Composite Programming for Electric Passenger Car Selection in Multiple Criteria Decision Making

C. Ardil

***Abstract*—**This paper discusses the use of the composite programming method to identify the optimum electric passenger automobile in multiple criteria decision making. With the composite programming approach, a set of alternatives are compared using an optimality measure that gauges how far apart they are from the optimum solution. In this paper, some key factors (range, battery, engine, maximum speed, acceleration) that customers should consider while purchasing an electric passenger car for daily use are discussed. A numerical illustration is provided to demonstrate the validity and applicability of the proximity measure approach.

***Keywords*—**Electric passenger car selection, multiple criteria decision making, proximity measure method, composite programming, entropic weight method.

I. Introduction

The choice of a car is a very important task for the customer because an electric passenger car is one of the essential demands for passenger transportation in real life environment.The quality of the electric passenger automobile varies depending on the evaluation criteria. Customers are looking for the best electric passenger car they can find in terms of evaluation criteria [1-9].

When a customer buys a compact electric passenger car for everyday use, there are countless areas of problems and uncertainties. Customers should choose which model electric passenger car to buy when making a purchasing decision. Also, customers should choose an electric passenger car based on the company's apparent value, product cost, product maintenance cost, product resale value, etc. It is normal for various customers to have different opinions about choosing an electric passenger car during the decision-making process. When choosing an electric passenger car, evaluation criteria such as price, boot volume, service costs, fuel/energy consumption, acceleration, such as safety, performance, economic aspect, exterior, convenience, dealer, warranty and emissions are considered [10-11].

An online questionnaire is used to follow the ranking set procedure to shortlist the evaluation criteria. Customers are asked to evaluate the list of factors/criteria that are very important to customers when choosing an electric passenger car. Each customer then assigns importance weights to the attributes listed in the online survey. Five important criteria, namely range, battery, engine, maximum speed, and acceleration, were determined by reviewing the literature and considering the customer's criteria evaluating [10-11].

In the electric passenger car selection problem, the objective criteria weights were determined by the entropic weight method. In the existing literature, there are many multiple criteria decision making (MCDM) methodologies such as Analytical Hierarchy Process, Fuzzy Set Theory, DEA, Preference Programming, Goal Programming, VIKOR, ELECTRE, PROMETHEE, and TOPSIS. Also, these MCDM techniques can be classified as compensatory and noncompensatory methodologies. Due to some limitations in classical MCDM approaches, modern MCDM techniques utilize fuzzy set theory and its extensions such as intuitionistic fuzzy sets and neutrosophic sets [12-66].

Considering the MCDM model, the MCDM problem consists of a set of *m* alternatives $a_i = (a_1, ..., a_i)$, a set of *n* criteria $g_j = (g_1, ..., g_j)$, and a set of *n* weights $\omega_j = (\omega_1, ..., \omega_j)$, $\omega_j \geq 0$, $\sum_{j=1}^{J} \omega_j = 1$, reflecting the relative importance of every criterion in the dataset for the decision maker. In MCDM problem, the value of alternative a_i under criterion g_j is denoted as x_{ij}. In this way, an MCDM approach uses a decision matrix as input and outputs a ranking of the alternatives. The approaches often give each alternative a numerical score value, which makes it simple to determine a ranking [42-57].

The current study outlines the selection process for choosing the optimum electric passenger car utilizing a multiple attribute decision-making method, specifically the technique for ranking preferences according to how closely they resemble the ideal solution based on various evaluation attributes. In this MCDM problem, there are ten options, and five factors are considered while choosing an electric passenger automobile. The proposed method aids in decision making process to overcome the complexity involved in the MCDM problem.

The rest of the paper is set up as follows: The composite programming model is then presented in Section 2. The proposed approach is used to address the problem of multiple criteria decision-making in Section 3. The paper concludes by outlining its findings, its limits, and its suggestions for future study.

II. Methodology

A. *Entropic Weight Method (EWM)*

An objective way to determine attribute weights is to use the entropic weight approach. Entropy is a concept that determine the essential information and usable information of a given dataset. Entropy theory states that a criterion's information entropy is low if the value of the criterion among

C. Ardil is with the National Aviation Academy, Baku, Azerbaijan. https://orcid.org/0000-0003-2457-7261

the alternatives under consideration differs significantly. More pertinent facts about the supplied dataset are provided by a criterion with low information entropy, and vice versa.

As a result, the criteria's weights should be provided in the information entropy's inverse order, meaning that a criterion with low information entropy should have a high weight and vice versa. The measured value of the *j*th factor in the *i*th sample is recorded as x_{ij} in this approach, which uses *J* factors and *I* sample for the evaluation. The exact steps to put this method into practice are as follows [67-71]:

Step 1. The normalization of measured values is the initial stage. The method used to calculate the *j*th factor's standardized value in the *i*th sample is designated as p_{ij} :

$$p_{ij} = \frac{x_{ij}}{\sum_{i=1}^{I} x_{ij}} \tag{1}$$

Step 2. The entropy value E_j of the *j*th factor is defined as

$$E_j = -\frac{\sum_{i=1}^{I} p_{ij} \ln p_{ij}}{\ln I} \tag{2}$$

In the actual evaluation using the EWM, $p_{ij} \ln p_{ij} = 0$, is generally set when $p_{ij} = 0$ for the convenience of calculation.

The range of entropy value E_j is [0, 1]. The larger the E_j is, the greater the differentiation degree of factor *J* is, and more information can be derived. Hence, a higher weight should be given to the factor.

Step 3. The calculation method of entropic weight (ω_j) is given by

$$\omega_j = \frac{1-E_j}{\sum_{j=1}^{J}(1-E_j)} \tag{3}$$

B. Composite Programming Method

Suppose that multiple criteria decision making analysis problem has *I* alternatives $a_i = (a_1,...,a_i)$, $i \in \{ i=1,...,I \}$, and *J* criteria $g_j = (g_1,...,g_j)$, $j \in \{ j=1,...,J \}$, and the importance weight of each criterion (ω_j, $j \in \{ j=1,...,J \}$) is defined. The composite programming method is performed according to the following procedural steps*:*

Step 1. Constructing the decision matrix $X = [x_{ij}]_{ixj}$

MCDM Model	ω_1	ω_2	$\cdots$	ω_j	$\cdots$	ω_n
	g_1	g_2	$\cdots$	g_j	$\cdots$	g_n
a_1	x_{11}	x_{12}	$\cdots$	x_{1j}	$\cdots$	x_{1n}
a_2	x_{21}	x_{22}	$\cdots$	x_{2j}	$\cdots$	x_{2n}
$\cdots$	$\cdots$	$\cdots$	$\cdots$	$\cdots$	$\cdots$	$\cdots$
a_i	x_{i1}	x_{i2}	$\cdots$	x_{ij}	$\cdots$	x_{in}
$\cdots$	$\cdots$	$\cdots$	$\cdots$	$\cdots$	$\cdots$	$\cdots$
a_m	x_{m1}	x_{m2}	$\cdots$	x_{mj}	$\cdots$	x_{mn}

(4)

Step 2. Normalizing the decision matrix $N = [n_{ij}]_{ixj}$. The decision matrix of the alternatives is normalized using the vector normalization scale.

$$n_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{I} x_{ij}^2}}, j \in B ; n_{ij} = 1 - \frac{x_{ij}}{\sqrt{\sum_{i=1}^{I} x_{ij}^2}}, j \in C \tag{5}$$

where *B* represents a criterion as large as possible, *C* represents a criterion as small as possible.

Step 3. Computing the weighted product value (ϕ_i)

$$\phi_i = \left(\prod_{j=1}^{J} n_{ij}^{\omega_j} \right)^{1/J} \tag{6}$$

where alternatives are ranked in descending order of rank according to the weighted product measure value (ϕ_i).

Step 4. Computing the weighted normalized value $Z = [z_{ij}]_{ixj}$

$$z_{ij} = \omega_j n_{ij} \tag{7}$$

Step 5. Computing the weighted sum value (φ_i)

$$\varphi_i = \sum_{j=1}^{J} \omega_j n_{ij} \tag{8}$$

where alternatives are ranked in descending order of rank according to the weighted sum measure value (φ_i).

Step 6. Determining the dispersion value (π_{ij}) from the ideal solution

$$\pi_{ij} = \begin{cases} z_j^{\max} - z_{ij} \quad , j \in B \left\{ \max\limits_j z_{ij} \right\} \\ z_{ij} \quad - z_j^{\min}, j \in C \left\{ \min\limits_j z_{ij} \right\} \end{cases} \tag{9}$$

where *B* represents a criterion as large as possible, *C* represents a criterion as small as possible.

Step 7. Computing proximity measure value (θ_i) which is the algebraic sum of dispersion

$$\theta_i = \sum_{j=1}^{J} \pi_{ij} \tag{10}$$

where alternatives are ranked in ascending order of rank according to the proximity measure value (θ_i).

Step 8. Computing composite programming value (γ_i) which is the compromise solution

$$\gamma_i = \lambda\varphi_i + (1-\lambda)\phi_i \tag{11}$$

where $\lambda = 0, 0.1, ..., 1$. In the composite programming method, a joint optimality criterion is sought based on two optimality criteria. Feasible alternatives are now ranked according to their (γ_i) values, and the best alternative has the highest (γ_i) value.

When λ value is 0, composing programming method turns into weighted product model, when λ value is 1, it becomes weighted sum method. It is applied in solving MCDM problems to increase the ranking accuracy and has the capability to achieve the highest prediction accuracy.

III. Application

In this section, the proposed entropic composite programming approach is applied to the electric passenger car selection problem. The alternatives and decision criteria for the selection of an electric passenger car were obtained after the thorough review of the literature and online customer survey.

Range (kilometers) (g_1), battery (kilowatt-hours) (g_2), engine (horse power) (g_3), maximum speed (kilometers per hour) (g_4), and acceleration (0–100 km/s) (g_5) are the five evaluation factors for making a decision in the MCDM selection problem.

In the MCDM problem, *B (benefit)* represents a criterion as large as possible, *C (cost)* represents a criterion as small as possible. *B (benefit)* criteria are range, battery, engine, and maximum speed attributes. *C (cost)* criterion *is* acceleration attribute. The double-engine electric car alternatives are listed in the initial decision-making matrix as shown in Table 1.

Table 1. Initial decision-making matrix

Alternatives	Decision criteria				
Electric SUVs	Range (km)	Battery (kWh)	Engine (HP)	MaxSpeed (km/h)	Acceleration (0-100km/s)
TOGG C-SUV	500	90	400	180	4,8
Mercedes EQC 400 4MATIC	462	80	408	180	5,1
Tesla Model Y Performance	480	80	456	241	3,7
Audi Q4 E-tron	390	77	295	180	5,8
BMW iX3	460	80	286	180	6,8
Jaguar I-Pace EV400	470	90	400	200	4,8
Ford Mustang Mach-E AWD Extended Range	540	98,8	351	180	4,8
Hyundai Ioniq 5	481	77,4	325	185	5,1
Kia EV6 Long Range AWD	506	77,4	325	187	5,2
Toyota bZ4X AWD	470	72,8	217	180	7,7

The objective criteria weights determined by the entropic weight method are given in Table 2.

Table 2. Entropic weights of decision criteria

	Decision criteria				
	Range (km)	Battery (kWh)	Engine (HP)	MaxSpeed (km/h)	Acceleration (0-100km/s)
E_j	0,999	0,998	0,992	0,998	0,992
$1-E_j$	0,001	0,002	0,008	0,002	0,008
ω_j	0,061	0,082	0,388	0,086	0,383

The priority vector of decision criteria is determined by the EWM as follows : $g_1 \prec g_2 \prec g_4 \prec g_5 \prec g_3$. Therefore, engine (HP) criterion (g_3) is assigned the highest priority in the selection problem. The second important criterion is acceleration (0-100 km/s) (g_5), and the range (km) (g_1) is given the least amount of weight for the decision criteria. The graphical representation of criteria weights is shown in Fig. 1.

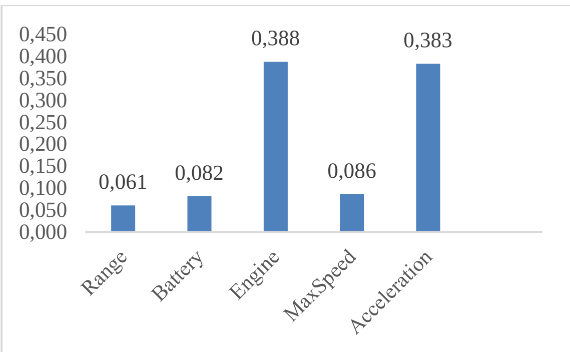

Fig. 1 Graphical representation of priority vector of evaluation criteria

The normalization of the measured values of the initial decision matrix is given in Table 3.

Table 3. Normalized decision-making matrix

Options	Decision criteria				
a_i	g_1	g_2	g_3	g_4	g_5
a_1	0,331	0,344	0,359	0,299	0,723
a_2	0,306	0,306	0,366	0,299	0,706
a_3	0,318	0,306	0,409	0,401	0,787
a_4	0,258	0,294	0,264	0,299	0,666
a_5	0,305	0,306	0,256	0,299	0,608
a_6	0,311	0,344	0,359	0,333	0,723
a_7	0,358	0,378	0,315	0,299	0,723
a_8	0,319	0,296	0,291	0,308	0,706
a_9	0,335	0,296	0,291	0,311	0,700
a_{10}	0,311	0,278	0,194	0,299	0,556

The weighted product values are given in Table 4.

Table 4. Normalized weighted product values (ϕ_i)

Options	Decision criteria				
a_i	g_1	g_2	g_3	g_4	g_5
a_1	0,935	0,916	0,672	0,901	0,883
a_2	0,930	0,907	0,677	0,901	0,875
a_3	0,932	0,907	0,707	0,924	0,912
a_4	0,921	0,905	0,597	0,901	0,856
a_5	0,930	0,907	0,590	0,901	0,827
a_6	0,931	0,916	0,672	0,910	0,883
a_7	0,939	0,923	0,638	0,901	0,883
a_8	0,933	0,905	0,620	0,904	0,875
a_9	0,936	0,905	0,620	0,904	0,872
a_{10}	0,931	0,900	0,530	0,901	0,799

The weighted sum values are given in Table 5.

Table 5. Normalized weighted sum values (φ_i)

Options	Decision criteria				
a_i	g_1	g_2	g_3	g_4	g_5
a_1	0,020	0,028	0,139	0,026	0,277
a_2	0,019	0,025	0,142	0,026	0,270
a_3	0,019	0,025	0,159	0,034	0,301
a_4	0,016	0,024	0,103	0,026	0,255
a_5	0,019	0,025	0,099	0,026	0,233
a_6	0,019	0,028	0,139	0,029	0,277
a_7	0,022	0,031	0,122	0,026	0,277
a_8	0,019	0,024	0,113	0,026	0,270
a_9	0,020	0,024	0,113	0,027	0,268
a_{10}	0,019	0,023	0,075	0,026	0,213

The proximity measure values are given in Table 6.

Table 6. Proximity measure values (θ_i)

Options	Decision criteria				
a_i	g_1	g_2	g_3	g_4	g_5
a_1	0,002	0,003	0,019	0,009	0,936
a_2	0,003	0,006	0,017	0,009	0,943
a_3	0,002	0,006	0,000	0,000	0,912
a_4	0,006	0,007	0,056	0,009	0,958
a_5	0,003	0,006	0,059	0,009	0,980
a_6	0,003	0,003	0,019	0,006	0,936
a_7	0,000	0,000	0,037	0,009	0,936
a_8	0,002	0,007	0,046	0,008	0,943
a_9	0,001	0,007	0,046	0,008	0,945
a_{10}	0,003	0,008	0,083	0,009	1,000

The comparison of ranking order of alternatives based on weighted product model (ϕ_i), weighted sum model (φ_i) and proximity measure model (θ_i) are given in Table 7.

Table 7. Comparison of ranking order of alternatives

Options	Ranking orders of alternatives					
	ϕ_i	Rank	φ_i	Rank	θ_i	Rank
a_1	0,855	3	0,490	3	0,969	3
a_2	0,853	4	0,482	4	0,977	4
a_3	0,872	1	0,539	1	0,920	1
a_4	0,826	8	0,423	8	1,036	8
a_5	0,820	9	0,402	9	1,057	9
a_6	0,856	2	0,492	2	0,967	2
a_7	0,849	5	0,478	5	0,981	5
a_8	0,838	7	0,454	6	1,005	6
a_9	0,838	6	0,453	7	1,006	7
a_{10}	0,796	10	0,356	10	1,103	10

The correlation analysis of the ranking orders of weighted product model (ϕ_i), weighted sum model (φ_i) and proximity measure model (θ_i) is given in Table 8.

Table 8. The correlation analysis of the ranking orders of weighted product model (ϕ_i), weighted sum model (φ_i) and proximity measure model (θ_i)

	ϕ_i	φ_i	θ_i
ϕ_i	1		
φ_i	0,99	1	
θ_i	0,99	1	1

The weighted sum model (φ_i) and proximity measure model (θ_i) yield the same ranking pattern order of alternatives. The correlation coefficient between the weighted product model (ϕ_i) and the other two methods is

0,99. The alternative (a_3) ranks first (1), the alternative (a_6) ranks second (2), and the alternative (a_1) ranks third in the compared methods. The composite programming approach was used in the MCDM problem to improve ranking accuracy and the capability to reach the maximum prediction accuracy. The findings are shown in Tables 9 and 10. The composite programming values are given in Table 9.

Table 9. Composite programming values (θ_i)

λ_i	0	0,1	0,3	0,5	0,7	0,9	1
a_1	0,855	0,819	0,746	0,673	0,600	0,527	0,490
a_2	0,853	0,816	0,741	0,667	0,593	0,519	0,482
a_3	0,872	0,839	0,772	0,705	0,639	0,572	0,539
a_4	0,826	0,785	0,705	0,624	0,544	0,463	0,423
a_5	0,820	0,778	0,695	0,611	0,527	0,444	0,402
a_6	0,856	0,820	0,747	0,674	0,601	0,528	0,492
a_7	0,849	0,812	0,738	0,663	0,589	0,515	0,478
a_8	0,838	0,800	0,723	0,646	0,569	0,492	0,454
a_9	0,838	0,800	0,723	0,645	0,568	0,491	0,453
a_{10}	0,796	0,752	0,664	0,576	0,488	0,400	0,356

Finally, the ranking patterns of composite programming values are given in Table 10.

Table 10. Composite programming values (γ_i)

λ_i	0	0,1	0,3	0,5	0,7	0,9	1
a_1	3	3	3	3	3	3	3
a_2	4	4	4	4	4	4	4
a_3	1	1	1	1	1	1	1
a_4	8	8	8	8	8	8	8
a_5	9	9	9	9	9	9	9
a_6	2	2	2	2	2	2	2
a_7	5	5	5	5	5	5	5
a_8	7	7	6	6	6	6	6
a_9	6	6	7	7	7	7	7
a_{10}	10	10	10	10	10	10	10

Furthermore, the composite programming method is used to rank the electric passenger automobiles. In the form of a radar chart, Fig. 2 displays the rankings of various electric passenger cars based on the validity analysis.

Fig. 2 makes it clear that the disparity in ranks thus created is quite malleable. Therefore, it can be said that the combined MCDM techniques utilized in this research are effective at producing reliable ranks of electric passenger automobiles.

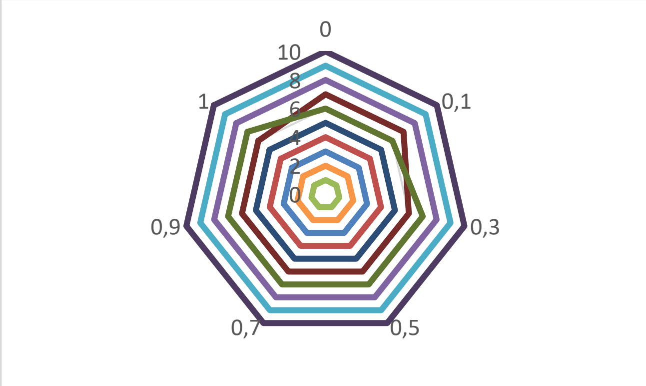

Fig. 2 Validity analysis results

The proposed method is put to the test using composite programming analysis, the weighted product method (WPM), the weighted sum method (WSM), and the proximity measure method (PMM).

Tesla Model Y Performance (a_3) ranks first , Jaguar I-Pace EV400 (a_6) ranks second, and TOGG C- SUV (a_1) ranks third in the MCDM evaluation.

Even when identical dataset and criteria weights for the decision criteria are used, MCDM algorithms can produce different rankings of the alternatives. Different normalization scales can also produce different rankings of the alternatives. This is because each MCDM technique has a unique solution algorithm.

IV. Conclusion

The paper has made some contributions in the following areas. It proposes a comparative evaluation based on minimum deviation from optimal solution for the electric passenger cars utilizing proximity measure model:

(1) The proposed method considers a comparative MCDM analysis to consider the performance and characteristic values of electric passenger automobiles.

(2) The objective weights of criteria were determined by the entropic weight method.

(3) The composite programming technique between the weighted sum model and weighted products model is applied to improve ranking accuracy and the capability to reach the maximum prediction accuracy.

In MCDM analysis, five decision criteria are considered when evaluating the ten electric passenger car alternatives. Tesla Model Y Performance (a_3) was found to be the top alternative, followed by the Jaguar I-Pace EV400 (a_6) and the TOGG C- SUV (a_1), according to the hybridized MCDM analysis.

The development of a novel method for multiple criteria decision-making was another goal of this study. It was intended to help the decision-maker in a decision problem involving the selection of an electric passenger car from a set of alternatives and several evaluation criteria.

To validate the findings, the ranking pattern of alternatives were examined and compared with three MCDM models and composite programming. The ranking outcomes demonstrate that the proposed method chooses the same electric passenger vehicle. Finally, the proposed approach can be used in a secure manner to address other complex engineering selection problems. The MCDM problem will eventually be considered within the continuous fuzzy information environment.

REFERENCES

[1] European Climate Law, https://climate.ec.europa.eu/eu-action/european-green-deal/european-climate-law_en accessed on November 01, 2022.

[2] Sources of Greenhouse Gas Emissions, https://www.epa.gov/ghgemissions/sources-greenhouse-gas-emissions accessed on November 01, 2022.

[3] Zhang, R., Fujimori, S. (2020). The role of transport electrification in global climate change mitigation scenarios. *Environ Res Lett* 15:034019.

[4] Zhang R., Hanaoka, T. (2021) Deployment of electric vehicles in China to meet the carbon neutral target by 2060: provincial disparities in energy systems, CO2 emissions, and cost effectiveness. *Resour Conserv Recycl* 170:105622.

[5] Wei, Q., Zhou, C. (2022). A multi-criteria decision-making framework for electric vehicle supplier selection of government agencies and public bodies in China. *Environ Sci Pollut Res*.

[6] Xiong, S., Wang. Y., Bai. B., Ma. X. (2021). A hybrid life cycle assessment of the large-scale application of electric vehicles. *Energy* 216:119314.

[7] Linn. J., McConnell. V. (2019). Interactions between federal and state policies for reducing vehicle emissions. Energy Policy 126:507–517.

[8] Melese, F., Fan, J. (2020). Rethinking government supplier decisions: the economic evaluation of alternatives (EEoA). *Def Peace Econ* 0:1–19.

[9] Schramm, VB., Cabral, LPB., Schramm, F. (2020) Approaches for supporting sustainable supplier selection - a literature review. *J Clean Prod* 273:123089.

[10] Sakthivel,G., Ilangkumaran,M., Nagarajan, G., Raja, A., Ragunadhan, P.M., Prakash,J. (2013). A hybrid MCDM approach for evaluating an automobile purchase model, *International Journal of Information and Decision Sciences*, Inderscience Enterprises Ltd, vol. 5(1), pages 50-85.

[11] Pamučar, D. S., Savin, L. M. (2020). Multiple-criteria model for optimal off-road vehicle selection for passenger transportation: Bwm-copras model. *Vojnotehnički Glasnik*, 68(1), 28-64. https://doi.org/10.5937/vojtehg68-22916.

[12] Ardil, C. (2022). Multiple Criteria Decision Making for Turkish Air Force Stealth Fighter Aircraft Selection. *International Journal of Aerospace and Mechanical Engineering*, 16(12), 375 - 380.

[13] Ardil, C. (2023).Hospital Facility Location Selection Using Permanent Analytics Process. *International Journal of Urban and Civil Engineering*, 17(1), 13 - 23.

[14] Ardil, C. (2022). Aircraft Selection Problem Using Decision Uncertainty Distance in Fuzzy Multiple Criteria Decision Making Analysis. *International Journal of Mechanical and Industrial Engineering*, 16(3), 57 - 64.

[15] Ardil, C. (2022).Aircraft Selection Using Preference Optimization Programming (POP).*International Journal of Aerospace and Mechanical Engineering*, 16(11), 292 - 297.

[16] Ardil, C. (2022). Fighter Aircraft Selection Using Fuzzy Preference Optimization Programming (POP). *International Journal of Aerospace and Mechanical Engineering*, 16(10), 279 - 290.

[17] Ardil, C. (2022). Vague Multiple Criteria Decision Making Analysis Method for Fighter Aircraft Selection. *International Journal of Aerospace and Mechanical Engineering*, 16(5),133-142.

[18] Ardil, C. (2022).Fuzzy Uncertainty Theory for Stealth Fighter Aircraft Selection in Entropic Fuzzy TOPSIS Decision Analysis Process. *International Journal of Aerospace and Mechanical Engineering*, 16(4), 93 - 102.

[19] Ardil, C. (2022). Aircraft Selection Problem Using Decision Uncertainty Distance in Fuzzy Multiple Criteria Decision Making Analysis. *International Journal of Mechanical and Industrial Engineering*, 16(3), 62 - 69.

[20] Ardil, C. (2022). Fighter Aircraft Selection Using Neutrosophic Multiple Criteria Decision Making Analysis. *International Journal of Computer and Systems Engineering*, 16(1), 5 - 9.

[21] Ardil, C. (2022). Military Attack Helicopter Selection Using Distance Function Measures in Multiple Criteria Decision Making Analysis. *International Journal of Aerospace and Mechanical Engineering*, 16(2), 20 - 27.

[22] Ardil, C. (2021). Airline Quality Rating Using PARIS and TOPSIS in Multiple Criteria Decision Making Analysis. *International Journal of Industrial and Systems Engineering*, 15(12), 516 - 523.

[23] Ardil, C. (2021). Fighter Aircraft Evaluation and Selection Process Based on Triangular Fuzzy Numbers in Multiple Criteria Decision Making Analysis Using the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS). *International Journal of Computer and Systems Engineering*, 15(12), 402 - 408.

[24] Ardil, C. (2021). Military Combat Aircraft Selection Using Trapezoidal Fuzzy Numbers with the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS). *International Journal of Computer and Information Engineering*, 15(12), 630 - 635.

[25] Ardil, C. (2021). Freighter Aircraft Selection Using Entropic Programming for Multiple Criteria Decision Making Analysis. *International Journal of Mathematical and Computational Sciences*, 15(12), 125 - 132.

[26] Ardil, C. (2021). Advanced Jet Trainer and Light Attack Aircraft Selection Using Composite Programming in Multiple Criteria Decision Making Analysis Method. *International Journal of Aerospace and Mechanical Engineering*, 15(12), 486 - 491.

[27] Ardil, C. (2021). Comparison of Composite Programming and Compromise Programming for Aircraft Selection Problem Using Multiple Criteria Decision Making Analysis Method. *International Journal of Aerospace and Mechanical Engineering*, 15(11), 479 - 485.

[28] Ardil, C. (2021). Neutrosophic Multiple Criteria Decision Making Analysis Method for Selecting Stealth Fighter Aircraft. *International Journal of Aerospace and Mechanical Engineering*, 15(10), 459 - 463.

[29] Ardil, C. (2020). Regional Aircraft Selection Using Preference Analysis for Reference Ideal Solution (PARIS). *International Journal of Transport and Vehicle Engineering*, 14(9), 378 - 388.

[30] Ardil, C. (2020). A Comparative Analysis of Multiple Criteria Decision Making Analysis Methods for Strategic, Tactical, and Operational Decisions in Military Fighter Aircraft Selection. *International Journal of Aerospace and Mechanical Engineering*, 14(7), 275 - 288.

[31] Ardil, C. (2020). Trainer Aircraft Selection Using Preference Analysis for Reference Ideal Solution (PARIS). *International Journal of Aerospace and Mechanical Engineering*, 14(5), 195 - 209.

[32] Ardil, C. (2020). Aircraft Selection Process Using Preference Analysis for Reference Ideal Solution (PARIS). *International Journal of Aerospace and Mechanical Engineering*, 14(3), 80 - 93.

[33] Ardil, C. (2019). Aircraft Selection Using Multiple Criteria Decision Making Analysis Method with Different Data Normalization Techniques. *International Journal of Industrial and Systems Engineering*, 13(12), 744 - 756.

[34] Ardil, C. , Pashaev, A. , Sadiqov, R. , Abdullayev, P. (2019). Multiple Criteria Decision Making Analysis for Selecting and Evaluating Fighter Aircraft. *International Journal of Transport and Vehicle Engineering*, 13(11), 683 - 694.

[35] Ardil, C. (2019). Fighter Aircraft Selection Using Technique for Order Preference by Similarity to Ideal Solution with Multiple Criteria Decision Making Analysis. *International Journal of Transport and Vehicle Engineering*, 13(10), 649 - 657.

[36] Ardil, C. (2019). Military Fighter Aircraft Selection Using Multiplicative Multiple Criteria Decision Making Analysis Method. *International Journal of Mathematical and Computational Sciences*, 13(9), 184 - 193.

[37] Sánchez-Lozano, J.M., Correa-Rubio, J., Fernández-Martínez, M. (2022). A double fuzzy multi-criteria analysis to evaluate international high-performance aircrafts for defense purposes. *Engineering Applications of Artificial Intelligence*,Volume 115, October 2022, 105339.

[38] Maêda, S.M., Costa, I.P., Castro Junior, M.A., Fávero, L., Costa, A.P., Corriça, J.V., Gomes, C.F., & Santos, M.D. (2021). Multi-criteria analysis applied to aircraft selection by Brazilian Navy. Production.

[39] Sánchez-Lozano, J.M., Rodríguez, O.N. (2020). Application of Fuzzy Reference Ideal Method (FRIM) to the military advanced training aircraft selection. *Appl. Soft Comput*., 88, 106061.

[40] Kiracı, K., Akan, E. (2020). Aircraft selection by applying AHP and TOPSIS in interval type-2 fuzzy sets. *Journal of Air Transport Management*, 89, 101924 - 101924.
[41] Sánchez-Lozano, J.M., Serna, J., Dolón-Payán, A. (2015). Evaluating military training aircrafts through the combination of multi-criteria decision making processes with fuzzy logic. A case study in the Spanish Air Force Academy. *Aerospace Science and Technology*, 42, 58-65.
[42] Saaty, T. L. (1990). How to make a decision: The Analytic Hierarchy Process. European Journal of Operational Research, 48(1), 9-26. doi: 10.1016/0377-2217(90)90057-I
[43] Saaty, T. L. (2008). Decision making with the analytic hierarchy process. International Journal of Services Sciences, 1(1), 83-98. doi: 10.1504/IJSSCI.2008.017590
[44] Saaty, T.L. (1980). Analytic Hierarchy Process: Planning, Priority Setting, Resource Allocation. McGraw-Hill, New York.
[45] Roy, B. (1991). The outranking approach and the foundation of ELECTRE methods. Theory and Decision, 31(1), 49–73.
[46] Fei, L., Xia, J., Feng, Y., Liu, L. (2019) An ELECTRE-Based Multiple Criteria Decision Making Method for Supplier Selection Using Dempster-Shafer Theory. IEEE Access, 7, 84701-84716.
[47] Brans JP., Mareschal B. (2005). Promethee Methods. In: Multiple Criteria Decision Analysis: State of the Art Surveys. International Series in Operations Research & Management Science, vol 78, pp 163-186. Springer, New York, NY. https://doi.org/10.1007/0-387-23081-5_5.
[48] Brans, J., Ph. Vincke. (1985). A Preference Ranking Organisation Method: (The PROMETHEE Method for Multiple Criteria Decision-Making). Management Science, 31(6), 647-656.
[49] Brans, J.P., Macharis, C., Kunsch, P.L., Chevalier, A., Schwaninger, M., (1998). Combining multicriteria decision aid and system dynamics for the control of socio-economic processes. An iterative real-time procedure. European Journal of Operational Research 109, 428-441.
[50] Brans, J.P., Vincke, Ph., Mareschal, B., (1986). How to select and how to rank projects: the PROMETHEE method. European Journal of Operational Research, 24, 228-238.
[51] Hwang, C.L.; Yoon, K. (1981). Multiple Attribute Decision Making: Methods and Applications. New York: Springer-Verlag.
[52] Chu, T.C. (2002. Facility location selection using fuzzy TOPSIS under group decisions", International Journal of Uncertainty, Fuzziness and Knowledge-Based Systems, Vol. 10 No. 6, pp. 687-701.
[53] Choudhary, D. and Shankar, R. (2012. A STEEP-fuzzy AHP-TOPSIS framework for evaluation and selection of thermal power plant location: a case study from India", Energy, Vol. 42 No. 1, pp. 510-521.
[54] Zavadskas, E.K., Mardani, A., Turskis, Z., Jusoh, A., Nor, K.M. (2016) Development of TOPSIS method to solve complicated decision-making problems: An overview on developments from 2000 to 2015. International Journal of Information Technology & Decision Making, 15, 645-682.
[55] Opricovic, S. (1998). Multicriteria Optimization of Civil Engineering Systems. PhD Thesis, Faculty of Civil Engineering, Belgrade (in Serbian).
[56] Opricovic, S. (2007). A fuzzy compromise solution for multicriteria problems. International Journal of Uncertainty, Fuzziness and Knowledge-Based Systems, 15(3), 363–380.
[57] Opricovic, S., Tzeng, G.-H. (2004). Compromise solution by MCDM methods: A comparative analysis of VIKOR and TOPSIS. European Journal of Operational Research, 156(2), 445–455.
[58] Buckley,J.J. (1985). Fuzzy hierarchical analysis, Fuzzy Sets and Systems, 17, 233–247.
[59] Hsu, H.M., Chen, C.T. (1997). Fuzzy credibility relation method for multiple criteria decision-making problems, *Inform. Sci.* 96,79–91.
[60] Hsu, H.M., Chen, C.T. (1996). Aggregation of fuzzy opinions under group decision making, *Fuzzy Sets and Systems*, 79, 279–285.
[61] Chen, C.-T. (2000). Extensions of the TOPSIS for group decision-making under fuzzy environment. *Fuzzy Sets Syst.* 114, 1–9.
[62] Bellman, R.E., Zadeh, L.A. (1970). Decision-making in a fuzzy environment. *Management Science*, 17(4), 141–164.
[63] Zadeh L.A., (1965). Fuzzy Sets. *Information and Control*, 8, 338-353.
[64] Zadeh, L.A. (1975). The concept of a linguistic variable and its application to approximate reasoning, *Inform. Sci.* 8, 199–249(I), 301–357(II).
[65] Delgado, M., Verdegay, J.L., Vila, M.A. (1992). Linguistic decision making models, *Int. J. Intelligent System* 7, 479–492.
[66] Herrera, F., Herrera-Viedma, E., Verdegay, J.L. (1996). A model of consensus in group decision making under linguistic assessments, *Fuzzy Sets and Systems*, 78,73–87.
[67] Li, X. G., Wei, X., Huang, Q. (2012). Comprehensive entropy weight observability-controllability risk analysis and its application to water resource decision-making, *Water SA*, vol. 38 (4), 573–579.
[68] Dong, G. H., Shen,J. Q., Jia, Y. Z., Sun, F. H. (2018). Comprehensive evaluation of water resource security: case study from Luoyang City, China, *Water*, 10(8), 1106.
[69] Cao, C., Slobounov, S.(2011). Application of a novel measure of EEG non-stationarity as 'Shannon- entropy of the peak frequency shifting' for detecting residual abnormalities in concussed individuals, *Clinical Neurophysiology*, vol. 122, no. 7, pp. 1314–1321.
[70] Wang,J.-J., Miao, Z.-H., Cui,F.-B., Liu,H.-C.(2018). Robot evaluation and selection with entropy-based combination weighting and cloud TODIM approach, *Entropy* 2018, 20, 349; doi:10.3390/e20050349
[71] Vaid,S. K., Vaid,G., Kaur, S., Kumar,R., Sidhu,M. S.(2021), Application of multi-criteria decision-making theory with VIKOR-WASPAS-Entropy methods: a case study of silent Genset,*Materials Today: Proceedings*, https://doi.org/10.1016/j.matpr.2021.10.259.