Does the Evaluation Horizon Matter? A Temporal Extension of SPOTIS for Normalization-Bound Sensitivity Analysis

Bartłomiej Kizielewicz[1,2][0000−0001−5736−4014] and Jarosław Wątróbski[3][0000−0002−4415−9414]

1 National Institute of Telecommunications, Szachowa 1, 04-894 Warsaw, Poland
b.kizielewicz@il-pib.pl
2 Research Team on Intelligent Decision Support Systems, Department of Artificial Intelligence and Applied Mathematics, Faculty of Computer Science and Information Technology, West Pomeranian University of Technology in Szczecin, ul. Żołnierska 49, 71-210 Szczecin, Poland
3 Institute of Management, University of Szczecin, ul. Cukrowa 8, 71-004 Szczecin, Poland
jaroslaw.watrobski@usz.edu.pl

Abstract. In multi-criteria decision analysis (MCDA), normalization bounds are typically derived from a single observation period and treated as fixed. When additional temporal data become available, the observed range of criterion values may expand, altering the reference framework against which alternatives are evaluated. This paper introduces Progressive Temporal SPOTIS (PT-SPOTIS), a framework that extends the SPOTIS method by progressively expanding the temporal window used to determine normalization bounds. The evaluated alternatives correspond to a single fixed historical year, while the reference limits are recalculated using cumulative data from the evaluated year and all subsequent observation periods. The approach is applied to Eurostat energy data for 27 European countries over 2013–2024. The results show that updating normalization bounds alters the ranking in the majority of cases. Rankings generally converge as the temporal window expands, but convergence is non-monotonic and can be disrupted by external shocks that introduce new extreme values into the dataset. The bottom of the ranking is substantially more robust than the top, indicating that worst-performing countries are reliably identified regardless of the normalization window, whereas best-performing designations remain sensitive to the information horizon.

Keywords: MCDA · SPOTIS · Temporal normalization · Ranking stability · Energy indicators

1 Introduction

In many real-world decision problems, alternatives are evaluated at a specific point in time using only the data available at that moment. However, the range

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of possible values of the criteria is often not fully known, and additional observations collected in subsequent years may reveal broader variability of the system. This raises the question of whether an evaluation reflects the properties of the assessed year itself, or rather the limited knowledge used to construct the reference framework at the time of assessment.

Multi-criteria decision analysis (MCDA) methods are widely used to aggregate heterogeneous indicators into a single evaluation measure [6]. In standard MCDA applications, normalization bounds are derived exclusively from the dataset used in the assessment, typically corresponding to a single observation period. Consequently, the decision model implicitly assumes that the available data adequately describe the full decision space, and the reference framework constructed from these data is treated as fixed.

If the observed dataset does not fully reflect the true range of criterion values, the normalization bounds become dependent on the sample rather than on the underlying system [7, 11]. As additional observations are collected over subsequent years, newly identified extreme values may shift the reference limits applied in the method. Although sensitivity analysis and uncertainty quantification have been widely examined in MCDA, relatively little attention has been given to how rankings depend on the temporal scope of data used to establish normalization bounds [2, 12]. Consequently, rankings are often interpreted as inherent properties of the evaluated alternatives, rather than as outcomes shaped by the adopted reference space. Assuming that the feasible range of the system remains relatively stable over time, incorporating additional temporal observations should improve the estimation of the true bounds of the decision space.

Existing temporal extensions of MCDA primarily analyze changes of alternatives over time, for example by comparing rankings obtained for successive years [1, 8]. In such approaches, the alternative itself evolves and the decision problem is interpreted as a dynamic evaluation process. However, a different question remains largely unexplored: whether the evaluation of a fixed historical alternative depends on how much information is used to determine the normalization bounds.

This issue is particularly relevant for methods based on range normalization and distance from a reference point, where the position of the alternative is determined relative to the minimal and maximal values of criteria. In such cases, the ranking may change even when the evaluated data remain identical, solely because the limits defining the reference framework are updated. Therefore, these methods provide a suitable environment for investigating the dependence of rankings on the information horizon.

In this study, we extend the SPOTIS method [5] by introducing a progressively expanding temporal window used to determine normalization bounds. The evaluated alternative corresponds to a single fixed historical year, while the reference limits are recalculated using cumulative data from the evaluated year and all subsequent observation periods. The proposed approach, termed Progressive Temporal SPOTIS (PT-SPOTIS), enables analysis of how rankings depend on

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the degree of knowledge about the decision space rather than on changes in the alternative itself.

To formalize this investigation, the following research questions are addressed:

(RQ1): Does updating normalization bounds using progressively accumulated temporal data alter the ranking of alternatives evaluated for a single fixed year in SPOTIS?
(RQ2): Does the ranking of a fixed historical year converge or stabilize as the temporal window used to define normalization bounds expands?
(RQ3): What are the implications of ranking instability under expanding normalization bounds for the interpretability of single-year MCDA assessments?

By addressing these questions, the study introduces a temporally adaptive normalization perspective in MCDA and analyzes ranking stability with respect to the progressive acquisition of information about the decision space.

The remainder of this paper is organized as follows. Section 2 reviews related work on temporal perspectives in MCDA. Section 3 presents the SPOTIS method, formalizes the PT-SPOTIS framework, and describes the analysis procedure. Section 4 introduces the dataset and reports the empirical results structured around the three research questions. Section 5 discusses the findings, and Section 6 concludes the paper.

2 Related Works

In many MCDA applications, alternatives are observed across successive years and the results are interpreted as temporal trajectories of performance [4, 6]. However, these frameworks focus on the variability of alternative evaluations over time, while less attention has been given to how time-varying information influences the structure of the decision model, particularly the reference framework used to position alternatives within the decision space.

Existing temporal MCDA methods typically treat each year as an independent decision problem, constructing rankings separately and comparing them post hoc [1, 8]. These approaches assume static normalization bounds within each period and do not examine what happens when information from future periods is incorporated. Dynamic extensions, such as tensor-based formulations or prescriptive methods that weight recent observations more heavily, similarly maintain fixed normalization rules [3, 13]. As Table 1 summarizes, existing temporal approaches account for the dynamics of alternative attributes but keep the reference system structurally unchanged: the temporal dimension enters through criterion values or aggregation mechanisms (e.g., weights) but not through the boundaries defining the reference space.

In distance-based methods such as SPOTIS [5], changes in normalization bounds directly affect relative positions even when the observed values of alternatives remain constant. When bounds are derived empirically rather than specified a priori, they become sample-dependent and subject to revision as the

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Table 1. Comparison of temporal perspectives in MCDA. The proposed PT-SPOTIS approach is the only one in which the normalization bounds evolve while the evaluated alternative remains fixed.

Temporal perspective	Dynamic over time	Structurally fixed	Ref.
Temporality of alternatives (yearly series)	Performance of alternatives across yearly decision matrices and resulting rankings	Criteria set, weights, normalization rule, and aggregation structure (BWM–WASPAS)	[8]
Temporal variability of alternatives (DARIA–MARCOS)	Annual alternative performance and ranking evolution	Criteria set and compromise-based aggregation structure	[1]
Temporal features of criteria (tensor TOPSIS)	Extracted time-series features of criteria (e.g., trend, dispersion, level)	Alternatives, criteria definitions, and tensor-based TOPSIS framework	[3]
Dynamic / prescriptive DMCDM	Observed and predicted future performance, time-period weights	Alternatives, criteria, and grey relational aggregation structure	[13]
Spatio-temporal MCDA (3D space–time)	Spatial configuration and suitability values evolving across time steps	Criteria, weights, suitability functions, and WLC aggregation structure	[9]
Progressive Temporal SPOTIS (this work)	Normalization bounds progressively expanded using cumulative temporal data	Fixed historical alternative, criteria, weights, aggregation structure	–

dataset grows [7, 11]. This introduces a form of temporal instability distinct from changes in alternative performance. Sensitivity analysis addresses robustness to parameter perturbations but typically considers small variations around a fixed reference state rather than the systematic expansion of observed bounds over extended temporal horizons [2, 12].

The literature has rarely addressed the situation in which the alternative is frozen in time while the normalization space continues to evolve. This gap is particularly relevant for longitudinal sustainability assessments, where indicators from a given year remain unchanged but later observations reveal broader system variability. Understanding how progressive expansion of the normalization horizon affects ranking stability directly motivates PT-SPOTIS and the research questions posed in this study.

3 Methodology

3.1 SPOTIS Method

The Stable Preference Ordering Towards Ideal Solution (SPOTIS) is a multi-criteria decision-making method proposed by Dezert et al. [5]. Unlike methods that rely on relative comparisons between alternatives, SPOTIS evaluates each

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alternative independently against a fixed reference point, which guarantees immunity to the rank reversal phenomenon.

Let $S = (S_{ij})_{M \times N}$ denote the decision matrix, where S_{ij} is the performance score of alternative A_i on criterion C_j. For each criterion C_j $(j = 1, 2, \ldots, N)$, the decision maker specifies bounds $S_j^{\min}$ and $S_j^{\max}$ that define the feasible range of criterion values. The Ideal Solution Point (ISP) $S^* = (S_1^*, \ldots, S_N^*)$ is determined from these bounds according to the criterion type: $S_j^* = S_j^{\max}$ for benefit criteria and $S_j^* = S_j^{\min}$ for cost criteria.

The SPOTIS algorithm proceeds in three steps. First, the normalized distance of each alternative to the ISP is calculated for each criterion:

$$d_{ij}(A_i, S_j^*) = \frac{|S_{ij} - S_j^*|}{|S_j^{\max} - S_j^{\min}|} \tag{1}$$

Second, the weighted normalized distance from the ISP is computed as:

$$d(A_i, S^*) = \sum_{j=1}^{N} w_j \, d_{ij}(A_i, S_j^*) \tag{2}$$

where $w_j \geq 0$ and $\sum_{j=1}^{N} w_j = 1$ are the criteria importance weights. Third, alternatives are ranked in ascending order of $d(A_i, S^*)$, so that the alternative closest to the ISP is ranked first.

A key property of SPOTIS is that the bounds $S_j^{\min}$ and $S_j^{\max}$ are defined a priori, independently of the alternatives present in the current evaluation. This decouples the evaluation of each alternative from the composition of the alternative set and ensures that adding or removing alternatives does not alter existing distances [5]. However, in practice, the bounds are frequently derived from the observed data rather than specified exogenously. When the dataset evolves over time, the bounds may change, and this effect forms the basis of the temporal analysis proposed in this study.

3.2 Progressive Temporal SPOTIS

We now formalize the Progressive Temporal SPOTIS (PT-SPOTIS) framework. Let $\mathcal{T} = \{t_0, t_0{+}1, \ldots, t_{\text{end}}\}$ denote the set of observation years. For each year $t \in \mathcal{T}$, the decision matrix $X^{(t)}$ of dimension $M \times N$ contains the criterion values of all M alternatives observed at time t. Each criterion is classified as either a cost type (lower values preferred) or a benefit type (higher values preferred), and in the present study we deliberately adopt equal weights $w_j = \frac{1}{N}$ to isolate the effect of evolving normalization bounds from confounding variation in criteria importance.

For a given base year t and expanding window endpoint $T \in \mathcal{T}$ with $T \geq t$, the cumulative normalization bounds are constructed from all observations in the interval $[t, T]$:

$$S_j^{\min}(t, T) = \min_{t \leq \tau \leq T} \min_i X_{ij}^{(\tau)}, \quad S_j^{\max}(t, T) = \max_{t \leq \tau \leq T} \max_i X_{ij}^{(\tau)} \tag{3}$$

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Because the window only expands, the bounds satisfy the monotonicity property: $S_j^{\min}(t,T) \leq S_j^{\min}(t,T-1)$ and $S_j^{\max}(t,T) \geq S_j^{\max}(t,T-1)$ for all j. Consequently, the normalization range $\delta_j(t,T) = S_j^{\max}(t,T) - S_j^{\min}(t,T)$ is non-decreasing in T.

The PT-SPOTIS ranking of a base year t evaluated under the window endpoint T (where $T \geq t$) is obtained by applying the standard SPOTIS procedure using the bounds from (3). We denote this ranking as $R^{(t,T)}$. When $T = t$, the bounds reduce to those derived from the data of the base year alone, so $R^{(t,t)}$ coincides with the standard local-bounds ranking. For a fixed base year t, the sequence $\{R^{(t,t)}, R^{(t,t+1)}, \ldots, R^{(t,t_{\text{end}})}\}$ captures how the ranking of alternatives in year t evolves as the information horizon expands, even though the performance data $X^{(t)}$ remain unchanged.

Three reference configurations emerge as special cases. The *local bounds* configuration uses $T = t$, so that normalization bounds are derived exclusively from the data of the evaluated year. The *global bounds* configuration uses $T = t_{\text{end}}$, so that bounds reflect the full range from the evaluated year to the end of the observation period. PT-SPOTIS interpolates between these two extremes by treating T as a parameter that controls the amount of accumulated temporal information beyond the base year.

3.3 Analysis Framework

The proposed analysis framework consists of four stages (Figure 1). In Stage 1, longitudinal energy data are collected from a public database. In Stage 2, the data are preprocessed: countries with incomplete temporal coverage or zero-valued observations are removed, and the criteria types are assigned. In Stage 3, three SPOTIS model variants are computed: (i) local bounds, (ii) PT-SPOTIS with expanding windows, and (iii) global bounds. In Stage 4, the three research questions are addressed through comparative analysis of the ranking sequences produced in Stage 3.

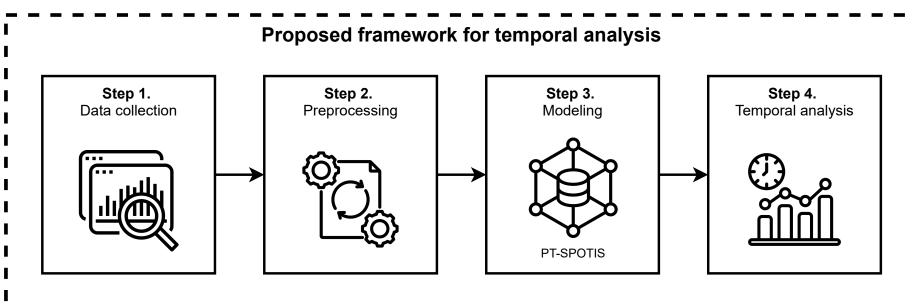

Fig. 1. Proposed analysis framework for temporal ranking stability evaluation using PT-SPOTIS.

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4 Research

4.1 Data and Experimental Setup

The dataset comprises annual energy statistics for 27 European countries from 2013 to 2024, sourced from Eurostat[1]. Six indicators are used as criteria, covering three energy categories: electricity, natural gas, and renewables including biofuels. Each category is represented by a consumption and a supply variable. Consumption criteria (C_1, C_3, C_5) are treated as cost type (lower values preferred), while supply criteria (C_2, C_4, C_6) are treated as benefit type (higher values preferred). All values are expressed in KTOE.

After filtering for complete 12-year records and excluding countries with zero-valued observations in any criterion, the final dataset comprises $M = 27$ alternatives observed over $|\mathcal{T}| = 12$ years. To keep the focus on bound expansion rather than preference modelling, all six criteria are assigned equal weights $w_j = \frac{1}{6}$. The decision matrix for the initial year 2013 is presented in Table 2. Rankings obtained under local and global bounds configurations are shown in Figure 2 and Figure 3, respectively. The expanding-window procedure yields 78 distinct evaluation configurations (base year and window endpoint pairs), each producing a ranking of all 27 alternatives.

4.2 Impact of Updating Criteria Boundary Values on Rankings

To assess the impact of expanding normalization bounds on rankings, we compare the local-bounds ranking $R^{(t,t)}$ with the expanding-window ranking $R^{(t,T)}$ for each base year t and each window endpoint $T \geq t$. Ranking similarity is quantified using the weighted Spearman correlation coefficient r_w [10]. Figure 4 presents a heatmap of $r_w(R^{(t,t)}, R^{(t,T)})$ for all evaluated-year and window-endpoint combinations. The diagonal entries equal 1.0 by construction, since at $T = t$ the expanding-window bounds coincide with local bounds. Reading along each row reveals how the ranking of a fixed year changes as the normalization window extends.

It can be seen that year 2013 exhibits the strongest degradation, with r_w declining from 1.00 to 0.84 when evaluated under the full window ($T = 2024$). In contrast, more recent base years such as 2019 show high stability ($r_w = 0.97$ at $T = 2024$), because fewer additional years are available to shift the bounds. The rightmost column ($T = 2024$) is particularly informative: it shows the cost of incorporating full temporal information. Notable degradation is visible for years 2021 ($r_w = 0.85$) and 2022 ($r_w = 0.84$), indicating that periods close to external shocks are especially sensitive to subsequent bound expansion.

Table 3 quantifies these rank shifts. Across all years, an average of 61.1% of alternatives change position, with a mean absolute shift of $\overline{|\Delta R|} = 1.65$. The year 2024 shows zero shift by construction, since the expanding window

[1] Data available at `https://doi.org/10.2908/TEN00123` and `https://doi.org/10.2908/TEN00122`.

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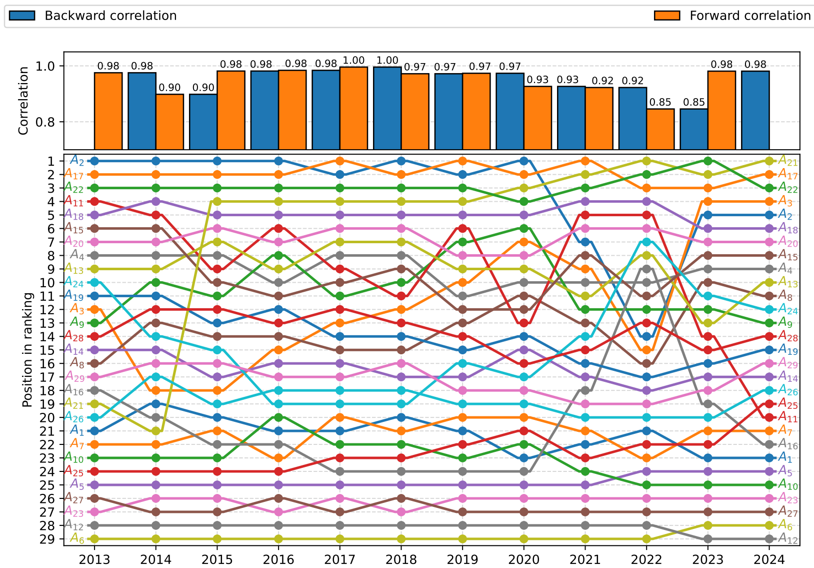

Fig. 2. Ranking flow and inter-year correlation under local bounds configuration. Each year is evaluated independently using normalization bounds derived solely from its own data.

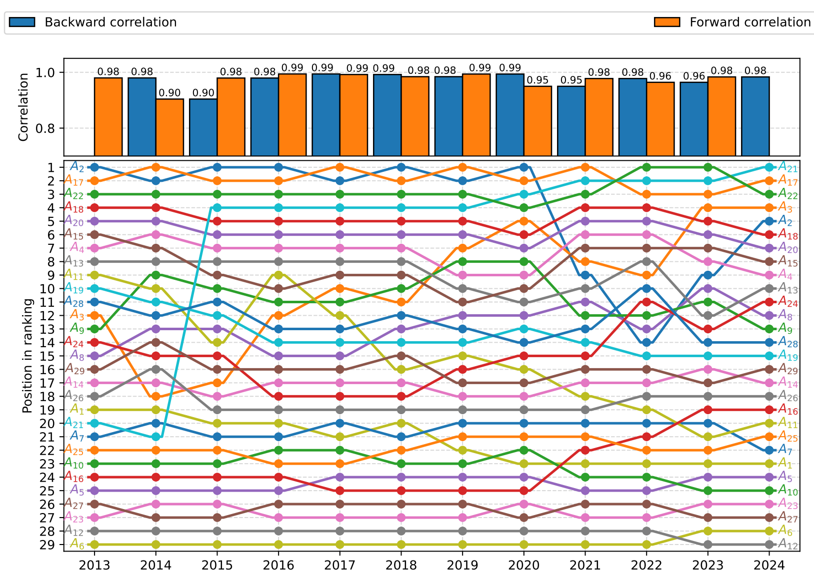

Fig. 3. Ranking flow and inter-year correlation under global bounds configuration. All years are evaluated using normalization bounds derived from the full 2013–2024 dataset.

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Table 2. Decision matrix for 2013: energy consumption and supply values (KTOE) for the 27 evaluated countries.

A_i	Country	Electricity Cons.	Electricity Sup.	Natural gas Cons.	Natural gas Sup.	Renewables and biofuels Cons.	Renewables and biofuels Sup.
A_1	AT	5258.03	625.15	4728.82	7060.52	4218.96	10232.19
A_2	BE	7073.41	828.89	9798.74	14533.61	1826.35	3620.66
A_3	BG	2367.33	-531.47	1155.95	2397.73	1254.90	1881.27
A_4	CZ	4575.84	-1452.02	5366.98	6946.41	2679.41	4130.19
A_5	DE	44910.58	-2768.10	52845.56	73101.74	16948.11	37632.14
A_6	DK	2674.64	93.04	1579.91	3315.94	1464.81	4456.38
A_7	EE	586.41	-308.51	250.04	554.90	477.74	851.14
A_8	EL	4195.27	162.25	907.55	3236.31	1382.75	2676.08
A_9	ES	19783.92	-580.48	14792.34	26163.38	5034.18	17716.02
A_{10}	FI	6875.41	1351.25	704.42	2856.39	4962.38	9861.52
A_{11}	FR	38772.00	-4166.90	33258.00	38816.13	14374.36	25808.33
A_{12}	HR	1295.96	332.67	993.27	2281.86	1261.51	2097.31
A_{13}	HU	2998.54	1021.24	5333.75	7704.06	2426.14	3111.54
A_{14}	IE	2137.71	192.79	1624.92	3852.83	330.60	894.17
A_{15}	IT	24711.78	3623.22	35222.27	57386.72	8498.17	26370.63
A_{16}	LT	769.99	597.25	552.04	2164.51	732.58	1212.27
A_{17}	LU	532.98	425.11	601.28	889.90	104.87	154.86
A_{18}	LV	565.43	116.51	343.62	1204.69	1018.54	1611.38
A_{19}	NL	8989.84	1568.10	19482.03	33380.68	1184.43	3517.45
A_{20}	NO	9581.59	-430.44	418.11	5617.78	1605.94	13143.36
A_{21}	PL	10623.99	-388.74	8883.65	13735.89	5714.68	8655.09
A_{22}	PT	3891.40	238.69	1566.68	3755.87	2216.72	5300.91
A_{23}	RO	3493.38	-173.35	5681.13	9838.95	3708.03	5550.96
A_{24}	RS	2328.03	-218.14	1002.13	1866.55	1031.50	1929.28
A_{25}	SE	10749.44	-860.02	496.37	955.29	7127.43	18366.33
A_{26}	SI	1073.00	-110.92	540.63	691.85	722.42	1218.69
A_{27}	SK	2156.84	7.83	2996.30	4558.04	1103.59	2105.03

Table 3. Rank shift summary when comparing local vs. full expanding-window rankings per base year.

Year t	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024
$\overline{\lvert\Delta R\rvert}$	2.67	2.00	1.63	1.93	1.78	1.41	1.04	1.85	2.15	2.22	1.11	0.00
$\max\lvert\Delta R\rvert$	12	7	6	8	14	12	5	9	17	16	12	0
% changed	70.4	77.8	66.7	74.1	66.7	59.3	48.1	66.7	77.8	77.8	48.1	0.0

cannot extend beyond the last available year. However, the maximum shifts for other base years are substantial, reaching up to 17 positions (year 2021), indicating that individual countries can be severely affected. The country-level analysis reveals that Italy exhibits the largest mean absolute rank shift, followed by Finland and Norway. These countries have atypical energy profiles: Italy is a

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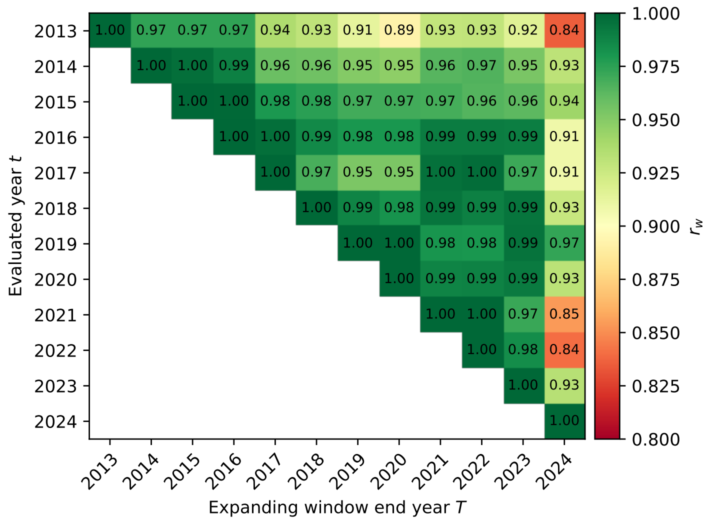

Fig. 4. Weighted Spearman correlation r_w between local-bounds ranking $R^{(t,t)}$ and expanding-window ranking $R^{(t,T)}$. Each cell shows r_w for base year t (row) evaluated under window endpoint T (column).

large gas consumer but moderate electricity producer, while Norway and Finland have distinctive renewable energy structures. In contrast, Germany, France, and Sweden remain nearly unaffected, because their extreme criterion values tend to define the bounds themselves. When the bounds expand, these "anchor" countries remain stable.

4.3 Convergence of Rankings

To assess convergence, we track how the PT-SPOTIS ranking of each base year t approaches the final-window ranking $R^{(t,t_{\text{end}})}$ as T increases. Figure 5 presents two complementary views. Panel (a) shows $r_w(R^{(t,T)}, R^{(t,t_{\text{end}})})$ as a function of T for each base year. The correlation generally increases with T, confirming that rankings approach their terminal form as more data accumulate. However, convergence is not monotonic: for early base years such as 2013 and 2014, a visible dip occurs around $T = 2017$, followed by partial recovery and renewed degradation near $T = 2024$. This pattern reflects successive waves of bound expansion driven by different criteria. Panel (b) shows the mean absolute rank distance to the final ranking, which for the earliest base years starts above 2.0 positions and decreases toward zero as T approaches t_{end}.

The mechanism behind non-convergence is revealed by the bounds expansion analysis (Figure 6), which shows the ratio $\delta_j(t,T)/\delta_j(t,t)$ of the normalization range at window endpoint T relative to the initial local range, illustrated for base year $t = 2013$. Criterion C_2 (electricity supply) exhibits a sudden jump

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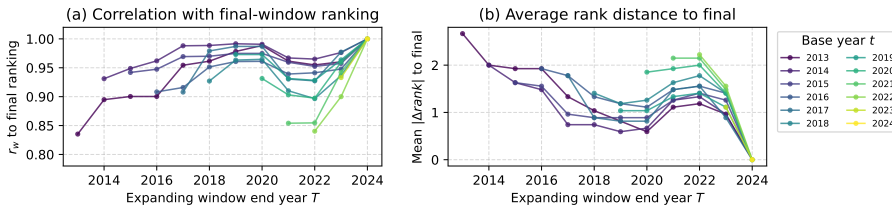

Fig. 5. Convergence of PT-SPOTIS rankings toward the final-window ranking. (a) Weighted Spearman correlation $r_w(R^{(t,T)}, R^{(t,t_{\text{end}})})$ as a function of window endpoint T. (b) Mean absolute rank distance to the final ranking.

Table 4. Instability index per base year, measured as the mean and maximum rank range (difference between the highest and lowest rank observed) across all expanding windows.

Year t	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024
Mean range	3.11	2.37	2.04	2.11	1.81	2.00	1.52	2.15	2.26	2.30	1.11	0.00
Max range	12	8	9	8	14	14	11	13	17	16	12	0

to approximately 1.57× at $T = 2024$, caused by an extreme observation in the most recent year. Criterion C_6 (renewable supply) grows monotonically to approximately 1.33×, reflecting the secular trend of increasing renewable energy production across Europe. In contrast, C_1 (electricity consumption) remains flat at 1.0×, indicating that the initial bounds already captured the full range. Criteria with actively expanding bounds act as persistent sources of ranking instability: as long as at least one criterion continues to produce new extrema, the ranking under PT-SPOTIS cannot fully stabilize.

Table 4 summarizes the instability for each base year. The mean range is highest for year 2013 (3.11) and initially decreases to a minimum of 1.52 for year 2019, but then rises again for 2020–2022 (reaching 2.30), mirroring the pattern observed in the convergence analysis: base years whose expanding windows encompass the post-2020 structural shifts in the European energy system exhibit elevated instability despite having shorter expansion horizons. The maximum range remains persistently high (8–17 positions for most years), indicating that even base years with moderate average instability contain individual countries with substantial positional uncertainty. The year 2024 shows zero instability by construction, as only one window configuration is available.

4.4 Interpretability Implications

The practical relevance of ranking instability depends on which countries are affected and whether the top and bottom of the ranking remain identifiable despite bound-induced variation. Figure 7 presents rank uncertainty bands for two representative base years. The left panel shows year 2013 (evaluated across 12

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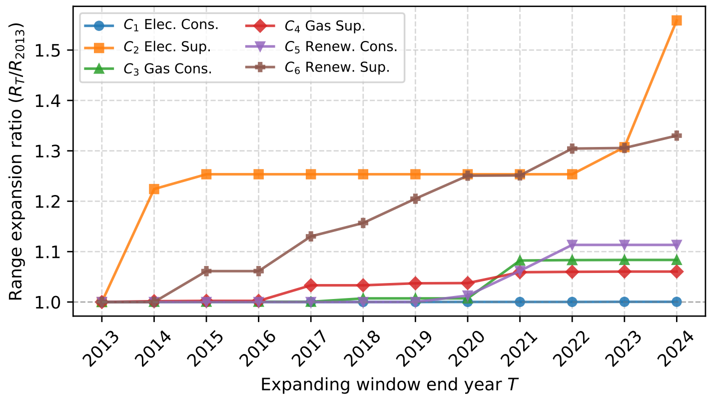

Fig. 6. Normalization range expansion ratio $\delta_j(t,T)/\delta_j(t,t)$ for each criterion as a function of the expanding window endpoint T, shown for base year $t = 2013$. A ratio exceeding 1.0 indicates that the criterion range has grown beyond its initial extent.

expanding windows) and the right panel shows year 2018 (7 windows). Each horizontal bar spans the minimum-to-maximum rank observed for a given country, and the dot marks the mean rank.

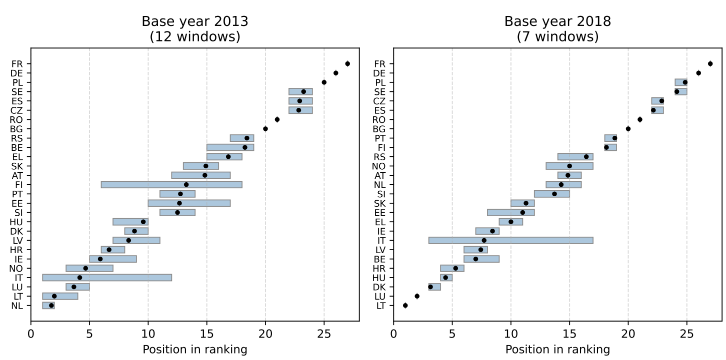

Fig. 7. Rank uncertainty bands for base years 2013 (left, 12 windows) and 2018 (right, 7 windows). Each bar spans the minimum-to-maximum rank observed across all expanding-window evaluations, and the dot marks the mean rank.

It can be seen that Italy exhibits the widest uncertainty band in both years, spanning more than 10 positions in 2013 and an even wider range in 2018. The wider band in 2018 arises because the expanding windows from 2018 onward cover the European energy crisis, which disproportionately affects Italy as a major gas importer. Finland, Estonia, and Norway also display substantial rank

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variability. In contrast, the highest-ranked countries (France, Germany, Poland) and the lowest-ranked (Lithuania, Luxembourg) exhibit tight bands of 1–2 positions, indicating high positional stability.

Figure 8 quantifies this asymmetry through top-k and bottom-k membership frequency across all expanding-window evaluations ($k = 3$). Lithuania appears in the top 3 in the vast majority of evaluations, followed by Luxembourg. Several other countries, including Italy, Denmark, the Netherlands, and Croatia, compete for the remaining top-3 positions with lower frequencies, making these rank assignments sensitive to the chosen window. The bottom 3 is substantially more stable: Germany and France appear in nearly all evaluations, Sweden in the majority of cases, and Poland occasionally.

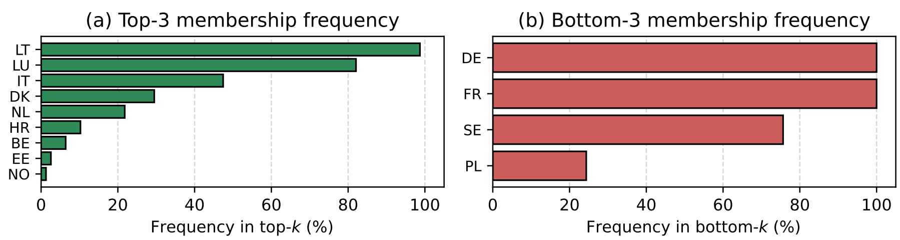

Fig. 8. Top-3 and bottom-3 membership frequency across all expanding-window evaluations. (a) Countries appearing in the top 3. (b) Countries appearing in the bottom 3.

These findings carry direct implications for policy interpretation. Rankings of the worst-performing countries are reliable regardless of the temporal scope of the normalization bounds, whereas rankings of the best performers are contingent on the information horizon. Decision makers should therefore exercise greater caution when interpreting top-k designations than bottom-k designations when the normalization bounds are empirically derived from evolving datasets.

5 Discussion

The results reveal a structural property of distance-based MCDA methods: the ranking of a fixed set of alternatives can change solely because the normalization bounds are updated with new temporal observations, even though the underlying performance data remain unchanged. Countries occupying extreme positions in the decision space act as natural anchors and remain positionally stable, whereas interior alternatives with heterogeneous criterion profiles, such as Italy, are disproportionately sensitive to rescaling effects. PT-SPOTIS makes this dependence explicit by treating the information horizon as a parameter and showing that the same historical alternative can receive different rankings under different assumptions about the decision space. In this sense, PT-SPOTIS

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is best interpreted as an ex-post diagnostic for reassessing past MCDA results under expanded knowledge, rather than as a prescriptive ex-ante decision rule, and it reinforces the argument of the original SPOTIS design that normalization bounds should whenever possible be specified exogenously using domain knowledge [5].

The non-monotonic convergence patterns correspond to periods in which new extreme observations enter the dataset and abruptly shift the normalization bounds, as seen for electricity and renewable supply after 2020. Such shocks cause rapid expansion of the feasible range on affected criteria, effectively compressing earlier observations and amplifying rank instability for countries whose profiles are aligned with the shocked dimensions. This sensitivity suggests that, in practical applications, empirically derived min–max bounds should be complemented with more robust constructions, for example winsorised or percentile-based bounds, or bounds anchored in policy targets or physical limits, all of which can be seamlessly incorporated into the PT-SPOTIS framework. Embedding PT-SPOTIS as an analytic module in management information systems—for instance, in dashboards used for energy-policy monitoring or sustainability composite indices—would allow decision makers to routinely compare published single-year rankings with their temporally expanded counterparts and to flag those alternatives and periods where conclusions critically depend on the chosen information horizon.

6 Conclusions

This study introduced Progressive Temporal SPOTIS (PT-SPOTIS), a framework that extends SPOTIS by progressively expanding the temporal window used to determine normalization bounds. The empirical analysis on Eurostat energy data for 27 European countries (2013–2024) yielded three findings. First, updating bounds alters the ranking in the majority of cases, with 61.1% of alternatives changing position and individual shifts reaching 17 ranks (RQ1). Second, rankings converge toward a terminal form but non-monotonically, as external shocks that introduce new extrema disrupt the process (RQ2). Third, the bottom of the ranking is substantially more robust than the top: worst-performing countries are reliably identified regardless of the normalization window, whereas best-performing designations remain sensitive to the information horizon (RQ3).These findings imply that when normalization bounds are derived empirically from evolving datasets, rankings should be treated as outcomes conditional on the available reference information rather than as definitive properties of the evaluated alternatives. PT-SPOTIS provides a tool for quantifying this conditionality and assessing the robustness of specific ranking positions.

The study is subject to several limitations: it uses equal criterion weights, a single application domain (European energy indicators), a purely cumulative forward-expanding window, and focuses on one distance-based method (SPOTIS), so the quantitative instability patterns observed here may not transfer directly to other weighting schemes, temporal window structures or MCDA for-

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malisms. Future work should therefore explore explicit weight–bound interactions, compare forward, backward and rolling normalization windows, experiment with robust and percentile-based bounds, and extend the temporal normalization perspective to other distance- and reference-point-based methods.

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