

A Lexicographic Approach to Sustainable Multi-Objective Assignment Optimization

Dr Abha Tenguria¹, Somya Dubey²

¹Professor and Head, Department of Mathematics, Govt. M.L.B Girls P.G. (Auto) college, Bhopal, Madhya Pradesh, India

²Research Scholar, Department of Mathematics, Govt. M.L.B Girls P.G. (Auto) college, Bhopal, Madhya Pradesh, India

ARTICLE INFO	ABSTRACT
Published Online: 30 September 2026	The classical assignment problem allocates jobs to agents while optimizing a single performance criterion. Modern allocation decisions often require simultaneous consideration of economic, operational, resource, and environmental consequences. This paper formulates a four-objective multi-objective assignment problem in which total cost, total completion time, resource consumption, and environmental impact are minimized simultaneously. Binary integer programming is developed for assigning (n) tasks to (n) agents subject to one-to-one assignment constraints. Each task-agent combination is characterized by four coefficients representing cost, time, resource consumption, and environmental burden. Since these objectives may conflict, a single solution that independently minimizes all criteria generally does not exist. The Lexicographic Method is adopted to incorporate explicit priority information from the decision maker. The model provides a transparent framework for sustainable task allocation and can be applied to workforce, machine, logistics, project, and service assignment environments. A numerical instance demonstrates the sequential optimization procedure and resulting trade-offs.
Corresponding Author: Somya Dubey	
KEYWORDS: Multi-Objective Assignment Problem; Lexicographic Method; Assignment Problem, Multi-Criteria Decision Making.	

INTRODUCTION

The assignment problem is one of the fundamental models of operations research and combinatorial optimization. It concerns the allocation of a set of jobs or tasks to a corresponding set of persons, machines, or resources under one-to-one assignment restrictions. The mathematical structure of the classical assignment problem was systematically developed through the work of Kuhn and Munkres, with the Hungarian method providing a polynomial-time solution procedure for the linear assignment problem [1,2]. The assignment problem has subsequently become an important model in workforce allocation, scheduling, production planning, logistics, transportation, and resource allocation. Burkard, Dell'Amico, and Martello provide a comprehensive treatment of assignment problems, including linear assignment, quadratic assignment, matching, theoretical foundations, and computational methods [3]. The assignment can be represented as a bijective mapping between two finite sets, which is equivalent to a permutation representation of the solution.

Multi-objective optimization provides a suitable framework for such situations. In a multi-objective optimization problem, several objective functions are optimized simultaneously, and the objectives may conflict with each other. Steuer developed an important foundation for multiple-criteria optimization, while Ehrgott established a comprehensive mathematical framework for multicriteria optimization, including efficient solutions and Pareto optimality [4,5]. Marler and Arora reviewed major classes of multi-objective optimization methods and emphasized the importance of selecting a suitable solution strategy according to the decision maker's preference information [6]. The presence of multiple objectives changes the nature of optimality. Instead of one solution that is simultaneously best for every criterion, there may exist several non-dominated or Pareto-optimal solutions. A solution is Pareto optimal when no other feasible solution can improve one objective without deteriorating at least one other objective. This concept has become fundamental in multi-objective mathematical programming and evolutionary

optimization [5,7]. Ehrgott and Gandibleux subsequently provided an extensive survey and annotated bibliography covering multi-objective combinatorial optimization, including exact, heuristic, and metaheuristic approaches [8]. The multi-objective assignment problem extends the classical assignment model by associating more than one cost or benefit matrix with the same assignment structure. Przybylski, Gandibleux, and Ehrgott developed two-phase algorithms for the bi-objective assignment problem and demonstrated the generation of efficient solutions for conflicting assignment criteria [9]. Their work established an important connection between multiobjective combinatorial optimization and the assignment problem.

The same research direction was subsequently extended to three-objective assignment problems. Przybylski, Gandibleux, and Ehrgott proposed a two-phase method for multi-objective integer programming and applied it to an assignment problem with three objectives [10]. The approach distinguishes supported efficient solutions from non-supported non-dominated solutions and demonstrates the increasing complexity associated with multiple objective functions. The increasing number of objectives makes the selection of an appropriate decision-making procedure increasingly important. Evolutionary multi-objective optimization has become one of the principal approaches for generating multiple Pareto-optimal solutions. Schaffer's vector-evaluated genetic algorithm was an early evolutionary approach to multi-objective optimization [11]. Srinivas and Deb subsequently proposed nondominated sorting within genetic algorithms to identify multiple Pareto-optimal solutions simultaneously [12]. Deb et al. later developed the Non-dominated Sorting Genetic Algorithm II (NSGA-II), which introduced fast non-dominated sorting, elitism, and crowdingdistance-based diversity preservation [13]. Zitzler, Deb, and Thiele conducted systematic empirical comparisons of multi-objective evolutionary algorithms and demonstrated the importance of algorithmic design and elitism in multi-objective search [14].

Other multi-objective optimization approaches have also been developed to generate or approximate Pareto fronts. Das and Dennis proposed the Normal-Boundary Intersection method for generating well-distributed Pareto-optimal solutions [15]. They also examined limitations of conventional weighted-sum approaches, particularly for non-convex Pareto fronts [16]. These studies demonstrate that the choice of solution methodology can substantially influence the solutions obtained from a multi-objective model. Weighted-sum methods are attractive because they transform several objectives into a single scalar objective. However, appropriate weights must be selected, and the resulting solution can be sensitive to the weight vector. Athan and Papalambros discussed limitations of weighted criteria methods for generating compromise solutions, particularly in non-convex objective spaces [17]. Goal programming provides another established multi-objective methodology, with Charnes and Cooper providing an important foundation

for goal programming and multipleobjective optimization [18].

The mathematical foundations of lexicographic multi-criteria optimization were investigated by Rentmeesters, Tsai, and Lin, who distinguished lexicographic optimization from conventional Pareto-based multi-criteria optimization [19]. More recently, lexicographic approaches have continued to receive attention because they allow decision makers to express strict priority relationships between objectives. Recent research on lexicographic multi-objective optimization confirms the continuing relevance of this approach for problems in which objectives possess an explicit priority order [20,21]. The environmental dimension has become increasingly important in assignment and allocation problems. Liu et al. developed an eco-friendly multi-skilled worker assignment and assembly-line balancing model incorporating cost and energy consumption as simultaneous objectives [22]. Their study demonstrates that assignment decisions can have direct implications for energy consumption and sustainability. Similarly, multi-objective environmental-economic optimization has demonstrated the importance of treating environmental impact as an explicit optimization criterion rather than merely as a post-optimization performance measure. Abido, for example, formulated environmental/economic dispatch as a multi-objective optimization problem involving competing cost and emission objectives [23]. The simultaneous treatment of economic and environmental criteria is also relevant to sustainable logistics and resource allocation. Tang, Wu, and Li investigated customer allocation within a multi-objective sustainable location problem and considered economic and carbonemission-related criteria [24]. This line of research supports the inclusion of environmental impact directly within mathematical optimization models.

The proposed model is intended to be solved using the **Lexicographic Method**. The methodology allows the decision maker to specify a strict priority order among the four objectives without assigning subjective numerical weights. Thus, the proposed framework combines the classical structure of the assignment problem with contemporary multi-objective and sustainability-oriented decision-making.

Multi-Objective Assignment Problem:

A Multi-Objective Assignment Problem (MOAP) is a generalization of the classical assignment problem in which a set of n jobs or tasks is assigned to n agents or resources on a one-to-one basis while simultaneously optimizing two or more objective functions. Formally, let $I = \{1, 2, \dots, n\}$ denote the set of jobs and $J = \{1, 2, \dots, n\}$ denote the set of agents. The decision variable x_{ij} is defined as

Let

$$x_{ij} = \begin{cases} 1, & \text{if worker } i \text{ is assigned to task } j \\ 0, & \text{otherwise} \end{cases}$$

Objectives:

Let $o_{ij}^1, o_{ij}^2, o_{ij}^3, \dots, o_{ij}^r$ represent the cost coefficients associated with the r objectives. The multi-objective assignment problem can be stated as:

Objective 1: Minimize Cost

Let c_{ij} denote the cost of assigning worker i to task j . The total assignment cost is

$$\min Z_1 = Z_1(x) = \sum_{i=1}^n \sum_{j=1}^n c_{ij} x_{ij}$$

Objective 2: Minimize Time

Let t_{ij} represent the completion time, processing time, or estimated duration associated with assigning worker i to task j . Then

$$\min Z_2 = Z_2(x) = \sum_{i=1}^n \sum_{j=1}^n t_{ij} x_{ij}$$

Objective 3: Resource Consumption

Let r_{ij} represent the amount of resource consumed when task i is assigned to resource j . Then

$$\min Z_3 = Z_3(x) = \sum_{i=1}^n \sum_{j=1}^n r_{ij} x_{ij}$$

Objective 4: Minimize Environmental Impact

Let e_{ij} denote the environmental impact associated with assignment (i, j) . It may represent estimated carbon emission, energy consumption, environmental burden, or a composite sustainability score. The total environmental impact is

$$\min Z_4 = Z_4(x) = \sum_{i=1}^n \sum_{j=1}^n e_{ij} x_{ij}$$

A lower value therefore represents better environmental performance.

Therefore $\min F(X) = [Z_1(x), Z_2(x), Z_3(x)]$

The assignment constraints are:

$$\sum_{i=1}^n x_{ij} = 1, \quad i = 1, 2, \dots, n$$

and

$$\sum_{j=1}^n x_{ij} = 1, \quad j = 1, 2, \dots, n$$

also

$$x_{ij} \in \{0, 1\}$$

LEXICOGRAPHIC METHOD

The **Lexicographic Method** is a sequential optimization technique used to solve a multiobjective assignment problem when the objectives have a strict priority order. In this method, the most important objective is optimized first. Its optimal value is then fixed, and the second-priority objective is optimized subject to preserving the optimum of the first

$$\min Z_r = Z_r(x) = \sum_{i=1}^n \sum_{j=1}^n o_{ij}^r x_{ij}$$

objective. The process continues until all objectives have been considered.

Working procedure of Lexicographic Method as follows:

Step 1: Define the objectives,

Identify all objective functions and arrange them according to their importance

$$Z_1 > Z_2 > Z_3 > \dots > Z_r$$

Step 2: Optimize the first objective,

Solve $\min Z_1 = Z_1(x)$. Let the optimal value be Z_1^* .

Step 3: Preserve the first optimum,

Add the constraint $Z_1 = Z_1^*$ and optimize the second objective $\min Z_2 = Z_2(x)$. Let Z_2^* be the optimum.

Step 4: Preserve the first two optima,

Add the constraint $Z_1 = Z_1^*$ and $Z_2 = Z_2^*$ and solve $\min Z_3 = Z_3(x)$ than obtained Z_3^* .

Step 5: Optimize the r^{th} objective,

Add the constraints $Z_1 = Z_1^*, Z_2 = Z_2^*, Z_3 = Z_3^*, \dots, Z_{r-1} = Z_{r-1}^*$ and solve $\min Z_r = Z_r(x)$ than obtain Z_r^* .

Step 6: Obtain the final assignment,

The resulting assignment is the lexicographically optimal assignment. Thus

$$Z^* = (Z_1^*, Z_2^*, Z_3^* \dots Z_r^*)$$

is optimal according to the specified priority structure.

Numerical Problem:

Here we consider there are five workers W_1, W_2, W_3, W_4, W_5 and five tasks T_1, T_2, T_3, T_4, T_5 . Each worker must be assigned to exactly one task, and each task must be assigned to exactly one worker. The objective is to determine assignments that simultaneously minimize:

1. Objective 1 $Z_1 = \text{Assignment Cost}$
2. Objective 2 $Z_2 = \text{Processing Time}$
3. Objective 3 $Z_3 = \text{Resource Consumption}$
4. Objective 4 $Z_4 = \text{Environmental Impact}$

Objective 1: Assignment Cost Matrix

$$\min Z_1 = \begin{bmatrix} 8 & 6 & 9 & 7 & 10 \\ 7 & 9 & 6 & 8 & 5 \\ 9 & 8 & 7 & 6 & 9 \\ 6 & 10 & 8 & 9 & 7 \\ 10 & 7 & 9 & 5 & 8 \end{bmatrix}$$

Objective 2: Processing Time Matrix

$$\min Z_2 = \begin{bmatrix} 9 & 8 & 7 & 10 & 9 \\ 8 & 9 & 6 & 7 & 8 \\ 10 & 7 & 8 & 6 & 9 \\ 7 & 10 & 9 & 8 & 6 \\ 9 & 6 & 10 & 7 & 8 \end{bmatrix}$$

Objective 3: Resource Consumption Matrix

$$\min Z_3 = \begin{bmatrix} 6 & 1 & 4 & 5 & 6 \\ 1 & 2 & 6 & 6 & 2 \\ 6 & 8 & 4 & 4 & 7 \\ 5 & 8 & 2 & 9 & 9 \\ 5 & 2 & 1 & 3 & 6 \end{bmatrix}$$

Objective 4: Environmental Impact Matrix

$$\min Z_4 = \begin{bmatrix} 6 & 4 & 8 & 7 & 9 \\ 7 & 8 & 5 & 6 & 4 \\ 9 & 7 & 6 & 5 & 8 \\ 5 & 9 & 7 & 8 & 6 \\ 8 & 5 & 9 & 4 & 7 \end{bmatrix}$$

As per step 1 arrange all the objective function according to their importance in table 1

Table 1: Priority of Objectives

Objective	Priority Order
I	$Z_1 > Z_2 > Z_3 > Z_4$
II	$Z_2 > Z_3 > Z_4 > Z_1$
III	$Z_3 > Z_4 > Z_1 > Z_2$
IV	$Z_4 > Z_3 > Z_2 > Z_1$

Here we are going to apply Hungarian method to obtained optimal solution of our MOAP in each condition as follows:

Condition I: According to Lexicographic Method firstly we solve our MOAP for Assignment Cost then Processing Time, Resource Consumption and Environmental impact.

Now after the implementation of Hungarian method in First Objective, we obtained the work allocation as follows

$W_1 \rightarrow T_2, W_2 \rightarrow T_5, W_3 \rightarrow T_3, W_4 \rightarrow T_1, W_5 \rightarrow T_4$
and optimal solution of all objective function of assignment problem as follows

Table 2: Optimal Solution as per I Condition

Objective	Name of Objective	Optimal Solution
Z_1^*	Assignment Cost	Rs 29
Z_2^*	Processing Time	Rs 38
Z_3^*	Resource Consumption	15 Units
Z_4^*	Environmental Impact	23

Condition II: According to Lexicographic Method firstly we solve our MOAP for Processing Time then Resource Consumption, Environmental impact and Assignment Cost. Now after the implementation of Hungarian method in second objective, we obtained the work allocation as follows

$W_1 \rightarrow T_3, W_2 \rightarrow T_1, W_3 \rightarrow T_4, W_4 \rightarrow T_5, W_5 \rightarrow T_2$
and optimal solution of all objective function of assignment problem as follows

Table 3: Optimal Solution as per II Condition

Objective	Name of Objective	Optimal Solution
Z_1^*	Assignment Cost	36
Z_2^*	Processing Time	33
Z_3^*	Resource Consumption	20
Z_4^*	Environmental Impact	31

Condition III: According to Lexicographic Method firstly we solve our MOAP for Resource Consumption then Environmental impact, Assignment Cost and Processing Time

Now after the implementation of Hungarian method in third objective, we obtained the work allocation as follows

$W_1 \rightarrow T_2, W_2 \rightarrow T_5, W_3 \rightarrow T_4, W_4 \rightarrow T_1, W_5 \rightarrow T_3$
and optimal solution of all objective function of assignment problem as follows

Table 4: Optimal Solution as per III Condition

Objective	Name of Objective	Optimal Solution
Z_1^*	Assignment Cost	32
Z_2^*	Processing Time	39
Z_3^*	Resource Consumption	13
Z_4^*	Environmental Impact	27

Condition IV: According to Lexicographic Method firstly we solve our MOAP for Environmental impact then Assignment Cost and Processing Time, and Resource Consumption

Now after the implementation of Hungarian method in fourth objective, we obtained the work allocation as follows

$W_1 \rightarrow T_2, W_2 \rightarrow T_5, W_3 \rightarrow T_3, W_4 \rightarrow T_1, W_5 \rightarrow T_4$
and optimal solution of all objective function of assignment problem as follows

Table 5: Optimal Solution as per IV Condition

Objective	Name of Objective	Optimal Solution
Z_1^*	Assignment Cost	29
Z_2^*	Processing Time	38
Z_3^*	Resource Consumption	15
Z_4^*	Environmental Impact	23

Table 6: Summary of Optimal Solution of All the Objective according priority

Objectives of MOAP	I Condition	II Condition	III Condition	IV Condition
	$Z_1 > Z_2 > Z_3 > Z_4$	$Z_2 > Z_3 > Z_4 > Z_1$	$Z_3 > Z_4 > Z_1 > Z_2$	$Z_4 > Z_3 > Z_2 > Z_1$
Assignment Cost	29	36	32	29
Processing Time	38	33	39	38
Resource Consumption	15	20	13	15
Environmental Impact	23	31	27	23

RESULT AND DISCUSSION

Table 6 presents the optimal solutions obtained under four different priority conditions of the multi-objective assignment problem. When ($Z_1 > Z_2 > Z_3 > Z_4$), the solution achieves the lowest assignment cost of 29, whereas prioritizing ($Z_2 > Z_3 > Z_4 > Z_1$) produces the lowest processing time of 33. Under ($Z_3 > Z_4 > Z_1 > Z_2$), resource consumption reaches its minimum value of 13. The fourth condition, ($Z_4 > Z_3 > Z_2 > Z_1$), produces the lowest environmental impact of 23 while also maintaining a low assignment cost of 29. These results demonstrate that changing objective priorities significantly influences the resulting optimal solution.

CONCLUSION

This study demonstrates the effectiveness of the Lexicographic Method for solving a fourobjective Multi-Objective Assignment Problem involving assignment cost, processing time, resource consumption, and environmental impact. The numerical results confirm that different priority structures lead to different optimal objective values. When cost receives the highest priority, the minimum assignment cost is obtained, while prioritizing processing time, resource consumption, or environmental impact respectively improves the corresponding objective. The results highlight the inherent trade-offs among competing objectives and demonstrate the flexibility of the proposed approach in incorporating decision-maker preferences. The developed

framework can support practical assignment decisions where economic, operational, resource, and environmental considerations must be simultaneously addressed within a structured optimization framework.

REFERENCES

1. Kuhn, H. W. (1955). The Hungarian method for the assignment problem. *Naval Research Logistics Quarterly*, 2(1–2), 83–97. DOI: <https://doi.org/10.1002/nav.3800020109>
2. Munkres, J. (1957). Algorithms for the assignment and transportation problems. *Journal of the Society for Industrial and Applied Mathematics*, 5(1), 32–38. DOI: <https://doi.org/10.1137/0105003>
3. Burkard, R. E., Dell’Amico, M., & Martello, S. (2012). *Assignment Problems: Revised Reprint*. SIAM. DOI: <https://doi.org/10.1137/1.9781611972238>
4. Steuer, R. E. (1986). *Multiple Criteria Optimization: Theory, Computation, and Application*. Wiley.
5. Ehrgott, M. (2005). *Multicriteria Optimization*. Springer. DOI: <https://doi.org/10.1007/3-54027659-9>
6. Marler, R. T., & Arora, J. S. (2004). Survey of multi-objective optimization methods for engineering. *Structural and Multidisciplinary Optimization*, 26, 369–395. DOI: <https://doi.org/10.1007/s00158-003-0368-6>

7. Ulungu, E. L., & Teghem, J. (1994). Multi-objective combinatorial optimization problems: A survey. *Journal of Multi-Criteria Decision Analysis*, 3(2), 83–104. DOI: <https://doi.org/10.1002/mcda.4020030204>
8. Ehrgott, M., & Gandibleux, X. (2000/2003). A survey and annotated bibliography of multiobjective combinatorial optimization. *OR Spectrum*, 22, 425–460. DOI: <https://doi.org/10.1007/s002910000046>
9. Przybylski, A., Gandibleux, X., & Ehrgott, M. (2008). Two phase algorithms for the bi-objective assignment problem. *European Journal of Operational Research*, 185(2), 509–533. DOI: <https://doi.org/10.1016/j.ejor.2006.12.054>
10. Przybylski, A., Gandibleux, X., & Ehrgott, M. (2010). A two phase method for multi-objective integer programming and its application to the assignment problem with three objectives. *Discrete Optimization*, 7(3), 149–165. DOI: <https://doi.org/10.1016/j.disopt.2010.03.005>
11. Schaffer, J. D. (1985). Multiple objective optimization with vector evaluated genetic algorithms. In *Proceedings of the First International Conference on Genetic Algorithms*, 93–100.
12. Srinivas, N., & Deb, K. (1994). Multiobjective optimization using nondominated sorting in genetic algorithms. *Evolutionary Computation*, 2(3), 221–248. DOI: <https://doi.org/10.1162/evco.1994.2.3.221>
13. Deb, K., Pratap, A., Agarwal, S., & Meyarivan, T. (2002). A fast and elitist multiobjective genetic algorithm: NSGA-II. *IEEE Transactions on Evolutionary Computation*, 6(2), 182–197. DOI: <https://doi.org/10.1109/4235.996017>
14. Zitzler, E., Deb, K., & Thiele, L. (2000). Comparison of multiobjective evolutionary algorithms: Empirical results. *Evolutionary Computation*, 8(2), 173–195. DOI: <https://doi.org/10.1162/106365600568202>
15. Das, I., & Dennis, J. E. (1998). Normal-boundary intersection: A new method for generating the Pareto surface in nonlinear multicriteria optimization problems. *SIAM Journal on Optimization*, 8(3), 631–657. DOI: <https://doi.org/10.1137/S1052623496307510>
16. Das, I., & Dennis, J. E. (1997). A closer look at drawbacks of minimizing weighted sums of objectives for Pareto set generation in multicriteria optimization problems. *Structural Optimization*, 14, 63–69. DOI: <https://doi.org/10.1007/BF01197559>
17. Athan, T. W., & Papalambros, P. Y. (1996). A note on weighted criteria methods for compromise solutions in multi-objective optimization. *Engineering Optimization*, 27(2), 155–176. DOI: <https://doi.org/10.1080/03052159608941404>
18. Charnes, A., & Cooper, W. W. (1977). Goal programming and multiple objective optimizations: Part 1. *European Journal of Operational Research*, 1(1), 39–54. DOI: [https://doi.org/10.1016/S03772217\(77\)81007-2](https://doi.org/10.1016/S03772217(77)81007-2)
19. Rentmeesters, M. J., Tsai, W. K., & Lin, K.-J. (1996). A theory of lexicographic multi-criteria optimization. *Proceedings of the IEEE International Conference on Engineering of Complex Computer Systems*, 76–79. DOI: <https://doi.org/10.1109/ICECCS.1996.558386>
20. Lai, L., Fiaschi, L., Cococcioni, M., et al. (2023). Pure and mixed lexicographic-paretian many-objective optimization: State of the art. *Natural Computing*, 22, 227–242. DOI: <https://doi.org/10.1007/s11047-022-09911-4>
21. Tappenden, R., et al. (2018). Lexicographic multi-objective linear programming using Grossone methodology: Theory and algorithm. *Applied Mathematics and Computation*, 318, 298–311. DOI: <https://doi.org/10.1016/j.amc.2017.05.058>
22. Liu, R., Liu, M., Chu, F., et al. (2021). Eco-friendly multi-skilled worker assignment and assembly line balancing problem. *Computers & Industrial Engineering*, 151, 106944. DOI: <https://doi.org/10.1016/j.cie.2020.106944>
23. Abido, M. A. (2003). A niched Pareto genetic algorithm for multiobjective environmental/economic dispatch. *International Journal of Electrical Power & Energy Systems*, 25(2), 97–105. DOI: [https://doi.org/10.1016/S0142-0615\(02\)00027-3](https://doi.org/10.1016/S0142-0615(02)00027-3)
24. Tang, X., Wu, J., & Li, R. (2020). Efficient allocation of customers to facilities in the multi-objective sustainable location problem. *Sustainability*, 12(18), 7634. DOI: <https://doi.org/10.3390/su12187634>
25. Murata, T., Ishibuchi, H., & Tanaka, H. (1996). Multi-objective genetic algorithm and its applications to flowshop scheduling. *Computers & Industrial Engineering*, 30(4), 957–968. DOI: [https://doi.org/10.1016/0360-8352\(96\)00045-9](https://doi.org/10.1016/0360-8352(96)00045-9)
26. Chang, P.-C., Hsieh, J.-C., & Wang, C.-Y. (2007). Adaptive multi-objective genetic algorithms for scheduling of drilling operation in printed circuit board industry. *Applied Soft Computing*, 7(3), 800–806. DOI: <https://doi.org/10.1016/j.asoc.2006.02.002>
27. Foschini, L., Guns, T., et al. (2026). Anytime lexicographic enumeration of the Pareto front in multi-objective combinatorial optimisation. *Journal of Multi-Criteria Decision Analysis*. DOI: <https://doi.org/10.1002/mcda.70029>