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An Integrated Entropy-TOPSIS Approach for Electric Vehicle Selection

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Abstract: Electric vehicles (EVs) have gained a significant role in reducing emissions of harmful greenhouse gases, which can result in serious effects like global warming, deteriorating air quality, etc. Thus, it helps tackle concerns related to the environment and health of the general public. Many nations are switching towards this new era of electric mobility, thus promoting and contributing to the goal of sustainable development. Due to the rapid evolution and expanding scope of the electric vehicle market, selecting the best alternative between various existing EV models was tedious. In this paper, the electric vehicle in the Indian market context was considered along with the TOPSIS approach as a multi-criteria decision-making tool (MCDM) for choosing and ranking the best available choice for the electric vehicle present in the Indian market for the customer. The entropy method is used to obtain the weights associated with the criteria. For this study, thirteen electric vehicles have been selected as alternatives. This study contributes by giving a real preference order, considering a broad set of selection criteria, and evaluating the best alternative from the existing EVs.

Introduction

Increasing concern over environmental degradation, focus on sustainability, and detrimental health effects in recent years are motivating humans to switch from combustion vehicles to other alternatives to tackle this menace (Knez et al., 2019). Unfortunately, the vast majority of vehicles, even today, are vehicles that run on fossil fuels and release toxic substances into the environment, causing environmental degradation. In recent decades, the world has been under the threat of global warming and climate change as never before (Das et al., 2019; Ecer, 2021) due to non-renewable-based technologies such as internal combustion engine vehicles (Khan et al., 2020) Kumar and Alok (Kumar and Alok, 2020) claimed that the transport sector is the main actor in air pollution and ozone depletion ending in climate change by reason of greenhouse gas (GHG) emissions like CO, CH_4, N_2O, and CO_2; these have necessitated road transport electrification. Knowing the environmental concerns and technical advancements, combustion vehicles are being slowly replaced with cleaner ones, which use green energy alternatives that contribute to the overall betterment of the environment. But there is a ray of hope in this aspect. From the view of sustainable development, sustainable transport has several environmental, social, and economic advantages that could support sustainable development (Wei et al., 2020). Both to struggle with the environmental pollution problem and support sustainable development, many developed countries worldwide have shifted toward electric vehicles (EVs) (Babar et al., 2021). This is why EVs have been regarded as convenient solutions for improving hazardous gas reductions (Tran et al., 2020). Changing trends in automotive markets and ever-increasing environmental concerns have presented us with a whole new concept of electric vehicles. The recent

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century will be the century of electric vehicles. The onset of 21st century third decade has initiated a new era of electric vehicles (Secinaro et al., 2020). Electric cars have been increasingly accepted as a substitute for conventional cars.

Electric cars offer various advantages over conventional combustion vehicles, primarily characterized by their higher efficiency rates and minimal environmental impact (Zahoor et al., 2023). Amid the growing urban pollution and, consequently, the negative effects on people's health, governments across the globe are seeking effective solutions. This is why Electric vehicles are increasingly seen as an alternative to the conventional combustion vehicles.

Therefore, the widespread use of EVs will play a vital role in solving environmental and global economic problems in the automotive industry (Hoque et al., 2017). Notwithstanding, some authors noted that the environmental advantages of clean vehicles and the EU's zero-emission target on transportation could only be accomplished if the electricity is produced from clean resources like solar and wind (Neves et al., 2019). As per the report published by the International Energy Agency (IEA), the CO_2 equivalent emissions from EVs were about 38 million tons on a well-to-wheel basis in 2018, whereas the conventional fleets were about 78 million tons, respectively. Further, it is estimated that the demand for oil products will reduce by 4.3 million barrels per day thanks to EVs in the 2030s (International Energy Agency (IEA). Global EV Outlook 2019, 2020).

Today, the drawbacks of EVs, such as high cost, short battery range, and low top speed, have been partially eliminated. EVs have thus become one of the best alternatives for conventional versions (Ecer, 2021).

Consumers have recently adopted EVs (Samaie et al., 2020). Therefore, the number of EVs and electric mobility has exponentially increased, and this rise is still continuing (Emadi et al., 2005). In parallel with the e-car industry's rapid growth, the development of logistics services utilizing these vehicles has been observed (Yan et al., 2023). Besides their fundamental role in goods and people transportation, such vehicles exhibit zero environmental impact – an increasingly pertinent feature in contemporary society (Yan et al., 2023). It has been noted that fossil fuel vehicles consume more fuel within the urban environment than open roads, thereby significantly contributing to urban air pollution (Liu et al., 2023; Russo et al., 2021). This is being addressed through the incorporation of e-cars into urban logistics, emerging as a critical segment within green logistics (Strale, 2019).

Research Methodology

TOPSIS method

TOPSIS is a numerical method for solving multi-criteria decision-making problems (Wei et al., 2020). The method is based on the assumption that the chosen alternative should have the shortest Euclidean distance from the optimal solution and the shortest Euclidean distance from the negative positive solution Optimal Solution Edge Imaginary solution in which all the values of the components coincide with the highest value in database showing a satisfactory solution. The negative optimal solution is related to the concept of a search solution in which all feature values are the minimum attribute values in the database. Thus, TOPSIS provides a solution that is theoretically closest to the optimal solution and theoretically farthest from the worst-case solution. The basic multi-criteria decision-making process of the TOPSIS method is described to select the best alternative among the available ones.

Assumptions

In this study thirteen electric vehicle Tata Tiago EV (Ev1), MG Comet EV (Ev2), Mahindra XUV400 (Ev3), Tata Nexon EV (Ev4), Hyundai Kona Electric (Ev5), BMW i4 (Ev6), Kia EV6 (Ev7), MG ZS EV (Ev8), BYD E6 (Ev9), BYD Atto3 (Ev10), Tata Nexon EV Prime (Ev11), Hyundai Ioniq 5 Long Range RWD (Ev12), Hyundai Ioniq 5 Long Range AWD (Ev13) were taken under consideration with the following essential criteria: Price, Acceleration, Battery Capacity, Maximum Power, Range, Charging Time which has been described as below:

1. Price (Cr1): Price of the Electric vehicle varied across different showrooms in India (Price in ₹ Lakhs).
2. Acceleration (Cr2): Acceleration of the vehicle as measured from 0-100 kmph speed achieved in seconds (Acceleration (0-100 km/h) in seconds).
3. Battery capacity (Cr3): Battery capacity refers to the power stored in a single charge (Battery capacity (kWh)).
4. Maximum power (Cr4): Maximum power as measured in bhp of electric vehicle (Max Power (kW)).
5. Range (Cr5): Maximum range of electric vehicle in a single full charge of the vehicle (Range (km)).
6. Charging time (Cr6): the time taken by the vehicle to charge to full capacity (Charging time (0-80%) hours).

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Among the criteria thus considered, Price (Cr1) and Charging time (Cr6) are Cost criteria, whereas Acceleration (Cr2), Battery capacity (Cr3), Maximum power (Cr4) and Range (Cr5) are benefit criteria.

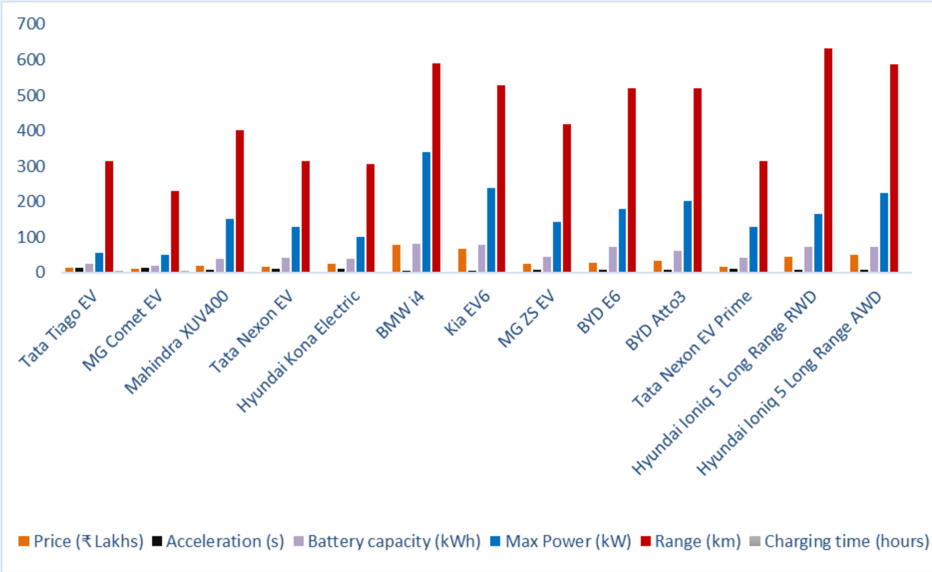

Figure 1. Comparison of various specifications of the thirteen electric vehicles.

Results and Discussion

Steps Involved in Employing TOPSIS Methods

Step 1. Construction of the decision matrix

Create a decision matrix that comprises Alternative and Attributes for selecting the best alternative as represented in eq. (1),

Alternatives: i = 1,2,3,4,.....m

Attributes: j = 1, 2, 3,....n

Decision Matrix: X = [xij] (1)

Table 1 displays a general specification decision matrix with three sparks plug manufacturing businesses. Rows represent options, while columns represent attributes.

The data for the following table has been taken from website of car dekho (https://www.cardekho.com/).

Matrix rank: m*n

Table 1. Decision matrix of various specifications of the thirteen electric vehicles.

Electric Vehicle/ Criteria	Cr1	Cr2	Cr3	Cr4	Cr5	Cr6
Ev1	12.04	11.9	24	55	315	5.5
Ev2	9.98	12.95	17.3	50	230	5.5
Ev3	18.99	8.3	39.4	150	400	0.833
Ev4	16.99	9.9	40.5	129	315	1
Ev5	24.04	9.7	39.2	100	305	1
Ev6	77.5	5.7	80.7	340	590	0.5166
Ev7	65.95	5.2	77.4	239	528	0.3
Ev8	23.38	8.5	44.5	143	419	0.833
Ev9	27.99	8.5	71.7	180	520	1
Ev10	33.99	7.3	60.48	201	521	1
Ev11	14.74	9.2	40.5	129	315	1
Ev12	44.95	7.6	72.6	165	631	0.3
Ev13	48.95	6.1	72.6	225	587	0.3

Step 2. Calculate the normalized decision matrix

Elements of the matrix are divided by the square root of the sum of each squared element as depicted in eq. (2),

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

Table 2. Normalized Decision Matrix

Electric Vehicle/Criteria	Cr1	Cr2	Cr3	Cr4	Cr5	Cr6
Ev1	0.0875	0.3750	0.1184	0.0854	0.1920	0.6698
Ev2	0.0725	0.4080	0.0854	0.0776	0.1402	0.6698
Ev3	0.1380	0.2615	0.1944	0.2328	0.2439	0.1014
Ev4	0.1234	0.3119	0.1998	0.2002	0.1920	0.1218
Ev5	0.1746	0.3056	0.1934	0.1552	0.1859	0.1218
Ev6	0.5630	0.1796	0.3982	0.5277	0.3597	0.0629
Ev7	0.4791	0.1638	0.3819	0.3709	0.3219	0.0365
Ev8	0.1699	0.2678	0.2196	0.2219	0.2554	0.1014
Ev9	0.2033	0.2678	0.3538	0.2794	0.3170	0.1218
Ev10	0.2469	0.2300	0.2984	0.3120	0.3176	0.1218
Ev11	0.1071	0.2899	0.1998	0.2002	0.1920	0.1218
Ev12	0.3266	0.2395	0.3582	0.2561	0.3847	0.0365
Ev13	0.3556	0.1922	0.3582	0.3492	0.3579	0.0365

The normalized decision matrix is acquired and shown in Table 2.

Step 4: Calculating the Criteria Weights

The Entropy Value is used by the Entropy technique to determine the weight values of the criterion. The Entropy Value and the criterion weight increase with increasing data dispersion. On the basis of different attributes, a weighted matrix was established and shown in Table 3. The steps in this method's evolution are as follows:

They are calculating the Entropy (E_i) Value as depicted in eq. (3). Here, all of the data in the normalized decision matrix have their natural logarithm values (ln) calculated. The normalized data is then multiplied by these values, and the resulting product is divided by the number of options' natural logarithm (ln(n)).

$$E_i = \frac{\sum_{j=1}^{n} p_{ij} \ln p_{ij}}{\ln n} \quad (3)$$

Calculate the weight values for the criteria. After completing the (1 − Ei) calculation, these values are totalled for each criterion. Next, the final weight of the criteria is determined as per eq. (4),

$$w_i = \frac{1-E_i}{\sum_{j=1}^{n}(1-E_i)} \quad (4)$$

Table 3. Weighted Matrix

Criteria	Cr1	Cr2	Cr3	Cr4	Cr5	Cr6
weight	0.149993	0.2217	0.198154	0.184525	0.216054	0.029574

Step 3. Weighted normalized decision matrix

The weighted normalized value V_{ij} was calculated as eq. (5),

$V_{ij}=w_{ij} * n_{ij}$, i=1,2,3,4……m, j=1,2,3,4….n (5)

where $V_{ij} = W_{ij\times}n_{ij}$

The obtained normalized weighted matrix is presented in Table 4.

Step 4. Determining the positive and negative ideal solutions

In the case of advantageous qualities (those with higher values that are desired for the specific application), V_j^+ represents the higher value of the attribute, as specified in eq. (6).

$$V_j^+ = \{(\sum_i^{max} v_{ij}/j\varepsilon J, \sum_i^{min} v_{ij}/j\varepsilon J')/i = 1,2,..N\} = \{V_1^+, V_2^+ V_3^+ \ldots V_M^+\}$$

In the case of non-beneficial attributes (i.e., those of which lower values are desired for the given application),V_j^- indicates the lowest value of the attribute as presented eq. (7),

$$V_j^- = \{(\sum_i^{min} v_{ij}/j\varepsilon J, \sum_i^{max} v_{ij}/j\varepsilon J')/i = 1,2,..N\} = \{V_1^-, V_2^- V_3^- \ldots V_M^-\}$$

where J = (j = 1, 2, …, M) /j is associated with beneficial attributes, and J' = (j = 1, 2, …, M) /j is associated with non-beneficial attributes

The Positive and Negative ideal solutions are shown in Tables 5 and 6,

Step 5. Calculate the Difference measure (S_i^+ and S_i^-) for each alternative A_j from PIS and NIS

Difference measured given by Euclidean for each alternative have been calculated using eq. (8) and (9). The obtained results are tabulated in Table 7.

Table 4. Normalized Weighted Matrix (V_{ij})

Electric Vehicle/Criteria	Cr1	Cr2	Cr3	Cr4	Cr5	Cr6
Ev1	0.0131	0.0831	0.0235	0.0158	0.0415	0.0198
Ev2	0.0109	0.0905	0.0169	0.0143	0.0303	0.0198
Ev3	0.0207	0.0580	0.0385	0.0430	0.0527	0.0030
Ev4	0.0185	0.0692	0.0396	0.0369	0.0415	0.0036
Ev5	0.0262	0.0678	0.0383	0.0286	0.0402	0.0036
Ev6	0.0845	0.0398	0.0789	0.0974	0.0777	0.0019
Ev7	0.0719	0.0363	0.0757	0.0684	0.0695	0.0011
Ev8	0.0255	0.0594	0.0435	0.0410	0.0552	0.0030
Ev9	0.0305	0.0594	0.0701	0.0516	0.0685	0.0036
Ev10	0.0370	0.0510	0.0591	0.0576	0.0686	0.0036
Ev11	0.0161	0.0643	0.0396	0.0369	0.0415	0.0036
Ev12	0.0490	0.0531	0.0710	0.0473	0.0831	0.0011
Ev13	0.0533	0.0426	0.0710	0.0644	0.0773	0.0011

$$S_i^+ = d\left(V_{ij,}V_j^+\right) = \sqrt{(v_{ij} - v_j^+)^2} \quad (8)$$

and

$$S_i^- = d\left(V_{i,}V_j^-\right) = \sqrt{(v_{ij} - v_j^-)^2} \quad (9)$$

for i=1,2,3……….m

Table 5. Positive ideal solution (PIS)

V_j^+	0.0109	0.0905	0.0789	0.0974	0.0831	0.0011

Table 6. Negative ideal solution (NIS)

V_j^-	0.0845	0.0363	0.0169	0.0143	0.0303	0.0198

Step 6. Calculate the corresponding closeness coefficient (CC_i) of the alternatives

Table 7. Alternate from PIS and NIS.

Alternative	S_i^+	S_i^-
Ev1	0.1090	0.0863
Ev2	0.1178	0.0913
Ev3	0.0817	0.0813
Ev4	0.0863	0.0827
Ev5	0.0947	0.0735
Ev6	0.0895	0.1154
Ev7	0.0876	0.0918
Ev8	0.0800	0.0796
Ev9	0.0612	0.0968
Ev10	0.0666	0.0886
Ev11	0.0875	0.0829
Ev12	0.0736	0.0932
Ev13	0.0726	0.0949

The alternative's corresponding closeness coefficient (CCi) was calculated using eq. (10) as follows:

$$CC_i = \frac{S_i^-}{(S_i^+ + S_i^-)} \quad \text{for } i=1,2,3\ldots..m \quad (10)$$

The obtained result is presented in Table 8.

Step 7. Rank the preference order or select the alternatives closest to 1

The TOPSIS approach was used to determine preference order, which is displayed in Table 9 and Figure 2.

The TOPSIS method has been successfully applied in the study. The determined findings have proven that BYD E6 had the uppermost priority (Rank 1), BYD Atto3 had the second uppermost (Rank 2), and Hyundai Ioniq 5 Long Range

AWD ranked third (Rank 3). In contrast, Hyundai Kona Electric (Rank 12) and MG Comet EV (Rank 13) rank lowest, taking into consideration the various criteria mentioned earlier (from a customer point of view).

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Table 8. Corresponding closeness coefficient (CC_i) of the alternatives.

Alternatives	CC_i	Alternatives	CC_i
Tata Tiago EV	0.4419	Hyundai Kona Electric	0.4370
MG Comet EV	0.4367	BMW i4	0.5633
Mahindra XUV400	0.4987	Kia EV6	0.5117
Tata Nexon EV	0.4894	MG ZS EV	0.4986
BYD E6	0.6127	BYD Atto3	0.5709
Tata Nexon EV Prime	0.4866	Hyundai Ioniq 5 Long Range RWD	0.5586
Hyundai Ioniq 5 Long Range AWD	0.5665		

Table 9. Obtained preference order.

Rank	Brand/Manufacturer	Rank	Brand/Manufacturer
1	BYD E6	**7**	Mahindra XUV400
2	BYD Atto3	**8**	MG ZS EV
3	Hyundai Ioniq 5 Long Range AWD	**9**	Tata Nexon EV
4	BMW i4	**10**	Tata Nexon EV Prime
5	Hyundai Ioniq 5 Long Range RWD	**11**	Tata Tiago EV
6	Kia EV6	**12**	Hyundai Kona Electric
		13	MG Comet EV

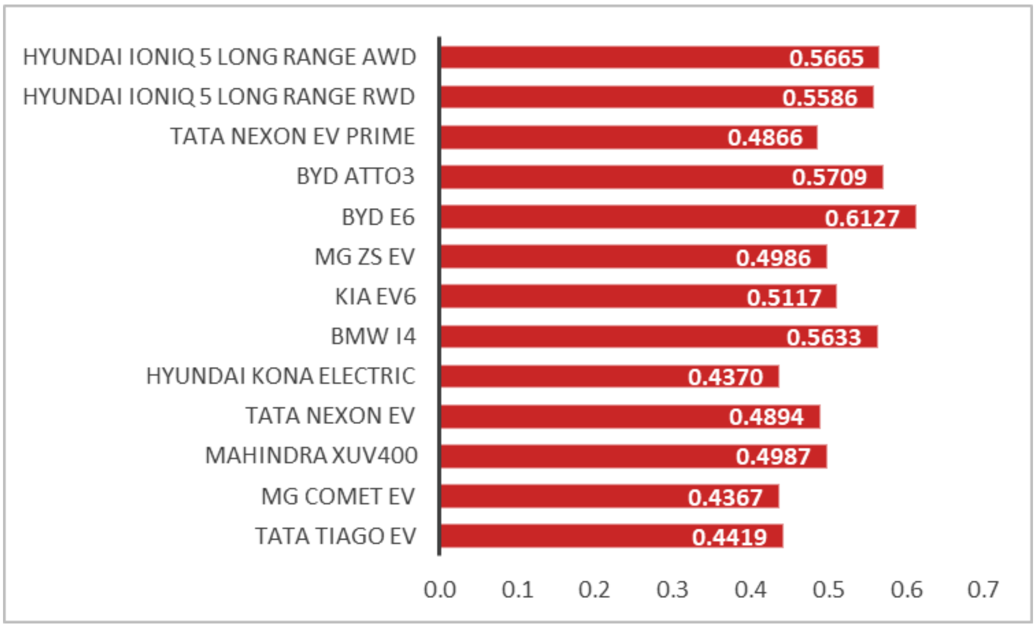

Figure 2. Corresponding closeness coefficient.

Conclusion

This paper on the selection of various electric vehicles present in the Indian market through the TOPSIS approach has provided valuable insights into the tedious process of selecting an electric vehicle that suits best from the consumer's point of view. Our paper encompassed a range of criteria such as cost, acceleration, battery capacity, charging time, etc., reflecting the multi-faceted nature of this decision-making process.

Through applying the TOPSIS method of multi-criteria decision-making, we have systematically analyzed, assessed, and ranked the available electric vehicles in the market. This approach has allowed us to evaluate trade-offs (conflicting interests) objectively and make informed decisions.

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In a nutshell, this study makes a good contribution to the ever-expanding and evolving market and knowledge space in the era of electric mobility. Also, it highlights how techniques related to multi-criteria decision-making can be used in this emerging field. The various insights gained from this paper will lead to more efficient choices among consumers and various other stakeholders of electric mobility.

Future scope

This study has also underlined the significance of employing TOPSIS (MCDM) in the context of electric vehicle selection and its potential for broader applications in decision-making across various areas. Focusing on the quantitative aspect of decision-making and comparing various criteria makes it possible to have a structured and data-driven approach for addressing multi-criteria decision problems.

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Conflict of Interest

The authors declare no known conflict of interest for this article.

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