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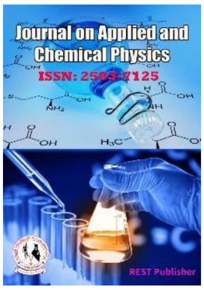

The Selection of Li-Ion Batteries Used in Electric Vehicles (EV)'s Using the TOPSIS Method

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Abstract: *This study focuses on choosing lithium-ion cells for electric vehicles in order to increase its functionality and effectiveness. In the selection process, variables including energy density, longevity, cost, or environmental impact are considered. To determine which battery technology is best for EV applications, many different types of batteries and their properties are examined. The research intends to increase EV performance overall, decrease charging time, and increase driving range. The research advances environmentally friendly transport options and broadens the shift to electric mobility. For decision-makers, producers, and other industry participants, the study offers useful insights. Introduction: Lithium-ion battery selection for electrically powered cars is a crucial choice that has an impact on both the individual vehicle's efficiency and overall performance. The selection of battery technology has a direct impact on variables like Distance, charging time, and longevity because batteries are the main source of power for EVs. Power weight, cycle life, safety, price, and environmental effect are important factors to consider when choosing a battery. To achieve optimal performance, a longer driving range, and customer happiness, these aspects must be in balance. The choice of lithium-ion batteries will have a significant impact on how sustainable transportation develops in the future as the EV industry grows. Research significance: The ability of Li-ion batteries to increase overall performance and dependability as an environmentally friendly transport solution underlies the research significance of choosing them for electric vehicles. Effective battery selection can address major issues with EV adoption by increasing driving range, cutting down on charging time, and improving overall energy efficiency. Additionally, improvements in battery technology help to lessen environmental impacts and carbon emissions. The choice of affordable and dependable battery options is also essential to the commercial viability and general acceptance of EVs. The advancement of technology, innovation, and the shift to a more environmentally friendly transportation system can all be sped up by this kind of research.*
Method: A multi-criteria decision-making process called TOPSIS (process of Prioritisation through Similarity to Ideal Solution) is used to assess and rank alternatives depending on many factors. To evaluate their relative proximity, options are compared with a superior option and a worse solution. a combination of similarity to the most effective answer and closeness to the worst solution, the approach determines an evaluation of performance for each alternative. The option with the greatest score is regarded as the best option. In difficult decision-making scenarios, TOPSIS offers a methodical method for objectively assessing and ranking alternatives. Alternate parameters: Lithium- Cobalt Oxide Battery (LiCoO2) – LCOB, Lithium-Manganese Oxide Battery (LiMn2O4)-LMOB, Lithium-Nickel Manganese Cobalt Oxide Battery (LiNiMnCoO2)-LNMCOB, Lithium Iron Phosphate Battery (LiFePO4)-LFPB, Lithium-Titanate Battery (Li4Ti5O12) LTOB. Evaluation parameters: Reliability, Safety, Specific power, Specific energy density, Price. Result: Lithium- Cobalt Oxide Battery (LiCoO2) – LCOB is in 5th rank, Lithium-Manganese Oxide Battery (LiMn2O4)- LMOB is in 4th rank, Lithium-Nickel Manganese Cobalt Oxide Battery (LiNiMnCoO2)-LNMCOB is in 3rd rank, Lithium Iron Phosphate Battery (LiFePO4)-LFPB is in 1st rank, Lithium-Titanate Battery (Li4Ti5O12) LTOB is in 2nd rank. Conclusion: the selection of li ion batteries used in electric vehicles (ev)'s Lithium- Cobalt Oxide Battery (LiCoO2) – LCOB is in 5th rank, Lithium-Manganese Oxide Battery (LiMn2O4)- LMOB is in 4th rank, Lithium-Nickel Manganese Cobalt Oxide Battery (LiNiMnCoO2)-LNMCOB is in 3rd rank, Lithium Iron Phosphate Battery (LiFePO4)-LFPB is in 1st rank, Lithium-Titanate Battery (Li4Ti5O12) LTOB is in 2nd rank.

Key words: *Reliability, Safety, Specific power, Specific energy density, LNMCOB.*

1. INTRODUCTION

Electric automobiles with batteries are progressively replacing those with internal combustion engines. However, because the research and creation of more efficient batteries is still ongoing, this is occurring at a far slower rate. The development of battery technology must adhere to tight specifications, including quick charging, high driving range, long battery life, and low cost. The most popular lithium-ion (Li-ion) batteries can deliver a respectable performance, but they are costly and have a limited lifespan. The performance, price, and lifespan of a battery are significantly influenced by the materials chosen for the electrodes. Based on the components used to create the electrodes, Li-ion batteries in use today are categorised. The issue in practise is that it is challenging for EV producers to select the finest Li-ion battery while making compromises An MCDM-based strategy for choosing of lithium-ion cells according to cathode/anode materials is proposed in this research, which is important for Ev's in order to choose the most suitable battery and optimise the price and performance of EVs [1]. The solar vehicle from Northern Regional University is powered by a lithium-ion battery pack. Fuji Laser Desert Rose, an in 1999 Global Solar Challenge WSC competitor. Why Li-ion batteries are preferable to silver-zinc batteries The administration of cells and cell protection boards are detailed, along with the construction methods used. Data from pre-race testing and during the race are shown, along with an analysis of the battery's coulombic & power capacities. Conclusion: For these kinds of traction applications, Li-ion batteries clearly outperform other commercially available batteries. High-performance electric vehicles can benefit from the use of lithium-ion Li-ion batteries. Li-ion batteries have the greatest amount of specific energy and the most charge-discharge cycles when compared to other batteries that can be recharged. The price is also fair. Because of this, Li-ion batteries [2]. Environmental problems brought on by conventional vehicles' emissions have sped up the use of batteries-powered cars also known as for urban transportation. The most likely battery technology for closely meeting the US Advance Battery Consortium's (USABC) minimal objectives for the commercialization of EVs is lithium-ion technology. EVs are powered by a variety of lithium-ion batteries, but the performance parameters associated with these cells have not yet been precisely defined in a comparable way. Considering their capabilities and usefulness as a power source in EVs, four kinds of frequently utilised lithium-ion batteries are reviewed in this article along with an analysis of their specifications. The findings can be utilised as standards for choosing lithium-ion batteries for electric vehicle (EV) battery control system (BMS) designs. In recent decades, investigators, supporters of the environment, and other groups have begun to pay more attention to the greenhouse gases that conventional automobiles release, particularly the environmentally conscious electric vehicles (EVs). Electricity is utilised to power electric motors and the fundamental components of a battery-powered EV, which is a significant property of EVs. It consists of a battery pack, a power converter, an electric motor, and a mechanical gearbox. When driving or regeneration, the energy flow can be either forward or backward. Depending on the source of power, Batteries electric automobiles (BEVs), electric hybrids (HEVs), hybrid electric vehicles with plug-in technology (PHEVs), solar electric vehicle (PEVs) and fuel cell cars (FCVs) are the main categories under which EVs fall. Due to its cutting-edge technology, battery packs that recharge have been extensively embraced as the primary power sources in EVs [3]. With the development of EVs, numerous charger strategies have been proposed, including unchanged flow (CTC), constant electricity (CC), constant power (CV), as well as constant current constant electricity (CCCV) battery charging strategies. The CCCV charging technique has historically been the most popular type. The power source is charged at CC during the CCCV charging procedure until the voltage hits the higher cut-off voltage. Up until the present level hits a predetermined minimum value, the battery will go through the CV charging procedure. Several strategies have been put forth by researchers to enhance battery charging efficiency. To find the most rapid charging method, they developed an Ant-Colony-System also known as the based algorithm, although the suggested multistage CC charging methodology did not account for the charging duration at each stage. Controller to alter the default charging mode for CVs. Surman suggested a fuzzy system genetic optimisation approach for recharging larger Ni Cd batteries for high power charging. Ullah et al. created a rapid battery charger for Ni Cd battery pack utilising National Proprietary Neural Network-based Neu Fuzz technology viewed the Li-ion battery as a grey system and used the grey prediction technique to develop a grey-predicted Li-ion battery charge system [4]. Enhance the factors that affect lithium-ion (Li-Ion) battery air cooling in electric vehicles (EVs). Investigated is a battery pack made from 150-cylinder Li-Ion battery cells enclosed in a PVC case. When the car is parked or ambient air is moving, a comparable number of pipes are employed in the power pack as a cooling medium for the battery. The factors affecting the battery's air cooling are investigated and optimised while taking into account their real-world limitations. The development of the goal function and the transfer unit number (NTU). Finally, the choice factors are optimised using a genetic algorithm technique. The study's findings indicate that by enlarging the battery's tubes' diameter and maintaining their internal air velocity, their NTU can be maximised a specific range. A generator, electric motor drive, battery, and an ultra-capacitor are used to power electric cars. Battery charging stations are connected to the mains. When in use, electric vehicles emit no greenhouse gases and have the potential for exceptional energy efficiency. The primary limitations of electric cars are problems with battery size and temperature management, a lack of charging stations, a lack of battery life, and high vehicle costs [5]. Raising the marketplace's share for electric vehicles (EVs) faces significant obstacles in terms of cost, efficiency, dependability, and safety. These problems are intimately related to how EVs store their energy. As the go-to battery for EVs, lithium-ion batteries have revolutionised the EV sector. This is a result of their exceptional qualities, which also include their capacity for rapid charging and discharging rates, high voltage, minimal self-discharge, and energy density. The engine and auxiliary components in EVs are powered by lithium-ion batteries that are coupled in series or parallel. However, the battery that uses lithium- may not operate to its full capacity when included in a battery pack for electric vehicles because of the EVs' working conditions. The incorporation of a battery powered by lithium-ion into this work for an EV Various battery chemistry, cell packing, wiring and oversight, thermal control, installation, and service and maintenance are some of the topics included in the investigation of the battery pack. As an additional benchmarking research, a lithium-ion, iron-phosphate cell with various cell packaging is used as a means of storing energy. This study offers fundamental recommendations for EV battery pack cell choice and cell integration [6]. Although the environmental viability of this practise is unknown, recycling spent batteries in communications base stations (CBSs) is a potential solution to get rid of large retired lithium-ion batteries (LIPs) in electric vehicles (EVs). This study compares the environmental effects of recovered EV LIBs, which with lead-acid battery packs (LABs) used in traditional energy storage facilities (ESSs) of CBSs using life cycle assessment (LCA). Economically based allocation techniques are employed in multifunctional systems. According to the LCA results, the environmental effects of recovered LIBs are primarily attributable to the production and recycling processes, whereas recycling of batteries can lessen these effects. Additionally, in all the chosen categories, with the exception of one, the secondary usage of EV LIBs had a smaller effect on the environment than the utilisation of LABs. A sensitivity analysis is carried out to evaluate the effects of cycle life, power sources, and two alternative allocation strategies on the outcomes. The usage of used LIBs with a 50/50 allocation scheme was found to have poor ecological performance and little advantage over the use of LABs. A more environmentally friendly energy mix and prolonging the useful life of disposable LIPs both greatly lessen environmental effects. This study offers suggestions for addressing the end-of-life management issue with EV LIBs, such as an end-of-life management platform, efficient supply chain integration, and hints for the ongoing "green" shift in the communications sector. [7]. A sensitivity analysis is carried out to evaluate the effects of cycle life, power sources, and two alternative allocation strategies on the outcomes. The usage of used LIBs with a 50/50 allocation scheme was found to have poor ecological performance and little advantage over the use of LABs. A more environmentally friendly energy mix and prolonging the useful life of disposable LIPs both greatly lessen environmental effects. This study offers suggestions for addressing the end-of-life management issue with EV LIBs, such as an end-of-life management platform, efficient supply chain integration, and hints for the ongoing "green" shift in the communications sector [8]. Forecasting and proper management of lithium-ion batteries in EV applications is the primary responsibility of BMS. The stability, reliability, security, or any aspect of the whole EV of the battery system can be directly impacted by a healthy state. Researchers and engineers are therefore eagerly awaiting an accurate calculation of SOH. A data-driven approach creates a model with enough test cycle data to predict cell change over the entire cycle with some chosen features rather than creating a battery ageing model using previous understanding of the cell's chemical mechanism. Additionally, free source datasets are what motivates the development of data-driven PHM. Machine learning algorithms frequently occur in the literature due to their nonlinear properties and improved capacity to adapt to complicated systems and complex interactions. To avoid random estimating mistakes from the network, a neural network and Markov chain were utilised to calculate the battery SOH. A lithium-ion battery's capacity decline and ageing process were modelled using an SVR. The model's RMSE was calculated and it was discovered to be 20mAh. a battery ageing model via GPR enhanced with covariance kernel function and similarity measurements of input data. This model's RMSE is roughly 1% [9]. Electric vehicles (EVs) frequently employ lithium-ion Because of its large battery capacity, high energy density, lengthy lifespan, and comparatively low self-discharge rate, batteries are very useful. For the purpose of supplying power as well as electricity for automobiles, thousands of photovoltaic cells are connected. a collection that creates a fantastic battery pack. A battery management system (BMS) is created to keep track of each cell and assess each component of the battery pack while taking safety management and efficient utilisation of numerous cells into account. In both diesel and gasoline vehicles, the state on charge (SoC) and remaining fuel are important baseline metrics. SoC estimation in battery packs differs from SoC estimation for battery cells, and the differences must be taken into account. Efficient & low-complexity estimation of costs for battery packs is usually challenging due to both intrinsic and extrinsic variability between cells. Using the "per-cell" method. Tesla's Model S has a sophisticated battery system made up of 95 series-connected battery modules. Because it primarily relies on filter-based estimate, this method has a significant computational cost and necessitates the replication of 96 filters. An very difficult assignment for the microcontroller in the BMS [10]. Electric cars with batteries for power (BEVs) are an important part of the mobility future. It is unclear what effects lithium-ion (Li-ion) battery manufacture, use, and disposal will have. Comparing the environmental impacts of BEVs with vehicles with gasoline or diesel engines (ICEVs) is therefore difficult. As a result, an in-depth life cycle assessment for Li-ion batteries and a flawless Epc of BEV-based motors were created. The analysis shows that the environmental costs are the same whether a gasoline-fueled electric-fueled BEV is employed. The battery is accountable for 15% of the overall environmental impact of electric drives, as determined by 99 environmental indicator points. a big contributor to the harm batteries do to the environment. This work offers a strong framework for comprehensive environmental evaluations of battery-powered electronic mobility [11]. The demand for energy security has raised interest in power produced from renewable sources, particularly solar and wind energy. However, storage of electricity (EES) is a desirable solution since grid operators face considerable challenges as a result of disruptions in the supply of solar and wind energy. Numerous sources of energy storage, such as hydroelectric energy, air-compressed flywheels in particular capacitors, and batteries, are making it possible for a future smart grid [12]. In the often-utilised battery battery backup systems in electric vehicles, precise calculation of The capability of battery deterioration characteristics over the course of the battery's lifespan is established and evaluated using a 3-D reaction surface-based SoC-open circuits voltage (OCV) capability approach. Genetic algorithms, also known as GA, are used to assess the battery's capabilities and initialise the CPU round an initial RC model in order to track the battery's health and power status. To validate the suggested method, six instances with batteries at various ages and data calculation rates are considered. The findings show that for batteries at different stages of ageing, the big capacity or SoC error estimations are around 5%. And. The recommended GA-based battery capacity computation and initialization are accurate, stable, and secure. For lithium-ion batteries, the effect of temperature on the precision of calculations for the battery's voltage in an open circuit is considered. Without altering the model's hierarchy, the accuracy of battery terminal voltage calculations is increased. The initial concept of the model was based on his model as well as the voltage and charge state in an open circuit. The parts of the battery model were established using polynomials fitting and a genetic algorithm, respectively, based on the results of the tests of the combined energy pulsed characteristic test and the open-circuit voltage test. In voltage open-circuit tests and composite impulse characteristic tests, temperature factors were applied. [14]. In recent years, numerous electric vehicles (EVs) have been created to solve the pollution issues brought on by fuel-injected engines' emissions. Environmental concerns are the driving force behind the launch of the newest batch of electric vehicles for urban transportation. It is well acknowledged that one of the disadvantages of electric vehicles is their battery system. Vehicle autonomy and, subsequently, the precise identification of battery present condition (SoC) and charge projected life, i.e., battery health, are two of the primary problems holding back the adoption of electric automobiles in the consumer market. An electric scooter might be a more useful EV. They may eventually replace the ordinary utility vehicle if the cost, safety, and efficiency of the drive are equivalent to genuine combustion vehicles due to their affordability, especially in Europe and Asia [15]. Early notification of EOL for repair purposes is made possible by a mechanism for predicting the condition of the lithium-ion batteries on board. There are two types of battery SOH evaluation techniques. In the primary group, battery SOH is calculated using electrochemical or comparable circuit models in conjunction with cutting-edge filtering methods like Kalman and particle filters. Based on observed current, voltage, and temperature, these techniques may calculate battery SOH online. Typically needed and so collected offline is the connection between voltage in the open circuit (OCV) and condition of charge (SOC) at various battery SOHs and temperatures. The application of these technologies in a system for battery management (BMS) is restricted by the need for computationally demanding methods to mimic the intricate electrochemical characteristics of lithium-ion batteries [16]. Due to energy and global warming issues, lithium-ion batteries, which are used in electric vehicles (EVs), have recently attracted a lot of attention. Nevertheless, because lithium is very unpredictable, a strong and sophisticated battery control system (BMS) is needed to constantly track every state of the batteries when operating EVs and guarantee a secure and dependable power source for the batteries. The ion battery. In particular, and state-of-power (SOP) can all be utilised to infer nearly any battery issue. Current, voltage, and temperature were all measured. As a result, researchers have made great efforts to investigate various battery kinds and technologies [17]. The voltage curve's data collecting interval was chosen depending on the writers' prior experiences, therefore it might not be the perfect interval. In contrast to earlier research, this one makes accurate predictions of battery SOH using compression power and SOC changes over an improved partial charging time. This allows for the estimation of the battery SOH while charging for electric vehicles without adding more strain to the network [18]. The environmental sustainability of reused batteries from electric automobiles in conventional automotive applications was examined using a parameterized life cycle model. The model assumes that a lithium-i or Li-ion, EV batteries have longer lived and incorporates recycling and reuse of materials into storing energy for utility usage. A 56% decrease in emissions of carbon dioxide is possible relative with employing gasoline as a source for high energy production because an EV battery may be utilised for storing clean electricity during off-peak hours to fulfil peak demand. Reusing battery cells can reduce CO2 emissions in a similar way to switching from using conventional to electric vehicles, which involves extending the lifespan of EV batteries, using cheap electricity, and making better use of cheap, clean electricity [19].The lifespan and security for lithium-ion batteries used in electric vehicles (EVs) are increased by a battery temperature management system (BTMS), a sophisticated system that employs a variety of methods for heat evacuation and temperature control tactics to maintain batter packages at optimal thermal conditions. However, because there are so many subsystems and/or departments involved, BTMS' ideal architecture is still difficult to implement. The battery the laws of thermodynamic fluid dynamics, structural, and lifetime modelling subsystems and/or subfields of the air-based BTMS are hierarchically divided to handle this issue [20].

2. MATERIALS AND METHOD

TOPSIS is a popular estimating technique for resolving MCDM issues. It has several practical uses, including comparing business performance, analysing financial ratios for a specific industry, and investing money in cutting-edge manufacturing methods. It does, however, have some restrictions. Up until now, efforts to enhance the original TOPSIS approach have primarily focused on weight optimisation to achieve the R value. Additionally, the R value formula, or "Miqiezhi method," has been improved. To comprehend the fundamental connection among the value of R and the alternative estimate, a better and easier method is required due to the complexity of estimating difficulties. The D+ D plane's length among options and reference points is calculated in this report's innovative, modified TOPSIS (M-TOPSIS) method, which also creates a R value to assess the quality of alternatives. This issue was resolved using a MATLAB programme. The key distinction among the M-TOPSIS technique and TOPSIS is the ranking both x8.x8, which is placed fourth in the M-TOPSIS technique and third by TOPSIS, ahead of x3 and x7. The observed ratio for x8 equals 0.4, which is which is close to the minimum (0.3), and x3/x8 is 25.8 based on the data in Table 1. This had a big impact on the x8 in MCDM quality. It follows that the M-TOPSIS evaluation result is clearly extremely reasonable [21]. Making decisions is a crucial aspect of daily and professional life for both individuals and organisations. Though techniques that use multiple criteria give decision-makers the essential tools, they vary in terms of underlying theory and assumptions. Therefore, making the best decision is just as crucial as using the appropriate decision-making process. Researchers have focused on the TOPSIS (Technique for Ordering Effectiveness Similar to Perfect Solution) method, one of the most popular multi-criteria decision-making techniques, and several enhanced variations of the technique have been suggested. The typical TOPSIS method is taken into consideration in this study, which employs a simulation technique to experimentally demonstrate the underlying causes of the method's drawbacks. The theoretical underpinnings of the TOPSIS approach are better understood and helped to be improved by detailed practical study using simulations with an application [22]. The foundation of TOPSIS, regarded to be one of the most traditional MCDM approaches, is the notion that the selected alternative should be the closest to the ideal solution that is positive and the furthest from the ideal solution that is negative. The selected option should be "a long way" from the ideal solution that is negative and "brief distances" from the beneficial ideal solution. This is the fundamental tenet of the TOPSIS technique. Two "reference" locations are introduced by the TOPSIS approach, but the relative significance of the journey from these points is not considered [23]. The alternative with the lowest OPV value is the best. Unfortunately, according on the data shown, these 220 modifications are insufficient to address RRP, even though they lessen its consequences by introducing or eliminating alternatives. RRP chose resources using decision-making exercises taken from the literature. According to their findings, the TOPSIS method performed the least well out of all the methodologies they examined [24]. The evaluations of many options, numerous subjective criteria, and the relative importance for all criteria are assessed using and via fuzzy numbers in the fuzzy TOPSIS approach for robot selection. To verify that the values of the goal criterion and the linguistic values are compatible, all values of the subjective criteria are translated into dimensionless indices. Of subjective criteria. Each weighted estimator's membership function is produced using fuzzy interval arithmetic. These weighted estimations are converted to smooth values by the rank approach for the average of eliminations in order to avoid the complicated aggregation of fuzzy numbers. By measuring the distance between the ideal and non-ideal solutions, the proximity coefficient is used to rank the alternatives in that order. The suggested method's computational process is illustrated by a numerical example [25]. The TOPSIS method uses finding the best solution to establish order preference. One of the most widely used multi-criteria decision-making (MCDM) techniques now is this one. The TOPSIS approach was primarily created to work with data that only had real values. It is frequently challenging to provide precise estimates of options with respect to local criteria, and as a result these estimates are considered gaps. There aren't many articles that focus on TOPSIS interval extensions, but the few that do are based on various heuristic methods for defining both beneficial and detrimental optimal solutions. Real numbers or ranges that cannot be reached in the choice matrix provide these ideal answers. In this research, we offer a new direct way to interval extending the TOPSIS method that is without the heuristic assumptions and constraints of existing approaches because this conflicts with the basic principles of the original TOPSIS method. We demonstrate with numerical examples how the findings of a "direct intervals extension for the TOPSIS method" may drastically differ from those of the results produced by using established methods [26]. Hwang & Yoon (1981) developed the TOPSIS approach, a method of choosing an order by finding the best answer. A solution that maximises the benefit criteria or attributes while minimising the cost criteria or attributes is referred to as an ideal solution (also known as a positive ideal solution), whereas a solution that maximises and minimises the cost criteria or attributes is referred to as an anti-optimal solution. Advantage Standards or Qualities. The price criteria/attributes are for minimization, whereas the allegedly benefit criteria/attributes are for maximisation. The ideal option, which is farthest from the unfavourable ideal solution and closer to the ideal solution, is the optimal alternative [27]. TOPSIS application requires certain procedures, such as numerical evaluations of the relative relevance of qualities and the effectiveness of each choice on these attributes. However, precise data may be challenging to ascertain accurately because human judgements are frequently erroneous in a variety of circumstances. Consequently, TOPSIS model generalisation to fuzzy environments is a logical extension of TOPSIS models. For each m n combination, the consistency rate gauges overall level of coherence among two relative preference orders provided by various distances. 10,000 test observations were used to get the results for each paired comparison. According to computational findings, consistency rates are quite high (i.e., 80% to fifty percent or 40%) when a decision problem has few alternatives. Therefore, one should not worry about the distance term to apply if the amount of decision options is limited. However, as a problem's number of alternatives rises, this trait of great stability vanishes. Stability rates drastically decline as m rises. Additionally, the stability ratio typically approaches Zero when the value of m exceeds 13. It should be emphasised at this point that the interval-valued fuzz Topsy technique's priority ordering are not equal when alternative distance metrics are used [28]. The fundamental tenet of the technique is that the alternative should be picked if it is closest to the ideal positive outcome and farthest from the adverse one. The weights of the estimations and criteria are exactly known in conventional MCDM approaches. The relative importance of the criteria and ratings of the options in the traditional TOPSIS technique are by actual values, which. The traditional TOPSIS approach has been effectively applied in a few disciplines. an exhaustive examination of TOPSIS applications. However, depending on local standards, it might be challenging to precisely ascertain the true values of the assessment of alternatives, and therefore, these evaluations are frequently given as confusing values. The fundamental tenet of the classical TOPSIS approach is that the best option should be the one that is closest to the ideal solution that is positive and farthest from the ideal solution that is negative. The ideal solution is simple to specify provided every nearby criterion is monotonically rising or decreasing [29]. The refinement and expansion of current security assessment techniques are crucial. Using stochastic value and TOPSIS, an extensive model of coal coal mine security is developed in this research and utilised to assess the four coal mines' safety conditions, to raise the bar for safety management, and to guarantee coal mines' safe operation. Determining the index weight is crucial to a multi-index thorough assessment model. In this study, the entropy weight technique efficiently avoids subjectivity by utilising the specialised scoring method, resulting in more objective results while simultaneously fully utilising the inherent information of the indexes possible. The relative degree of approximation, the optimal solution, the negative ideal solution, and the optimal solution are all computed in this study using TOPSIS. The security conditions of coal mines are then assessed based on the relative degree of approximation [30].

Alternative parameters:

Lithium- Cobalt Oxide Battery ($LiCoO_2$) – LCOB: The most typical material for the cathode in lithium-ion batteries that are rechargeable is lithium-cobalt dioxide batteries ($LiCoO_2$), additionally referred to as LCOP. Its high density of power and solid all-around performance makes it appropriate for an array of uses, such as electric vehicles and compact devices. However, LCOB has many disadvantages, including a short cycle life, poor thermal stability, and safety issues with cobalt. Exploring material changes & alternative cathode materials is being done to increase efficiency and get around these difficulties. Overall, in the world of lithium-ion batteries, LCOB continues to be a commonly utilised and thoroughly researched battery technology.

Lithium-Manganese Oxide Battery ($LiMn_2O_4$)- LMOB: A form within cathode material that's utilised by lithium-ion batteries is lithium-manganese oxides battery ($LiMn_2O_4$), sometimes referred to as LMOB. Relative to other cathode materials, LMOB has several benefits, including excellent thermal resistance, good protective qualities, and inexpensive cost. It is perfect for uses like car batteries and power tools since it has an average energy density and a long cycle life. However, in contrast to certain other cathode materials, LMOB exhibits a low specific capacity. In order to increase its use in the expanding battery sector, present study focuses on increasing the density of energy and general efficiency.

Lithium-Nickel Manganese Cobalt Oxide Battery ($LiNiMnCoO_2$)-LNMCOB: The most typical material for the cathode utilised by batteries with lithium ion is LNMCOB, commonly known as lithium-nickel chrome cobalt dioxide battery. By combining the advantages of nickel, manganese, and cobalt, it strikes a balance between energy density, energy efficiency, and cycle life. LNMCOB is appropriate for tremendous-performance, long-range applications like electric cars because of its high energy density. It has excellent thermal stability and defence qualities. However, LNMCOB units tend to be pricier and may have supply and environmental effect difficulties compared to alternative cathode materials. The present research emphasis is on improving efficiency and efficiency.

Lithium Iron Phosphate Battery ($LiFePO_4$)-LFPB: Lithium-ion batteries frequently use the cathode material lithium iron phosphate batteries ($LiFePO_4$), commonly referred to as LFPB. In comparison to other cathode materials, it provides higher thermal stability, increased protection, and longer cycle life. Industries where security is a top consideration, like electric cars, clean energy storage facilities, and backup power options, frequently use LFPB. Its solid performance, dependability, and lower danger of thermal runaway problems are the main reasons for its widespread acceptance.

Lithium-Titanate Battery (Li4Ti5O12) LTOB: A special anode material distinguishes the lithium-titanate battery (Li4Ti5O12), sometimes referred to as LTOB, from other lithium-ion battery types. In comparison to conventional lithium-ion batteries, LTOB delivers greater energy efficiency, quicker charging, and extended cycle life. It is frequently employed in fast-charging applications such energy storage systems, hybrid electric vehicles, and electric buses. Because of its outstanding performance qualities, LTOB is a good option for demanding as well as high power applications.

Evaluation parameters:

Reliability: A system, product, or process's reliability is determined by its capacity to carry out its intended function over an extended length of time and under a given set of conditions. To ensure safe and reliable operations, high reliability is crucial in a variety of industries, including engineering, manufacturing, healthcare, and transportation. Increased reliability is a result of factors like product uniformity, quality assurance procedures, maintenance practises, and adherence to standards. Potential failures are identified and minimised using reliability engineering approaches like failure analysis, risk assessment, and predictive maintenance. Increased customer satisfaction, decreased downtime, greater safety, and cost savings are all benefits of increased reliability.

Safety: Being secure means that you are safe from harm, risk, or danger.

Keeping people safe is crucial in many areas, including jobs, transportation, and consumer goods. To limit possible hazards and assure people's safety, safety procedures include risk assessment, risk identification, execution of preventative measures, and continual monitoring.

Specific power: The power output of a computer or other equipment based on its weight or volume is referred to as specific power. This is a crucial parameter for high power density applications like electric cars and portable electronics. A system's capacity to provide more power in relation to its dimension or weight, allowing for effective and high-performance activities, is referred to as having high specific power.

Specific energy density: The quantity of energy that is contained in a system or device per volume or mass per unit is referred to as specific energy density. This is a crucial measurement for long-term or prolonged energy storage applications, like grid-scale energy storage and electric automobiles. A system with a high energy density can store more energy compared to its dimensions or weight, leading to longer working durations or more storage space. To increase the overall effectiveness and variety of energy storage systems, cell research and development is heavily focused on optimising specific energy density.

Price: The cost or monetary value of a good, service, or item is referred to as the price. It has a big impact on consumers' purchasing choices and the level of market competition. Production expenses, demand and supply dynamics, competitiveness, and economic variables are some of the factors that determine price. Pricing strategies try to balance market positioning, profitability, and client affordability.

3. ANALYSIS AND DISSECTION

TABLE 1. The selection of Li-Ion batteries used in electric vehicles (EVs)

	Reliability	Safety	Specificpower	Specific energy density	Price
LCOB	3	3	3	5	4
LNMCOB	4	4	4	5	4
LMOB	3	4	4	4	2
LFPB	5	5	5	3	2
LTOB	5	5	4	3	1

The selection of different types of Li ion battery are displayed in Table 1. LCOB, LNMCOB, LMOB, LFPB, LTOB are available as the alternative parameters. Reliability, Safety, Specific power, Specific energy density, Price are the evaluation parameters. Reliability, Safety, Specific power, Specific energy density are beneficial parameters price is the non-beneficial parameter.

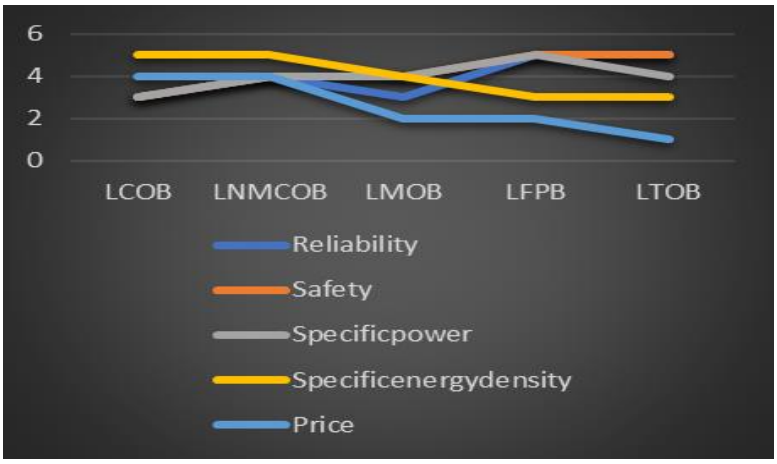

FIGURE 1. different types of Li-ion batteries

Figure 1 illustrates the different types of Li ion batteries LCOB, LNMCOB, LMOB, LFPB, LTOB are available as the alternative parameters. Reliability, Safety, Specific power, Specific energy density, Price are the evaluation parameters. Reliability, Safety, Specific power, Specific energy density are beneficial parameters price is the non-beneficial parameter.

TABLE 2. Normalized matrix

NORMALIZED MATRIX				
0.981981	0.943456	0.993884	2.727724	2.49878
1.745743	1.677256	1.766904	2.727724	2.49878
0.981981	1.677256	1.766904	1.745743	0.624695
2.727724	2.620712	2.760788	0.981981	0.624695
2.727724	2.620712	1.766904	0.981981	0.156174

Table2. shows the normalized matrix values for the given decision matrix TOPSIS method.

TABLE 3. Weighted matrix

0.2	0.2	0.2	0.2	0.2
0.2	0.2	0.2	0.2	0.2
0.2	0.2	0.2	0.2	0.2
0.2	0.2	0.2	0.2	0.2
0.2	0.2	0.2	0.2	0.2

Table 3. shows the weighted matrix among the evaluation parameters.

TABLE 4. weighted normalized matrix

0.196396	0.188691	0.198777	0.545545	0.499756
0.349149	0.335451	0.353381	0.545545	0.499756
0.196396	0.335451	0.353381	0.349149	0.124939
0.545545	0.524142	0.552158	0.196396	0.124939
0.545545	0.524142	0.353381	0.196396	0.031235

Table 4 shows the weighted normalized matrix. Here we multiply the normalized matrix and the weighted matrix.

TABLE 5. positive matrix

0.545545	0.524142	0.552158	0.545545	0.031235
0.545545	0.524142	0.552158	0.545545	0.031235
0.545545	0.524142	0.552158	0.545545	0.031235
0.545545	0.524142	0.552158	0.545545	0.031235
0.545545	0.524142	0.552158	0.545545	0.031235

Table 5 shows the positive matrix of the alternate parameters. The positive matrix is obtained by multiplying the maximum into to the beneficial parameters and multiplying the minimum with negative parameters.

TABLE 6. Negative matrix

0.196396	0.188691	0.198777	0.196396	0.499756
0.196396	0.188691	0.198777	0.196396	0.499756
0.196396	0.188691	0.198777	0.196396	0.499756
0.196396	0.188691	0.198777	0.196396	0.499756
0.196396	0.188691	0.198777	0.196396	0.499756

Table 6 shows the negative matrix of the alternate parameters. The positive matrix is obtained by multiplying the minimum into to the beneficial parameters and multiplying the maximum into the negative parameters.

TABLE 7. Si+, Si-, Ci, Rank

Si+	Si-	Ci	Rank
0.760804	0.349149	0.314562	5
0.577235	0.436668	0.43068	4
0.494341	0.457452	0.480621	3
0.361504	0.706964	0.661661	1
0.401767	0.691265	0.632429	2

Table 7 shows the si plus, si minus, ci, rank of the different types of Li-ions. Here the rank of LCOB is 5th. LNCOB is 4th. LMOB is 3rd. LFPB is 1st. LTOB is 2nd.

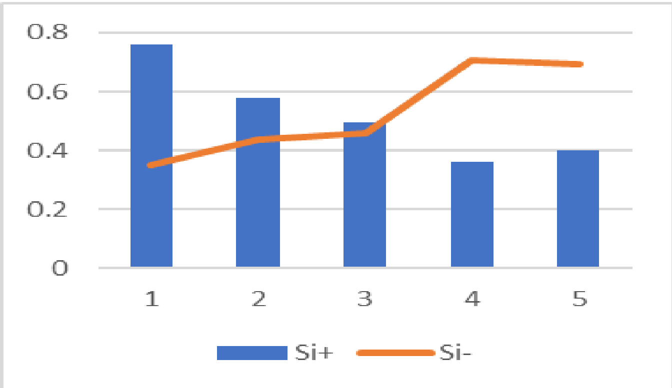

Figure 2. si+ &si-

Figure 2 graph shows the si plus and si minus of the alternative parameters.

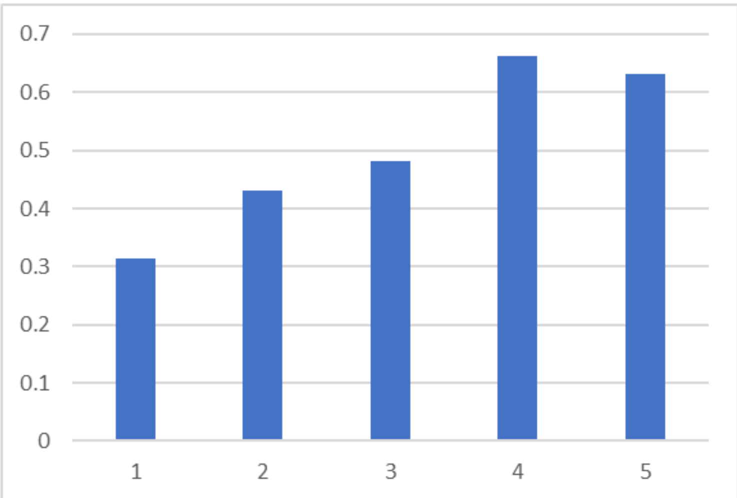

FIGURE 3. ci

The graph shows the ci values. The ci value obtained by si- divided by the sum of si+ and si -.

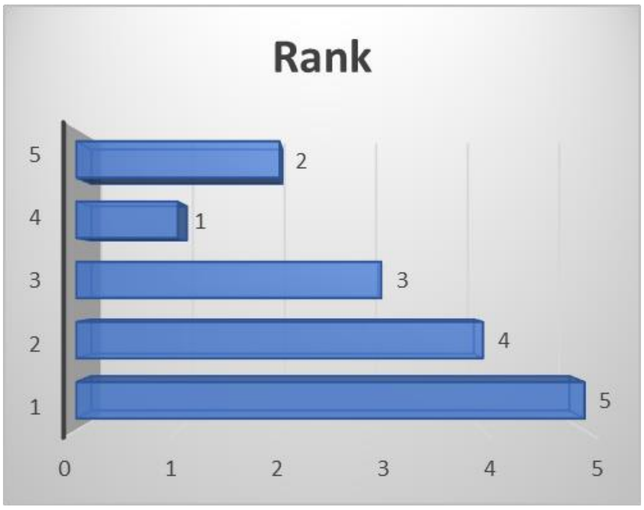

FIGURE 4. Rank

The figure 4 shows the rank of the alternative parameters. The rank is awarded to the alternative parameters by the beneficial and non-beneficial parameters

4. CONCLUSION

In order to maximise the functionality and efficiency of electric vehicles, this study emphasises the choice of lithium-ion batteries. Variables like energy density, durability, cost, or ecological impact are considered throughout the selecting process. The choice of lithium-ion battery for electric vehicles is a crucial decision that affects both the performance of each individual vehicle and the performance of the entire fleet. Given that batteries are the primary power source for EVs, the selection of battery technology directly affects aspects like range, charging time, and longevity. When choosing a battery, it's crucial to take energy to pounds, cycle life, safety, cost, and environmental impact into account. Internal combustion engines are being gradually replaced by battery-powered vehicles Due to continued research and development into more effective batteries, this is taking place at a much slower rate. Tight requirements, such as quick charging, great range for driving, long battery life, and cheap cost, must be met when developing battery technology. The most common lithium-ion (Li-ion) batteries are expensive and have a limited lifespan despite being able to deliver an acceptable performance. The materials selected for the electrodes have a considerable impact on the battery's efficiency, cost, and lifespan. Current Li-ion batteries are categorised based on the materials used to create the electrodes. When EV manufacturers make concessions, the practical issue is that selecting the ideal Li-ion battery is difficult. This research suggests an MCDM-based technique for choosing lithium-ion cells based on the cathode/anode materials, which is crucial for choosing the best battery for EVs and enhancing the price and performance of EVs. A lithium-ion battery pack powers the solar vehicle used by Northern Regional University. Fujifilm Laser Desert Rose, a competitor in the 1999 World Solar Challenge. The oversight of cells and their protection boards, as well as the construction techniques employed, are covered in detail, along with reasons why Li-ion batteries are favoured over silver-zinc batteries. With study about the battery's coulombic & energetic capabilities, results from pre-race research along with the race are displayed. Li-ion batteries perform better than other readily available batteries in such kinds of traction applications. Lithium-ion batteries can help high-performance electric vehicles. batteries. Compared to conventional rechargeable batteries, lithium-ion packs offer greater capacities and longer charge-discharge cycles. Furthermore, the cost is affordable. As a result, Li-ion batteries. TOPSIS is a well-liked estimating method for resolving MCDM issues. It can be used for a variety of practical purposes, such as assessing corporate performance, examining financial metrics for a certain industry, and making investments in innovative production techniques. It does, however, have some limitations. Up till now, weight optimisation to reach the R value has been the focus of efforts to enhance the original TOPSIS methodology. The "Miqiezhi method" or R value formula has also been enhanced. Due to the complexity of estimation challenges, a better and easier technique is required to comprehend the underlying connection with the cost of R and other valuation. The distance of the D+ D plane between alternatives is calculated using the novel, altered TOPSIS (M-TOPSIS) method presented in this research.The MATLAB programme was used to resolve this issue. The placement for both approaches x8.x8, which is placed fourth by M-TOPSIS approach and third by TOPSIS before x3 and x7, is the primary distinction between the two methods. Based on the information in Table 1, the calculated proportion for x8 is equivalent to 0.4, that is the lowest (0.3), so x3/x8 is 25.8. On the MCDM norm x8, this had a significant effect. It is obvious that the M-TOPSIS evaluation result is perfectly reasonable. For both individuals and organisations, decision-making is an essential part of everyday and professional life. Despite providing decision-makers with crucial tools, multicriteria approaches have different underlying theories and assumptions. Making the right choice is therefore just as crucial as using the appropriate decision-making process. One of the most widely used multi-criteria decision-making strategies, TOPSIS (Technique for Optimising Efficiency Optimisation), has been the subject of research, and various improved variations of the method have been proposed. This study, which employs the use of simulation to experimentally show the origins of the method's flaws, considers the traditional TOPSIS method. The TOPSIS approach's theoretical foundations have undergone significant practical investigation with applied simulations, which has improved them.

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