is evaluated based on six criteria: power density, controllability, efficiency, reliability, cost, and technological maturity. These criteria are rated on a scale from 1 to 5. The cumulative scores (ΣΣ Total) reflect overall achievement in various categories. The Induction Motor received the highest overall score of 27, signifying superior performance in this testing setting. The PMSM and SRM values are 25 and 23, respectively. The BLDC motor trails behind with a total score of 22. This comprehensive evaluation provides substantial insights into the benefits and drawbacks of each type of motor, allowing for well-informed judgments for specific EV applications depending on the prioritized qualities.

Table 3. Distribution of characteristics for 4 different EV motors

Electric Motors/Parameters	**BLDC** 	**IM** 	**PMSM** 	**ARM** 
Power density	2.5	3.5	5	3.5
Controllability	5	5	4	3
Efficiency	2.5	3.5	5	3.5
Reliability	3	5	4	5
Cost	4	5	3	4
Technological maturity	5	5	4	4
∑Total	22	27	25	23

Using SAW to make motor selection decisions. The motor data and the four decision matrix characteristics are separated into four levels: low (1-2p), medium (2.5-3.5p), high (4p), and very high (4.5-5p).

4.1.1 Different criteria

a) Criteria 1: Power density (P_D)

An electric motor's power density (P_D) is measured by dividing its power output (P) by its volume (V) or mass (M). The following equation can describe the density of motor power:

$$P_D = \frac{P}{V} \tag{20}$$

The motor's P_D is denoted in watts per kilogram or per cubic meter. The variables denoted as P (power output in watts), V (volume in cubic meters), and M (mass in kilograms) represent the motor, where P represents power output and V represents volume. Power density is a critical parameter when assessing the effectiveness and efficacy of electric motors, particularly in applications where weight and space constraints are substantial, as in the case of portable devices and EVs. When volume or mass is insufficient to generate power, a motor with a higher power density can accomplish this, which is advantageous for applications where weight and size restrictions are of the utmost importance [75, 76].

b) Criteria 2: Efficiency (η)

In the realm of electric motors, efficiency (η) denotes how the motor transforms electrical input power into mechanical output power with optimal effectiveness. This critical parameter is denoted as a percentage and is utilized to evaluate the performance of electric motors. The formula for calculating efficiency is:

$$\eta = \frac{P_{Output}}{P_{Input}} \tag{21}$$

η represents the motor's efficacy. The power supply to the motor is denoted by P_{Input} and P_{Output}, both measured in watts [77]. Efficiency is critical when choosing electric motors, particularly for energy-conserving applications such as industrial apparatus, appliances, and EVs. An increased efficacy of a motor results in decreased electrical energy consumption and waste heat generation, promoting overall energy conservation and mitigating environmental harm.

c) Criteria 3: Controllability (C)

In the context of electric motors, the term "controllability" refers to the ease and accuracy with which the behavior of the motor may be changed and controlled by the user. It covers various topics, including the motor's responsiveness to control inputs, dynamic properties, and the system's overall controllability. Although controllability is frequently a qualitative feature, several quantitative measurements can be considered in various applications. The degree to which a motor reacts to control signals, such as input voltage or current, is an important aspect of its degree of controllability. The motor's dynamic response to changes in control signals is referred to as its dynamic behavior, and it plays an important part in the controllability of the system. The equations that govern the dynamic behavior of the motor can be fairly complex. Differential equations are often used to represent these equations since they reflect the relationship between input and output over time [47].

d) Criteria 4: Reliability (R)

In the context of electric motors and systems, "reliability" refers to the motor's ability to perform its intended function consistently and predictably over a given period and in line with a set of predetermined operating parameters. It is critical to consider when considering a motor's performance and suitability for a specific application. In the context of electric motors, dependability is often characterized by the device's longevity and the frequency with which operational breakdowns occur [78]. It can be influenced by factors like Mean Time Between Failures (MTBF) and failure rate. External factors such as MTBF and failure rate may impact it.

The MTBF metric is frequently employed to quantify reliability. It signifies the mean duration of operation for which a motor fails. An increased MTBF signifies enhanced dependability [79].

$$MTBF = \frac{TOTAL_{Operating\ Time}}{Number\ of\ Failures} \tag{22}$$

e) Criteria 5: Technological (T)

The technological component may include innovative manufacturing processes, sophisticated materials, or novel designs, among other elements, contingent on the specific context. A particular equation about technological aspects might lack universal applicability [80].

f) Criteria 6: Cost (C)

The cost can be represented as:

$$C = C_{Initial} + C_{Operational} \tag{23}$$

where, C is the overall cost, $C_{Initial}$ is the initial cost of the motor, $C_{Operational}$ is the operational cost over the motor's lifecycle.

It is crucial to acknowledge that the following equations have been simplified and may necessitate modification in accordance with the unique specifications and attributes of the electric motor selection procedure in your specific application. In addition to mathematical equations, qualitative factors such as dependability, controllability, and technological aspects frequently necessitate a comprehensive evaluation [81].

The decision matrix utilized to assess four distinct EV motors (Motor 1, Motor 2, Motor 3, and Motor 4) using six criteria denoted as C1 through C6 is presented in Table 4. The performance scores assigned to each motor are denoted by the numerical values in each cell for the corresponding criterion. A greater score signifies superior performance. Technological maturity (C6), power density (C1), controllability (C2), efficiency (C3), dependability (C4), and cost (C5) are the criteria. Motor 2 exhibits remarkable performance across the board, emphasizing efficiency, controllability, and technological advancement significantly. Motor 3 performs admirably, nevertheless, concerning power density and dependability. The Decision Matrix presents an all-encompassing graphical depiction of the performance of each motor concerning the predetermined criteria. This process enables a thorough assessment and allows decision-makers to choose the most suitable vehicle for a specific purpose, considering their individual goals and preferences.

Table 5 presents the Normalized Decision Matrix, a derivative of the original Decision Matrix. The purpose of generating this matrix is to ensure a uniform collection of scores that can be exploited to evaluate and equate the performance of four different EV motors (Motor 1, Motor 2, Motor 3, and Motor 4) concerning six criteria (C1 through C6). The normalization process involves dividing every score in the Decision Matrix by the column containing the highest value. The data are rescaled to a range of 0 to 1 during the normalization process; the greatest score achieved for each criterion is denoted by 1. Motor 1, with a normalized Power Density (C-1), demonstrates the maximum power density among the evaluated motors, as its score is 1. Utilizing the Normalized Decision Matrix enhances the fairness of the comparison by emphasizing the comparative merits and demerits of each vehicle according to the predetermined criteria while preventing any influence from the scale or range of the initial scores. The standardized representation of EV motor performance facilitates the comprehension and comparison of various motors' performance by decision-makers, thereby aiding them in identifying the most appropriate solution in accordance with their specific priorities.

Table 4. Decision matrix for 4 different EV motors

Alternatives	C1	C2	C3	C4	C5	C6
Motor 1	2.5	2.5	5	3	5	4
Motor 2	3.5	3.5	5	5	5	5
Motor 3	5	5	4	4	4	3
Motor 4	3.5	3.5	3	5	4	4

Table 5. Normalized decision matrix

Alternatives	C1	C2	C3	C4	C5	C6
Motor 1	1	0.5	1	0.6	1	0.8
Motor 2	0.7142	0.7	1	1	1	1
Motor 3	0.5	1	0.8	0.8	0.8	0.6
Motor 4	0.7142	0.7	0.6	1	0.8	0.8

An indispensable element of the MCDM procedure, Table 6 is also referred to as the Weighted Normalised Matrix. In order to generate the weighted scores for the specified criteria (C1 to C6), the normalized performance ratings from the Normalised Decision Matrix are integrated with the weights assigned to each criterion for each alternative (in this case, EV motors). Multiplying each designated weight for a given criterion by its corresponding standardized score yields the calculation. The Power Density (C1) weighted score is computed in Motor 1 through the multiplication of the designated weight (16.67%) by the normalized score (0.1667). Iteratively applying the procedure to each criterion generates a set of weighted scores to illustrate each criterion's relative importance in the decision-making process. Motor 2, Motor 3, and Motor 4 each utilize the same methodology. The Weighted Normalized Matrix is an essential instrument when assessing the comprehensive performance of each alternative using the designated criteria and weights. The results facilitate a definitive assessment of how each EV motor corresponds with the decision-maker's preferences. A comprehensive and informed decision-making process is guaranteed through a systematic approach that considers both the ascribed significance of each criterion and the standardized performance.

Table 6. Weighted normalized matrix

Alternatives	C1	C2	C3	C4	C5	C6
Motor 1	0.1667	0.083	0.1667	0.1	0.1667	0.1333
Motor 2	0.119	0.1166	0.1667	0.1667	0.1667	0.1667
Motor 3	0.083	0.1667	0.1333	0.1333	0.1333	0.1
Motor 4	0.119	0.1166	0.1	0.1667	0.1333	0.1333

Table 7. The CPS and alternative ranking in descending order

Rank	SAW	
	Alternative	CPS
1	Motor 1	0.8164
2	Motor 4	0.7689
3	Motor 3	0.7496
4	Motor 2	0.7357

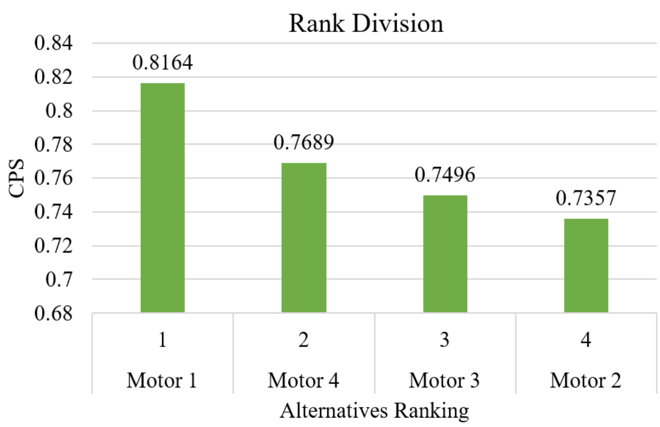


Figure 5. Plot for the CPS

The final outcomes of the decision-making process utilizing the SAW method are presented in Table 7. The rank distribution for these outcomes is illustrated in Figure 5. In terms of CPS, the various EV motors (Motor 1, Motor 2, Motor 3, and Motor 4) are presented in descending sequence. Motor 1 has the greatest rank, with a CPS score of 0.8164, indicating the best overall performance compared to the other criteria under consideration. Motor 4 is close behind Motor 1, ranking second with a CPS rating of 0.7689, showing solid performance but somewhat lower than Motor 1. Motor 3 is rated third with a CPS (cycles per second) value of 0.7496, and Motor 2 is ranked fourth with the lowest CPS value of 0.7357. The ranking order provides a distinct and prioritized comprehension of the performance of EV motors to decision-makers. This assists in determining which option is most suitable given the predetermined criteria and their respective weights.

4.2 Validation using TOPSIS

Before selecting motors, the following criteria are utilized to generate the decision matrix, to which weights are subsequently assigned according to their significance. Table 8 presents the weights assigned to various criteria.

Table 9 looks to be a decision matrix utilized in the TOPSIS method, which is a way for making multi-criteria decisions. In this matrix, the rows represent several alternatives (Motor 1 to Motor 4), and the columns reflect various criteria (C1 to C6) used to evaluate these alternatives. Each cell's values represent a single alternative's performance or score in relation to a certain criterion. For example, Motor 1 has scores of 4, 5, 4, 5, 5, and 3 for criteria C1 through C6. The bottom row labeled "Sum" shows the aggregated performance of all alternatives across each criterion. Subsequent computations in the TOPSIS method are determined using these aggregates as input. These computations consist of normalization, identification of positive and negative ideal solutions, computation of the approach to the ideal solution, and weighted normalized decision matrix determination. In conclusion, proximity ratings assist in evaluating alternatives according to their comprehensive performance across the specified criteria.

Table 8. Assigning the weights for different criteria

Criteria	C1	C2	C3	C4	C5	C6
Weights	0.4	0.2	0.3	0.1	0.2	0.2

Table 9. Decision matrix TOPSIS

Attributes	C1	C2	C3	C4	C5	C6
Motor 1	4	5	4	5	5	3
Motor 2	3	4	5	4	3	5
Motor 3	2	3	5	4	4	2
Motor 4	2	2	3	3	2	4
Sum	5.744	7.348	8.660	8.124	7.348	7.348

Table 10 depicts the normalized choice matrix using the TOPSIS technique. Each column in this matrix contains a normalized score for a particular alternative (Motor 1 to Motor 4) in relation to a certain criterion (C1 to C6). Normalization is an important stage in TOPSIS because it guarantees that the scores from various criteria are uniform, allowing for a fair comparison. Higher normalized scores indicate better performance. For example, Motor 1 normalized scores across criteria vary from 0.369 to 0.696, indicating its performance on a scale of 0 to 1.

Similarly, the normalized scores for Motor 2, Motor 3, and Motor 4 are displayed. The normalized values are utilized as the basis for subsequent procedures in TOPSIS, culminating in ranking alternatives according to their overall performance across the specified criteria. This includes the weighted normalized decision matrix computation and identifying positive and negative ideal solutions.

Table 10. Normalized decision matrix

Attributes	C1	C2	C3	C4	C5	C6
Motor 1	0.696	0.680	0.461	0.615	0.615	0.369
Motor 2	0.522	0.544	0.577	0.492	0.369	0.615
Motor 3	0.348	0.408	0.577	0.492	0.492	0.246
Motor 4	0.348	0.272	0.346	0.369	0.246	0.492

Table 11 shows the weighted normalized choice matrix, an important intermediate step in the TOPSIS technique. Each cell in this matrix represents an alternative (Motor 1 to Motor 4) or criterion (C1 to C6). The values in the table are calculated by multiplying the normalized scores from the previous step by the weights allocated to each criterion. These weights indicate the relative importance of each criterion in the decision-making process. The positive and negative ideal solutions, denoted in the bottom rows as "V^{+}" and "V^{-}", were obtained by locating the highest and lowest values for each criterion across all possible outcomes. A positive ideal solution represents optimal efficiency, whereas a negative ideal solution represents the bare minimum of performance. These solutions are utilized during the final phases of TOPSIS when the distances between the beneficial and detrimental ideal solutions are calculated in order to determine the alternatives by their proximity to the ideal solution.

Table 12 shows the TOPSIS technique results, summarising the calculated performance scores for each alternative (Motor 1 to Motor 4). The columns "Si+" and "Si-" show the distances between each alternative and the positive (ideal) and negative (anti-ideal) solutions, respectively. The Si+ values represent the proximity of an option to the positive ideal solution, with lower values indicating greater performance. In contrast, Si- values are near the negative ideal solution, with greater values indicating worse performance. The final column, "Performance Score (PI)," is calculated by comparing Si- to the total of Si+ and Si-, yielding an overall performance score. Following this, the alternatives are assessed based on their PI values, where lesser scores indicate superior performance compared to the ideal options. Motor 1 is the most favorable option in this context due to its superior performance score of 0.609. Motor 2, Motor 3, and Motor 4 follow in decreasing performance order. The TOPSIS-based rank allocation of motors is depicted in Figure 6.

Table 11. Weighted normalized decision matrix

Attributes	C1	C2	C3	C4	C5	C6
Motor 1	0.278	0.136	0.138	0.061	0.061	0.036
Motor 2	0.208	0.108	0.173	0.049	0.036	0.061
Motor 3	0.139	0.081	0.173	0.049	0.049	0.024
Motor 4	0.139	0.054	0.103	0.036	0.024	0.049
V+	0.278	0.054	0.173	0.036	0.061	0.061
V-	0.139	0.136	0.103	0.061	0.024	0.024

Table 12. Ideal maximum and ideal minimum Euclidean distances

Attributes	(S_i^{+})	(S_i^{-})	Performance Score (P_I)
Motor 1	0.092	0.143	0.609
Motor 2	0.089	0.102	0.534
Motor 3	0.142	0.088	0.384
Motor 4	0.155	0.085	0.35418

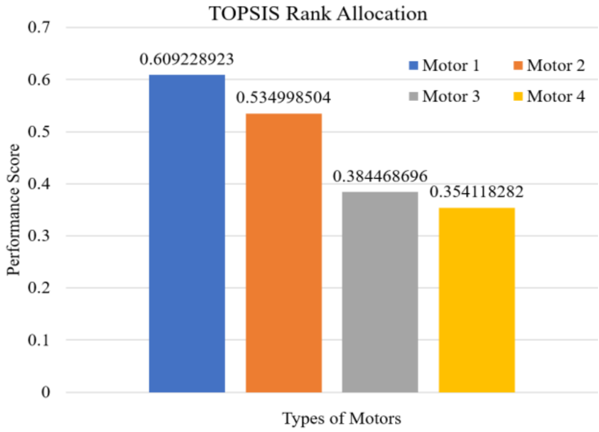


Figure 6. Rank allocation based on performance score

4.3 Validation using AHP

A pairwise comparison matrix delineating the relative importance of six criteria (C1 through C6) in a decision-making scenario is presented in Table 13. Every individual element within the matrix represents the degree of preference that one criterion has over another. As an illustration, a score of 5.0 signifies that C2 is five times more critical in importance than C1. The diagonal elements, denoted as C1 versus C1, each possess a value of 1.00, indicating that each criterion is equally important in and of itself. The aggregate significance of each criterion is quantified by the sum of the values in each column; greater sums denote greater significance. With a sum of 20.00, C2 has the highest total sum in this matrix; therefore, it is considered the most essential criterion. Pairwise comparisons are fundamental elements of methodologies such as the AHP, which encompasses a systematic approach to decision-making through capturing and quantifying subjective assessments regarding the relevance of criteria.

The normalized values of pairwise comparisons for six criteria (C1 to C6) are included in the standardized matrix shown in Table 14. The relative importance of each criterion is represented in this matrix in a standardized and comparable fashion. The proportionate significance assigned to each criterion relative to the others is denoted by the scaled values of the matrix, which range from 0 to 1. For example, greater significance is denoted by an increased value. The percentages of weight placed on each criterion represent how much it influences the overall decision-making process. C6 holds the most conspicuous position in this representation, weighing 35.3%. C1, in turn, is positioned at a distance of 26.1%. By enabling a consistent evaluation of criteria, standardization improves understanding of the relative importance of each criterion in the context of the given decision and streamlines the decision-making procedure.

Table 15 appears to be related to the AHP, which is often used for decision-making with numerous criteria. Each row of the matrix, from C1 to C6, has normalized scores indicating the relative relevance of one criterion vs another. The "SUM" column averages the numbers in each criterion's column to provide an overall relevance assessment. The following column, "SUM/Weight," shows the average relevance of each criterion. The eigenvalue (λMax) of 0.07 is the major eigenvector's biggest eigenvalue.

Regarding consistency, the CI is reported as -1.18, while the CR is given as -0.95. It is vital to note that the CR value for larger matrices is normally less than 0.1 to maintain a fair level of consistency in the decision-making process. The negative values for CI and CR may be unorthodox; nonetheless, the major aim is normally to ensure the CR remains below 0.1 for dependable outcomes. In Figure 7, according to the weights, a decision is formed that Criteria (C6) Cost is the most important in the current market scenario, followed by Criteria (C1), Criteria (C5), Criteria (C3), Criteria (C4) and last Criteria (C2) at least priority. But in terms of EV parameters, all these criteria are equally important for the motor selection.

Table 13. Pairwise comparison matrix

	Criteria					
Description	**C1**	**C2**	**C3**	**C4**	**C5**	**C6**
C1	1.00	5.00	3.00	4.00	2.00	0.50
C2	0.20	1.00	0.50	0.33	0.25	0.20
C3	0.33	2.00	1.00	2.00	1.00	0.33
C4	0.25	3.00	0.50	1.00	0.50	0.25
C5	0.50	4.00	1.00	2.00	1.00	0.33
C6	2.00	5.00	3.00	4.00	3.00	1.00
Total ∑	4.28	20.00	9.00	13.33	7.75	2.62

Table 14. Standardized matrix

Criteria	C1	C2	C3	C4	C5	C6	Weightage (%)
C1	0.23	0.25	0.33	0.30	0.26	0.19	26.1%
C2	0.05	0.05	0.06	0.03	0.03	0.08	4.8%
C3	0.08	0.10	0.11	0.15	0.13	0.13	11.6%
C4	0.06	0.15	0.06	0.08	0.06	0.10	8.3%
C5	0.12	0.20	0.11	0.15	0.13	0.13	13.9%
C6	0.47	0.25	0.33	0.30	0.39	0.38	35.3%

Table 15. Worksheet of CI and CR values

Criteria	C1	C2	C3	C4	C5	C6	SUM	SUM/Weight
C1	0.26	0.24	0.35	0.33	0.28	0.18	2.65	1.10
C2	0.05	0.05	0.06	0.03	0.03	0.07	0.29	0.06
C3	0.09	0.10	0.12	0.17	0.14	0.12	0.65	0.05
C4	0.07	0.14	0.06	0.08	0.07	0.09	0.58	0.06
C5	0.13	0.19	0.12	0.17	0.14	0.12	1.14	0.08
C6	0.52	0.24	0.35	0.33	0.42	0.35	2.21	0.06
λ_{Max}					0.07			
C.I					-1.18			
C.R.					-0.95			

Note: The consistency ratio value is acceptable below 0.1 for the larger matrices

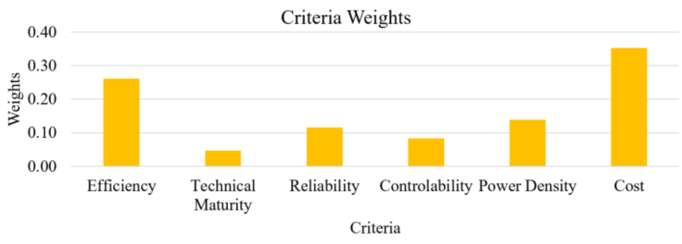


Figure 7. Weights of criteria

5. MCDM TECHNIQUES LIMITATIONS

SAW, TOPSIS, and AHP are effective MCDM strategies for supporting complicated scenario decision-making. However, like any other approach, they have a set of limits. One key disadvantage of these systems is that they are prone to the initial subjective judgments provided by the individuals making the decisions [82]. Pairwise comparisons in AHP, for example, necessitate those participants designate numerical values to the relative importance of alternatives and criteria, which can be difficult due to ignorance or personal biases. The precision of the ultimate determination is substantially contingent upon the caliber and uniformity of these assessments. Likewise, within SAW and TOPSIS, the determination of weights and the normalization process entail subjective judgments, and even minor discrepancies in these parameters can result in notably distinct conclusions [83]. An additional significant limitation pertains to the presumption of autonomous criteria, which might not consistently hold when confronted with true-life dilemmas. Criteria can occasionally be interconnected, so alterations to one criterion may influence others. Frequently, MCDM approaches operate under the assumption that the criteria are autonomous from each other. This supposition can lead to the abandonment of intricate interrelationships that possess the capacity to impact the decision-making process [84]. Such oversimplification may result in less-than-ideal consequences, particularly when applied to dynamic and complex environments.

Furthermore, the computing complexity of these methods may limit their effectiveness. The computation of eigenvectors and eigenvalues in AHP is a computationally costly procedure, especially when dealing with large decision matrices. Furthermore, SAW and TOPSIS necessitate many mathematical computations, which become increasingly difficult as the number of choices and criteria analyzed grows. This may provide a pragmatic problem when presented with enormous datasets or the necessity for quick decision-making [85, 86].

Additionally, these methods are constrained by the assumption of linearity. The assumptions made by SAW, TOPSIS, and AHP generally posit linear associations between criteria and alternatives. Although this simplification contributes to improved computational efficiency, it might not faithfully depict the intricacies of real-life decision scenarios, which frequently involve non-linear relationships. Inaccurate assessments may result from the inaccurate representation of decisions impacted by non-linear factors [87]. Moreover, MCDM techniques may encounter difficulties when encountering ambiguous or imprecise data. Numerous decision problems are inherently uncertain, and methods that rely on precise numerical inputs may fail to sufficiently account for the intrinsic vagueness or ambiguity in decision data. This constraint assumes particular significance in decision-making situations where data is limited, insufficient, or susceptible to substantial fluctuations. An additional obstacle emerges due to the possible lack of consistency in decision-maker preferences [88]. As an illustration, the CR is employed by AHP to evaluate the consistency of pairwise comparisons. However, achieving absolute consistency in practice proves challenging; decision-makers may inadvertently introduce inconsistencies into their assessments. The existence of these inconsistencies possesses the capacity to compromise the reliability of the decision model and erode the caliber of the results [89].

Moreover, it is common for these MCDM techniques to operate under the assumption that preferences remain constant over time, thereby disregarding the possibility of shifts in decision-makers preferences or the ever-changing characteristics of the decision environment [90]. Preferences are susceptible to change due to many factors, including external circumstances, newly acquired information, and organizational priorities. Neglecting to consider these ever-changing elements may lead to decisions that are superseded or less under the present objectives of the organization. Ethical and social considerations are not explicitly integrated into the development of these methodologies. MCDM techniques emphasize quantitative factors and might not sufficiently consider ethical or qualitative considerations when making decisions [91]. For example, inadequate consideration of social and environmental consequences, cultural subtleties, and ethical ramifications of choices could result in omitting vital ethical aspects.

In summary, although MCDM techniques such as SAW, TOPSIS, and AHP offer valuable decision support frameworks, their implementation is not devoid of constraints [92]. Critical drawbacks include sensitivity to subjective judgments, assumptions of independence and linearity, computational complexity, difficulties in managing uncertainty, and disregard for dynamic preferences. Professionals must acknowledge these constraints to employ these approaches prudently. They should augment them with qualitative observations and consistently improve and validate models to fortify their resilience across various decision-making scenarios [93, 94].

5.1 Future recommendations

MCDM is an exceptional approach for addressing complex decision-making problems involving numerous diametrically opposed criteria. The traditional MCDM approach referred to as the SAW method, rates alternatives according to the performance of criteria that are assigned weights. As society progresses, several suggestions can be put forth to enhance the effectiveness and practicality of the SAW methodology across diverse decision-making procedures [95]. In the first place, technological progress has enabled the integration of SAW with other nascent technologies, including AI and ML. This results in a multitude of benefits. SAW could become more dynamic and adaptable by incorporating predictive analytics into its design. This will allow decision-makers to react in real-time to changing environmental conditions. Combining regular MCDM procedures with cutting-edge technologies can improve decision-making accuracy and efficiency. This is especially useful in firms requiring immediate flexibility to change market trends.

Furthermore, resolving uncertainties and including risk management strategies, which include the SAW approach, are critical to the future of MCDM [96]. Ambiguity & unpredictability are usually identified as defining aspects of the decision-making environments. Developing robust models that effectively manage uncertainty, unpredictability, and risk should be the primary objective of forthcoming SAW research and applications. To offer decision-makers a comprehensive comprehension of potential outcomes and their associated risks, this involves incorporating probabilistic methodologies, scenario analysis, and sensitivity analysis into the SAW framework. The SAW approach can be modified to incorporate ecological, social, and economic factors when environmental and sustainable decision-making is considered. Decision-makers require tools capable of conducting comprehensive analyses of the environmental, social, and economic repercussions of different alternatives, given the current global predicament, which includes the acceleration of climate change and the depletion of natural resources. Subsequent investigations should explore alternative methodologies for incorporating sustainability considerations into the SAW process. This facilitates decision-makers ability to make selections that align with enduring environmental and social goals [97].

Collaborative decision-making is an additional domain in which the SAW technique may encounter future expansion. Problems involving decision-making are frequently complex and involve many parties with varying interests. To optimize the advantages offered by this methodology, subsequent SAW implementations ought to explore alternative methods of engaging a diverse array of stakeholders in the deliberative procedure. This improves the judgments' validity and ensures that a broader range of perspectives and values are considered during the assessment process. Integrating SAW with other MCDM approaches is a potentially fruitful field for further study [98]. Hybrid models, which combine the benefits of many methodologies, can provide more robust and nuanced decision support. Researchers should look into how SAW can be efficiently combined with other methods like AHP, TOPSIS, and ELECTRE to create hybrid models that benefit from the advantages of each methodology. Creating user-friendly software and decision support tools is one of the future recommendations for utilizing the SAW technology. This refers to the method's practical implementation. The ease of access to MCDM tools across various enterprises and decision settings is critical for their widespread adoption. User interfaces should be built to make the input of criteria, weights, and performance data as simple as possible while delivering clear and intelligible results [99].

5.2 Future scope of electric motors for sustainable transportation

A wealth of opportunities for innovation and optimization exists in EVs and sustainable transportation, as evidenced by the extensive research conducted on electric motor optimization for environmentally friendly EVs. Subsequent research endeavors might explore enhancing motor performance by integrating cutting-edge technologies such as intelligent control systems, enhanced materials, and artificial intelligence [100]. Electric motor efficiency and power-to-weight ratios could be greatly improved using novel materials, such as advanced alloys or composites, and exploring 3D-printed components. Further optimization of electric motor functions, guaranteeing dynamic responsiveness to driving conditions, and maximizing energy economy may be possible by integrating AI algorithms for real-time performance monitoring and adaptive control systems [101]. In the future, EV sustainability may surpass basic motor economy concerns. The comprehensive life cycle of an EV is examined to mitigate its environmental footprint, encompassing activities such as responsible waste disposal or recycling and raw material extraction. Coordination between material scientists, environmental engineers, and recycling specialists would be required to implement a closed-loop system following circular economy principles [102].

Electric motor optimization, intelligent transportation systems, and vehicle-to-everything (V2X) communication are all areas that could be investigated in the context of connected and autonomous EVs, which could be the focus of the study. Better traffic management, less congestion, and more efficient use of energy could result from taking this strategy. Exploring the convergence of EVs with smart grids is also crucial, as is investigating how improved electric motors might contribute to grid stability, demand response, and energy storage options, thereby encouraging a more sustainable energy ecosystem [103]. The advent of Industry 4.0 technology presents doors for new manufacturing procedures, and the study could look into adopting smart manufacturing processes for electric motor production. The creation and customization of electric motors could benefit from investigating techniques like additive manufacturing and digital twins, which can streamline the manufacturing process, decrease waste, and speed up the prototype process [104]. Potential future extensions of the study may encompass socio-economic assessments, legislative recommendations, and technological advancements. A comprehensive shift towards intelligent, eco-friendly EVs necessitates knowledge of the policy frameworks necessary to incentivize sustainable practices in the automotive sector and an evaluation of the economic feasibility of adopting optimized electric motors on a large scale. The development of strategies that support global sustainability goals could be enhanced through cooperation with industry participants, policymakers, and economists. Ultimately, research into the optimization of electric motors for intelligent, eco-friendly EVs has a vast and multifaceted future [105]. The research possesses the capacity to make a substantial contribution to the continuous development of sustainable transportation through the integration of emerging technologies, examination of the complete life cycle of EV components, exploration of the intersections between connected and autonomous systems, adoption of advanced manufacturing techniques, and incorporation of socio-economic factors. This all-encompassing strategy keeps the study cutting edge, directing the development of EV technology toward a more sustainable and performance-driven future [106].

5.3 Implications of the study for providing sustainable energy

Exploring the field of MCDM procedures in sustainable energy is analogous to beginning a voyage through a terrain filled with various possibilities and challenges. These methods, which have become influential tools in decision science, are essential for dealing with the complex network of factors related to sustainable energy solutions. The essence of MCDM resides in the capacity to concurrently evaluate and harmonize several factors, thereby converting decision-making processes into a refined art that smoothly corresponds to the intricacies of the sustainable energy domain [107].

The consequences of employing MCDM techniques are especially significant when striving to achieve sustainable energy objectives, as the risks involved are substantial, and the decisions made have enduring effects on our environment and future welfare. Imagine a scenario where the world is actively working towards shifting away from its reliance on fossil fuels and instead embracing a balanced combination of renewable energy sources [108]. MCDM techniques serve as a dependable instrument that aids decision-makers in navigating the intricate array of alternatives. These methodologies empower decision-makers to contemplate the environmental and social ramifications of their choices in addition to the economic ones. One significant benefit of MCDM is its ability to provide a systematic structure for evaluating numerous possibilities. Envision oneself at the juncture of an extensive array of renewable energy systems, including but not limited to solar, wind, and hydro. MCDM enables a comprehensive analysis by considering societal acceptance, carbon footprint, and energy efficacy [109]. It is akin to possessing a multidimensional lens that enables decision-makers to comprehend the comprehensive consequences of their decisions. Being new to this sector, I am amazed by how MCDM converts potentially daunting decisions into an organized, well-informed procedure [110]. Let's examine the concept of Pareto efficiency in MCDM, which I find fascinating due to its elegant and practical nature. Pareto efficiency is achieved when an option is considered ideal and cannot be improved without hurting another alternative. Depicting solutions that provide comprehensive benefits to the environment, society, and economy is a critical undertaking in the pursuit of sustainable energy; thus, this notion is extremely significant. After initially confronting its foundational principles, progressively comprehending the profound ramifications of Pareto efficiency has proven to be an intellectually stimulating and enlightening voyage [111].

5.4 Sustainable development goals (SDGs) for EV

EVs are critical in facilitating sustainable development goals (SDGs), including features connected to the environment, economy, and civilization. By increasing the use of renewable energy sources and decreasing reliance on fossil fuels, EVs contribute to generating affordable, environmentally friendly energy. This satisfies the criteria outlined in SDG 7. SDG 9, which encompasses industry, infrastructure, and innovation, is enhanced by advocating for innovation in the automotive industry. EVs are of utmost importance in urban settings for achieving Sustainable Development Goal 11, as they reduce air pollution and greenhouse gas emissions, thereby fostering the development of sustainable communities and cities [112]. SDG 13 objectives for climate action are furthered by the extensive adoption of EVs, which significantly mitigate the adverse effects of climate change. Following SDG 12, the production and operation of EVs adhere to responsible consumption and production patterns. Employment opportunities are also created as a result of the expansion of the EV industry, which contributes to the attainment of SDG 8 (decent work and economic growth). Enhanced EV utilization positively impacts public health and contributes to SDG 3 [113]. Providing populations that are disproportionately affected by air pollution with access to cleaner alternatives through the use of EVs is one way in which accessible and sustainable transportation options contribute to the reduction of inequalities SDG 10. Although only indirectly, the transition to environmentally responsible modes of transportation, such as EVs, correlates with SDG 16 by supporting environmental sustainability and ethical business practices. Overall, the incorporation of EVs into transportation systems plays a varied role in the advancement of interconnected SDGS, contributing to a future that is more sustainable and inclusive [114]. The United Nations has identified a set of SDGs, and EVs play a significant part in helping to contribute to those goals. Several important SDGs can be addressed more effectively by promoting the widespread usage and acceptance of EVs). An examination of the EV's role in advancing sustainable development is presented here. The SDGs that are pertinent to the development of EVs are depicted in Figure 5. These SDGs will play an essential part in the process.

6. CONCLUSIONS

In conclusion, utilizing the SAW technique has resulted in the provision of final decision-making outcomes in the process of selecting motors for EVs. According to the ranking based on CPS, Motor 1 has been determined to be the best-performing choice. It has received a CPS score of 0.8164, which indicates that it has the best overall performance among the parameters considered. The CPS value of Motor 4 is 0.7689, which places it in second place, closely followed by Motor 3, which holds the third position, and Motor 2, which holds the fourth position. The decision-makers are provided with a clear and prioritized understanding of the performance of the motors through this ranked order, which assists in selecting the most suitable alternative based on the criteria set and the weights that correspond to them. In addition, the decision-making process is reinforced by the TOPSIS method, which generates calculated performance scores for every alternative (Motor 1 through Motor 4). This enhances the efficacy of the decision-making process as a whole. Motor 1 is the preferred option based on their respective performance levels, with the highest PI of 0.609. Motor 2, Motor 3, and Motor 4 are ranked in descending performance sequence after that. This underscores the importance of incorporating diverse methodologies to develop a comprehensive decision-making strategy. By incorporating the AHP methodology into the decision-making process, the significance of several factors has been shed light on. Given the present market conditions, the AHP's criteria evaluation establishes Cost (C6) as the most pivotal element in the ranking. The factors designated C1, C5, C3, C4, and C2 are presented in descending order of priority in the sequence above.

Nevertheless, a thought-provoking contrast emerges when scrutinizing the EV specifications. Each of these components is considered equally significant in ascertaining the motor utilized. The contentious nature of this issue has brought to light the contextual sensitivity of the decision-making process, in which the significance of criteria may differ according to the particular requirements of a given sector or industry. Integrating SAW, TOPSIS, and AHP methodologies provides decision-makers with a comprehensive and nuanced approach to selecting motors for EVs. In summary, this motor selection methodology offers several benefits. In contrast to SAW, which computes a basic ranking utilizing Composite PI, TOPSIS presents an alternative viewpoint by implementing Performance Scores and prioritizing alternatives according to their proximity to optimal solutions.

On the contrary, AHP assigns significant weight to the idea that the applicability of criteria may differ depending on the circumstances. Those in positions of authority can make more informed and situation-dependent decisions when they recognize the results produced by these methodologies. The reason for this is the ever-changing environment surrounding the selection of motors for EVs. The findings derived from the SAW and TOPSIS methodologies are inappropriate, as demonstrated by the analysis. Based on these results, BLDC motors are the most viable choice for EVs. The order above of preference is then applied to the induction motor, PMSM, and SRM. On the contrary, the motor selection process in the current EV technology market has become prohibitively complex because the AHP method has produced the most optimal prioritization criteria.

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