Monitoring multidimensional phenomena with a multicriteria composite performance interval approach

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Abstract: In the last two decades, the construction of composite indicators to measure and compare multidimensional phenomena in a broad spectrum of domains has increased considerably. Different methodological approaches are used to summarise huge datasets of information in a single figure. This paper proposes a new approach that consists in computing a multicriteria composite performance interval based on different aggregation rules. The suggested approach provides an additional layer of information as the performance interval displays a lower bound from a non-compensability perspective, and an upper bound allowing for full-compensability. The outstanding features of this proposal are: 1) a distance-based multicriteria technique is taken as the baseline to construct the multicriteria performance interval; 2) the aggregation of distances/separation measures is made using particular cases of Minkowski L_p metric; 3) the span of the multicriteria performance interval can be considered as a sign of the dimensions or indicators balance.

Keywords: composite indicators; multicriteria decision making; compensability; performance interval.

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1 Introduction

Composite indicators provide a one-dimensional metric to assess, monitor and predict the performance of complex phenomena approached from a multidimensional perspective such as human development, sustainability, innovation, or well being. According to Saisana and Tarantola (2002), a composite index involves the combination of a set of indicators that represent the different dimensions of the phenomenon to be measured. Despite the fact that there is no single commonly accepted definition of a composite indicator, there is a common pattern in which the starting point is a complex phenomenon that includes different components that are to be compiled into a single indicator (Greco et al., 2017). Although the proliferation of composite indicators has grown exponentially over the last decade, there is no agreed consensus on an international standard for their construction.

The first attempt to establish a common guideline to construct a composite indicator targeted at policy-makers, academics, the media and other interested parties was the *Handbook of Constructing Composite Indicators* (European Commission, 2008). In this manual, a ten-step process from the development of a theoretical framework to the presentation and dissemination of a composite indicator is proposed to enhance the transparency and the soundness of the selected methodology. Main concerns around composite indicators are related to the lack of quality control and training for users, which can lead sending misleading and non-robust messages. Due to its relevance in policy-making decisions, the construction of composite indicators seems to be an important research issue from both theoretical and operational points of view (Munda and Nardo, 2009; Saisana et al., 2005; Mazziotta and Pareto, 2017; Terzi et al., 2021).

A frequent criticism of the construction of a composite indicator appears in the aggregation stage because this step defines the tool to add the criteria. The debate about the compensability that appears when a deficit in one dimension can be offset by a surplus in another, supports the development of two groups: aggregators versus non-aggregators. Basically, an aggregation approach can be compensatory or non-compensatory depending on whether it permits compensability or not among indicators or dimensions (Tarabusi and Guarini, 2013). While the compensatory techniques deal with the imbalances of indicators and employ linear functions, unbalance-adjusted functions are used in non-compensatory approaches.

Over the last few years, in multidimensional frameworks, when highly different dimensions should be aggregated, multi-criteria decision-making (MCDM) methodologies have been claimed to be highly suitable alternatives for constructing composite indicators (Gibari et al., 2019). These methodologies have been widely used in selecting the weights and in the aggregation stage. As to the multicriteria methods proposed to derive weights, we observe a high number of contributions applying data-based methods such as data envelopment analysis (DEA) (Charnes et al., 1978) as well as participatory-based methods such as the analytical hierarchy process (AHP) (Saaty, 1977). Regarding the aggregation stage, a significant group of MCDM methodologies adopt distance-based methods to construct composite indicators.

This work aims to design a multicriteria composite performance interval (MCPI) instead of a single composite indicator looking at one of its technical weaknesses: the aggregation rule used for its construction. In our approach, we opted for the TOPSIS multicriteria tool, which is based on additive aggregation functions representing the distances to ideal and anti-ideal values. The proposal's novelty is to provide two indicators depending on the choice of the type of aggregation for the separation measures. The proposed methodology's added value implies extending the information provided by the classical relative closeness to the ideal solution score. Thus, the MCPI is composed of a lower and upper bound. The lower bound corresponds to non-compensability perspective, whereas the upper bound involves a full compensatory approach. As an example of implementation and to demonstrate the advantages of using the proposed MCPI, it has been applied to measure the circular economy performance of EU countries on the basis of the structure of indicators provided by the EU monitoring framework. The proposed circular economy MCPI is developed to paint a comprehensive picture of the circular economy performance in 28 European countries and provide warning signals to policymakers on the areas where the dimensions need further improvements.

The paper is organised as follows. Section 2 reviews the compensability debate in constructing composite indicators and how some MCDM techniques have been applied to overcome this problem. In Section 3, the MCPI methodology is developed. In Section 4, an application of the proposed method to construct a circular economy MCPI is presented. Section 5 provides the conclusions as well as future lines of research.

2 The compensability debate and MCDM approaches

The selection of the aggregation procedure is one of the most discussed issues when constructing a composite indicator. Based on the literature review of composite indicators, the most widely applied aggregation procedures are linear aggregation rules implying complete substitutability among the various components considered. However, their applicability depends on several strong theoretical and operational assumptions. The first one is the assumption of preferential independence, which in practice becomes very difficult to accomplish. The second one is related to the meaning of weights, which are viewed as substitution rates instead of important coefficients. Despite these drawbacks, linear aggregation rules are a very intuitive and easy-to-use option.

A deep understanding of different aggregation rules in the framework of constructing composite indicators is provided in Munda and Nardo (2009), Munda (2012) and El Gibari et al. (2021). The authors revised the debate on the use of aggregation rules by describing their relative pros and cons. Finally, they concluded that the use of nonlinear/non-compensatory aggregation rules is advisable for reasons of theoretical consistency when weights are interpreted as importance coefficients or when the assumption of preferential independence does not hold. Under some conditions, these authors pointed out the benefits of using multicriteria aggregation procedures. While the compensatory techniques deal with the imbalances of indicators and employ linear functions, unbalance-adjusted functions are used in non-compensatory approaches.

According to Tarabusi and Guarini (2013), in non-compensatory approaches the dimensions to be measured must be balanced and require the use of nonlinear aggregation functions such as the geometric mean or the minimum to penalise unbalance. The Mazziota Pareto index (MPI) introduced in 2007 (Mazziotta and Pareto, 2007) is one of the first proposals to address the compensability issue. Later, the same authors develop a newer variant of the previous method for spatio temporal comparisons known as adjusted Mazziota Pareto index (AMPI). In an attempt to overcome the problem of calculating a single figure, these authors have recently proposed a performance interval depending on the level of compensability of individual indicators (Mazziotta and Pareto, 2020). It should be noted that the previous work has inspired our proposal. However, while it relies on the power mean of order r to deal with the compensability issue, we have introduced the use of performance intervals in the field of multicriteria decision making (MCDM) methodologies.

Also in the literature of composite indicators, several authors claim that MCDM techniques are well suited for aggregating single indicators in a composite one in multidimensional frameworks (see Saisana and Tarantola, 2002; European Commission, 2008). An overview of MCDM methodologies used to construct composite indicators was presented in Gibari et al. (2019). By looking at the analysis performed in the previous research, the use of distance-based methodologies is remarkable. Within this category, some techniques allow for different compensation techniques such as, the double reference point method proposed by Ruiz et al. (2011), Cabello et al. (2014) and Ruiz et al. (2019). Although this method does not use the concept of an interval, the authors proposed to build more than one composite indicator (that could be considered as a performance interval), either under a strong or non-compensatory aggregation perspective or under a weak or fully compensatory perspective. In addition, the method allows the decision-maker to define reference levels by using scalarising achievement functions. In Ceberio and Modave (2006), an interval-based Choquet integral technique is developed to solve the issue of imprecise weights given by the decision-maker to different criteria. This is an interesting approach to rank alternatives by using performance intervals when the decision-maker introduces the subjective preferences about the importance of each criterion and the interaction between them. Besides, researches have extended many conventional MCDM methods such as VIKOR, ELECTREE, CODAS, MULTIMOORA, or TOPSIS to deal with vague and imprecise information, where the initial data are given in terms of an interval. These approaches have been called interval-valued MCDM methods (Jahanshahloo et al., 2009; Dymova et al., 2013; Keshavarz Ghorabaee et al., 2016; Hafezalkotob and Hafezalkotob, 2017,?), and have been applied to rank alternatives in a wide variety of domains. Our work has proposed a different multi-criteria approach leading to the derivation of assessment intervals, where the initial information is not provided in terms of interval data but through a unique assessment of each criterion.

Other outranking multicriteria methodology where a full compensability prevails is the 'technique for ranking preferences by similarity to ideal solutions' (TOPSIS) initially introduced by Yoon and Hwang (1981). This technique uses a compensatory aggregation rule of geometric distances to ideal and anti-ideal values. Some examples applying TOPSIS to construct composite indicators can be found in Wang et al. (2017), Escrig-Olmedo et al. (2017), Rosić et al. (2017) and Fu et al. (2020).

On the other hand, outranking related approaches such as elimination and choice expressing reality (ELECTRE) (Roy, 1968) or preference ranking organisation method for enrichment evaluation (PROMETHEE) (Brans et al., 1986) can avoid compensation thanks to the presence of veto threshold and ordinal comparison among alternatives. Some examples of application can be found in Attardi et al. (2018) to construct a land-use policy efficiency index, or Lopes et al. (2018) to assess regional tourism competitiveness.

To sum up, despite the studies mentioned above, the debate on the compensability issue is continuing. Some recent studies emphasised the need to overcome linear aggregation rules in MCDM techniques by incorporating non-compensatory aggregation functions. However, no previous work has dealt with the integration of both perspectives by providing a multicriteria composite performance interval for different compensability degrees. Thus, by looking at the upper bound of the MCPI proposed in this paper, we can get a big picture of the phenomenon under the compensability logic. In contrast, by looking at the lower bound, we can track the alternatives' specific weakness to be measured as it provides the worst performance by dimension or by indicator.

3 Methodology: constructing the MCPI

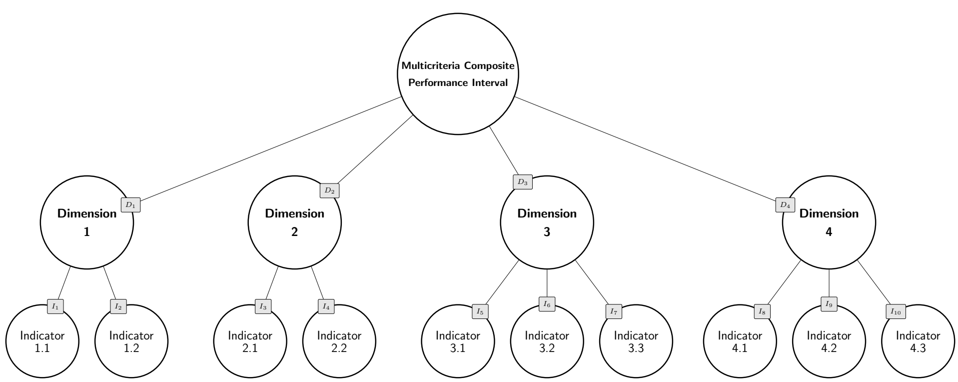
In this paper, the TOPSIS multicriteria technique is proposed as a starting point to tackle the construction of the MCPI. The main feature of the proposed methodology is the choice of different compensability levels in the distance aggregation functions. In this way, the alternatives are classified according to an index that considers the 'shortest distance' from the ideal solution and the 'farthest distance' from the 'ideal-negative' solution.

In general, TOPSIS (Tzeng and Huang, 1981) is implemented by the following stepwise procedure. After defining the decision matrix, including alternatives and criteria, the following step consists in normalising the data. This is followed by computing the weighted normalised decision matrix. Next, the positive and negative ideal solutions are identified to derive the separation measures. Thus, the aggregation is made for each alternative's separation measures. Finally, the procedure ends by computing the relative closeness coefficient. The set of alternatives can be ranked according to the descending order of the closeness coefficient. In what follows, we extend the traditional formulation of this methodology, which in the earliest stages coincides with the steps for building a composite indicator to derive the proposed MCPI.

3.1 Theoretical framework and data issues

Composite indicators are often constructed in a series of hierarchical 'levels' in which indicators are grouped into clusters, known as 'pillars' or 'dimensions' when they share similar conceptual characteristics. In our approach we consider a given theoretical framework from which the multidimensional phenomenon to be measured can be described in terms of alternatives, dimensions and indicators following a hierarchical structure (see Figure 1 for an example of a hierarchy of criteria).

Figure 1 Example on a hierarchy of criteria for two levels with four dimensions and ten elementary criteria



Given a theoretical framework, the data are organised in a decision matrix $X = x_{ij}$ $(i = 1, \dots, n;\ j = 1, \dots m)$ where n denotes the number of alternatives, and m the number of indicators. In addition, we denote J_k as the set of indicators belonging to dimension k, and l_k as the number of criteria included. A previous data analysis should be performed to study the overall structure of the dataset. At this stage the imputation of missing data and the application of multivariate analysis techniques are of great importance. To allow for comparability, the normalisation of single indicators is a prior and necessary step as they are often expressed in different units of measurement. Starting from the initial data decision matrix, the normalised matrix $N = n_{ij}$ is constructed, where the normalised value of each indicator is obtained by applying the following transformation:

$$n_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{n}(x_{ij})^2}} \qquad (i = 1, \dots, n;\ j = 1, \dots, m) \tag{1}$$

3.2 Weighting and distances to ideal and anti-ideal values

Once the normalised matrix is obtained, the next step is the choice of weights and the aggregation method. The most common weighting and aggregation techniques rely on the simple arithmetic mean, which involves assigning equal weights to all indicators. There exist a wide array of alternative weighting methods. Some of them are based on statistics such as principal component analysis (PCA) and factor analysis (FA). In other cases, subjective opinions from experts, citizens or politicians are taken into account to derive the weights through participatory methodologies such as the benefit of the doubt (BOD) or the AHP (Becker et al., 2017).

As a starting point in our proposal, we have opted to assign equal weights to build the weighted normalised matrix $V = v_{ij}$ as follows:

$$v_{ij} = \omega_j n_{ij} \tag{2}$$

where $\omega^T = \omega_j = [\omega_1, \omega_2, \dots, \omega_m]$, with $\sum \omega_j = 1$.

The positive and negative ideal solutions or the ideal and anti-ideal values, respectively are:

$$V^+ = v_j^+ = \begin{cases} \max\limits_i v_{ij} & \forall j \in J_p \\ \min\limits_i v_{ij} & \forall j \in J_n \end{cases}$$

$$V^- = v_j^- = \begin{cases} \min\limits_i v_{ij} & \forall j \in J_p \\ \max\limits_i v_{ij} & \forall j \in J_n \end{cases}$$

where J_p is associated to benefit criteria and J_n is associated to cost criteria. Therefore, the criteria separation measure to the ideal is computed for each criterion:

Notice that originally TOPSIS refers to the Euclidean distance to obtain the separation measures to the ideal and anti-ideal values. In fact, the Euclidean distance is a special case of Minkowski L_p metric in an n-dimensional space (see Berberian, 2012).

$$L_p(x, y) = \left[\sum_{j=1}^{m} |x_j - y_j|^p\right]^{\frac{1}{p}} \tag{3}$$

where $p \geq 1$. For $p = 1$, we have the Manhattan distance involving an additive function and full compensability. When $p = 2$ the Euclidean distance is obtained, and finally $p = \infty$ refers to the Chebyshev distance which implies a non-compensatory approach.

3.3 Defining the multicriteria composite performance interval

At this stage, and to discuss how compensability among indicators can affect the overall ranking of alternatives, we propose to construct an interval instead of computing a single composite indicator based on the closeness to the ideal solution index. The MCPI generates a lower and upper bound for the composite index.

For the case of two hierarchical levels, indicators in each dimension are aggregated at a first level, such that each dimension is itself a MCPI characterising one aspect of the greater multidimensional phenomena to be measured. At a second level, the aggregated values of each dimension are then used as the inputs of the overall MCPI itself.

- Lower bound: The strong closeness to the ideal solution C_i^S. It involves a non-compensability choice in the aggregation stage of the separation measures. In this case an unbalance among indicators will have a negative effect on the value of the composite index. When considering the separation measure to the ideal values, under a strong perspective, a penalty should be given to those criteria involving a maximum distance to the ideal and a minimum distance to the anti-ideal. In this case, we use the Chebyshev distances assuming a value of $p = +\infty$ to aggregate the positive distances and a value of $p = -\infty$ for negative distances respectively.

$$\begin{aligned} C_{ik}^{S+} &= L_{+\infty}(v_{ij}, v_j^+) = \max_{j \in J_k} |v_{ij} - v_j^+| \\ C_{ik}^{S-} &= L_{-\infty}(v_{ij}, v_j^+) = \min_{j \in J_k} |v_{ij} - v_j^-| \end{aligned} \tag{4}$$

  where J_k denotes the set of criteria belonging to dimension k, and l_k is the number of criteria included.

  Finally, for each alternative we derive the strong closeness to the ideal solution C_{ik}^S as follows:

$$C_{ik}^S = \frac{C_{ik}^{S-}}{C_{ik}^{S+} + C_{ik}^{S-}} \tag{5}$$

  where $0 \leq C_{ik}^S \leq 1$.

- Upper bound: The weak closeness to the ideal solution C_i^W. It corresponds to the upper bound of the multicriteria performance interval involving a full compensability in the aggregation stage of the separation measure. In this case an unbalance among indicators has no effect on the value of the composite index. In the L_p metric, now we take the Manhattan distance with $p = 1$, which corresponds to the arithmetic mean of the separation measures.

$$\begin{aligned} C_{ik}^{W+} &= L_1(v_{ij}, v_j^+) = \frac{1}{l_k} \sum_{j \in J_k} |v_{ij} - v_j^+| \\ C_{ik}^{W-} &= L_1(v_{ij}, v_j^-) = \frac{1}{l_k} \sum_{j \in J_k} |v_{ij} - v_j^-| \end{aligned} \tag{6}$$

  Analogously, we derive the weak closeness to the ideal solution C_{ik}^W as follows:

$$C_{ik}^W = \frac{C_{ik}^{W-}}{C_{ik}^{W+} + C_{ik}^{W-}} \tag{7}$$

Thus, the MCPI for each dimension, δ_{ik}, takes the following form:

$$\delta_{ik} = \left[C_{ik}^{S}, C_{ik}^{W}\right] \tag{8}$$

Once the aggregation rule is made for the first level, namely, from indicators to dimensions, the modeller has several options to derive the overall MCPI when the dimensions are aggregated for the second level. In our case, we propose a lower bound which takes the minimum value of the dimensions, and an upper bound corresponding to the mean of the weak closeness to the ideal solution.

$$\gamma_i = \left[\min_k C_{ik}^{W}, \frac{1}{l}\sum_{k=1}^{l} C_{ik}^{W}\right] \tag{9}$$

The question now is, how should the user of the MCPI rank the alternatives? The answer is not trivial and depends on the subject under study and the modeller's objectives. A fairly sound option is to rank the alternative by the value of the upper limit, but looking at the span of the MCPI, which can be considered as a sign of the unbalance. For example, looking at the δ_{ik}, the greater the span of the interval, the greater the unbalance of the single indicators, whereas the unbalance between dimensions comes from the length of the γ_i.

Table 1 MCPI balance rating

Rating scale	*β-rating icon*
Well balanced-interval	⋆⋆⋆
Fair balanced-interval	⋆⋆
Unbalanced interval	⋆

Therefore, policy makers setting targets to improve a given multidimensional phenomenon could prioritise which alternative and in which dimensions to act on by looking at the span of the MCPI.

Thus, based on the balance property of the MCPI, computed as the difference between the interval upper and lower bound, the alternatives are assigned a balance rating (β-rating). Besides, in Table 1 we propose three levels of balance performance based on percentile scores of the β-rating to translate the magnitude of the balance into a common, easily understandable scale.

- Well-balanced interval: Alternatives with a MCPI span ranging from 0 % to 33.33 % of maximum span can receive a high β-rating icon (three stars).
- Fair balanced-interval: Alternatives with a MCPI span ranging from 33.33 % to 66.67 % of maximum span can receive a medium β-rating icon (two stars)
- Unbalanced interval: Alternatives with a MCPI span ranging above 66.67 % of maximum span can receive a low β-rating icon (one star).

Table 2 Selected indicators of circular economy and data issues

	Dimension/indicator	*Data source*	*Mean*	*st*	*Max*	*Min*	*Kurtosis*
	Production and consumption (PC)						
1a	Generation of municipal waste per capita (kg per capita)	European Statistical System	497.64	128.24	814.00	272.00	0.89
1b	Generation of waste excluding major mineral wastes per GDP unit [Kg per thousand euro, chain linked volumes (2010)]	European Statistical System	105.21	133.90	646.00	27.00	11.61
1c	Generation of waste excluding major mineral wastes per domestic material consumption (percentage)	European Statistical System	12.51	7.47	30.50	4.80	0.77
	Waste management (WM)						
2a	Recycling rate of municipal waste (percentage)	European Statistical System	38.69	14.81	67.10	10.00	-0.57
2b	Recycling rate of all waste excluding major mineral waste (percentage)	European Statistical System	49.43	18.12	80.00	10.00	-0.06
	Secondary raw materials (SRM)						
3a	Contribution of recycled material to raw materials demand	European Statistical System	9.26	6.75	29.00	1.50	1.43
3b	Trade in recyclable raw materials (tonnes)	European Statistical System	3,437,406.64	4,323,147.25	14,100,540.00	59,472.00	0.92
	Competitiveness and innovation (CI)						
4a	Persons employed (percentage of total employment)	European Statistical System	1.82	0.46	2.82	1.10	0.28
4b	Value added at factor cost (percentage of GDP at current prices)	European Statistical System	0.97	0.24	1.30	0.36	1.41
4c	Number of patents related to recycling and secondary raw materials	European Patent Office	0.59	0.64	2.58	0.00	2.40

Source: European Commission Monitoring Framework (2018)

4 Case study: the construction of the circular economy – MCPI

This section applies the MCPI approach following a set of circular economic indicators with data extracted from the EU circular economy monitoring framework (European Commission, 2019). In 2018, and in line with the highlighted relevance of sustainability concerns in Europe, a monitoring framework to assess circular economic issues' performance was presented by the European Commission. This is an instrument for monitoring key trends in the transition towards a more circular economy model in Europe, which makes it possible to assess whether the measures put in place and the involvement of all stakeholders have been sufficiently effective and identify best practices in the member states. An initial proposal to provide a composite indicator for EU member states by aggregating a different set of indicators was presented in Garcia-Bernabeu et al. (2020).

4.1 Circular economy monitoring framework, indicators and data

The circularity assessment of EU countries is accomplished according to the circular economy monitoring framework, which derives from ten key indicators including other sub-indicators and are grouped in the following four broad dimensions: production and consumption, waste management, secondary raw materials, and competitiveness and innovation. The indicators' data come from Eurostat, the Joint Research Centre, and the European Patent Office. To evaluate EU countries' progress towards circular economy, the information is disseminated throughout tables and graphs for cross-national comparison on the following web page https://ec.europsa.eu/eurostat/web/circular-economy/indicators/monitoring-framework.

From this monitoring framework, we select ten sub-indicators grouped into the four dimensions and aspects of the circular economy. A descriptive analysis of the selected indicators is provided in Table 2. In our application, a total of 280 observations are available for the 28 EU countries and ten indicators. The indicators with the highest averages relate to the amount of waste per capita measured in kilograms, waste per unit of GDP and trade in secondary raw materials measured in tonnes. It can be seen that the data, when considering all 28 countries, show little homogeneity, as indicated by the kurtosis coefficient, especially in the mean of the amount of waste per unit of GDP, the number of patents and the contribution of recycled raw materials to the demand for raw materials. This result is indicative of the heterogeneity of the dataset. Finally, it should be noted that in order to profile the circular economy performance of European countries, the individual indicators and dimensions have been aggregated using equal weights.

4.2 The circular economy – MCPI by dimensions

Table 3 shows the results of the MCPI by country and for the four dimensions of production and consumption δ_{PC}, waste management δ_{WM}, secondary raw materials δ_{SRM}, and competitiveness and innovation δ_{CI}. When the information is presented by dimension, the particular performance of each country in each of the areas could be analysed. By applying a compensatory approach to the indicators in each area, the value of the upper limit of the interval is obtained. Under a non-compensatory perspective, the lower limit indicates the value of the worst performing indicator in each dimension. On the other hand, the length of the MCPI provides information on the balance or imbalance of the indicators. For example, if we look at the case of Austria, we can see how the information displayed in the waste management dimension $[80.0, 81.1]$ presents a high value at both ends of the interval showing that all indicators of this dimension are balanced. However, we can observe that for the dimensions of production and consumption $[43.4, 83.2]$ and innovation and competitiveness $[8.1, 30.7]$ the length of the MPCI is considerable and therefore indicative that some indicators in these dimensions perform too poorly. From a policy perspective, attention should be paid to those dimensions either where the value is too low or where there is an imbalance.

Table 3 The MCPI of circular economy by dimension in Europe (year 2018)

	δ_{PC} (%)	δ_{WM} (%)	δ_{SRM} (%)	δ_{CI} (%)
Austria	[43.4, 83.2]	[80.0, 81.8]	[23.4, 29.5]	[8.1, 30.7]
Belgium	[4.7, 63.4]	[77.8, 87.3]	[72.6, 73.8]	[0.0, 37.5]
Bulgaria	[23.0, 44.2]	[24.3, 31.1]	[3.5, 4.1]	[0.0, 24.6]
Croatia	[70.5, 86.3]	[26.8, 43.1]	[3.0, 7.5]	[15.5, 40.5]
Cyprus	[32.7, 87.7]	[10.7, 20.2]	[0.0, 2.1]	[0.0, 22.8]
Czechia	[77.5, 90.2]	[42.9, 56.9]	[6.2, 14.7]	[9.3, 37.1]
Denmark	[0.0, 80.0]	[69.9, 71.3]	[9.6, 16.7]	[7.1, 35.6]
Estonia	[0.0, 12.2]	[0.0, 16.1]	[4.0, 23.7]	[28.3, 61.8]
Finland	[48.5, 85.0]	[38.6, 47.7]	[2.3, 8.9]	[24.7, 61.7]
France	[48.6, 81.6]	[61.1, 62.1]	[36.6, 50.8]	[10.8, 31.4]
Germany	[38.4, 79.5]	[61.4, 81.1]	[38.2, 70.1]	[9.2, 36.7]
Greece	[49.5, 78.3]	[17.7, 23.7]	[6.4, 8.4]	[0.0, 6.8]
Hungary	[70.3, 88.9]	[46.6, 47.6]	[5.1, 12.3]	[13.9, 30.0]
Ireland	[39.9, 88.1]	[44.3, 46.4]	[0.3, 1.7]	[9.3, 30.9]
Italy	[30.0, 70.3]	[69.7, 76.2]	[61.9, 63.2]	[8.9, 30.7]
Latvia	[75.1, 93.1]	[0.0, 13.6]	[4.3, 8.1]	[19.8, 46.1]
Lithuania	[59.5, 83.8]	[74.4, 78.6]	[7.8, 8.9]	[0.0, 34.0]
Luxembourg	[2.0, 78.6]	[68.3, 72.6]	[17.7, 25.5]	[100.0, 100.0]
Malta	[27.9, 82.6]	[0.0, 23.1]	[0.8, 12.0]	[0.0, 0.0]
Netherlands	[10.1, 65.1]	[80.4, 84.4]	[88.1, 93.9]	[2.4, 32.9]
Poland	[53.7, 79.4]	[41.7, 53.5]	[17.2, 23.3]	[26.6, 56.0]
Portugal	[56.6, 85.8]	[33.5, 46.5]	[2.2, 8.5]	[0.0, 17.0]
Romania	[64.0, 90.9]	[1.9, 15.0]	[0.0, 4.0]	[5.8, 17.3]
Slovakia	[62.1, 81.6]	[46.1, 47.3]	[3.5, 8.0]	[0.8, 16.8]
Slovenia	[60.5, 83.6]	[85.6, 92.7]	[7.9, 19.1]	[0.0, 29.9]
Spain	[42.6, 76.9]	[43.4, 47.4]	[29.4, 40.1]	[18.1, 39.8]
Sweden	[70.1, 89.1]	[55.7, 59.3]	[16.2, 17.5]	[9.6, 28.0]
UK	[31.1, 72.7]	[59.7, 64.1]	[53.8, 73.5]	[8.6, 29.9]

4.3 *The overall circular economy – MCPI*

To assess the overall performance in terms of EU member states' circular economy, we construct the circular economy – MCPI. Table 4 sorts the EU countries by the upper bound of the γ_i-MCPI. Moreover, we add a column to highlight the span of the MCPI. In the last column, we highlight those countries with more balance scores by the β-rating scale. Luxembourg, Netherlands and Germany are top ranked with the highest scores of the upper bound of the circular economy – MCPI. In contrast, Greece, Estonia and Bulgaria occupy the lowest positions in the ranking. Notice that, for Luxembourg, the best-positioned country, the span of the MCPI is the longest, which is indicative of a significant imbalance in one of the dimensions and for this reason it receives a β-rating of 1 star ($\star$). Then, we need to look at the information provided by dimensions in Table 3. It can be seen that a great imbalance in the production and consumption dimension is highlighted in $\delta_{PC} = [2.0, 78.6]$, which is compensated by the high performance of the competitiveness and innovation dimension $\delta_{CI} = [100.0, 100.0]$.

Table 4 Multicriteria composite performance interval of circular economy in Europe (year 2018)

	Rank	γ_i	*Span*	*β-rating*
Luxembourg	1	[25.5, 69.2]	43.7	⋆
Netherlands	2	[32.9, 69.1]	36.2	⋆
Germany	3	[36.7, 66.8]	30.2	⋆⋆
Belgium	4	[37.5, 65.5]	28.0	⋆⋆
Italy	5	[30.7, 60.1]	29.4	⋆⋆
UK	6	[29.9, 60.0]	30.2	⋆⋆
France	7	[31.4, 56.5]	25.1	⋆⋆
Slovenia	8	[19.1, 56.3]	37.3	⋆
Austria	9	[29.5, 56.3]	26.8	⋆⋆
Poland	10	[23.3, 53.1]	29.7	⋆⋆
Lithuania	11	[8.9, 51.3]	42.4	⋆
Spain	12	[39.8, 51.0]	11.2	⋆⋆⋆
Denmark	13	[16.7, 50.9]	34.2	⋆
Finland	14	[8.9, 50.8]	41.9	⋆
Czechia	15	[14.7, 49.7]	35.1	⋆
Sweden	16	[17.5, 48.5]	30.9	⋆⋆
Hungary	17	[12.3, 44.7]	32.4	⋆⋆
Croatia	18	[7.5, 44.4]	36.8	⋆
Ireland	19	[1.7, 41.8]	40.1	⋆
Latvia	20	[8.1, 40.2]	32.2	⋆⋆
Portugal	21	[8.5, 39.4]	31.0	⋆⋆
Slovakia	22	[8.0, 38.4]	30.4	⋆⋆
Cyprus	23	[2.1, 33.2]	31.1	⋆⋆
Romania	24	[4.0, 31.8]	27.8	⋆⋆
Malta	25	[0.0, 29.4]	29.4	⋆⋆
Greece	26	[6.8, 29.3]	22.5	⋆⋆
Estonia	27	[12.2, 28.5]	16.2	⋆⋆⋆
Bulgaria	28	[4.1, 26.0]	21.9	⋆⋆⋆

The monitoring framework designed in 2018 was the first proposal to measure and track countries' commitment to the circular economy. A new circular economy action plan is proposed in 2020 (European Commission, 2020), highlighting the need to review the initial proposal to develop a sound monitoring framework which contributes to reflect new policy priorities and develop further indicators on resource use, including consumption and material footprints. Even though the methodological framework is being revised, when applying our proposal, we notice that the competitiveness and innovation (CI) dimension has a considerable impact on the overall assessment. There is no doubt that the CE monitoring framework should include this dimension to measure the effect of circular economy principles on job creation and growth. Furthermore, it is widely known that the concept of circular economy is fundamentally governed by the 3Rs, reduce, reuse and recycle principles (Manickam and Duraisamy, 2019).

Table 5 Multicriteria composite performance interval of circular economy in Europe for the main 3Rs dimensions (year 2018)

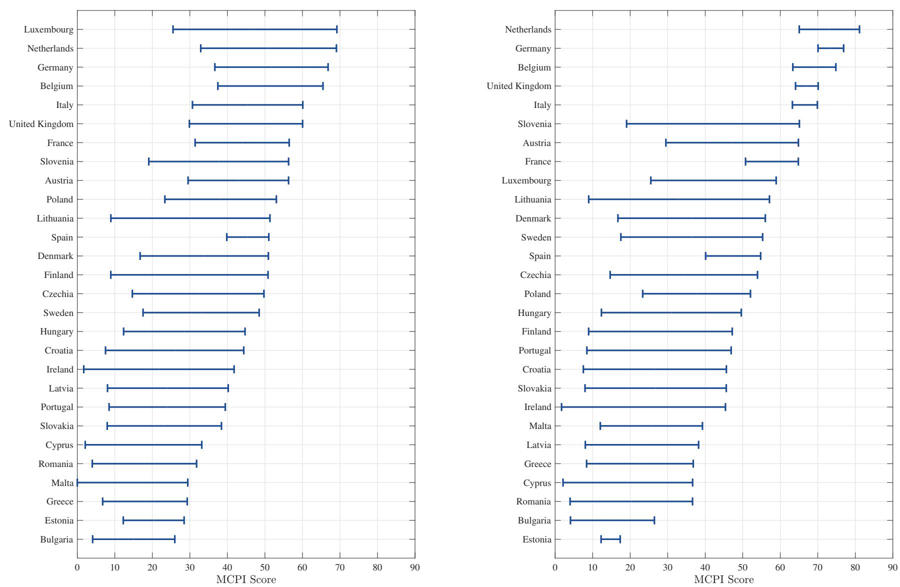
	Rank	*Δrank*	γ_i	*Span*	*β-rating*
Netherlands	1	+1	[65.1, 81.1]	16.1	⋆⋆⋆
Germany	2	+1	[70.1, 76.9]	6.8	⋆⋆⋆
Belgium	3	+1	[63.4, 74.8]	11.5	⋆⋆⋆
UK	4	+2	[64.1, 70.1]	6.0	⋆⋆⋆
Italy	5	+0	[63.2, 69.9]	6.7	⋆⋆⋆
Slovenia	6	+2	[19.1, 65.1]	46.1	⋆
Austria	7	+2	[29.5, 64.8]	35.3	⋆
France	8	–1	[50.8, 64.8]	14.1	⋆⋆⋆
Luxembourg	9	–8	[25.5, 58.9]	33.4	⋆⋆
Lithuania	10	+1	[8.9, 57.1]	48.2	⋆
Denmark	11	+2	[16.7, 56.0]	39.3	⋆
Sweden	12	+4	[17.5, 55.3]	37.8	⋆
Spain	13	–1	[40.1, 54.8]	14.7	⋆⋆⋆
Czechia	14	+1	[14.7, 53.9]	39.3	⋆
Poland	15	–5	[23.3, 52.1]	28.7	⋆⋆
Hungary	16	+1	[12.3, 49.6]	37.3	⋆
Finland	17	–3	[8.9, 47.2]	38.3	⋆
Portugal	18	+3	[8.5, 46.9]	38.4	⋆
Croatia	19	–1	[7.5, 45.6]	38.1	⋆
Slovakia	20	+2	[8.0, 45.6]	37.6	⋆
Ireland	21	–2	[1.7, 45.4]	43.7	⋆
Malta	22	+3	[12.0, 39.3]	27.2	⋆⋆
Latvia	23	–3	[8.1, 38.2]	30.2	⋆⋆
Greece	24	+2	[8.4, 36.8]	28.4	⋆⋆
Cyprus	25	–2	[2.1, 36.6]	34.5	⋆
Romania	26	–2	[4.0, 36.6]	32.6	⋆⋆
Bulgaria	27	+1	[4.1, 26.5]	22.4	⋆⋆
Estonia	28	–1	[12.2, 17.3]	5.1	⋆⋆⋆

Hence, we decide to monitor the essential dimensions contributing to the 3Rs (production and consumption, waste management and secondary raw materials) and compare the results with an overall assessment, including all the CE monitoring framework dimensions. Table 5 displays the MCPI for the essential dimensions contributing to the 3Rs. It also provides the rank position, and its variation for the overall ranking. We observe how Luxembourg now is downgraded eight places and, finally, how Netherlands, Germany and Belgium top the ranking. Moreover, we can also see that they are more balanced as shown by the β-rating.

Figure 2 graphically shows the compared MCPI scores when including all four dimensions and without the competitiveness and innovation dimension. As can be seen, in the latter case, the leading countries present a shorter MCPI than when all dimensions are included.

It should be noted that the circular economy MCPI within dimensions and for the overall performance provides much richer information than a single composite index allowing the modeller to interpret the meaning of the composite measures and apply corrective measures where necessary.

Figure 2 Overall circular economy multicriteria composite performance interval (MCPI), (a) overall MCPI (b) 3Rs Overall MCPI (see online version for colours)



(a) (b)

5 Conclusions

It is increasingly common to assess a multidimensional phenomenon through a composite indicator, and indeed the number of composite indicators used internationally has been growing steadily. Surprisingly, there is no international agreement on their construction to date, and a different methodological approach accompanies each phenomenon. For the sake of simplicity in its construction, a single number is expected to synthesise very complex phenomena without emphasising their limitations.

An important issue when constructing composite indicators comes from the choice of the aggregation methodology, which involves the discussion about if compensability should or not be allowed. In this paper, we have proposed an alternative way to assess a multidimensional issue's performance by building a composite performance interval instead of obtaining only a real number. The MCPI allows for overcoming the criticism of composite indicators that show a 'big-picture' by providing a range of values. Making use of distance-based multicriteria techniques and different versions of the Minkowski L_p metric, we have built two composite indicators which are presented as the lower and upper bound of the MCPI. In this proposal, we have used the TOPSIS method primarily because of its ease of implementation in a wide variety of situations, with no restrictions on the number of alternatives or criteria. The lower bound corresponds to a non-compensability aggregation rule and provides the worst performance of the group of indicators or dimensions that has been aggregated. The upper bound is constructed allowing for full compensation using a linear rule based on weighted or additive aggregation. Finally, based on the balance property of the MCPI, we propose a β-rating to identify those alternatives in which there exists a great MCPI span and, therefore they need to be analysed in greater depth to detect the dimension where action is needed with higher priority.

As an example of application we have computed the MCPI to assess the circular economy performance of European member states by using the structure of indicators and dimensions provided by the European Commission circular economy monitoring framework. The overall circular economy MCPI has been calculated also at the dimension level, thus providing a valuable tool to identify areas where countries need to concentrate their efforts to boost their circular economy performance. If we consider the four dimensions initially proposed in the circular economy theoretical framework, the ranking is headed by Luxembourg, although the dimensions are quite unbalanced. On the other hand, when the MCPI is constructed by considering the dimensions that most contribute to the 3Rs principles, the results seem more coherent, with Netherlands, Germany and Belgium leading the ranking with a better β-rating.

Moving forward, we see a promising line of future research in testing the applicability of the proposed MCPI by adopting other multicriteria techniques such as the reference point-based method or ELECTREE. Besides, in the coming years, we plan to investigate if and how the MCPI could be applied to other domains in which composite indicators have been previously used, from sustainability to quality of life assessment, to cite but a few relevant applications.

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