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Selection of Electric Vehicles Using MCDM Techniques

Rahul Sejwal [a,1], Sagar Pal [a], Nitish Kumar Singh [a], Rajat Saini [a] N. Yuvraj [a]
[a] *Department of Mechanical Engineering, Delhi Technological University, Delhi, India*

Abstract. Now a days, it is an arduous task for the customers to buy an electric car due to day-to-day increased market competition, advanced technology, diversified product etc. To conquer this problem, we have used MCDM techniques to distinguish and select a best car among all the alternatives. In this study, we have taken eight different electric vehicles of different brands and eight different criteria for optimization. The main criteria's considered for the analysis are identified by reading literature reviews and interviews with professionals from the Indian automotive industry and consumers are as follow- cost, driving range, acceleration, battery charging time and top speed. AHP methodology is used to define weights for different criteria used in study. Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) and Multi-Objective Optimization based on Ratio Analysis (MOORA) techniques have been used for analysis and the results are compared. Byd E6 is considered to have better performance in both the methods. The results obtained from the method used will be beneficial for customers to distinguish between different electric cars in the current industry.

Keywords. MCDM, EVs, TOPSIS, MOORA, Ranking, AHP.

1. Introduction

As we develop in today's world, the electric car industry is also expanding due to environmental pollution and rising fuel prices. Today, governments around the world are promoting the use of electric vehicles by providing support to both manufacturers in the form of tax breaks and consumers by providing subsidies. In India, the government is trying its best to promote the conversion of conventional IC vehicles to EVs by adopting policies such as the National Electric Mobility Mission Plan (NEMMP) and Faster Adoption and Manufacturing of (Hybrid) and electric vehicles (FAME). With so much competition, the constant change of consumer ideas and features of different electric vehicles, it is a daunting task to choose the most suitable EV. With the help of MCDM techniques, we can solve this complex problem by considering all the important features needed to buy an electric car. This research will help customers find the appropriate electric car available in the market.

The MCDM (multidisciplinary decision-making) is a method used to make multi-disciplinary decisions linked to identification and problem-solving. In addition, MCDM can be broadly divided into MADM (multidisciplinary decision making) and MODM (multi-purpose decision making). MADM focuses on the problems of different decisions

[1] Corresponding Author: Rahul Sejwal, Department of Mechanical Engineering, Delhi Technological University, 110042 Delhi, India; E-mail: rahulsejwal621@gmail.com.

and is associated with a few other pre-determined approaches. The MODM incorporates many competing goals that need to be developed simultaneously and is linked to a few other unresolved alternatives. The MCDM approach has many strategies in which we can solve the problem of choosing between different vehicles by using more than one strategy together in an integrated way. Here are a few MCDM techniques used over the past several years: 1. TOPSIS (Preferred Planning Strategy as the Best Solution) 2. MOORA (Multiple Goal Development through Measurement Analysis) 3.AHP (Analytic Hierarchy Process) 4.ANP (Network Analysis Process) 5. ELECTRE (Termination and Selection Reveals the Truth).

2. Literature review

[1] Loganathan and Bikash et al. (2020) used MCDM methods to select the best Lithium-ion battery used in electric vehicles. They considered factors such as cost, performance, capacity, and reliability and concluded that Lithium titanate (Li4Ti5O12) is the ideal choice for electric vehicle applications.

[2] Ali and Ihsan et al. (2018) used the unconventional MCDM method in their research to select the location of the electric vehicle charging station. They found that the comfort of traffic and the security of the power system were the best and most important conditions in the whole selection process.

[3] Aryan and Shubham et al. (2020) proposed electric motorcycle selection method which uses the MCDM method such as COPRAS and TOPSIS. Both methods have shown similar results so any of them can be used to select alternatives

[4] Biswas and Tapas et al. (2018) worked on Fuzzy AHP-MABAC techniques and used it to selected commercially available electric vehicles. They used seven different alternative and ranked them on the basis of speed, range, economy and prices. The stability of the results were further confirmed by sensitivity analysis.

[5] Vahdani B, Zandieh M, Tavakkoli-Moghaddam R. et al. (2011) used fuzzy TOPSIS and fuzzy preference selection index (PSI) methodologies to evaluate alternative fuel-based buses, taking into account many criteria such as capability, pricing, and energy usage. CNG, and LPG and conventional diesel engines are the best choices, according to the data. Furthermore, even if the alternatives perform similarly, the ranking outcomes of various MCDM approaches can differ significantly, causing inconsistencies in the decision-making process [6]. Despite the fact that the literature disagrees on the exact combination of vehicle attributes that are the most important factors in car sales, studies have found that consumers interested in clean vehicle technologies are mostly concerned with performance qualities [7]. The price, range of EV, battery capacity, and charging, among other features, set EVs apart from the competition [8]

[9] Nazari F, Rahimi E, Mohammadian AK et al. (2019) studied the main factors affecting purchasing of Electric Vehicles may be separated into four categories: people's socioeconomic and demographic traits, vehicle characteristics, subsidies offered by government, and attitudes toward electric vehicles

[10] Zhang H, Song X, Xia T, Yuan M, Fan Z, Shibasaki R, Liang Y.et al. (2018) predicted the demand for electric vehicles in terms of travel and adoption in japan Consumers, predictably, examine technological issues when determining whether or not to buy an electric vehicle. Some researchers have looked into the importance of a short charging time. According to their findings, rapid charging is more important than improving battery capacity in encouraging EV adoption.

[11] Tang X, Jia T, Hu X, Huang Y, Deng Z, Pu H et al. (2020) discovered that the acceleration of the vehicle is also a significant component in the adoption of electric vehicles. Also, it was discovered that acceleration had an impact on purchasers' choice for clean vehicles.

[12] Egner F, Trosvik L et al. (2018) found that when considering the long-term expenses of ownership, EVs are more economical than conventional fuel-based vehicles. They also pointed out that, despite their high purchase price, EVs have a lower total cost of ownership during their lifetime than their fossil-fuel-powered counterparts the purchase price of EVs is frequently investigated in the literature as a key barrier to EV purchase. Electric vehicles have high purchasing prices due to their novel technologies, which is unsurprising. To put it another way, high purchasing prices have been demonstrated to be a barrier to EV sales. Jena looked studied consumer attitudes about electric vehicles in India and found that, similar to the other countries, the purchase price of electric vehicles is one of the most important factors for buyers.

[13] With the growing popularity of electric cars, the demand and availability of options in the market are growing. According to FY2021 data, 5905 e-PVs units were sold and 6251 e-PVs units were sold in just six months (September) of FY2022. In India, Tata Motors has emerged as a major EV retailer making up to 70% of market.

3. Methodology

In this study, we came up with EV, as this is the emerging market in the automobile industry in INDIA. There are many options available among them, but concerning what some well-established EV manufacturers provide, we have to go too far. Here we focused on the EV selection problems faced by the common man. As there are many options to choose from, with a neck to neck pricing it becomes hectic to come to a decision. So, to encounter this problem we tried to formulate the problem with the help of MCDM techniques and find a reasonable option according to our needs. In this study we focused on a common man who wants to get an EV which must be available in the Indian market, considering the fact that it should be pocket friendly as well. While considering the crucial criteria to judge the alternative, it is important that it should reflect the need of the buyer and the performance of the alternative as well. In this case of EV, a car first of all must be in the budget of the buyer then it should have some parameters which show the performance of the vehicle and cost to customers. But in the case of EV, some more elements come into the race i.e., charging time, battery capacity, etc. So, for considering EV we selected the most basic parameters which are essential to judge a car i.e. price, driving range, battery capacity, charging time. Apart from that for the performance section, we decided to come up with i.e., speed, power, torque, acceleration [Table 1].

Table 1. Detailed Specifications of electric vehicles

Electric vehicles/ Parameters	Cost (in lakhs)	Driving range (in km)	Charging (in hours)	Speed (in kmph)	Acceleration (in 0-100m/sec)	Battery (in KWh)	Torque (in N-m)	Power (in bhp)
Tata Tigor	12	306	8	120	12.63	26	170	55
Tata Nexon	14	312	8.5	120	9.14	30.2	245	94.8
Hyundai Kona Electric	23.8	452	6.1	165	9.7	39.2	395	100
MG ZS EV	21	419	7	140	8.5	44.5	353	105
Mahindra E-Verito	12.7	110	8.5	120	10	22	91	42
ByD E6	29.15	415	8	130	7.6	72	180	94
Audi E-Tron	117	441	9	200	5.7	95	664	300
Mercedes EQC	106	463	11	180	5.1	80	760	300

This study aims to provide a method for selecting electric cars using different selection criteria which involve many conflicting decisions. We select TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) and MOORA (Multi-Objective Optimization based on Ratio Analysis) to solve the given problem.

Table 2. Abbreviations

Criteria	Abbreviation	EVs	Abbreviation
Cost	M1	Tata Tigor	N1
Driving Range	M2	Tata Nexon	N2
Charging	M3	Hyundai Kona Electric	N3
Speed	M4	MG ZS Ev	N4
Acceleration	M5	Mahindra E-Verito	N5
Battery	M6	ByD E6	N6
Torque	M7	Audi E-Tron	N7
Power	M8	Mercedes EQC	N8

3.1. TOPSIS METHOD

If we apply many criteria and many more, the process of choosing the perfect option becomes more complicated. There are many different decision-making methods available in these decision-making cases on many terms. It is a simple and effective way to solve problem-making problems on many terms. In this method, some methods are compared between the minimum and maximum conditions. The one approach that is closest to PIS (the best solution) and the farthest from NIS (the wrong solution) is the right solution. The various steps include –

- After deciding all the test methods and alternatives create a resolution matrix.

$$A_{ij} = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ a_{m1} & a_{m2} & \cdots & a_{mn} \end{bmatrix} \quad (1)$$

  Here columns (1, 2, 3. . . n) Refer to the terms criteria M1, M2, M3. . . and line (1, 2, 3. . . m) Means alternative N1, N2 and N3.

- Make the decision matrix (normalize) using the given equation.

$$r_{ij} = \frac{a_{ij}}{\sqrt{\sum_{i=1}^{m} a_{ij}^2}} \quad (2)$$

- Calculate the matrix for the standard weight decision by multiplying part of each column with the conditional weights (w_j) listed earlier.

$$Z_{ij} = w_j * R_{ij} \quad (3)$$

- PIS (+ve ideal solution) A + and NIS (-ve ideal solution) A- calculated with the help of Z_{ij} matrix.

  PIS = A+= [Z1+, Z2+, Z3+. Zn+] (4)

  Where Z_j^+ = [min of Z_{ij} if j ε J; max of Z_{ij} if j ε J']

  NIS = A^- = [Z_1^-, Z_2^-, Z_3^-....... Z_n^-] (5)

  Where Z_j^- = [max of Z_{ij} if j ε J; min of Z_{ij} if j ε J']

  Zj+ and Zj- are correlated to beneficial and non-beneficial attributes.

- Calculate the separation distance of the alternatives from PIS and NIS. Where i and j are criterion and alternative.

$$S^+ = \sqrt{\sum_{j=1}^{n} (Z_{ij} - Z_j^+)^2} \quad (6)$$

$$S^- = \sqrt{\sum_{j=1}^{n} (Z_{ij} - Z_j^-)^2} \quad (7)$$

- Find the closeness associated with the appropriate solution for each location.

$$C = \frac{s_i^-}{s_i^- + s_i^+} \quad \text{where } 0 \le C \le 1,\ i = 1, 2 \ldots m \tag{8}$$

- Using the above figure, measure a set of alternatives. With the help of a very high value, we can organize ourselves in a rising way.

3.2. MOORA METHOD

MOORA stands for Multi-Objective Optimization based on Ratio Analysis. This approach helps to solve a complex MCDM problem where two or more features need to be upgraded. The first two steps are similar to the TOPSIS method.

- After deciding all the test methods and alternatives create a resolution matrix.

$$A_{ij} = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ a_{m1} & a_{m2} & \cdots & a_{mn} \end{bmatrix} \tag{9}$$

Here columns (1, 2, 3. . . n) Refer to the terms criteria M1, M2, M3. . . And line (1, 2, 3. . . m) Means alternative N1, N2 and N3.

- Make the decision matrix (normalize) using the given equation.

$$r_{ij} = \frac{a_{ij}}{\sqrt{\sum_{i=1}^{m} a_{ij}^2}} \tag{10}$$

- After practice, these responses are added or subtracted according to the case in order to maximize and minimize to full use.

$$B_i = \sum_{j=1}^{e} a_{ij} - \sum_{i=e+1}^{n} a_{ij} \tag{11}$$

Where e an

d n-e are many attributes it needs to be increased and reduced.

- Continues with the Bi values obtained above which are measured from the highest to the lowest and another with the highest value of Bi is the alternative.

4. Results and Discussion

4.1. TOPSIS METHOD

In this MCDM technique, we have used 8 criteria which have been selected according to user's demands and necessary things. Also, we have used 8 EVs which are currently present in the Indian market. By the use of decision matrix and putting it into the equation 2, we will get the normalized matrix shown below in the table 3.

Table 3. Normalized matrix

Electric vehicles/ Parameters	Cost	Driving Range	Charging	Speed	Acceleration	Battery	Torque	Power
Tata Tigor	0.072649325	0.283622843	0.337847598	0.283374539	0.50493488	0.160634882	0.142224013	0.116302974
Tata Nexon	0.084757546	0.289184075	0.358963073	0.283374539	0.36540814	0.186583594	0.204969901	0.200464036
Hyundai Kona Electric	0.144087828	0.41894616	0.257608794	0.389639991	0.38779638	0.242187976	0.330461676	0.211459953
Mg Zs Ev	0.127136319	0.388359382	0.295616649	0.330603629	0.33982157	0.274932779	0.295323979	0.222032951
Mahindra E-Verito	0.076887202	0.101955924	0.358963073	0.283374539	0.39979009	0.135921823	0.076131677	0.08881318
Byd E6	0.176477318	0.384651894	0.337847598	0.306989084	0.30384046	0.444835059	0.150590131	0.198772356
Audi E-Tron	0.708330918	0.408750567	0.380078548	0.472290898	0.22788035	0.586935147	0.555510261	0.63437986
Mercedes EQC	0.641735704	0.429141752	0.464540448	0.425061808	0.20389294	0.494261176	0.635824998	0.63437986

Since all conditions are unequal and some of them compared to others is very important to the user, they should provide a moderate weight. Therefore, the weights of these methods are calculated using the AHP method and these weights are multiplied by the correct column using equation (3).

Table 4. Weightage normalized matrix

Electric vehicles/ Parameters	Cost	Driving Range	Charging	Speed	Acceleration	Battery	Torque	Power
Tata Tigor	0.024351034	0.066305648	0.033273431	0.013057413	0.01531661	0.033507999	0.003135141	0.002964959
Tata Nexon	0.028409539	0.067605759	0.035353021	0.013057413	0.01108423	0.038920829	0.004518291	0.005110511
Hyundai Kona Electric	0.048296217	0.097941676	0.025370991	0.017953943	0.01176335	0.050519752	0.007284592	0.005390834
Mg Zs Ev	0.042614309	0.090791067	0.029114252	0.015233648	0.01030809	0.057350229	0.006510028	0.005660376
Mahindra E-Verito	0.025771511	0.023835364	0.035353021	0.013057413	0.01212716	0.028352922	0.001678222	0.00226415
Byd E6	0.059152719	0.089924327	0.033273431	0.014145531	0.00921664	0.092791381	0.003319561	0.005067384
Audi E-Tron	0.237422577	0.09555814	0.03743261	0.021762355	0.00691248	0.122433072	0.012245491	0.016172503
Mercedes EQC	0.215100797	0.100325213	0.045750968	0.019586119	0.00618485	0.103101535	0.014015923	0.016172503

In [Table 4] weightage matrix, the best and worst values would be taken for the sake of getting the best suitable EV's

Table 5. Best and Worst Cases

Ideal Best	0.02435 1034	0.100325 213	0.025370 991	0.021762 355	0.006184 85	0.122433 072	0.014015 923	0.016172 503
Ideal Worst	0.2374 22577	0.023835 364	0.045750 968	0.0130574 13	0.015316 61	0.028352 922	0.001678 222	0.002264 15

Here equations (5) and (6) are in play to calculate separation between the best and worst options and get an overall average of profitability by the method [Table 5, 6].

Table 6. Relative closeness of each alternatives

	Ideal separation S+	**Ideal separation S-**	**S+ + S-**	**Ci**
Tata Tigor	0.097874632	0.217688046	0.315562678	0.689840913
Tata Nexon	0.092050651	0.214140553	0.306191204	0.699368728
Hyundai Kona Electric	0.077186511	0.205535999	0.28272251	0.726988449
Mg Zs Ev	0.070005029	0.208843611	0.27884864	0.748949721
Mahindra E-Verito	0.123532095	0.211930328	0.335462423	0.631755789
Byd E6	0.050649361	0.20125815	0.251907511	0.798936678
Audi E-Tron	0.213474482	0.12048212	0.333956601	0.360771787
Mercedes EQC	0.192819242	0.111391149	0.304210391	0.36616484

For each associated case, the relative closeness of the each location with respect to the ideal solution is computed. The maximum value of relative closeness is the best.

Table 7. Rankings based on TOPSIS method.

Cars	rank
Tata Tigor	**5**
Tata Nexon	**4**
Hyundai Kona Electric	**3**
Mg Zs Ev	**2**
Mahindra E-Verito	**6**
Byd E6	**1**
Audi E-Tron	**8**
Mercedes EQC	**7**

4.2. MOORA METHOD

The normal and weighted matrix is the same as that we have calculated above the method of TOPSIS [Table 3, 4]. After obtaining a matrix for the normal weight we will add to the beneficial process values and remove the conditions that should be minimal. As mentioned in equation 3 under MOORA. These values give Bi and when Bi is organized in increasing order provides the level of product we can consider using it [Table 8].

Table 8. Overall performance parameters

Electric vehicles	Bi
Tata Tigor	0.046030088
Tata Nexon	0.054366017
Hyundai Kona Electric	0.093660242
Mg Zs Ev	0.093508699
Mahindra E-Verito	-0.004063622
Byd E6	0.10360539
Audi E-Tron	-0.013596109
Mercedes EQC	-0.013835324

Ranking based on MOORA method from least to highest where least is the best suitable electric vehicle while highest is the worst.

Table 9. Ranking based on MOORA

Cars	rank
Tata Tigor	**5**
Tata Nexon	**4**
Hyundai Kona Electric	**3**
Mg Zs Ev	**2**
Mahindra E-Verito	**6**
Byd E6	**1**
Audi E-Tron	**7**
Mercedes EQC	**8**

5. Conclusion

After using these two methods in the specification of different parameters, features, it concludes that the proposed models are simpler, more efficient, more reliable compared to other strategies because the process time is less and result output is high. By the results of the study, following conclusions could be derived-

- An integrated TOPSIS-MOORA MCDM approach is suggested to select the best electric vehicle. The criteria's weightage is calculated using AHP methodology and driving range and cost emerged as the main factor on analysis.

- In this paper, TOPSIS and MOORA both gave almost similar results. Byd E6 was the best electric vehicle, Audi E-tron was rated as worst alternative as per TOPSIS and Mercedes E-6 was the worst performer as per MOORA method.
- However, results may vary if different criteria are used. As EV market is continuously evolving, new studies can be conducted using the modified parameters.

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