Integrated Machine Learning Algorithms and MCDM Techniques in Optimal Ranking of Battery Electric Vehicles

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Abstract. The automobile industries across the world of this present age are streamlining the manufacture of battery electric vehicles (BEV) as a step towards creating pollution free environment. BEVs are used as an alternate strategy to alleviate the carbon emission at global level. As environmental conservation is one of the long standing sustainable 1f ?developmental goals it is the need of the hour to make a paradigm shift from fossil fuels to renewable energy sources, at the same time this also gives rise to a decision-making problem on making optimal choice of the electric vehicles. In this paper a decision making problem based on ten alternative BEVs and eleven criteria is considered from the earlier works of Faith Ecer. The new ranking method of multi-criteria decision making MCRAT(Multiple Criteria Ranking by Alternative Trace) is used together with three different criterion weight computing methods of AHP(Analytical Hierarchy Process) ,CRITIC (CRiteria Importance Through Intercriteria Correlation) & MEREC (MEthod based on the Removal Effects of Criteria). The results obtained are compared and validated using random forest machine learning algorithm. This research work conjoins multi-criteria decision making methods and machine learning algorithms to make optimal decisions on Battery electric vehicles and this integrated approach yields optimal ranking results and it will certainly create new rooms in decision-making approaches in coming days.

Key words: Random Forest, MCRAT, AHP, CRITIC, MEREC, Optimal decision making

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1. Introduction

Transportation is quite an inevitable process that employs vehicles of all kinds to displace people and commodity to the required places. Environmental pollution is one of the major impacts of Transportation by means of vehicles based on fossil fuels. The automobile industries across the globe are making stern research on promoting green planet with the introduction of battery electric vehicles comprising different features and accessories. With the vision of attaining the sustainable goal of carbon neutral communities, the production of BEVs is accelerated to reduce and nullify the carbon emission. The sales of electric vehicles at global markets are increasing and it is expected that 30% of the vehicles will turn electric by the end of 2030. Though BEVs are a means of abating pollution, the reluctancy of purchasing electric vehicles still exists amidst buyers. One of the prime reasons is the question on the longevity of the battery used in the electric vehicles. The choice of the battery is highly influenced by several factors such as costs of maintenance, charging time, performance, capacity and many other. Faith Ecer has presented the detailed study on the eleven criteria for choosing the optimal battery and has also described the ranking of ten alternative BEVs using seven MCDM methods with the criterion weights calculated using the method of SECA. Though several decision methods are applied to 10 ×11 decision-making matrix, the criterion weights are computed using only one method. Also the ranking results of Ecer, 2021 [1] obtained using MCDM methods are validated using other MCDM methods of BORDA and COPELAND.

The decision matrix developed by Faith Ecer serves as the motivation for this research work. The methodology developed in this paper is a step to overcome the following research gaps identified in the works of Faith Ecer.

- Different methods to calculate criterion weights are not employed to rank the alternatives
- Lack of heterogeneity techniques to validate the MCDM ranking results

The new initiatives taken in this research work are

- Application of three methods to compute criterion weights
- Ranking of alternatives using two other different methods of MCRAT and RAPS
- Validation of MCDM ranking results using machine learning algorithms

The remaining contents are organized into the following subsections as follows, section 2 consists of the literature review of the earlier works, section 3 discusses the methodology, section 4 applies the proposed agglomerated decision making method to the 10 × 11 decision making matrix and section 5 compares the results and concludes the work.

2. Literature Review

Multi criteria decision making is a process of making optimal decisions based on several criteria. The objective of every MCDM method is to find the optimal ranking of the alternatives using criterion weights. Several methods exist in literature to find the criterion weights and ranking of the alternatives. Researchers have applied various MCDM methods to make many decisions related to battery electric vehicles. To mention a few, Van De Kaa et al.,[2] and Onat et al., [3] on the suitability of the electric vehicles, Bucsan et al., [4] on the efficiency of the electric vehicles, Kane et al., [5] , De Souza and Dedini, [6] on the comparative efficacy of hybrid vehicles over fossil fuel based vehicles, Domingues et al., [7] and Domingues-Olavarría., [8] on the assessments of the electric vehicles, optimization of systems associated with electro mobility.

Leirós-Rodrígueza, et al.[9] used evolutionary algorithms to evaluate electric vehicles. Onat et al., [10] have applied MCDM methods such as TOPSIS in combination with Life cycle assessment to make decisions on alternative vehicles. Chang et al., [11] applied hesitant fuzzy decision model to supplier selection of battery vehicles. Yang et al., [12] used the method of bidirectional projection using pythagorean hesitant fuzzy representations to select the recycling mode of power batteries of electric vehicles. Wilken et al.,[13] compared electric vehicles with engine vehicles, Liu and Dai [14] used MOPSO and theory of cumulative prospect to make decisions on the charging stations of electric vehicles. Kishor and Fraile-Ardanuy [15], employed the optimization techniques to make decisions on scheduling of charging and discharging, Tarei et al., [16] on the barriers of adopting electric vehicles.

Loganathan et al., [17] used MCDM method to make selection of Li-ion batteries of electric vehicles, R. Wang et al., [18] used Triangular fuzzy entropy method to find the criterion weights and MULTIMOORA method to rank the suppliers of batteries. Aboushaqrah et al.,[19] made use of the combination of Life cycle assessment and neutrosophic MCDM to select alternate fuel taxis, Ren et al., [20] used sentimental analysis and MCDM methods to select strategies for battery selection, Tian et al.,[21] applied hierarchical MCDM and decision tools based on data driven for choosing battery electric vehicles, Patil & Mujumdar[22,23], presented the key factors persuading electric vehicles. Nayana [24], used genetic algorithms together with MCDM to make optimal scheduling of electric vehicles, A. Ghosh et al., [25] applied the MCDM methods of AHP and TOPSIS to select the optimum electric rickshaws, Yang et al.,[26] presented hesitant fuzzy MULTIMOORA method in supplier selection of batteries. Bhuyan et al.,[27] evaluated recycling of lithium-ion batteries. By using MCDM, Ekel [28], made optimal decisions on charging capacities, Bhattacharjee et al.,[29] on eco designing, Patil and Majumdar [23], on the key deciding factors of electric vehicles. Loganathan et al., [17] presented a review on the MCDM techniques applied to make decisions on advanced batteries of electric vehicles. In all the earlier works of MCDM decision on BEVs only very few ranking methods such as TOPSIS, MULTIMOORA, AHP are used. In continuation, Ecer [1], applied seven ranking MCDM methods and only one method of obtaining the criterion weights. The validation of ranking results is done using MCDM methods which are homogeneous in nature. On identification of the research gaps as presented in section 1, a new integrated MCDM method with a machine learning algorithm is developed in section 3 to rank the BEVs. The newly developed integrated MCDM and ML method is a combination of the MCDM methods of criterion weight calculation AHP, CRITIC, MEREC with the ranking MCDM method of MCRAT and the supervised machine learning algorithm of Random Forest Algorithm.

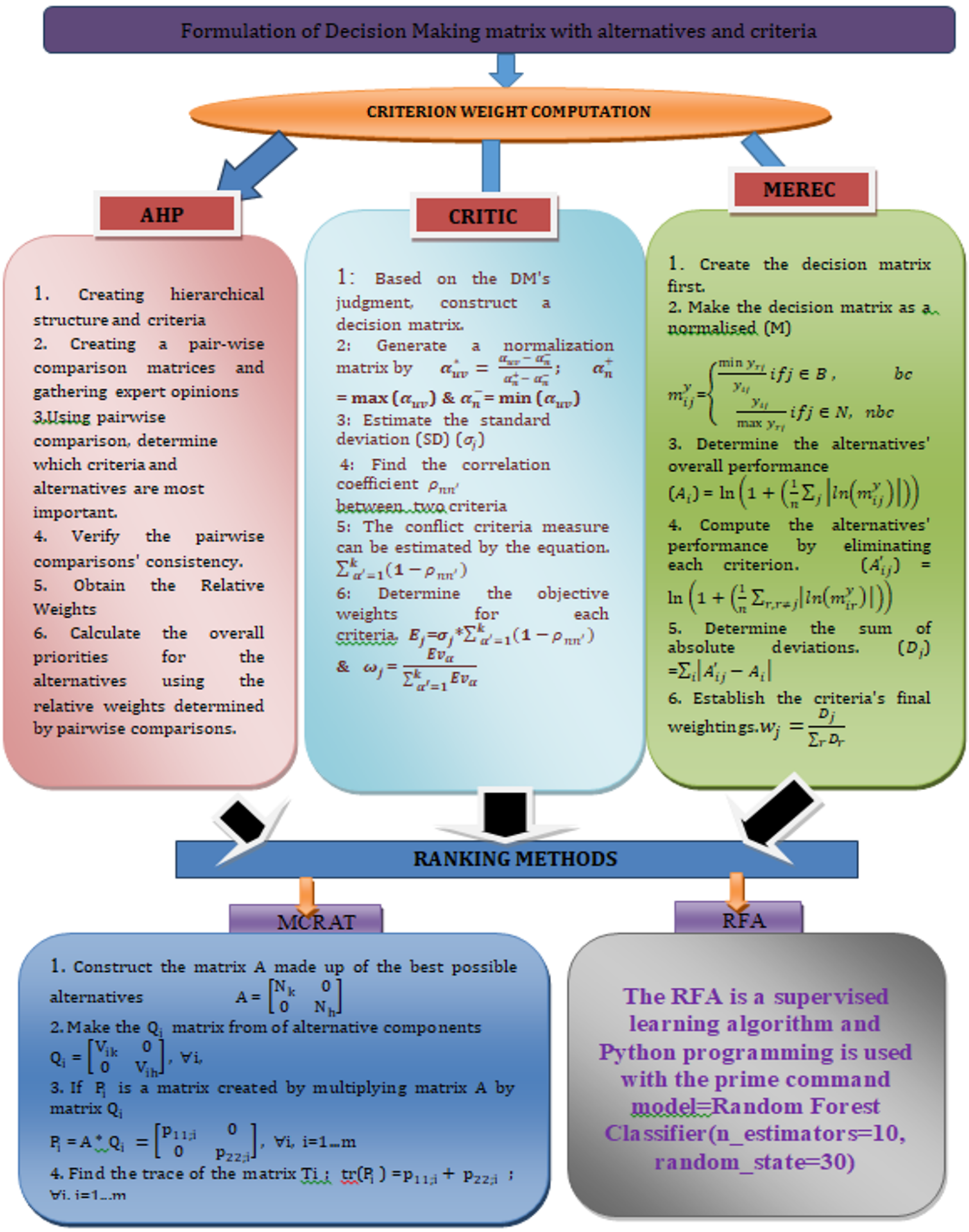
MCRAT is one of the recently developed MCDM methods. This method of ranking the alternatives is based on traces. Urošević et al., [30] has applied this method to rank the alternatives of blasting patterns in mining industry, Gligorić et al., [31] applied to make optimal decisions on coal supplier. In these applications, the usual methods of pair wise comparison are used to obtain the criterion weights. The methods of AHP, CRITIC or MEREC are not used with MCRAT to obtain the criterion weights. This has motivated us to develop an integrated MCDM with the combinations of AHP, CRITIC, MEREC with MCRAT.

AHP is the method developed by Saaty [32], and it is widely applied to obtain the criterion weights. This method comprises three main steps namely hierarchy formation, pairwise comparison and consistency checking. The method of AHP is applied in different fields to determine the criterion weights of the decision making problem. A few recent applications are Belay et al.,[33] in construction projects, Kim and Kim,[34] in software up gradation, Anuradha and Gupta,[35] in forest sustainability, Veisi et al.,[36] in agriculture irrigation system. This method is also used in integration with other ranking methods and also used in different environments of fuzzy and extended fuzzy forms. CRITIC is another method of finding the criterion weights and it is proposed by Diakoulaki et al.,[37]. This method is based on correlation analysis. The method of CRITIC is recently applied by Nguyen et al., [38] in appraising financial performances, Aksakal et al., [39] in material evaluation, Petkovski et al., [40] in determining the energy indicators. The method of MEREC is developed by Keshavarz-Ghorabaee et al., [41] is one of the MCDM methods used to determine the criterion weights based on analysis of variances. The method of MEREC is applied by Raut et al.,[42] in supplier selection, Shanmugasundar et al., [43] in selection of painting robot, Ivanović et al.,[44] in truck selection, S. Ghosh and Bhattacharya, [45] in financial performances, Ulas et al., [46] in dealing with banking problems, Fattouch et al., [47] in IoT affairs. These criterion weight computation methods are extensively applied in various other fields in crisp forms, fuzzy and extended fuzzy forms of intuitionistic, Neutrosophic and Plithogenic.

At recent times, the MCDM methods are integrated with machine learning algorithms, especially with the random forest algorithms, one of the most commonly used supervised ML algorithm. In line with it, researchers have used many MCDM methods in combination with RFA, a few recent works are presented as follows, Arabameri et al.,[48] in making predictions on gully erosion, Musbah et al., [49] in Energy Management, Srivastava and Eachempati,[50] in employee retention, Q. He et al.,[51] in prediction analysis, Pham et al.,[52] in land slide vulnerability, Z. He et al., [53] in textile chemical processing, Kadkhodazadeh et al.,[54] in climate change , Mustapha et al.,[55] in breast cancer screening, Khosravi et al., [56] in flood susceptibility, Z. Wang et al., [57] in chemical engineering , García et al., [58] in credit affairs, Ali et al.,[59] in landslide modeling , Pourkhodabakhsh et al., [60] in human resource management, Chowdhury et al., [61] in COVID-19 classification, Baqer et al.,[62] in pollutant prediction, Jassim et al., [63] in diagnosis of adult autism, Al-Bawi et al.,[64] in gully erosion. In the above mentioned combinations of MCDM and RFA, various decision making methods such as COPRAS, VIKOR, MULTIMOORA are used. To the best of our knowledge the combination of the criterion weight computing methods of AHP, CRITIC, MEREC with ranking method of MCRAT along with Random Forest algorithm do not exist in the literature. This has motivated us to construct an integrated MCDM and ML decision making methods.

3. Methodology

This section presents the steps involved in finding the criterion weights and ranking procedure of the alternatives. In this the integrated MCDM and ML decision making approach is presented



In the above flow chart representation, the decision making matrix is first formulated with alternatives and criteria based on expert's opinion. The criterion weights are determined using any of the methods of CRITIC, AHP or MEREC, then after finding the criterion weights the alternatives are ranked using the method of MCRAT and later validated using Random forest algorithm.

4. Application of the Integrated Method

In this section, the decision making on optimal alternatives of battery electric vehicles is made based on the following 10×11 decision matrix taken from Faith Ecer. The initial decision making matrix comprises of 10 alternatives and eleven criteria in which six are cost criteria and remaining five are benefit criteria. Let C1,C2……..C11 represents a criteria of BEVs and A1,A2………..A10 denotes Alternatives of batteries.

Table 1 : Decision matrix

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11
	Min	Min	Min	Min	Min	Min	Max	Max	Max	Max	Max
A1	90	7.9	7.5	35180	1732	18	62	382	90	150	450
A2	25	7.3	20	44450	1320	13	33.2	260	160	170	425
A3	100	7.8	9.5	36620	1616	28	60	320	146	200	480
A4	40	2.4	7	74490	2107	18.6	70	539	260	503	420
A5	30	10	10	23500	1500	15	41	300	168	92	434
A6	54	9.9	6	52940	1527	15.1	100	311	172	120	462
A7	60	9.6	9.6	36025	1567	15	36	201	150	134	341
A8	54	11.2	9	37000	1506	15.7	64	448	166	201	315
A9	45	12.7	7.5	24550	1200	21	62	132	130	82	185
A10	36	6.9	3.5	29900	1365	16	33	176	153	181	225

The criteria based on which the ranking of the alternatives is made are presented in Table 1 along with a concise description

Table 2: Description of Criteria

Criteria	**Description**	**Criteria**	**Description**
C1	Quick Charge Time	C7	Battery capacity
C2	Acceleration	C8	Range
C3	Full charge time	C9	Top speed
C4	Purchasing price	C10	Maximum power
C5	Curb weight	C11	Permitted load
C6	Energy Consumption		

The weights of the criteria are determined using the three methods of AHP, CRITIC and MEREC by following the steps stated in section 3. Table 3 presents the criterion weights.

Table 3 Criterion Weights

Criteria	Criterion Weights		
	AHP	**MEREC**	**CRITIC**
C1	0.240771	0.052511	0.113499
C2	0.106748	0.040301	0.097826
C3	0.116714	0.106865	0.109848
C4	0.186879	0.081915	0.079743
C5	0.063205	0.065187	0.060786
C6	0.085658	0.045177	0.114627
C7	0.082809	0.038176	0.100505
C8	0.038685	0.074601	0.076536
C9	0.028636	0.113716	0.120625
C10	0.028486	0.164853	0.078537
C11	0.02141	0.216698	0.047469

The sum of the criterion weights obtained in each of the three methods is equal to one. Fig.1, 2 and 3 presents the distribution of weights to all the eleven criteria.

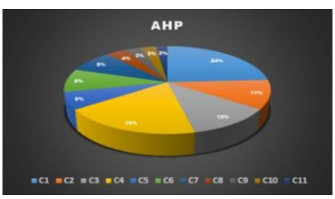


Fig.1 Criterion Weights by AHP

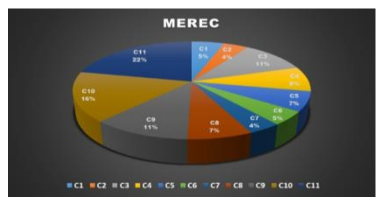


Fig. 2 Criterion Weights by MEREC

Fig. 3 Criterion Weights by CRITIC

By using the above criterion weights, the ten alternatives are ranked using the MCDM method of MCRAT as described in section 3. The score values of the ten alternatives are presented in Table 4 and the graphical representation presenting the ranking of the alternatives is given in Fig.4

Table 4 Score values of alternatives based on MCDM methods

Alternatives/ Ranking Methods	**MCRAT & AHP**	**MCRAT & MEREC**	**MCRAT & CRITIC**
A1	0.657331	0.082532012	0.054987205
A2	0.552846	0.072046055	0.056802214
A3	0.721481	0.083718694	0.05216873
A4	0.714603	0.092790767	0.076583922

A5	0.401033	0.070192848	0.058007494
A6	0.644047	0.093066784	0.061101992
A7	0.51977	0.070605822	0.043527548
A8	0.552443	0.081811711	0.0541517
A9	0.469883	0.075756668	0.047254251
A10	0.374928	0.066485205	0.056240779

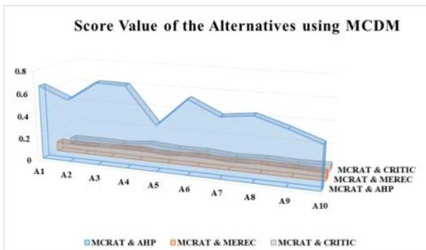


Fig.4 Score values of the Alternatives

As a means of testing the consistency of the MCDM methods, the machine learning algorithm is used with the criterion weights as given in Table 2. The score values of the alternatives using the method of Random Forest Algorithm is presented in Table 5.

Table 5 Score values of alternatives based on integrated methods of MCDM and ML

MCDM method integrated with ML	**A1**	**A2**	**A3**	**A4**	**A5**	**A6**	**A7**	**A8**	**A9**	**A10**
AHP	0	0	0	0	0.87	0	0.56	0.14	0.74	0.91
MEREC	0	0.51	0	0	0.84	0	0.62	0	0.48	0.93
CRITIC	0.45	0	0.72	0	0	0	0.96	0.54	0.83	0

The alternatives with score values 0 are more acceptable and the alternatives with maximum score values are highly rejected. The graphical representation of the score values is presented in Fig5.

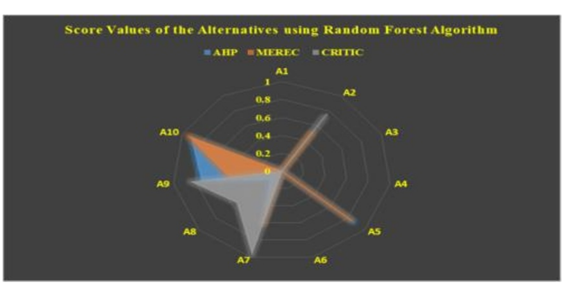


Fig. 5 Graphical Representation of Score Values of the alternatives using RFA

The ranking results of the alternatives based on MCRAT with the combination of three methods of criterion weight computation is presented in Table 6. The maximum score values are given priorities.

Table 6 Ranking results of alternatives based on MCDM method

Alternatives/ Ranking Methods	MCRAT & AHP	MCRAT &MEREC	MCRAT & CRITIC
A1	3	4	6
A2	5	7	4
A3	1	3	8
A4	2	2	1
A5	9	9	3
A6	4	1	2
A7	7	8	10
A8	6	5	7
A9	8	6	9
A10	10	10	5

The ranking results of the alternatives based on RFA is presented in Table 7. The alternatives are grouped into acceptable and rejectable and in each combination of the criterion weight computation methods the alternatives that fall into two of the groups vary.

Table 7 Ranking Result of alternatives based on integrated methods of MCDM and ML

Integrated MCDM & ML	Acceptable Alternatives					Alternatives to be Rejected				
AHP	A1	A2	A3	A4	A6	A5	A7	A8	A9	A10
MEREC	A1	A3	A4	A6	A8	A2	A5	A7	A9	A10
CRITIC	A2	A4	A5	A6	A10	A1	A3	A7	A8	A9

5. Discussion

The ranking results obtained from the applications of different MCDM methods by Faith Ecer is compared with the ranking results of MCRAT AHP, MCRAT CRITIC & MCRAT MEREC. Table 8 presents the comparative analysis of the ranking results.

Table 8 Comparison of the ranking results

	EDAS	**MABAC**	**WASPAS**	**CODAS**	**TOPSIS**	**Borda**	**Copeland**
MCRAT AHP	0.054545	-0.07879	-0.00606	0.030303	0.042424	0.018182	0.018182
MCRAT MEREC	0.127273	0.078788	0.115152	0.127273	0.175758	0.139394	0.139394
MCRAT CRITIC	0.927273	0.90303	0.866667	0.721212	0.890909	0.915152	0.915152

It is found that the ranking results obtained using MCRAT CRITIC is highly in line with almost all the ranking results of Faith Ecer. It is also observed that the ranking results obtained from the method of MCRAT CRITIC is more consistent in comparison with the results of MCRAT AHP & MCRAT MEREC.

Also from the Tables 6 & 7 the ranking results of the alternatives are found to be highly consensus with one another. The results obtained using machine learning algorithms ease the process of finding the acceptable alternatives. On grading the ten alternatives as acceptable and rejectable, the most feasible alternatives are determined. Then on applying the above ranking methods to the acceptable alternatives, the following results are obtained as in Table 9.

Table 9 Ranking results of integrated approach

Alternatives/ Ranking Methods	MCRAT & AHP	MCRAT & MEREC	MCRAT & CRITIC
A1	4	4	4
A2	3	2	2
A3	5	5	5
A4	1	1	1
A6	2	3	3

Also the ranking results obtained using MCDM method and the integrated MCDM & ML methods are compared and it is found that the results of the latter integrated method to be more feasible and the Table 10 vividly present the same.

Table 10 Comparative Analysis of the Integrated MCDM & ML ranking results

	MCRAT AHP	**MCRAT MEREC**	**MCRAT CRITIC**
MCRAT AHP	1	0.9	0.9
MCRAT MEREC		1	1
MCRAT CRITIC			1

In this case the results are more promising on integrating ML algorithms with MCDM methods. Also the burden of ranking all the ten alternatives is reduced. This will be highly beneficial to the decision makers in handling with many number of alternatives. The initial grouping of the alternatives as acceptable and rejectable using ML algorithms makes the decision process smoother. Then the acceptable alternatives are ranked using the MCDM methods. The optimal ranking of the alternatives thus obtained out of this integrated approach is A4 > A2 > A6 > A1 > A3.

6. Conclusion

This paper presents an integrated decision method of MCRAT and RFA with three different methods of obtaining criterion weights. The integrated approach simplifies the task of ranking alternatives. The grouping of the alternatives or the classification of alternatives as acceptable and rejectable lessens the difficulties of ordering the alternatives. The method of CRITIC used for determining the criterion weights is highly optimal in comparison with other methods. Also the reduction of alternatives helps in considering only the feasible alternatives and henceforth the ranking of the alternatives is made more easier is the advantage of this integrated approach. This method shall be applied to other decision making problems.

References:

1) F.Ecer., A consolidated MCDM framework for performance assessment of battery electric vehicles based on ranking strategies. *Renewable and Sustainable Energy Reviews*, *143*(January). (2021). https://doi.org/10.1016/j.rser.2021.110916
2) G.Van De Kaa ., D.Scholten ., J.Rezaei ., & Milchram C. The battle between battery and fuel cell powered electric vehicles: A BWM approach. *Energies*, *10*(11). (2017). https://doi.org/10.3390/en10111707
3) N.C.Onat ., M.Noori ., M.Kucukvar .,Y. Zhao ., O.Tatari ., & M.Chester., Exploring the suitability of electric vehicles in the United States. *Energy*, *121*(February), 631–642. . (2017). https://doi.org/10.1016/j.energy.2017.01.035
4) G Bucsan., M Balchanos., D. N Mavris., J. S Lee., M Ishigaki., & A Iwai. , Management of technologies for electric vehicle efficiency towards optimizing range. *2016 IEEE International Conference on Systems, Man, and Cybernetics, SMC 2016 - Conference Proceedings*, 3836–3841. (2017).https://doi.org/10.1109/SMC.2016.7844832
5) S. N Kane., A Mishra., & A. K Dutta., Preface: International Conference on Recent Trends in Physics (ICRTP 2016). *Journal of Physics: Conference Series*, *755*(1). (2016). https://doi.org/10.1088/1742-6596/755/1/011001
6) R. B De Souza., & F. G Dedini., Energy management strategy for hybrid electric vehicles. *SAE Technical Papers*, 1–4. (2009). https://doi.org/10.4271/2009-36-0328
7) A.R Domingues., P Marques., R Garcia., F Freire., L.C. Dias., Applying Multi-Criteria Decision Analysis to the Life-Cycle Assessment of vehicles. J. Clean. Prod. 2015, 107, 749–759, doi:10.1016/j.jclepro.2015.05.086
8) G Domingues-Olavarría., *Modeling, optimization and analysis of electromobility systems*. (2018).
9) R. Leirós-Rodrígueza, M.E. Arceb, C. Míguez-Álvarezc, J. L. G.-S. Article in Press Article in Press. *Effect of Grain Boundaries on Paraconductivity of YBCO*, *1*(1), 1–11. (2016).
10) N. C Onat., S Gumus., M Kucukvar., & O Tatari,. Application of the TOPSIS and intuitionistic fuzzy set approaches for ranking the life cycle sustainability performance of alternative vehicle technologies. *Sustainable Production and Consumption*, *6*(December 2015), 12–25., (2016). https://doi.org/10.1016/j.spc.2015.12.003.
11) J. P Chang., Z. S Chen., X. L Liu., W. T Kong., S. H Xiong., & L.Martinez,. Paradigm Shift Toward Aggregation Strategies in Proportional Hesitant Fuzzy Multi-Criteria Group Decision Making Models of Advanced Practice for Selecting Electric Vehicle Battery Supplier. *IEEE Access*, *7*, (2019),172534–172561. https://doi.org/10.1109/ACCESS.2019.2956393
12) C Yang., Q Wang., W Peng., J. Zhang ., & J Zhu,. A normal wiggly pythagorean hesitant fuzzy bidirectional projection method and its application in EV power battery recycling mode selection. *IEEE Access*, *8*, 62164–62180. ,(2020). https://doi.org/10.1109/ACCESS.2020.2984242
13) D Wilken., M Oswald., P Draheim., C Pade., U Brand., & T Vogt., Multidimensional assessment of passenger cars: Comparison of electric vehicles with internal combustion engine vehicles. Procedia CIRP, 90, 291–296. (2020). https://doi.org/10.1016/j.procir.2020.01.101
14) J Liu., & Q Dai,. Portfolio optimization of photovoltaic/battery energy storage/electric vehicle charging stations with sustainability perspective based on cumulative prospect theory and MOPSO. *Sustainability (Switzerland)*, *12*(3). (2020). https://doi.org/10.3390/su12030985

15) N Kishor., & J Fraile-Ardanuy,. ICT for electric vehicle integration with the smart grid. *ICT for Electric Vehicle Integration with the Smart Grid*, 1–426. (2020). https://doi.org/10.1049/PBTR016E
16) P. K Tarei., P Chand., & H Gupta,. Barriers to the adoption of electric vehicles: Evidence from India. *Journal of Cleaner Production*, *291*(April), 1–8. (2021). https://doi.org/10.1016/j.jclepro.2021.125847
17) M. K Loganathan., B Mishra., C. M Tan., T Kongsvik., & R. N Rai,. Multi-criteria decision making (MCDM) for the selection of Li-ion batteries used in electric vehicles (EVs). *Materials Today: Proceedings*, *41*(xxxx), 1073–1077. (2019). https://doi.org/10.1016/j.matpr.2020.07.179
18) R Wang., X Li., & C.Li,. Optimal selection of sustainable battery supplier for battery swapping station based on Triangular fuzzy entropy -MULTIMOORA method. *Journal of Energy Storage*, *34*(February), 1–7. (2021)https://doi.org/10.1016/j.est.2020.102013
19) N. N. M Aboushaqrah., N. C Onat., M Kucukvar., A. M. S Hamouda,., A. O Kusakci., & B Ayvaz., Selection of alternative fuel taxis: a ybridized approach of life cycle sustainability assessment and multi-criteria decision making with neutrosophic sets. *International Journal of Sustainable Transportation*, *16*(9), 833–846. (2022). https://doi.org/10.1080/15568318.2021.1943075
20) X Ren,, S Sun., & R Yuan,. A study on selection strategies for battery electric vehicles based on sentiments, analysis, and the MCDM model. *Mathematical Problems in Engineering*, (2021). https://doi.org/10.1155/2021/9984343
21) Z Tian,. peng, H Liang,. ming, R Nie,. xin, X Wang,. kang & J.Wang qiang. Data-driven multi-criteria decision support method for electric vehicle selection. *Computers and Industrial Engineering*, *177*(March), 2019–2024. (2023). https://doi.org/10.1016/j.cie.2023.109061
22) M Patil., & B. B. Majumdar, An investigation on the key determinants influencing electric two-wheeler usage in urban Indian context. *Research in Transportation Business and Management*, *43*(June), 12–14. (2022). https://doi.org/10.1016/j.rtbm.2021.100693
23) M Patil., & B. B. Mujumdar,. Analysis of the Key Determinants of Electric Two-Wheeler Use in the Indian Context. *Lecture Notes in Civil Engineering*, *219*, 47–60. (2022)https://doi.org/10.1007/978-981-16-8259-9_3
24) Nayana. Electric Vehicle Charging with Battery Scheduling and Multicriteria Optimization using Genetic Algorithm. *Journal of Electrical Engineering and Automation*, *2*(3), 123–128. (2021). https://doi.org/10.36548/jeea.2020.3.003
25) A Ghosh., M Dey., S. P Mondal,., A Shaikh., A Sarkar., & B Chatterjee,. Selection of best E-Rickshaw-A green energy game changer: An application of AHP and TOPSIS method. *Journal of Intelligent and Fuzzy Systems*, *40*(6), 11217–11230(2021). https://doi.org/10.3233/JIFS-202406
26) C Yang., Q Wang., M Pan, J Hu., W Peng., J Zhang., & L Zhang. A linguistic Pythagorean hesitant fuzzy MULTIMOORA method for third-party reverse logistics provider selection of electric vehicle power battery recycling. *Expert Systems with Applications*, *198*(July), 1–7. (2022). https://doi.org/10.1016/j.eswa.2022.116 A 808
27) A Bhuyan., A Tripathy., R. K Padhy,., & Gautam,. Evaluating the lithium-ion battery recycling industry in an emerging economy: A multi-stakeholder and multi-criteria decision-making approach. *Journal of Cleaner Production*, *331*(January), 1–7. (2022). https://doi.org/10.1016/j.jclepro.2021.130007
28) P. I Ekel,. *International Journal of Electrical Power & Energy Systems Fuzzy set-based approach for grid integration and operation of ultra- fast charging electric*

buses. *138*(June), 1–7. (2022)
29) D Bhattacharjee,., Ghosh, T., Bhola, P., Martinsen, K., & Dan, P. (2022). Ecodesigning and improving performance of plugin hybrid electric vehicle in rolling terrain through multi-criteria optimisation of powertrain. *Proceedings of the Institution of Mechanical Engineers, Part D: Journal of Automobile Engineering*, *236*(5), 1019–1039. https://doi.org/10.1177/09544070211027531
30) K Urošević., Z Gligorić., I Miljanović., C Beljić., & M Gligorić,. Novel methods in multiple criteria decision-making process (Mcrat and raps)— application in the mining industry. *Mathematics*, *9*(16). (2021). https://doi.org/10.3390/math9161980
31) M.Gligorić , K Urošević., S.Lutovac, & D.Halilovi, *Optimal Coal Supplier Selection for Thermal Power Plant Based on Mcrat Method*. (2021).
32) T. L Saaty,. Analytic Hierarchy Process. *Encyclopedia of Biostatistics*. (2005). https://doi.org/10.1002/0470011815.b2a4a002
33) S Belay., J Goedert., Woldesenbet, A., & Rokooei, S. (2022). AHP based multi criteria decision analysis of success factors to enhance decision making in infrastructure construction projects. *Cogent Engineering*, *9*(1). https://doi.org/10.1080/23311916.2022.2043996
34) D Kim,., & M.Kim, Hybrid Analysis of the Decision-Making Factors for Software Upgrade Based on the Integration of AHP and DEMATEL. *Symmetry*, *14*(1). (2022). https://doi.org/10.3390/sym14010172
35) Anuradha, & S Gupta,. AHP-based multi-criteria decision-making for forest sustainability of lower Himalayan foothills in northern circle, India—a case study. *Environmental Monitoring and Assessment*, *194*(12), 0–11. (2022). https://doi.org/10.1007/s10661-022-10510-0
36) H Veisi., R Deihimfard., A Shahmohammadi., & Hydarzadeh Y. (2022). Application of the analytic hierarchy process (AHP) in a multi-criteria selection of agricultural irrigation systems. *Agricultural Water Management*, *267*(9), 1–7. https://doi.org/10.1016/j.agwat.2022.107619
37) D Diakoulaki., G Mavrotas., & L Papayannaki., *D E T E R M I N I N G OBJECTIVE WEIGHTS IN M U L T I P L E CRITERIA PROBLEMS : THE CRITIC M E T H O D*. *22*(7), 763–770. (1995).
38) P. H Nguyen., J F Tsai., Y. C Hu,. & G. V. Ajay Kumar., A Hybrid Method of MCDM for Evaluating Financial Performance of Vietnamese Commercial Banks Under COVID-19 Impacts. *Studies in Systems, Decision and Control*, *382*, 23–45. (2022). https://doi.org/10.1007/978-3-030-79610-5_2
39) B Aksakal., A Ulutaş,. F Balo,. & D Karabasevic,. A New Hybrid MCDM Model for Insulation Material Evaluation for Healthier Environment. *Buildings*, *12*(5), 1–21. (2022). https://doi.org/10.3390/buildings12050655
40) I Petkovski,. I Mihajlovic,. & A Fedajev,. Hybrid CRITIC-TOPSIS model for prioritizing digitally developed countries in the light of energy indicators. *IMCSM Proceedings*, *XVIII*(1), 264–277. (2022).
41) M Keshavarz- Ghorabaee,. M Amiri., E. K Zavadskas., Z Turskis,. & J Antucheviciene,. Determination of objective weights using a new method based on the removal effects of criteria (Merec). *Symmetry*, *13*(4), 1–20. (2021). https://doi.org/10.3390/sym13040525
42) Raut, R. D., Bhasin, H. V., & Kamble, S. S. (2012). Supplier selection using integrated multi-criteria decision-making methodology. *International Journal of Operational Research*, *13*(4), 359–394. https://doi.org/10.1504/IJOR.2012.046223
43) G Shanmugasundar., G Sapkota., R Čep., & K Kalita,. Application of MEREC in Multi-Criteria Selection of Optimal Spray-Painting Robot. *Processes*, *10*(6).

(2022). https://doi.org/10.3390/pr10061172
44) B Ivanović., A Saha., Ž Stević., A Puška,. & E. K. Zavadskas,. Selection of truck mixer concrete pump using novel MEREC DNMARCOS model. *Archives of Civil and Mechanical Engineering*, *22*(4), 1–22. (2022)https://doi.org/10.1007/s43452-022-00491-9
45) S Ghosh,. M & Bhattacharya,. Analyzing the impact of COVID-19 on the financial performance of the hospitality and tourism industries: an ensemble MCDM approach in the Indian context. *International Journal of Contemporary Hospitality Management*, *34*(8), 3113–3142. (2022). https://doi.org/10.1108/IJCHM-11-2021-1328
46) U Ulas., Y Nese., & A Nuri,. Analysis of Efficiency and Productivity of Commercial Banks in Turkey Pre- and during COVID-19 with an Integrated MCDM Approach. *Mathematics*, *10*(13), 2300. (2022).
47) N Fattouch., I Ben Lahmar., M Rekik,., & K Boukadi,. Decision-Making Approach for an IoRT-Aware Business Process Outsourcing. *Digital*, *2*(4), 520–537. (2022). https://doi.org/10.3390/digital2040028
48) A Arabameri., M Yamani., B Pradhan., A Melesse., K Shirani., & D Tien Bui,. Novel ensembles of COPRAS multi-criteria decision-making with logistic regression, boosted regression tree, and random forest for spatial prediction of gully erosion susceptibility. *Science of the Total Environment*, *688*, 903–916. (2019). https://doi.org/10.1016/j.scitotenv.2019.06.205
49) H Musbah., G Ali., H. H Aly., & T. A Little,. Energy management using multi-criteria decision making and machine learning classification algorithms for intelligent system. *Electric Power Systems Research*, *203*, 1–6. (2022). https://doi.org/10.1016/j.epsr.2021.107645
50) P. R Srivastava., & P Eachempati,. Intelligent Employee Retention System for Attrition Rate Analysis and Churn Prediction: An Ensemble Machine Learning and Multi- Criteria Decision-Making Approach. *Journal of Global Information Management*, *29*(6). (2021). https://doi.org/10.4018/JGIM.20211101.oa23
51) Q He., X Li., D. W. N Kim., X Jia., X Gu., X Zhen., & L Zhou,. Feasibility study of a multi-criteria decision-making based hierarchical model for multi-modality feature and multi-classifier fusion: Applications in medical prognosis prediction. *Information Fusion*, *55*(September 2019), 207–219. (2020). https://doi.org/10.1016/j.inffus.2019.09.001
52) Q. B Pham., Y Achour., S. A Ali., F Parvin., M Vojtek., J Vojteková., N Al-Ansari., A. L Achu., R Costache., K. M Khedher., & D. T. Anh, .A comparison among fuzzy multi-criteria decision making, bivariate, multivariate and machine learning models in landslide susceptibility mapping. *Geomatics, Natural Hazards and Risk*, *12*(1), 1741–1777. (2021). https://doi.org/10.1080/19475705.2021.1944330
53) Z He., K. P Tran., S Thomassey., X Zeng., J Xu., & C Yi,. A deep reinforcement learning based multi-criteria decision support system for optimizing textile chemical process. *Computers in Industry*, *125*. (2021). https://doi.org/10.1016/j.compind.2020.103373
54) M Kadkhodazadeh., M. V Anaraki., A Morshed-Bozorgdel., & S Farzin,. A New Methodology for Reference Evapotranspiration Prediction and Uncertainty Analysis under Climate Change Conditions Based on Machine Learning, Multi Criteria Decision Making and Monte Carlo Methods. *Sustainability (Switzerland)*, *14*(5). (2022). https://doi.org/10.3390/su14052601
55) M. T Mustapha., D. U Ozsahin., I Ozsahin., & B Uzun,. Breast Cancer Screening Based on Supervised Learning and Multi-Criteria Decision-Making. *Diagnostics*,

12(6), 1–17. (2022). https://doi.org/10.3390/diagnostics12061326
56) K Khosravi., H Shahabi., B. T Pham., J Adamowski., A Shirzadi., B Pradhan., J Dou., H. B Ly., G Gróf., H. L Ho., H Hong,. K Chapi., & I Prakash,. A comparative assessment of flood susceptibility modeling using Multi-Criteria Decision-Making Analysis and Machine Learning Methods. *Journal of Hydrology*, *573*(November 2018), 311–323. (2019). https://doi.org/10.1016/j.jhydrol.2019.03.073
57) Z Wang., J Li., G. P Rangaiah., & Z Wu,. Machine learning aided multi-objective optimization and multi-criteria decision making: Framework and two applications in chemical engineering. *Computers and Chemical Engineering*, *165*(September), 1–8. (2022). https://doi.org/10.1016/j.compchemeng.2022.107945
58) V García., J. S Sánchez., & A. I Marqués,. Synergetic application of multi-criteria decision-making models to credit granting decision problems. *Applied Sciences (Switzerland)*, *9*(23). (2019). https://doi.org/10.3390/app9235052
59) S. A Ali., F Parvi., J Vojteková., R Costache., N. T. T Linh., Q. B Pham., M Vojtek., L Gigović., A Ahmad., & M. A Ghorbani,. GIS-based landslide susceptibility modeling: A comparison between fuzzy multi-criteria and machine learning algorithms. *Geoscience Frontiers*, *12*(2), 857–876. (2021). https://doi.org/10.1016/j.gsf.2020.09.004
60) N Pourkhodabakhsh., M. M Mamoudan., & A Bozorgi-Amiri,. Effective machine learning, Meta-heuristic algorithms and multi-criteria decision making to minimizing human resource turnover. *Applied Intelligence*. (2022). https://doi.org/10.1007/s10489-022-04294-6
61) N. K Chowdhury., M. A Kabir., & M. M Rahman,. *An Ensemble-based Multi-Criteria Decision Making Method for COVID-19 Cough Classification*. (2021).
62) N. S Baqer., A. S Albahri., H. A Mohammed., A. A Zaidan., R. A Amjed., A. M Al-Bakry., O. S Albahri., H. A Alsattar., A Alnoor., A. H Alamoodi., B. B Zaidan., R. Q Malik., & Z. H Kareem,. Indoor air quality pollutants predicting approach using unified labelling process-based multi-criteria decision making and machine learning techniques. *Telecommunication Systems*, *81*(4), 591–613. (2022). https://doi.org/10.1007/s11235-022-00959-2
63) M. M Jassim., M. H Ali., A. S Elamer., M. M Jaber., M. Q Mohammed., & A Alkhayyat,. Multi-Criteria Decision Making for Machine Learning Algorithms Using AHP-VIKOR techniques: Case Study Adult Autism Diagnosis. *IICETA 2022 - 5th International Conference on Engineering Technology and Its Applications*, 574–578. (2022). https://doi.org/10.1109/IICETA54559.2022.9888273
64) A. J Al-Bawi., A. M Al-Abadi., B Pradhan,. & A. M. Alamri,. Assessing gully erosion susceptibility using topographic derived attributes, multi-criteria decision-making, and machine learning classifiers. *Geomatics, Natural Hazards and Risk*, *12*(1), 3035–3062. (2021). https://doi.org/10.1080/19475705.2021.1994024