ACER
European Union Agency for the Cooperation of Energy Regulators

ACER's Decision on the alternative bidding zone configurations to be considered in the bidding zone review process for the Baltic region

ANNEX I

Description of the "Technique Order of Preference by Similarity to Ideal Solution (TOPSIS)", used to rank the performance of bidding zones and alternative bidding zone configurations

21 December 2023

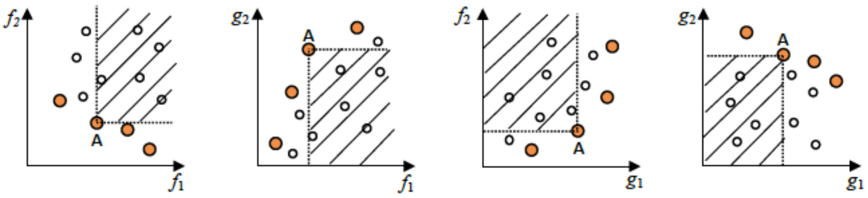
1. Introduction to the Pareto front concept and the Technique Order of Preference by Similarity to Ideal Solution (TOPSIS)

As part of the procedure to identify alternative bidding zone (BZ) configurations, both the selection of the BZs to reconfigure at each iteration and the ranking of alternative configurations resulting from each iteration can be considered multi-objective problems. Multi-objective problems are defined by considering different objectives simultaneously. In order to set up a multi-objective problem, the objectives considered have to be, or may be, in conflict with each other. The multi-objective optimisation yields as results not only the best values for the individual objectives, but also a number of compromise solutions seen as feasible decision-making alternatives. For the purpose of the Decision on BZ configurations, the objectives are maximisation of cross-zonal capacity and economic efficiency; such objectives are measured, respectively, through two performance indicators: i) The amount of internal flows and loop flows on cross-zonal relevant network elements; and ii) The level of price dispersion. In both cases, the lower the value of the indicator, the better the performance of the BZ (or configuration). When comparing two BZs (or alternative BZ configurations), it may well be that BZ (or alternative BZ configuration) 'A' performs better with respect to the objective internal and loop flows than BZ (or alternative BZ configuration) 'B', but B may perform better than A in terms of price dispersion. The multi-objective optimisation allows to determine whether A performs better than B overall or vice-versa.

In order to represent compromise solutions, the concept of dominance is applied. A solution is non-dominated when no other solution exists with better values for all individual objective functions. The compromise solutions are then found as the non-dominated solutions of the multi-objective problem. These non-dominated solutions form the so-called Pareto front. The resulting concept of Pareto dominance depends on the nature of the objective function, that is, on whether the objective function has to be maximised or minimised.

Figure 1 shows in the two-objective case how a given solution point dominates other points for different combinations of objective functions to be minimised (f_1 and f_2) or maximised (g_1 and g_2). In each plot, the shaded area corresponds to the points dominated by the point A indicated in the figure, and the orange circled points are the ones located on the Pareto front. The construction of the Pareto front is also a way to establish whether two or more objectives are in conflict with each other. In fact, for non-conflicting objectives the Pareto front converges to a single point. In practical applications, it could be infeasible to calculate the entire Pareto front. In these cases, the best-known Pareto front is determined as the computable set of non-dominated solutions [1]-[2].

Figure 1: Concept of Pareto dominance. The functions f1 and f2 are minimised. The functions g1 and g2 are maximised.



In the classical construction of the Pareto front, all the compromise solutions have the same importance so that a solution ranking mechanism has to be implemented to identify the most appropriate solution from the Pareto front. One of the methods that has been considered for ranking the points of the Pareto front is the Technique of Order Preference by Similarity to Ideal Solution (TOPSIS) [2]. The TOPSIS method is based on the concept that the chosen alternative should have the shortest distance from the positive ideal solution and the farthest distance from the negative ideal solution. TOPSIS can identify the best alternative from a finite set of alternatives quickly. The alternatives are the points of the Pareto front, and the criteria are represented by the objective functions.

Starting from the set $\boldsymbol{X} = \{\boldsymbol{x_{mz}}\}$ of $m = 1, \dots, M$ alternatives and $z = 1, \dots, Z$ criteria, the application of TOPSIS includes the following steps:

a) Construct the normalised decision matrix

The normalised decision matrix $\mathbf{R} = \{r_{mz}\}$ is constructed for each column $z = 1, \dots, Z$ as illustrated by equation (1):

$$r_{mz} = \frac{x_{mz}}{\sqrt{(x_{1z}^2 + \cdots + x_{Mz}^2)}} \qquad (1)$$

b) Construct the weighted normalised decision matrix

The weighting factors need to be defined for each criterion, to consider the importance the decision makers can assign to different criteria. The diagonal matrix $\mathbf{W}_{Z\times Z}$ contains the weighting factors w_{zz} on the diagonal. The sum of the weighting factors is equal to unity. In the context of the current Decision on alternative BZ configurations, the above mentioned two objectives are given equal weights.

The weighted normalised decision matrix is given by equation (2):

$$\mathbf{V} = \mathbf{R} \cdot \mathbf{W}_{Z\times Z} \qquad (2)$$

c) Identify the positive and negative ideal solutions

The positive and negative ideal solutions of the alternatives are taken from the best and worst elements of the matrix $\mathbf{V}$, respectively, according to equation (3):

$$\begin{aligned} \boldsymbol{a}^+ &= \{v_1^+, \dots, v_Z^+\} \\ \boldsymbol{a}^- &= \{v_1^-, \dots, v_Z^-\} \end{aligned} \qquad (3)$$

In the case of minimisation, the positive ideal solution is taken by computing the minimum value by column, and the negative ideal solution is taken by computing the maximum value by column.

In the case of maximisation, the positive ideal solution is taken by computing the maximum value by column, and the negative ideal solution is taken by computing the minimum value by column.

d) Distance of the alternatives from the ideal solutions

The distances of each alternative $m = 1, \ldots, M$ from the positive and negative ideal solutions are given by equation (4) and equation (5):

$$\delta_m^+ = \sqrt{\sum_{z=1}^{Z} (v_{mz} - v_z^+)^2} \qquad (4)$$

$$\delta_m^- = \sqrt{\sum_{z=1}^{Z} (v_{mz} - v_z^-)^2} \qquad (5)$$

e) Calculate the relative closeness to the ideal solution

The closeness coefficient c_m of each alternative $m = 1, \ldots, M$ is computed by equation (6):

$$c_m = \frac{\delta_m^-}{\delta_m^- + \delta_m^+} \qquad (6)$$

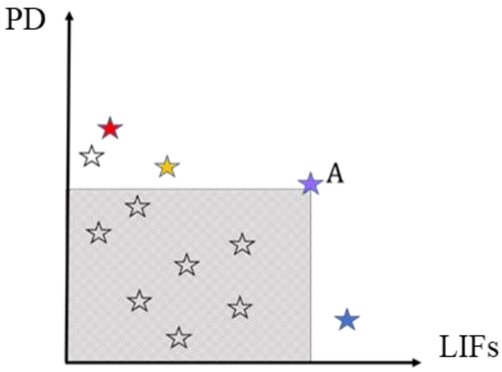
f) Rank the preference order

The alternatives are ranked in descending order of c_m. The best solution has the maximum value of c_m.

2. Selecting the BZ for reconfiguration at each iteration

The selection of a BZ for reconfiguration requires identifying the worst performing BZ at each iteration. To that end, two distinct parameters are considered: Price dispersion (PD) and the so-called Loop and Internal Flows (LIFs). Several metrics can be adopted to measure these quantities that, generally speaking, could be 'in conflict' with each other: for example, a BZ characterized by high price dispersion (indicating poor performance) can perform well with respect to LIFs, i.e., if this BZ creates a low amount of these flows. Therefore, a selection of the worst performing BZ should be considered a compromise between these parameters. In order to represent the compromise solutions, the concept of dominance of multi-objective problems described in Section 1 can be adopted: a solution is non-dominated when no other selection can extract a BZ characterized by greater PD and LIFs. These non-dominated selections form the Pareto front. In Figure 2, each star represents a BZ, the shaded area corresponds to the points dominated by BZ A, and the coloured stars are the ones located on the Pareto front. The worst performing BZ can be identified using the TOPSIS algorithm described in Section 1, maximising the objective functions, where the alternatives are the BZs that form the Pareto front and the criteria are the metrics to evaluate the PD and the LIFs.

Figure 2: Ranking the BZs to split. The problem requires the construction of the Pareto front (coloured BZs) and the maximisation TOPSIS algorithm. The BZs covered by the shaded rectangle are dominated by BZ A, which is identified as the worst performing BZ.



3. Ranking the alternative BZ configurations

The improvement at iteration j (which delivers an alternative BZ configuration j as an outcome) with reference to the initial (status quo) configuration i is calculated via indices ΔPD_{ji} and ΔLIFs_{ji}, which are the defined by equation (7) and equation (8):

$$\Delta PD_{ji} = PD_j - PD_i \qquad (7)$$
$$\Delta LIFs_{ij} = LIFs_j - LIFs_i \qquad (8)$$

The indices ΔPD_{ji} and ΔLIFs_{ij} can be 'in conflict' with each other: for example, an iteration characterized by a great decrement of the PD can have an increment of the LIFs. Therefore, the ranking should be performed considering these two indices simultaneously. Once again, a Pareto front can be computed considering all the non-dominated solutions (iterations), and the TOPSIS algorithm can be adopted to rank the iterations through the minimisation of the objective functions, where the alternatives are the iterations that form the Pareto front and the criteria are coefficients ΔPD_{ji} and $\Delta\text{LIFs}_{\text{ij}}$.

4. References

[1] Chicco G, Mazza A (2021), Metaheuristics for Transmission Network Expansion Planning, Chapter 2 in S. Lumbreras, H. Abdi, A. Ramos (ed.), Transmission Expansion Planning: The Network Challenges of the Energy Transition, Springer Nature Switzerland AG, 2021, https://link.springer.com/book/10.1007%2F978-3-030-49428-5, ISBN 978-3-030-49427-8, ISBN 978-3-030-49428-5 (eBook), https://doi.org/10.1007/978-3-030-49428-5.

[2] Hwang CL, Yoon K (1981) Multiple Attribute Decision Making: Methods and Applications, Springer-Verlag, New York.