Applying the COPRAS method for metaheuristic algorithm selection: The case of the economic dispatch problem

Milena Gajić

University of Belgrade, Technical Faculty in Bor, Serbia, mgajic@tfbor.bg.ac.rs

Sanela Arsić

University of Belgrade, Technical Faculty in Bor, Serbia, sarsic@tfbor.bg.ac.rs

Abstract: In recent literature, an increasing number of metaheuristic algorithms have been proposed for solving individual optimization problems. One such complex problem, widely studied and addressed with various algorithms, is the economic dispatch problem. Hence, this paper aims to establish a systematic approach for selecting the most suitable metaheuristic algorithm by employing the COPRAS (COmplex PRoportional ASsessment) method, a multi-criteria decision-making (MCDM) technique. The proposed methodology is applied to evaluate and rank five metaheuristic algorithms (MSA, FA, PSO, PSOGSA, and PSOCGSA) across four variants of the economic dispatch problem. The assessment considers multiple performance metrics, including best-obtained results, standard deviation, mean values, error rates, computation time, and convergence behaviour. To ensure the reliability of the ranking, the results were further validated using the EDAS method, confirming the robustness of the selection process. This study provides a structured framework for algorithm recommendation, aiding researchers and practitioners in choosing the most effective optimization approach for similar complex problems.

Keywords: metaheuristics, economic dispatch, MCDM, COPRAS method, EDAS method

1 Introduction

A wide range of metaheuristic algorithms has been proposed in the literature to address complex optimisation problems. These problems often have multiple subproblems, each characterised by distinct objective functions and constraints. According to the „No free lunch“ theorem [1], a single algorithm for resolving a multifaceted problem cannot be the optimal solution for each subproblem. Consequently, there has recently been growing interest in developing methodologies for selecting the most suitable algorithm from several proposed solutions to a specific multifaceted problem [2]. One such optimisation challenge is the Economic dispatch problem, which has received considerable attention in the literature due to its significance in power system operations [3]. In this study, we employ the COmplex PROportional Assessment (COPRAS) multi-criteria decision-making (MCDM) method [4] to identify the most appropriate metaheuristic algorithm for solving the economic dispatch problem. The algorithms under consideration include the Moth Swarm Algorithm (MSA) [5], Firefly Algorithm (FA) [6], Particle Swarm Optimisation (PSO) [7], PSOGSA [8], and PSOCGSA [2]. Given the comparable performance of these metaheuristic algorithms, a more detailed evaluation was conducted using a multi-criteria decision-making approach to establish a ranking based on their effectiveness across different functions. To ensure a comprehensive assessment, multiple performance metrics were considered, including the Best-obtained results (B), Standard Deviation (SD), Mean values (Mv), Error rates (Er), Computation time (Ct), and Convergence (C) for each algorithm. The most suitable algorithm for solving the Economic dispatch problem was identified by integrating these criteria according to four different functions. The COPRAS method enables a structured comparison and selection of the optimal algorithm. This methodology ensured that the ranking process accounted for the accuracy and robustness of the algorithms and their efficiency and stability across various problem variants.

2 Testing the algorithms

We test the selected algorithms on a standard IEEE 30-bus 6-generator system with a total load demand of 283.4 MW. Economic dispatch is the adjustment of the output power of several-generators in a thermal power plant to minimize fuel cost by satisfying the constraints in the system. In this optimization process, the four most commonly used objective functions (f_1, f_2, f_3, and f_4) are as follows:

$$\begin{aligned} f_1 &= \sum_{g \in G} \left(a_g + b_g P_g + c_g P_g^2 \right), \; g = 1, 2, \ldots, G \\ P_{loss} &= 0 \end{aligned} \tag{1}$$

where, f_1 ($/h) is the fuel cost function of all generator units in the thermal power plant that should be minimized; P_g is the output power of generator g (MW); G is the total number of generators; a_g, b_g and c_g are the cost coefficients. In this case, power losses P_{loss} in the power system to which the generators are connected are neglected (P_{loss}= 0).

$$\begin{aligned} f_2 &= \sum_{g \in G} \left(a_g + b_g P_g + c_g P_g^2 \right), \; g = 1, 2, \ldots, G \\ P_{loss} &= \sum_{g \in G} \sum_{j \in G} P_g B_{gj} P_j + \sum_{g \in G} B_{0g} P_g + B_{00} \end{aligned} \tag{2}$$

In this case, the objective function is the same as in the previous one, but the power losses P_{loss} in the system are taken into account. B_{gj} and B_{0g} are the coefficients of the ***B***-*loss* matrix, and B_{00} is a constant.

$$f_3 = \sum_{g \in G} \left(a_g + b_g P_g + c_g P_g^2 \right) + \sum_{g \in G} \left| d_g \sin\left(e_g \left(P_g^{\min} - P_g \right) \right) \right|, \; g = 1, 2, \ldots, G$$
$$P_{loss} = 0 \tag{3}$$

In this case, the fuel cost function (f_3) takes into account the valve point effect in the thermal power plant. $P_g^{\min}$ (MW) is the minimum power of the generator g; d_g and e_g are coefficients for valve point effect. P_{loss} are neglected.

$$f_4 = \sum_{g \in G} \left(a_g + b_g P_g + c_g P_g^2 \right) + \sum_{g \in G} \left| d_g \sin\left(e_g \left(P_g^{\min} - P_g \right) \right) \right|, \; g = 1, 2, \ldots, G$$
$$P_{loss} = \sum_{g \in G} \sum_{j \in G} P_g B_{gj} P_j + \sum_{g \in G} B_{0g} P_g + B_{00} \tag{4}$$

Function f_4 represents the fuel cost function, which accounts for both power loss and the valve-point effect. The constraint on generator power output remains consistent across all four optimization processes and is defined as follows:

$$P_g^{\min} \le P_g \le P_g^{\max} \tag{5}$$

where, $P_g^{\min}$ and $P_g^{\max}$ are the minimum and maximum power of generator g, respectively. During the optimization process the power balance in the system must be satisfied, i.e.:

$$\sum_{g \in G} P_g - P_D - P_{loss} = 0 \tag{6}$$

where, P_D is the total power of the consumer. Coefficients of fuel cost, emission and *B-loss* matrices are taken in this paper from [9]. The algorithms are implemented in MATLAB R2017a computational environment and run on 1.3 GHz, with 8.0 GB RAM. The best results of the simulations are obtained after 30 runs. The coefficients of the algorithms are shown in Table 1.

FA					MSA			PSOGSA and PSOCGSA						PSO			
N	t_{max}	α	$\beta_{\min}$	γ	N	t_{max}	N_c	N	t_{max}	G_0	α	C_1	C_2	N	t_{max}	C_1	C_2
50	200	0.25	0.20	1	50	200	6	50	200	1	20	0.5	1.5	50	200	0.5	1.5

Table 1.
Coefficients of the algorithms applied to the test system

The testing results indicate that the optimal fuel cost values are either identical or highly similar across all five algorithms. However, other performance metrics exhibit varying degrees of similarity or significant differences among the tested algorithms. In the next section, algorithms are ranked based on multiple evaluation metrics, overused functions of Economic dispatch problem.

3 COPRAS method in Multi-Criteria Decision-Making

The Complex Proportional Assessment (COPRAS) method is a widely used multi-criteria decision-making (MCDM) approach that facilitates the ranking and selecting alternatives based on multiple conflicting criteria. Introduced by Zavadskas, Kaklauskas, and Sarka in 1994, COPRAS is particularly effective in situations where decision-makers must evaluate alternatives by considering both beneficial and non-beneficial criteria while maintaining proportionality between the alternatives [10], [11]. This method follows a systematic process for ranking and evaluating options based on their relative importance and utility. By analysing best-case and worst-case scenarios, COPRAS ensures a well-balanced decision-making approach that effectively accounts for trade-offs between competing criteria. Key characteristics of the COPRAS method include its compensatory nature, which allows weaker criteria to be offset by stronger ones, its ability to maintain independence among attributes, and its capability to convert qualitative attributes into quantitative measures, making it a versatile tool for multi-criteria decision-making applications [12].

Step 1. Formulation of Decision Matrix

$$X = \left[x_{ij} \right] = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \tag{7}$$

Where x_{ij} is the estimated value of the *i*-th in relation to the *j*-th criterion, *m* is the number of alternatives and *n* is the number criteria.

Step 2. The Normalized Decision Matrix. Normalization of the initial decision matrix using the linear normalization procedure. The equation (8) is used for normalization in the COPRAS method:

$$R = \left[r_{ij} \right] = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}} \tag{8}$$

Step 3. The Weighted Normalized Decision Matrix. Equation (9) is used to calculates the values for the weighted normalized decision matrix.

$$D = \left[x_{ij} \right] = r_{ij} \cdot w_j \qquad i = 1, \ldots, m; \quad j = 1, \ldots, n \tag{9}$$

Where w_j is the normalized value of the *i*-th alternative in relation to the *j*-th criterion and w_j is the weight or importance of the *j*-th criterion. The sum of weighted normalized values for each criterion is always equal to the value of that criterion:

$$\sum_{i=1}^{m} y_{ij} = w_j \tag{10}$$

Step 4. The Maximizing and Minimizing Indexes

The indices for maximising and minimising each attribute are determined by whether the attributes are negative or positive, utilizing equations (11) and (12):

$$S_{+i} = \sum_{i=1}^{n} y_{+ij} \tag{11}$$

$$S_{-i} = \sum_{i=1}^{n} y_{-ij} \tag{12}$$

Where y_{+ij} and y_{-ij} are weighted normalized values for positive or negative criteria, respectively.

Step 5. The relative significance value. Determining the relative importance of each alternative. Relative weight Q_i for the *i*-th alternative is calculated using the equation (13) or equation (14):

$$Q_i = S_{+i} + \frac{\min_i s_{-1} - i \sum_{i=1}^{m} s_{-i}}{s_{-i} \sum_{i=1}^{m} \frac{\min_i s_i}{s_{-i}}} \tag{13}$$

$$Q_i = S_{+i} + \frac{\sum_{i=1}^{m} s_{-i}}{s_{-i} \sum_{i=1}^{m} \frac{1}{s_{-i}}} \tag{14}$$

Step 6. Final Ranking of Alternatives. The alternatives are arranged in descending order according to their relative importance values, with the highest final value ranked first.

The COPRAS method has been extensively applied across various fields due to its efficiency in handling multi-criteria decision-making problems. It has been widely utilized in engineering optimization [4], transportation planning [13], energy sector analysis [14], supply chain management [15], in risk assessment [16], [17], [18], investment project selection [19], manufacturing environments [20], logistics performance evaluation [21], public health and occupational safety [22], aerospace engineering [23]. These diverse applications underscore the robustness and adaptability of the COPRAS method, making it a powerful tool for tackling complex decision-making challenges across multiple industries. Compared to other MCDM methods, such as TOPSIS and VIKOR, COPRAS offers a straightforward computational process and ensures that the final ranking reflects the relative importance of each criterion while maintaining consistency in decision-making [14]. Therefore, in this research COPRAS method is used to rank algorithms according to different performance measures to solve mentioned Economic dispatch problem variants.

4 Results of ranking algorithms

Based on the findings from the previous research phase, the five algorithms tested, MSA, FA, PSO, PSOGSA, and PSOCGSA, were ranked using the COPRAS method. The initial decision matrix, presented in Table 2, displays key performance metrics for each algorithm, including the best (minimum) obtained values, mean values, standard deviation, error rate, convergence rate, and computation time.

After performing the linear normalization explained in step 2 equation (8) and weighting the normalized matrix equation (9), the weight-normalized decision matrix is obtained (Table 3).

Criteria →	**Best (B)** *min*				**Standard Deviation (SD)** *min*			
Alternatives↓	*B (f1)*	*B (f2)*	*B (f3)*	*B (f4)*	*f1 (SD)*	*f2 (SD)*	*f3 (SD)*	*f4 (SD)*
MSA	600.11140866	605.99836998	631.34826554	635.82880914	4.42645122E-06	6.81784E-06	7.823973065	6.627336699
FA	600.11140820	605.99836950	631.34937828	635.82395070	6.103360307E-04	0.030611058	4.615530333	0.255825779
PSO	600.11140819	605.99836946	631.90736059	635.90446527	6.893239936E+00	6.858534642	6.372535196	8.401397207
PSOGSA	600.11140819	605.99836946	631.33121085	635.82011047	3.468910298E-13	11.12599965	6.617598864	15.576524660
PSOCGSA	600.11140819	605.99836946	631.33122939	635.82041383	2.701100444E-08	7.285294731	4.945913872	8.722792025
Criteria →	**Mean value (Mv)** *min*				**Error rate (Er)** *min*			
	f1 (Mv)	*f2 (Mv)*	*f3 (Mv)*	*f4 (Mv)*	*f1 (Er)*	*f2 (Er)*	*f3 (Er)*	*f4 (Er)*

Alternatives↓								
MSA	600.11141342	605.99837820	639.59170422	639.62799639	8.713818E-07	1.44223E-06	1.3085116005	0.598893596
FA	600.11153488	606.00395852	633.36741788	636.03929498	2.111228E-05	0.000922291	0.3226120308	0.034472723
PSO	606.06077310	611.09555167	642.59481029	648.73761871	9.913767E-01	0.84112144	1.784190394	2.031629391
PSOGSA	600.11140819	616.65200830	636.37489520	661.44054499	5.683287E-14	1.758030943	0.7989832112	4.029509934
PSOCGSA	600.11140823	607.90362553	633.28208453	637.91709308	7.313727E-09	0.314399539	0.3090956101	0.329807531
Criteria→	**Computation time (Ct)** *min*				**Convergence (C)** *min*			
Alternatives↓	*f1 (Ct)*	*f2 (Ct)*	*f3 (Ct)*	*f4 (Ct)*	*f1 (C)*	*f2 (C)*	*f3 (C)*	*f4 (C)*
MSA	0.74757034	3.579557657	1.836055390	4.970300697	106	97	750	471
FA	1.79574585	3.931430443	4.551615297	6.506888597	66	68	252	334
PSO	1.08263050	3.162463743	1.304519950	3.054587227	43	38	98	156
PSOGSA	0.7845	1.6958	1.9987	1.5170	18	28	71	85
PSOCGSA	0.7856	2.3182	2.0949	4.7472	20	17	129	166

Table 2
The initial matrix for ranking tested algorithms

Criteria→	**Best (B)**				**Standard Deviation (SD)**			
Alternatives ↓	*B (f1)*	*B (f2)*	*B (f3)*	*B (f4)*	*f1 (SD)*	*f2 (SD)*	*f3 (SD)*	*f4 (SD)*
MSA	0.0083	0.0083	0.0083	0.0083	0.0000	0.0011	0.0107	0.0070
FA	0.0083	0.0083	0.0083	0.0083	0.0000	0.0000	0.0063	0.0003
PSO	0.0083	0.0083	0.0083	0.0083	0.0417	0.0110	0.0087	0.0088
PSOGSA	0.0083	0.0083	0.0083	0.0083	0.0000	0.0178	0.0091	0.0164
PSOCGSA	0.0083	0.0083	0.0083	0.0083	0.0000	0.0117	0.0068	0.0092
Criteria→	**Mean value (Mv)**				**Error rate (Er)**			
Alternatives↓	*f1 (Mv)*	*f2 (Mv)*	*f3 (Mv)*	*f4 (Mv)*	*f1 (Er)*	*f2 (Er)*	*f3 (Er)*	*f4 (Er)*

MSA	0.0083	0.0083	0.0084	0.0083	0.0000	0.0020	0.0121	0.0036
FA	0.0083	0.0083	0.0083	0.0082	0.0000	0.0000	0.0030	0.0002
PSO	0.0084	0.0084	0.0084	0.0084	0.0417	0.0115	0.0164	0.0121
PSOGSA	0.0083	0.0084	0.0083	0.0085	0.0000	0.0239	0.0074	0.0239
PSOCGSA	0.0083	0.0083	0.0083	0.0082	0.0000	0.0043	0.0028	0.0020
Criteria→ Alternatives↓	**Computation time (Ct)**				**Convergence (C)**			
	f1 (Ct)	*f2 (Ct)*	*f3 (Ct)*	*f4 (Ct)*	*f1 (C)*	*f2 (C)*	*f3 (C)*	*f4 (C)*
MSA	0.0060	0.0102	0.0065	0.0100	0.0175	0.0163	0.0240	0.0162
FA	0.0144	0.0112	0.0161	0.0130	0.0109	0.0114	0.0081	0.0115
PSO	0.0087	0.0090	0.0046	0.0061	0.0071	0.0064	0.0031	0.0054
PSOGSA	0.0063	0.0048	0.0071	0.0030	0.0030	0.0047	0.0023	0.0029
PSOCGSA	0.0063	0.0066	0.0074	0.0095	0.0033	0.0029	0.0041	0.0057

Table 3

Weight-normalized decision matrix

All criteria must be minimised. Employing equation (12) in step 4, the resulting matrix is obtained, which reveals the calculated total of the cost criteria. The obtained results from this step is present in Table 4.

Alternatives	**S_{-i} (min)**
MSA	0.2095
FA	0.1728
PSO	0.2691
PSOGSA	0.1996
PSOCGSA	0.1490

Table 4.

Presentation of gained values S_{-i}

Applying equation (13), a matrix with the following values is obtained based on which alternatives are ranked. The obtained results is present in Table 5.

Alternatives	***Qi***	***Rank***
MSA	0.1839	4
FA	0.2226	2
PSO	0.1429	5
PSOGSA	0.1928	3
PSOCGSA	0.2581	**1**

Table 5.
Ranking list of algorithm using COPRAS method

The best-ranked algorithm applied in four different functions according to the best results, standard deviation, computation time and convergence is PSOCGSA, followed by the FA, PSOGSA, MSA and PSO algorithm.

5 Validation of results using EDAS method

To further validate the results obtained through the COPRAS method and ensure the accuracy of the ranking, the EDAS (Evaluation Based on Distance from Average Solution) method was employed [24]. EDAS is a multi-criteria decision-making technique that evaluates alternatives based on their distances from an ideal or average solution [25], providing a complementary perspective to the COPRAS method. In this approach, the alternatives are assessed by calculating their positive (S_i^+) and negative (S_i^-) distances from the average solution, which represents a reference point in the decision space. These distances are then used to rank the alternatives, with the smallest positive distance indicating the best-performing alternative [26]. Table 6 displays the final rankings of the analyzed algorithms based on the EDAS method.

Alternatives	S_i^+	S_i^-	S_i	***Rank***
MSA	0.7107	0.4184	0.565	4
FA	1	0.6513	0.826	2
PSO	0.3018	0	0.151	5
PSOGSA	0.8770	0.4234	0.650	3
PSOCGSA	0.9836	0.9378	0.961	**1**

Table 6
Ranking list of algorithm using EDAS method

The results obtained by the ranked algorithms using the EDAS method showed consistency in the ranks obtained for different performance measures compared to the COPRAS method results. Namely, the application of the EDAS method indicates that the best-ranked algorithm is PSOCGSA (according to the best results, standard deviation, computation time, and convergence), which points out that the validity of the obtained results was achieved.

The application of the EDAS method allowed for the cross-validation of the results derived from COPRAS method, providing additional confidence in the robustness and consistency of the obtained ranking. By comparing the rankings from both methods, a more comprehensive and reliable assessment of the alternatives was achieved, enhancing the overall decision-making process.

Conclusion

This study applied the COPRAS multi-criteria decision-making method to rank and evaluate metaheuristic algorithms for solving the multi-objective Economic dispatch problem. The ranking criteria were based on multiple performance measures, assessing each algorithm's effectiveness in addressing different subproblems of the optimization task. By integrating these criteria, the PSOCGSA algorithm was identified as the most suitable solution for the Economic dispatch problem. The COPRAS method facilitated a structured and systematic comparison, ensuring that the final ranking considered the accuracy and robustness of the algorithms and their computational efficiency and stability across various problem variants. The EDAS method was employed to validate these findings, confirming our ranking procedure's reliability. The results of this study demonstrate that the proposed methodology is effective and can be extended to other optimization problems requiring the selection of the most appropriate metaheuristic algorithm.

Acknowledgement

The research presented in this paper was carried out with the financial support of the Ministry of Science, Technological Development and Innovation of the Republic of Serbia within the framework of financing scientific research work at the University of Belgrade, Technical Faculty in Bor, in accordance with the contract with registration number 451-03-137/2025-03/200131. The authors would also like to thank Sandra Vasković, English teacher, for proofreading the paper.

References

[1] Wolpert, D. H., & Macready, W. G. (1997). No free lunch theorems for optimization. IEEE Transactions on Evolutionary Computation, 1(1), 67-82.

[2] Gajić, M., Arsić, S., Radosavljević, J., Jevtić, M., Perović, B., Klimenta, D., & Milovanović, M. (2024) Behavior Analysis of the New PSO-CGSA

Algorithm in Solving the Combined Economic Emission Dispatch Using Non-parametric Tests. Applied Artificial Intelligence, 38(1), 2322335.

[3] Radosavljević, J. (2024). Metaheuristic Optimization in Power Engineering (2nd Edition), Volume 1 - Algorithms and Power Dispatch Using MATLAB®-Based Software, The Institution of Engineering and Technology IET, London, UK, ISBN-13: 978-1-83724-137-8

[4] Zavadskas, E., Antucheviciene, J., Adeli, H., & Turskis, Z. (2016). Hybrid multiple criteria decision making methods: A review of applications in engineering. Scientia Iranica, 23(1), 1-20.

[5] Jevtić, M., Jovanović, N., Radosavljević, J., & Klimenta, D. (2017). Moth Swarm Algorithm for Solving Combined Economic and Emission Dispatch Problem. Elektronika ir Elektrotechnika, 23(5), 21-28.

[6] Apostolopoulos, T., & Aristidis, V. (2011). Application of the Firefly Algorithm for Solving the Economic Emissions Load Dispatch Problem. International Journal of Combinatorics, 23, 1687-9163.

[7] Kumar, A.I.S., Dhanushkodi, K., Kumar, J.J., & Paul, C.K.C. (2003). Particle swarm optimization solution to emission and economic dispatch problem. In: Proceedings of TENCON 2003. Conference on Convergent Technologies for Asia-Pacific Region, Bangalore, India, 1, 435-439.

[8] Radosavljević, J. (2016). A solution to the combined economic and emission dispatch using hybrid PSOGSA algorithm. Applied Artificial Intelligence, 30(5), 445-474.

[9] Aydin, D., Ozyon, S., Yasar, C., & Liao, T. (2014). Artificial bee colony algorithm with dynamic population size to combined economic and emission dispatch problem. International Journal of Electrical Power & Energy Systems, 54, 144–153.

[10] Zavadskas, E.K., Kaklauskas, A., & Sarka, V. (1994). The new method of multicriteria complex proportional assessment of projects. Technological and Economic Development of Economy, 1(3), 131-139.

[11] Zavadskas, E. K., & Kaklauskas, A. (1996). Determination of an efficient contractor by using the new method of multicriteria assessment. In International Symposium for the Organization and Management of Construction, 94-104.

[12] Taherdoost, H., & Mohebi, A. (2024). A comprehensive guide to the copras method for multi-criteria decision making. Journal of Management Science & Engineering Research, 7(2), 1-14.

[13] Turskis, Z., & Zavadskas, E. K. (2010). A novel method for multi-criteria decision making (COPRAS-G) and its application in construction engineering. Archives of Civil and Mechanical Engineering, 10(1), 5-18.

[14] Mardani, A., Jusoh, A., & Zavadskas, E. K. (2015). Fuzzy multiple criteria decision-making techniques and applications - Two decades review from 1994 to 2014. Expert Systems with Applications, 42(8), 4126-4148.

[15] Brauers, W. K. M., & Zavadskas, E. K. (2006). The MOORA method and its application to privatization in a transition economy. Control and Cybernetics, 35(2), 445-469.

[16] Alinezhad, A., Khalili, J., & Amini, A. (2015). Application of the COPRAS method in risk assessment. Journal of Money and Economy, 10, 87-121.

[17] Valipour, M., Yahya, K., & Tamošaitienė, J. (2017). Risk assessment using COPRAS in civil engineering projects. Journal of Civil Engineering and Management, 23, 524-532.

[18] Haghighi, M. H., & Ashrafi, M. (2024). A novel framework for risk management of software projects by integrating a new COPRAS method under cloud model and machine learning algorithms. Annals of Operations Research, 338(1), 675-708.

[19] Popović, G., Kuzmanović, M., & Mladenović, I. (2012). Investment project selection using multi-criteria analysis. Serbian Journal of Management, 7, 257-269.

[20] Chakraborty, S., Chatterjee, P., & Das, P. P. (2024). Complex Proportional Assessment (COPRAS) Method. In Multi-Criteria Decision-Making Methods in Manufacturing Environments, 147-155. Apple Academic Press.

[21] Gelmez, E., Güleş, H. K., & Zerenler, M. (2024). Evaluation of Logistics Performances of G20 Countries Using SD-Based COPRAS and SAW Methods. Journal of Turkish Operations Management, 8(2), 339-353.

[22] Cai, J., Hu, Y., Peng, Y., Guo, F., Xiong, J., & Zhang, R. (2024). A hybrid MCDM approach based on combined weighting method, cloud model and COPRAS for assessing road construction workers' safety climate. Frontiers in Public Health, 12, 1452964.

[23] Balasubramaniam, S., Ramachandran, M., Saravanan, V., & Raja, C. Assessment of Selection of Suitable for Spar of the Human-Powered Aircraft Using COPRAS Method.

[24] Arsić, S., Gajić, M., & Jevtić, M. (2024). The TOPSIS method for experimental comparison of multiple metaheuristic algorithms over a set of problems: a case study of the multi-case CEED problem.

[25] Ghorabaee, M., Amiri, M., Zavadskas, E. K., Turskis, Z., & Antucheviciene, J. (2017). Stochastic EDAS method for multi-criteria decision-making with normally distributed data. Journal of Intelligent & Fuzzy Systems, 33(3), 1627-1638.

[26] Opricovic, S., & Tzeng, G. H. (2004). Defining appropriate criteria and evaluation measures for the selection of the best location for a distribution center**.** Journal of the Operational Research Society, *55*(1), 17-24.