



# Evaluation of social factors within the circular economy concept for European countries

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## Abstract

The circular economy (CE) is a rapidly growing theme, particularly in the European Union (EU), that encourages the responsible and circular use of resources in the field of contributing to long-term development. The environmental and economic magnitude of development are frequently debated in the subject of CE whereas, social aspects have been only rarely and sporadically combined into the CE. Therefore, this study involves a multidisciplinary holistic framework of clustering methods and Multi-Criteria Decision Making (MCDM) for evaluating the CE paradigm in relation to EU countries' social growth. In terms of the social impact of CE strategies, the k-means cluster analysis was used to group the 27 EU members with similar social impact levels. Subsequently, a novel integrated CRITIC (The criteria importance through intercriteria correlation) and MEREC (Method based on the Removal Effects of Criteria) methods were employed for determining the weights of social indicators in order to balance the two weighting methods. In order to select the best country in each cluster, a novel extension of the hybrid MARCOS (Measurement of Alternatives and Ranking according to Compromise Solution) method combined with Power averaging and Heronian operator was developed. According to final solutions, Western European countries in the first cluster have the lowest unemployment and corruption rates, with the Netherlands having the best performance in this cluster. The second cluster includes

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countries with the lowest employment rates following university graduates between the ages of 20 and 64. Accordingly, Croatia is the best social performance in this cluster. Countries with the highest income distribution and unemployment rate are in the 3rd cluster, the best country in this group is Lithuania. Finally, the results obtained from the innovative MCDM methods have validated in order to demonstrate the proposed methodology's applicability.

**Keywords** Circular economy · Social indicators · Clustering · CRITIC · MEREC · Heronian power operator · MARCOS

## Abbreviations

### CRITIC method

$X$	Decision Matrix
$m$	Set of alternatives
$n$	Set of criteria
$B$	Group of benefit criteria
$C$	Group of cost criteria
$x_{ij}$	The performance value of $i$ th alternative on $j$ th criterion
$r_{ij}$	The elements of normalized decision-matrix
$\rho_{jk}$	The correlation coefficient
$C_j$	The amount of information emitted by the $j^{\text{th}}$ criterion
$\sigma_j$	Standard deviation
$w_j$	Weight coefficients of the criteria

### MEREC method

$X$	Decision Matrix
$m$	Set of alternatives
$n$	Set of criteria
$B$	Group of benefit criteria
$C$	Group of cost criteria
$x_{ij}$	The performance value of $i$ th alternative on $j$ th criterion
$n_{ij}$	The elements of normalized decision-matrix
$S_j$	The overall performance of alternatives
$S'_{ij}$	The performance of the alternatives by removing each criterion
$E_j$	The summation of absolute deviations
$w_j$	Weight coefficients of the criteria

## Power Heronian MARCOS method

$\Omega$	Decision Matrix
$m$	Set of alternatives
$n$	Set of criteria
$B$	Group of benefit criteria
$C$	Group of cost criteria
$IA$	The ideal alternative
$AIA$	The anti-ideal alternative
$\Omega^N$	The normalized matrix
$PHWF_i$	The Power Heronian weighted function
$w_j$	Weight coefficients of the criteria
$\aleph_i \aleph_i$	The utility function

## 1 Introduction

The Circular Economy (CE) establishes new business concept models that alter traditional linear economic "make", "use" and "waste" models. A circular economy is a production and consumption paradigm that promotes the sharing, reusing, repairing, and recycling of existent resources and goods for as long as feasible. This unique concept attempts to maintain the value of products, materials, and resources for as long as possible by returning them to the production process, enhancing material reuse and recycling, decreasing waste, prolonging the product life of long-lasting consumer goods, and improving energy efficiency (Murray et al. 2017; European Commission 2015). In 2015, the European Commission published its first circular economy action plan which include circular practices in numerous industries, taking into account government rules and regulations. Additionally, it helps stimulate Europe's transformation to a circular economy, increases global competitiveness, creates new jobs, and promotes sustainable growth.

In the field of CE, the environmental and economic magnitude of development is generally discussed by practitioners and researchers (Ghisellini et al. 2016). However, CE's contribution to the social components is commonly mentioned as inadequate or without empirical evidence (Walker et al. 2021; Schroeder et al. 2019). Actually, the CE model is closely linked to social enterprise activity in order to benefit society, business, and planet (Robinson 2021). The CE's social goal is to make effective use of available resource capacity via communal and cooperative efforts, rather than individual consumer culture, through fostering a sharing and service economy and increasing employment. Korhonen et al. (2018). Keeping important resources moving throughout the economy helps to promote the market for secondary goods and materials in all locations, which might lead to the creation of new jobs in low-wage areas (Alliance 2015). It also satisfies the demand for higher-quality, longer-lasting products among consumers. According to the International Labor organization (ILO), the generation of renewable energy, increased efficiency, the adoption of electric cars, and improving building efficiency, may result in a net gain of 18 million jobs throughout the global

economy. Renewable energy sources require more labor than fossil-fuel-generated power (WESO 2018). Furthermore, the social impact of CE is also related to issues such as "Gender Equality", "Decent Work and Economic Growth" and "Reduced Inequalities" (Social Circular Economy 2018). Women's participation in CE through improving their awareness of sustainable consumption and production habits would contribute in the creation of better working conditions and increased security, promoting gender equality and a healthy circular loop (ILO 2015). However, there is still limited literature to evaluate social impact of CE concept (Murray et al. 2017). To fill this gap, this paper proposed an integrated methodology that includes k-means clustering algorithm and MCDM methods for evaluating the social aspects of CE practices in EU countries. The k-means cluster analysis was employed to arrange the EU countries with comparable degrees of social impact. A novel hybrid CRITIC (The criteria importance through intercriteria correlation) and MEREC (Method based on the Removal Effects of Criteria) model was implemented for evaluation the weights of social indicators then, a new extension of MARCOS (Measurement of Alternatives and Ranking according to Compromise Solution) approach combining Power averaging and the Heronian operator was proposed to select the country with the best performance within each cluster.

The k-means approach developed by (MacQueen 1967) is a popular descriptive method that is preferred due to its success in data processing. This approach consists of distance-based iterations. First,  $k$  objects are randomly chosen to be the centers of the clusters. All objects are then partitioned into  $k$  clusters based on the minimum squared-error criterion, which measures the distance between an object and the cluster center (Kuo et al. 2014). This method has some advantages: (i) it has the capacity to group large amounts of data in a very short period of time (Bain et al. 2016), (ii) In comparison to hierarchical clustering,  $k$ -means is particularly sensitive to dataset noise. EU countries are at different levels in terms of the social impact of CE strategies. As a result, comparing countries based on their similarities rather than in a single cluster would be a more realistic approach. Accordingly,  $k$ -means cluster analysis is used to create homogeneous groupings of EU countries based on their social indicators within CE.

The determination of criteria weights is a crucial component of a MCDM process (Kayapinar and Aycin 2021). In the literature, criteria weights are calculated with objective and subjective methods. CRITIC (The criteria importance through intercriteria correlation) method was proposed by Diakoulaki et al. (1995) to overcome the problems of subjective weighting methods such as reliability and consistency. This method uses the correlations among criteria to determine the objective weight coefficients. MEREC (Method based on the Removal Effects of Criteria) method was proposed by Keshavarz-Ghorabae et al. (2021) to utilize each criterion's removal effect on the performance of alternatives to evaluate the criteria weights. In this method, a criterion become more important when its removal leads to higher effects on alternatives' aggregate performances. This characteristic separates the MEREC method from other objective weighting methods such as entropy, CILOS, etc. In addition, ease of understanding, ease of computation, and a robust mathematical background can be lined up the major advantages of MEREC and CRITIC methods.

The preferences of decision-makers have no role in calculation process of criteria weights in objective weighting methods. Decision matrix which includes real data are using in the computational process of these methods. Due to the inclusion of real data related to the social indicators of the CE for EU countries in the present study, the CRITIC and MEREC methods were used for calculation of the weight coefficients of these indicators. Because each method has its own characteristics, the results extracted may differ. In order to increase the confidence of the results, the weight coefficients of criteria merged, which are obtained from MEREC and CRITIC methods.

The existence of subjective assessments and unreasonable arguments in the information used to create the initial matrix significantly complicates the entire decision-making process. To objectify and rationalize the decision-making process, researchers worldwide are making daily efforts to create new methodologies that enable objective processing of inaccuracies and subjectivity in information. Guided by this idea, this paper presents a novel multi-criteria framework based on applying the advanced MARCOS (Measurement of Alternatives and Ranking according to Compromise Solution) methodology (Stević et al. 2020). The improvement of the MARCOS methodology is reflected in implementing the hybrid Power Heronian function for defining the degree of utility of alternatives. The Power Heronian function is implemented as it allows the interrelationships between the evaluation criteria to be considered. Also, the application of the Power Heronian function eliminates the influence of extreme and unreasonable arguments in the initial decision matrix. These improvements to the MARCOS methodology enable efficient processing of subjectivity in expert preferences, which contributes to the objectivity of the decision-making process.

This paper presents an integrated comprehensive framework of clustering and MCDM methods for the analysis of the CE concepts in the relation to social development in EU countries. Specifically, the contribution of this paper is summarized as follows: k-means clustering method, one of the popular unsupervised machine learning algorithms was used to categorize EU countries according to their social indicators of CE concept. The MEREC and CRITIC methods were combined firstly to weight the social indicators of the CE concept. The MARCOS method powered by the Power Heronian operator was performed to assess the social level within the CE concept of EU countries as a case. A detailed sensitivity analysis is conducted to present the validation of the extended MARCOS method.

The rest of the paper is presented as follows: Sect. 2 discusses the literature review and research gaps. Section 3 presents some fundamental concepts of Power averaging and Heronian averaging are briefly explained in order to understand Power Heronian MARCOS methodology. The conceptual principles of proposed methods such as Power Heronian MARCOS, CRITIC, MEREC and k-means clustering are given in the Sect. 4. An illustrative example of determining the social level within the CE concept of EU countries are given in Sect. 5. The experimental results and discussion are presented in Sect. 6. A validation and sensitivity analysis of the integrated methods is made to demonstrate the importance of different parameters on decision making process in Sect. 7. Then, Sect. 8 presents managerial insights and practical implications. Finally, Sect. 9 summarizes a conclusion and future directions.

## 2 Literature review

In this paper, the literature section is divided into two subsections. The first section includes the papers that applied the CRITIC, MEREC and MARCOS methods. The second section includes the papers that related to CE concept with MCDM methods.

### 2.1 Related studies about CRITIC, MEREC and MARCOS methods

Weight coefficients of indicators can be calculated with objective methods such as CRITIC, MEREC, etc. CRITIC method was used for calculating the weight coefficients of criteria in various areas such as air conditioning selection (Vujicic et al. 2017), third party logistics service provider selection (Keshavarz Ghorabae et al. 2017), construction equipment evaluation (Keshavarz Ghorabae et al. 2018), R&D performance assessment of countries (Orhan and Aytakin 2020), location planning of electric vehicle charging station (Wei et al. 2020), personnel selection process (Ayçin 2020), intelligent healthcare management evaluation (Peng et al. 2021).

Although MEREC is a new weighting method, it has been used to determine the weight coefficients of criteria in recent studies such as: the location of logistics distribution centers (Keshavarz-Ghorabae 2021), documental classification (Sabaghian et al. 2021), the turning process (Trung and Thinh 2021), food waste treatment technology selection (Rani et al. 2021), selection of a green renewable energy source (Goswami et al. 2021), hospital location determination (Hadi 2022).

MARCOS method and its extensions was commonly used in various decision problems such as supplier selection (Badi and Pamucar 2020; Stević et al. 2020; Chakraborty et al. 2020; Bakır et al. 2021), project management software evaluation (Puška et al. 2020), stackers selection in the logistics (Ulutaş et al. 2020), healthcare performance assessment of insurance companies (Ecer and Pamucar 2021), evaluation of OECD countries in terms of social, economic and environmental aspects (Arsu and Ayçin 2021), evaluation of airports (Ozdoglu et al. 2021a, 2021b), personnel selection in civil aviation.

It can be clearly seen that these MCDM methods and their extensions are widely used in the various fields. However, no previous work has performed about the CE concept related to social aspects in EU countries.

### 2.2 MCDM methods in CE

The impact of the CE on the social dimension has not been sufficiently discussed in the literature. (Geissdoerfer et al. 2017) emphasized the effect of social factors on environmental and economic success, highlighting the importance of system level improvements. (Pitkänen et al. 2020) compiled the significant circular economy statements based on employment, health, and safety implications in Finland and the Netherlands. (Padilla-Rivera et al. 2021) systematically reviewed the conceptual literature review based on the social viewpoint of circular economy strategies. According to their review of sixty papers, employment, health and safety, and participation are considered the main contributions of the circular economy. However, social factors such

**Table 1** MCDM studies related to social factors within the CE

Author/s	Method/s	Purpose
Zhao et al. (2017)	Grey Delphi & Fuzzy VIKOR	Evaluating the comprehensive benefit of eco-industrial parks
Della Spina (2019)	Analytic Network Process (ANP)	Identifying and analyzing the economic, social, and urban dynamics of the urban district
Nikonorova et al. (2020)	MULTIMOORA & TOPSIS	Assessing social pillars such as human well-being, healthy aging, health, and social justice
Padilla-Rivera et al. (2021)	Fuzzy Delphi	Developing a method for investigating basic social dimensions of CE
Skvarciany et al. (2021)	AHP & EDAS	Evaluating sustainable development levels of OECD countries in terms of CE

as poverty, food security, and gender equity are not examined in their literature analysis. On the other hand, some social circularity indicators are not always clear about what they are not measuring or are not correctly positioned, resulting in a plethora of interpretations in the literature. The social circular economy is a multidimensional, sophisticated technique that has particular evaluation requirements (Padilla-Rivera et al. 2020).

There is no one metric that can be used to assess the CE. Nevertheless, a variety of existing indicators may be used to evaluate performance in a wide range of sectors that significantly contributes to the social development within CE. MCDM methods are capable of resolving the decision models includes various and contradictory dimensions (Lotfi et al. 2018; Kayapinar and Aycin 2021; Panchal et al. 2021) but there is limited study in the literature which regarded social factors within the concept of CE. Table 1 shows some related studies that used MCDM methods.

Considering the importance of social factors in CE practices and existence of limited studies related to social factors within CE, this study will fill this critical gap in the CE literature. For this purpose, a hybrid methodology that integrates clustering algorithms with MCDM methods has been developed to evaluate the social levels of EU countries within the framework of CE.

### 3 Preliminaires

In this section, the fundamental elements of the Power averaging (PA) and Heronian averaging (HA) operators are briefly presented. The HA operator was used because of its ability to consider the interrelationships between the evaluation criteria. The PA operator was used due to its ability to eliminate the influence of extreme and unreasonable arguments in the initial decision matrix. The formation of the hybrid Power Heronian function enabled the unification of the positive characteristics of PA

and HA operators, thus creating a powerful tool for the objective evaluation of matrix arguments in the MARCOS methodology.

In the following section, the essential preliminaries of PA and HA operators are presented.

**Definition 1** (Yu 2013): Let  $(\psi_1, \psi_2, \dots, \psi_n)$  be a set of non-negative numbers and let  $\varpi_1, \varpi_2 \geq 0$ . Then  $HA^{\varpi_1, \varpi_2}$  we call the operator for Heronian averaging, given in Eq. (1):

$$HA^{\varpi_1, \varpi_2}(\psi_1, \psi_2, \dots, \psi_n) = \left( \frac{2}{n(n+1)} \sum_{x=1}^n (\psi_i^{(x)})^{\varpi_1} \sum_{y=x}^n (\psi_j^{(y)})^{\varpi_2} \right)^{\frac{1}{\varpi_1 + \varpi_2}} \quad (1)$$

**Definition 2** (Zhao 2019): Let  $\varpi_1, \varpi_2 \geq 0$  and let  $(\psi_1, \psi_2, \dots, \psi_n)$  represents a set of non-negative numbers. Then we can define the weighted Heronian operator (WHM) using an Eq. (2):

$$WHA^{\varpi_1, \varpi_2}(\psi_1, \psi_2, \dots, \psi_n) = \left( \frac{2}{n(n+1)} \sum_{x=1}^n (nw_i \psi_i^{(x)})^{\varpi_1} \sum_{y=x}^n (nw_j \psi_j^{(y)})^{\varpi_2} \right)^{\frac{1}{\varpi_1 + \varpi_2}} \quad (2)$$

**Definition 3** (Yager 2001): Let  $(\psi_1, \psi_2, \dots, \psi_n)$  represents a set of non-negative numbers, then the Power averaging (PA) operator can be defined using an Eq. (3):

$$PA(\psi_1, \psi_2, \dots, \psi_n) = \sum_{i=1}^n \psi_i \cdot \frac{\sum_{i=1}^n (1 + T(f(\psi_i))) f(\psi_i)}{\sum_{i=1}^n (1 + T(f(\psi_i)))} \quad (3)$$

where  $f(\psi_i) = \frac{\psi_i}{\sum_{i=1}^n \psi_i}$ , while  $T(f(\psi_i)) = \sum_{j=1, j \neq i}^n Sup(f(\psi_i), f(\psi_j))$ . With

$Sup(\psi_i, \psi_j)$  we denote the degree of support that  $\psi_i$  receives from  $\psi_j$ , where  $Sup(\psi_i, \psi_j)$  satisfies three axioms (Djordjevic et al. 2019; Milovanovic, et al. 2021):

- $Sup(f(\psi_i), f(\psi_j)) = Sup(f(\psi_j), f(\psi_i))$ ;
- $Sup(f(\psi_i), f(\psi_j)) = [0, 1]$ ;
- $Sup(f(\psi_i), f(\psi_j)) > Sup(f(\psi_i), f(\psi_k))$ , if  $d(\psi_i, \psi_j) < d(\psi_i, \psi_k)$ , where  $d(\psi_i, \psi_j)$  represents the distance between the numbers  $\psi_i$  and  $\psi_j$ .



## 4 Theoretical background of the proposed methods

### 4.1 A hybrid power Heronian MARCOS model

In a multi-criteria framework, the hybrid Power Heronian function was used to fuse normalized weighted matrix elements. By integrating the Power Heronian function (PHF) into the MARCOS methodology, the shortcomings of the weighted averaging function used in the conventional MARCOS model have been eliminated. The following section presents the mathematical formulation of the Power Heronian MARCOS model.

*Step 1* Suppose that in a multi-criteria problem, it is necessary to evaluate  $m$  alternatives represented by the set  $A_i = \{A_1, A_2, \dots, A_m\}$ . Also, suppose that  $n$  criteria  $C_j = \{C_1, C_2, \dots, C_n\}$  are defined for the evaluation of alternatives. Then, we can form the initial decision matrix  $\Omega = [\zeta_{ij}]_{m \times n}$ , representing the sequence of the matrix  $\Omega$  representing the significance of the alternative  $i$  in relation to criterion  $j$ .

*Step 2* Using expression (4), the ideal alternative (IA) and the anti-ideal alternative (AIA) are identified. IA and AIA are defined, based on the nature of the criteria, for each criterion individually.

$$\begin{aligned}
 IA &= \max_{1 \leq i \leq m} (\zeta_{ij}) \text{ if } j \in B \text{ and } \min_{1 \leq i \leq m} (\zeta_{ij}) \text{ if } j \in C \\
 AIA &= \min_{1 \leq i \leq m} (\zeta_{ij}) \text{ if } j \in B \text{ and } \max_{1 \leq i \leq m} (\zeta_{ij}) \text{ if } j \in C
 \end{aligned}
 \tag{4}$$

where  $B$  represents the benefit group, while  $C$  represents the non-benefit group of criteria.

*Step 3* The elements of the normalized matrix  $\Omega^N = [\zeta_{ij}]_{m \times n}$  are obtained by applying the Eq. (5):

$$\zeta_{ij} = \begin{cases} \frac{\zeta_{ij}}{\zeta_j^+} & \text{if } j \in \text{Benefit} \\ \frac{\zeta_j^-}{\zeta_{ij}} & \text{if } j \in \text{Cost} \end{cases}
 \tag{5}$$

where  $\zeta_j^+ = \max_{1 \leq i \leq m} (\zeta_{ij}^+)$  and  $\zeta_j^- = \min_{1 \leq i \leq m} (\zeta_{ij}^-)$ .

*Step 4* Determining the utility degree of alternatives ( $\mathfrak{S}_i$ ). Using expressions (6) and (7), the utility degrees of alternative  $A_i (i = 1, 2, \dots, m)$  concerning IA and AIA are defined:

$$\mathfrak{S}_i^- = \frac{PHWF_i}{PHWF_i^{AIA}}
 \tag{6}$$

$$\mathfrak{S}_i^+ = \frac{PHWF_i}{PHWF_i^{IA}}
 \tag{7}$$

where  $PHWF_i$  ( $i = 1, 2, \dots, m$ ),  $PHWF_i^{IA}$  and  $PHWF_i^{AIA}$  represent the Power Heronian weighted function (PHWF) that we get weighted by averaging the matrix elements  $\Omega^N = [\zeta_{ij}]_{m \times n}$ . Through Theorem 1, the expression for the Power Heronian weighted function is presented in the following section.

**Theorem 1** Let  $\{\zeta_1, \zeta_2, \dots, \zeta_n\}$  be the set of normalized elements of the matrix  $\Omega^N$ . Also, let  $\varpi_1, \varpi_2 \geq 0$ , and let  $w_j = (w_1, w_2, \dots, w_n)^T$  ( $j = 1, 2, \dots, n$ ) represent the vector of weight coefficients, then the Power Heronian weighted function ( $PHWF_i^{\varpi_1, \varpi_2}$ ) can be represented as follows:

$$PHWF_i^{\varpi_1, \varpi_2} = \left( \frac{2}{n(n+1)} \sum_{x=1}^n \left( n \frac{n\widehat{w}_i w_i}{\sum_{t=1}^n \widehat{w}_t w_t} \psi_i^{(x)} \right)^{\varpi_1} \sum_{y=x}^n \left( n \frac{n\widehat{w}_i w_j}{\sum_{t=1}^n \widehat{w}_t w_t} \psi_j^{(y)} \right)^{\varpi_2} \right)^{\frac{1}{\varpi_1 + \varpi_2}} \quad (8)$$

where  $\varpi_1$  and  $\varpi_2$  represent the stabilization parameters of PHWF,  $w_j$  represents the weighting coefficient of criterion  $j$ , while  $\widehat{w}_t = \frac{(1+T(\zeta_i))}{\sum_{i=1}^n (1+T(\zeta_i))}$  and  $T(\zeta_i) =$

$\sum_{j=1, j \neq i}^n \text{Sup}(\zeta_i, \zeta_j)$ . The proof for Theorem 1 is presented in Appendix A1.

*Step 5* Based on the utility function  $\aleph_i$ , the significance of alternative  $A_i$  ( $i = 1, 2, \dots, m$ ) and its rank in the considered set of alternatives are defined.

$$\aleph_i = \frac{\aleph_i^+ + \aleph_i^-}{1 + \frac{1-\varphi_i^+}{\varphi_i^+} + \frac{1-\varphi_i^-}{\varphi_i^-}} \quad (9)$$

where  $\varphi_i^- = \aleph_i^+ / (\aleph_i^+ + \aleph_i^-)$  and  $\varphi_i^+ = \aleph_i^- / (\aleph_i^+ + \aleph_i^-)$  respectively represent utility functions in relation to AIA and IA.

*Step 6* The ranking of alternatives is done based on the value of utility functions, where the alternative should have the highest possible value  $\aleph_i$ .

## 4.2 CRITIC method

The CRITIC method was proposed by Diakoulaki et al. (1995) to overcome the problems of subjective weighting methods such as reliability and consistency. This method achieves outcomes by performing processes that are based on real data, and it eliminates the impact of decision-makers on the decision (Arsu and Ayçin 2021; Abdel-Basset and Mohamed 2020; Mukhametzyanov 2021). The differences and correlations among criteria are used to determine the objective weight coefficients (Simic et al. 2021; Milosevic et al. 2021). The following section presents the mathematical formulation of the CRITIC method (Diakoulaki et al. 1995).

*Step 1* The decision matrix includes a set of  $n$  criteria and  $m$  alternatives is shown in Eq. (10).

$$X = \begin{matrix} A_1 \\ A_2 \\ \vdots \\ A_m \end{matrix} \begin{bmatrix} x_{11} & x_{12} & \dots & x_{1n} \\ x_{21} & x_{22} & \dots & x_{2n} \\ \vdots & \vdots & \dots & \vdots \\ x_{m1} & x_{m2} & \dots & x_{mn} \end{bmatrix} \tag{10}$$

*Step 2* The normalized decision-making matrix is calculated by expressions (11), (12) where  $B$  represents a group of benefit criteria, while  $C$  represents a group of cost criteria.

$$r_{ij} = \frac{x_{ij} - x_j^{\min}}{x_j^{\max} - x_j^{\min}} \dots j = 1, 2, \dots, n \text{ if } j \in B \tag{11}$$

$$r_{ij} = \frac{x_j^{\max} - x_{ij}}{x_j^{\max} - x_j^{\min}} \dots j = 1, 2, \dots, n \text{ if } j \in C \tag{12}$$

*Step 3* The correlation coefficient matrix consisting of linear relationship coefficients is created to measure the degree of relationships between the criteria in this step. The correlation coefficient is calculated by using the expression (13).

$$\rho_{jk} = \frac{\sum_{i=1}^m (r_{ij} - \bar{r}_j) \cdot (r_{ik} - \bar{r}_k)}{\sqrt{\sum_{i=1}^m (r_{ij} - \bar{r}_j)^2 \cdot \sum_{i=1}^m (r_{ik} - \bar{r}_k)^2}} \quad j, k = 1, 2, \dots, n \tag{13}$$

*Step 4*  $C_j$  Values that represents the amount of information  $C_j$ , emitted by the  $j^{\text{th}}$  criterion can be calculated by using expression (14) and (15).

$$C_j = \sigma_j \cdot \sum_{k=1}^n (1 - \rho_{jk}) \quad j = 1, 2, \dots, n \tag{14}$$

$$\sigma_j = \sqrt{\frac{\sum_{i=1}^m (r_{ij} - \bar{r}_j)^2}{m - 1}} \tag{15}$$

*Step 5* In the last step of CRITIC method, weight coefficients of the criteria are calculated by using expression (16).

$$w_j = \frac{c_j}{\sum_{k=1}^n c_k} \tag{16}$$

### 4.3 MEREC method

The MEREC method was proposed by Keshavarz-Ghorabae et al. (2021) to determine the weight coefficients of the criteria. MEREC focuses on the change in the total criteria weight by disabling that criterion when determining the weighting of a criterion. This characteristic separates the MEREC method from other objective weighting methods such as entropy, CRITIC and CILOS. Ease of understanding, ease of computation, and a robust mathematical background can be listed as its major advantages in comparison with other objective weighting methods. The following section presents the mathematical formulation of the MEREC method (Keshavarz-Ghorabae et al. 2021).

*Step 1* The decision matrix includes a set of  $n$  criteria and  $m$  alternatives is shown in expression (17).

$$X = \begin{bmatrix} x_{11} & x_{12} & \dots & x_{1n} \\ x_{21} & x_{22} & \dots & x_{2n} \\ \vdots & \vdots & \dots & \vdots \\ x_{m1} & x_{m2} & \dots & x_{mn} \end{bmatrix} \quad (17)$$

*Step 2* The normalized decision-making matrix is calculated by expression (18) where  $B$  represents a set of beneficial criteria, while  $C$  represents a set of non-beneficial criteria.

$$n_{ij} = \begin{cases} \frac{\min_k x_{kj}}{x_{ij}} & \text{if } j \in B \\ \frac{x_{ij}}{\max_k x_{kj}} & \text{if } j \in C \end{cases} \quad (18)$$

*Step 3* The overall performance of the alternatives is calculated by using expression (19).

$$S_i = \ln \left( 1 + \left( \frac{1}{m} \sum_j |\ln(n_{ij})| \right) \right) \quad (19)$$

*Step 4* The performance of the alternatives by removing each criterion is calculated by using the expression (20). By removing each criterion from the whole criteria set,  $m$  sets of performances are gained with respect to  $m$  criteria.

$$S'_{ij} = \ln \left( 1 + \left( \frac{1}{m} \sum_{k, k \neq j} |\ln(n_{ik})| \right) \right) \quad (20)$$

*Step 5* The summation of absolute deviations is calculated by expression (21) whereas  $E_j$  represents the effect of removing the  $j$ th criterion.

$$E_j = \sum_i |S'_{ij} - S_i| \quad (21)$$

*Step 6* In the last step of MEREC method the weight coefficients of the criteria are calculated by expression (22).

$$w_j = \frac{E_j}{\sum_k E_k} \quad (22)$$

#### 4.4 K-means clustering algorithm

The k-means method, which is one of the descriptive methods in data mining, is an important method that is preferred for its success in processing data. This method was developed by (MacQueen 1967) as an iterative algorithm in which clusters are updated continuously until the optimal solution is reached. The k-means cluster method can produce better results than other hierarchical methods (Tinsley and Brown 2000). With the help of k-means clustering analysis, the number of groups is unknown and the ungrouped data is divided into k clusters according to their similarities.

By dividing the data into k clusters, it aims to maximize the similarities within the cluster and minimize the similarities between the clusters. The k-means cluster analysis is an iterative process. The following steps developed by (Wang et al. 2012) are as follows: (i) A dataset consisting of n data objects begins with k (number of clusters) randomly selected center points, (ii) Each object in the data set is assigned to the cluster of the closest center point (mean). The distance between two objects is determined by the Euclidean distance, (iii) Recalculate the cluster center to get a new object and reassign it to the nearest cluster, (iv) The iterations are repeated until the cluster centers are fixed. The pseudo-code representation of the k clustering algorithm is given in Table 2. The pseudo representation of the k-means clustering algorithm is as follows:

## 5 Research methodology

This study is focused on empirical data from Eurostat databases (Eurostat 2021) on various social indicators within the CE framework. The evaluation of social impact on CE is conducted based on 8 independent indicators, which are shown in Table 3, with their short descriptions, units. The assessment was based on data from 27 EU countries from 2019.

This paper aims to develop a hybrid methodology for the evaluation of the EU countries in terms of the social indicators of the Circular Economy. Whilst weighting of the social indicators, the CRITIC and MEREC methods are used to avoid subjective

**Table 2** Pseudo-code identification of the k-means algorithm**Algorithm: Pseudo code for k-means algorithm**

- 
- 1: Input:  
 2: the number of objects including  $m$  objects  
 $N = \{x_1, x_2, \dots, \dots, x_n\}$   
 3: the number of clusters ( $k$ )  
 4: Output:  
 5: Specify the number  $k$  of cluster to assign  $C = \{c_1, c_2, \dots, c_k\}$   
 6: Arbitrarily initialize set of  $k$  centroids  
 7: Repeat  
   8: Compute the Euclidean distance (Dist) between each object  $x_j$  to each of the  $i$ th cluster centroid ( $c_i$ )  
      $Dist(x_j, c_i) = \sqrt{\sum_i (x_j - c_i)^2}$ ,  
      $1 \leq j \leq n$  and  $1 \leq i \leq k$   
 9: Assign each object of the cluster  $x_j$  with its nearest cluster centroid  
 10: Calculate the new centroids of each cluster again  
 11: Repeat the centroid of each cluster is not change
- 

**Table 3** Social factors in accordance with circular economy perspective

Abb	Indicators (nature of criteria*)	Unit	Short description
C1	At-risk-of-poverty rate (C)	Percentage	The proportion of people below the poverty level
C2	Income distribution (C)	Ratio	The unbalanced distribution of income distribution
C3	Young people neither in employment nor education and training (C)	Percentage	The ratio of young individuals who are unemployed, uneducated, or untrained
C4	Employment rate by sex, age between 20–64 (B)	Percentage	The percentage of working population between the age of 20 and 64
C5	Employment rates of recent graduates by sex (B)	Percentage	Employment percentages of persons aged 20 to 34
C6	Life expectancy by age (B)	Years	Average period that a person may expect
C7	Corruption perceptions index (B)	Score Scale (0: high level corruption – 100: very clean country)	The ranking score of countries is based on how corrupt their government
C8	Duration of working life-annual data (B)	Year	The number of years a 15-year-old is expected to work in the labor force

\*B represents the benefit group, while C represents the non-benefit group of criteria

evaluations in this work. Then, the data for the indicators of the EU countries is analyzed with the Power Heronian MARCOS method. The steps of the proposed methodology for this study are illustrated in Fig. 1.

The decision matrix used in both the CRITIC & MEREC and the Power Heronian MARCOS methodologies was created as shown in Appendix A2.

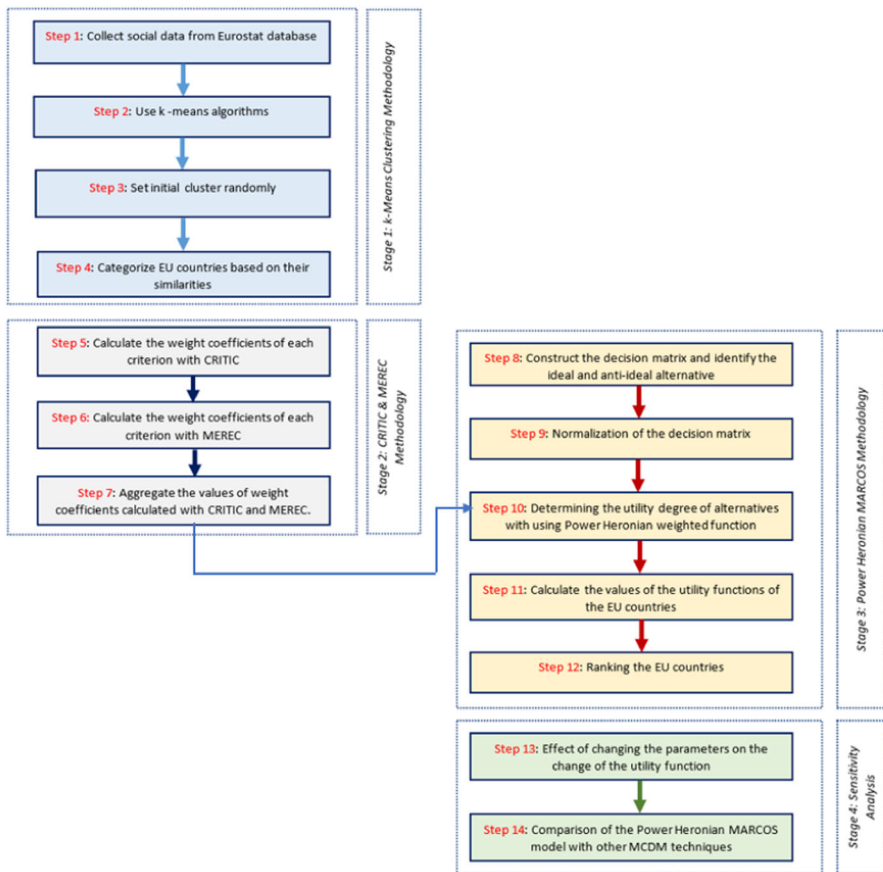
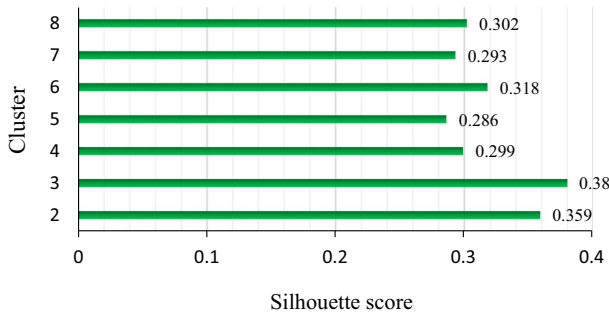


Fig. 1 Flowchart of the proposed methodology

## 6 Results and discussion

### 6.1 K -Means clustering analysis

K means cluster analysis was performed to obtain homogenous groups of EU countries with similar social characteristics within the CE perspective. For this reason, the Orange Data Mining & Machine Learning Tool is employed to apply the k-means clustering algorithm. Orange is an open-source data visual programming and data analysis software supported by machine learning algorithm is coded Python language (Ljubljana 2021). In this study, the silhouette method is used to obtain the optimal number of clusters. The silhouette metric score measures the similarity between the average distance to data in the same cluster (intra-cluster distance) and the average distance to data in the other cluster (nearest-cluster distance). The computation of silhouette score is given expression (23);



**Fig. 2** The silhouette score of different number of k clusters

$$s(i) = \frac{\delta(i) - \omega(i)}{\max\{\delta(i), \omega(i)\}} \quad \text{with} \quad \delta(i) = \min_k \{Dist(i, k)\} \quad (23)$$

where  $s(i)$  indicates the silhouette score,  $\delta(i)$  is the minimum average distance between  $i$ th data to the other clusters and  $\omega(i)$  is the average distance between the  $i$ th data and the other data of its cluster. In addition,  $Dist(i, k)$  defines the average distance from  $i$ th data to data in another cluster  $k$  (Leti et al. 2004; Wang et al. 2017).

EU countries are at different levels in terms of the social impact of CE strategies. For this reason, it would be a more realistic approach to compare countries according to their similarities rather than in a single cluster. Accordingly, k-means cluster analysis is performed to obtain homogenous groups of 27 EU countries according to their social dimensions of CE. Data consisting of 8 independent variables was obtained from Eurostat database (Eurostat 2021). At the beginning, the Orange widget applies the k-means clustering algorithm using the silhouette coefficient to find the optimal number of clusters. According to the results of k-means clustering method, the silhouette scores of different cluster numbers ranging from 2 to 8 are shown in Fig. 2. The result implies that the silhouette scores of different k cluster values are close to each other. The low k value will mean smaller average similarity of each object to all other objects in its cluster (Rousseeuw 1987; Aytaç 2020). The cluster value k was selected as 3, which had the largest silhouette score of 0.380 points in this study to form more homogeneous clusters and generate better intra-cluster solutions.

To understand the created clusters more deeply, scatter plots of the silhouette score and cluster were drawn by Orange to visually evaluate the consistency and quality of the cluster. With the help of this plot, EU countries can be visually distinguished from their similar cluster (See in Fig. 3).

As can be seen in Fig. 4, EU countries are divided into 3 different clusters according to their similarity rates. Accordingly, the 18 countries in the first cluster are located in the central and western European regions and 4 countries in the other clusters. Countries in Western Europe such as Sweden, Germany, Netherlands, Denmark, France, Austria have low unemployment rate. In addition, these countries are perceived as the least corrupt nations in the EU zone, ranking consistently high among international



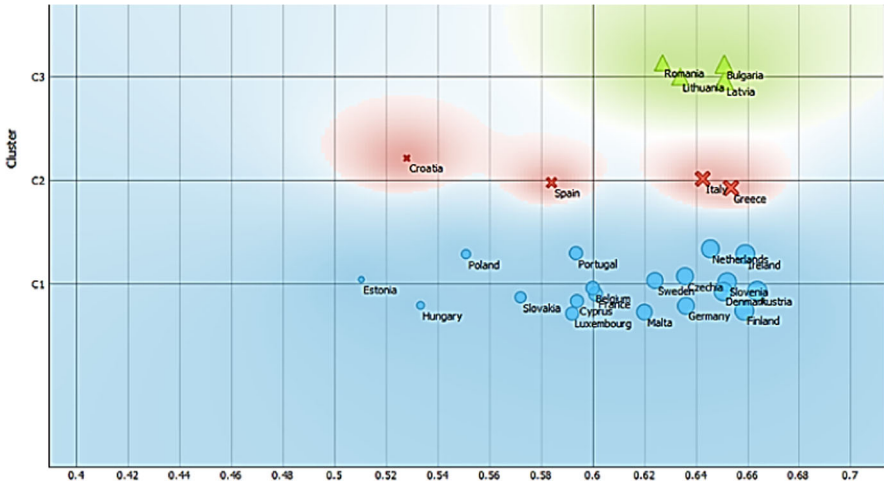


Fig. 3 The scatter plot of silhouette and k-means clustering

CLUSTER-1	CLUSTER-2	CLUSTER-3
<ul style="list-style-type: none"> <li>• Austria</li> <li>• Belgium</li> <li>• Cyprus</li> <li>• Czechia</li> <li>• Denmark</li> <li>• Estonia</li> <li>• Finland</li> <li>• France</li> <li>• Germany</li> <li>• Ireland</li> <li>• Luxembourg</li> <li>• Malta</li> <li>• Netherlands</li> <li>• Poland</li> <li>• Portugal</li> <li>• Slovakia</li> <li>• Slovenia</li> <li>• Sweden</li> </ul>	<ul style="list-style-type: none"> <li>• Croatia</li> <li>• Greece</li> <li>• Italy</li> <li>• Spain</li> </ul>	<ul style="list-style-type: none"> <li>• Bulgaria</li> <li>• Latvia</li> <li>• Lithuania</li> <li>• Romania</li> </ul>

Fig. 4 Optimal number of clusters of EU countries

public transparency. In the second cluster, mainly Southern European countries such as Croatia, Greece, Italy and Spain come to the last four in the rankings based on employment rates between the ages of 20 and 64 and employment rates after university students graduate. Most of the countries in the third cluster are located in Eastern Europe. These countries are generally among the top ten countries in income distribution and poverty risk rate criteria. Furthermore, Romania is both the highest poverty rate and the lowest relative poverty line of all EU countries.

### 6.2 Determining criteria weights with CRITIC and MEREC

After applying the clustering analysis, EU countries were grouped into three clusters. Eight criteria were used to evaluate these countries. The weight coefficients of criteria

**Table 4** Weight coefficients of criteria using CRITIC and MEREC Methods

Cluster	$w_1$	$w_2$	$w_3$	$w_4$	$w_5$	$w_6$	$w_7$	$w_8$
<i>CRITIC results</i>								
Cluster 1	0.1740	0.1752	0.0972	0.1065	0.1085	0.1179	0.1129	0.1078
Cluster 2	0.1827	0.1606	0.0842	0.0840	0.0772	0.1919	0.1428	0.0765
Cluster 3	0.1244	0.1290	0.0789	0.0846	0.2651	0.2346	0.0406	0.0428
<i>MEREC results</i>								
Cluster 1	0.2296	0.1317	0.2110	0.0504	0.0653	0.0311	0.2305	0.0504
Cluster 2	0.0955	0.1290	0.3125	0.0702	0.1513	0.0574	0.1350	0.0490
Cluster 3	0.0798	0.1978	0.2844	0.0876	0.0720	0.0063	0.2083	0.0638

**Table 5** Aggregate values of weighting coefficients of criteria

Cluster	$w_1$	$w_2$	$w_3$	$w_4$	$w_5$	$w_6$	$w_7$	$w_8$
Cluster 1	0.2018	0.1534	0.1541	0.0785	0.0869	0.0745	0.1717	0.0791
Cluster 2	0.1391	0.1448	0.1984	0.0771	0.1143	0.1247	0.1389	0.0628
Cluster 3	0.1021	0.1634	0.1817	0.0861	0.1686	0.1205	0.1244	0.0533

for each cluster of countries obtained by CRITIC and MEREC methods after the operations seen in expressions (10)–(22) were calculated as shown in Table 4.

Aggregate values of weight coefficients were implemented in the Power Heronian MARCOS methodology as shown in Table 5. The aggregation of weight coefficients was performed using the following expression.

$$w_j^{agg} = \frac{\delta \cdot w_j^{MEREC} + (1 - \delta) \cdot w_j^{CRITIC}}{\sum_{j=1}^n (\delta \cdot w_j^{MEREC}) + \sum_{j=1}^n ((1 - \delta) \cdot w_j^{CRITIC})} \tag{24}$$

where  $w_j^{MEREC}$  and  $w_j^{CRITIC}$  respectively represent the weighting coefficients obtained using the MEREC and CRITIC methodology, while  $\delta \in [0, 1]$  represents the correction coefficient.

When calculating the aggregate weights of the criteria, the value of the corrective coefficient  $\delta = 0.5$  was adopted. This enabled the weighting coefficient obtained by applying the MEREC and CRITIC methodology to participate in evaluating methods equally.

### 6.3 Evaluation of alternatives–power Heronian MARCOS methodology

The Power Heronian MARCOS methodology was applied to each cluster individually to define the ranks of EU countries within the cluster.

*Step 1* The initial decision matrix for individual clusters is shown in Table 6.

*Step 2* By applying expression (4) for each criterion  $C_j$ , IA and AIA alternatives are defined, Table 7.

The following section presents the procedure for defining IA and AIA for cluster 1:

**Table 6** Initial decision matrix for each cluster

Country/Criterion	C1	C2	C3	C4	C5	C6	C7	C8
<i>Cluster 1</i>								
Austria	13.3	4.17	9.5	78.3	89	81.8	77	37.7
Belgium	14.8	3.61	12	71.8	83.5	81.7	75	33.6
Cyprus	14.7	4.58	15.3	75.8	81.7	82.9	58	37.4
Czechia	10.1	3.34	11	80.2	87.3	79.1	56	36.3
Denmark	12.5	4.09	10.2	79.4	85.1	81	87	40.1
Estonia	21.7	5.08	11.2	81.2	83.3	78.5	74	39.1
Finland	11.6	3.69	10.3	77.9	84.4	81.8	86	38.9
France	13.6	4.27	14	79	75.7	82.8	69	35.4
Germany	14.8	4.89	8.6	82.7	92.7	81	80	39.1
Hungary	12.3	4.23	14.7	75.3	85.6	76.2	44	34.5
Ireland	13.1	4.03	7	75	84.5	82.2	74	37.5
Luxembourg	17.5	5.34	7.7	70.1	89.4	82.3	80	33.9
Malta	17.1	4.18	9.4	76.1	93.4	82.5	54	36.3
Netherlands	13.2	3.94	5.7	81	91.9	81.9	82	41
Poland	15.4	4.37	12.9	73	84	77.7	58	33.6
Portugal	17.2	5.16	11	76.2	80.3	81.5	62	38.3
Slovakia	11.9	3.34	15.2	73.4	83.9	77.4	50	34.2
Slovenia	12	3.39	9.2	76.6	86	81.5	60	35.9
Sweden	17.1	4.33	7.2	84.5	87.9	82.6	85	42
<i>Cluster 2</i>								
Croatia	18.3	4.76	14.6	66.8	75.8	78.2	47	32.6
Greece	17.9	5.11	18.7	61.5	59.4	81.9	48	33.2
Italy	20.1	6.01	23.3	63.4	58.7	83.4	53	32
Spain	20.7	5.94	17.3	68.7	73	83.5	62	35.4
<i>Cluster 3</i>								
Bulgaria	22.6	8.1	18.1	75	80.7	75	43	34
Latvia	22.9	6.54	11.9	78.6	84.1	75.1	56	37
Lithuania	20.6	6.44	13	78.2	80.1	76	60	37.2
Romania	23.8	7.08	16.6	70.9	76.1	75.3	44	33.8

**Table 7** IA and AIA alternatives

AI/AIA	C1	C2	C3	C4	C5	C6	C7	C8
<i>Cluster 1</i>								
AI	10.10	3.34	5.70	84.50	93.40	82.90	87.00	42.00
AIA	21.70	5.34	15.30	70.10	75.70	76.20	44.00	33.60
<i>Cluster 2</i>								
AI	17.90	4.76	14.60	68.70	75.80	83.50	62.00	35.40
AIA	20.70	6.01	23.30	61.50	58.70	78.20	47.00	32.00
<i>Cluster 3</i>								
AI	20.60	6.44	11.90	78.60	84.10	76.00	60.00	37.20
AIA	23.80	8.10	18.10	70.90	76.10	75.00	43.00	33.80

$$\begin{aligned}
 IA^{C1} &= \min\{13.3, 14.8, 14.7, \dots, 17.1\} = 10.10, & AIA^{C1} &= \max\{13.3, 14.8, 14.7, \dots, 17.1\} = 21.70, \\
 IA^{C2} &= \min\{4.17, 3.61, 4.58, \dots, 4.33\} = 3.34, & AIA^{C2} &= \max\{4.17, 3.61, 4.58, \dots, 4.33\} = 5.34, \\
 IA^{C3} &= \min\{9.50, 12.00, 15.30, \dots, 7.20\} = 5.70, & AIA^{C3} &= \max\{9.50, 12.00, 15.30, \dots, 7.20\} = 15.30, \\
 IA^{C4} &= \max\{78.3, 71.8, 75.8, \dots, 84.5\} = 84.50, & AIA^{C4} &= \min\{78.3, 71.8, 75.8, \dots, 84.5\} = 70.10, \\
 \dots & & \dots & \\
 IA^{C8} &= \max\{37.70, 33.60, 37.40, \dots, 42.00\} = 42.00, & AIA^{C8} &= \min\{37.70, 33.60, 37.40, \dots, 42.00\} = 33.60.
 \end{aligned}$$

*Step 3* By applying expression (5), the elements of the aggregated matrix are standardized into a unique interval [0,1], Table 8.

*Step 4* Using expressions (6) and (7), the utility degrees of alternatives to IA and AIA are defined in Table 9.

The calculation of the utility degree of alternative A1 (Austria) within cluster 1 is presented in the following section:

1. Using the Power Heronian weighted function ( $PHWF_i^{\varpi_1, \varpi_2}$ ), expression (8) gives the sum of the weighted elements of the normalized matrix for alternative A1 (Austria). The following section shows the calculation of the function  $PHWF_1^{\varpi_1, \varpi_2}$ .
  - a. The normalized functions of the matrix elements  $\Omega^N = [\zeta_{ij}]_{19 \times 8}$  for alternatives A1 (Austria) within cluster 1 are obtained as follows:
 
$$\begin{aligned}
 f(\zeta_{11}) &= \frac{0.76}{0.76+0.80++0.60\dots+0.90} = 0.112; & f(\zeta_{12}) &= \frac{0.80}{0.76+0.80++0.60\dots+0.90} = 0.118. \\
 f(\zeta_{13}) &= \frac{0.60}{0.76+0.80++0.60\dots+0.90} = 0.088; & f(\zeta_{18}) &= \frac{0.90}{0.76+0.80++0.60\dots+0.90} = 0.132.
 \end{aligned}$$
  - b. Calculating the degree of support:
 
$$\begin{aligned}
 Sup(f(\zeta_{11}), f(\zeta_{12})) &= 0.0061; & Sup(f(\zeta_{11}), f(\zeta_{13})) &= 0.0234; \\
 Sup(f(\zeta_{11}), f(\zeta_{14})) &= 0.0246; \dots; & Sup(f(\zeta_{11}), f(\zeta_{18})) &= 0.0203.
 \end{aligned}$$

That's how we get values:  $T(f(\zeta_{11})) = 0.155, T(f(\zeta_{12})) = 0.130, T(f(\zeta_{13})) = 0.295, \dots, T(f(\zeta_{18})) = 0.106.$

- c. By applying expression (8), we calculate  $PHWF_1^{\varpi_1, \varpi_2}$ :

**Table 8** Normalized matrix

Country/Criterion	C1	C2	C3	C4	C5	C6	C7	C8
<i>Cluster 1</i>								
Austria	0.759	0.801	0.600	0.927	0.953	0.987	0.885	0.898
Belgium	0.682	0.925	0.475	0.850	0.894	0.986	0.862	0.800
Cyprus	0.687	0.729	0.373	0.897	0.875	1.000	0.667	0.890
Czechia	1.000	1.000	0.518	0.949	0.935	0.954	0.644	0.864
Denmark	0.808	0.817	0.559	0.940	0.911	0.977	1.000	0.955
Estonia	0.465	0.657	0.509	0.961	0.892	0.947	0.851	0.931
Finland	0.871	0.905	0.553	0.922	0.904	0.987	0.989	0.926
France	0.743	0.782	0.407	0.935	0.810	0.999	0.793	0.843
Germany	0.682	0.683	0.663	0.979	0.993	0.977	0.920	0.931
Hungary	0.821	0.790	0.388	0.891	0.916	0.919	0.506	0.821
Ireland	0.771	0.829	0.814	0.888	0.905	0.992	0.851	0.893
Luxembourg	0.577	0.625	0.740	0.830	0.957	0.993	0.920	0.807
Malta	0.591	0.799	0.606	0.901	1.000	0.995	0.621	0.864
Netherlands	0.765	0.848	1.000	0.959	0.984	0.988	0.943	0.976
Poland	0.656	0.764	0.442	0.864	0.899	0.937	0.667	0.800
Portugal	0.587	0.647	0.518	0.902	0.860	0.983	0.713	0.912
Slovakia	0.849	1.000	0.375	0.869	0.898	0.934	0.575	0.814
Slovenia	0.842	0.985	0.620	0.907	0.921	0.983	0.690	0.855
Sweden	0.591	0.771	0.792	1.000	0.941	0.996	0.977	1.000
<i>Cluster 2</i>								
Croatia	0.978	1.000	1.000	0.972	1.000	0.937	0.758	0.921
Greece	1.000	0.932	0.781	0.895	0.784	0.981	0.774	0.938
Italy	0.891	0.792	0.627	0.923	0.774	0.999	0.855	0.904
Spain	0.865	0.801	0.844	1.000	0.963	1.000	1.000	1.000
<i>Cluster 3</i>								
Bulgaria	0.912	0.795	0.657	0.954	0.960	0.987	0.717	0.914
Latvia	0.900	0.985	1.000	1.000	1.000	0.988	0.933	0.995
Lithuania	1.000	1.000	0.915	0.995	0.952	1.000	1.000	1.000
Romania	0.866	0.910	0.717	0.902	0.905	0.991	0.733	0.909

**Table 9** The utility degrees of alternatives

Country	$\mathfrak{S}_i^-$	$\mathfrak{S}_i^+$
<i>Cluster 1</i>		
Austria	1.371	0.813
Belgium	1.298	0.770
Cyprus	1.179	0.700
Czechia	1.397	0.829
Denmark	1.413	0.838
Estonia	1.183	0.702
Finland	1.443	0.856
France	1.246	0.739
Germany	1.358	0.806
Hungary	1.178	0.699
Ireland	1.425	0.845
Luxembourg	1.289	0.765
Malta	1.242	0.737
Netherlands	1.529	0.907
Poland	1.182	0.701
Portugal	1.188	0.705
Slovakia	1.256	0.745
Slovenia	1.384	0.821
Sweden	1.398	0.829
<i>Cluster 2</i>		
Croatia	1.195	0.945
Greece	1.107	0.875
Italy	1.033	0.817
Spain	1.156	0.914
<i>Cluster 3</i>		
Bulgaria	1.021	0.838
Latvia	1.190	0.977
Lithuania	1.188	0.975
Romania	1.040	0.854

$$\begin{aligned}
 PHWF_1^{\varpi_1=\varpi_2=1} &= \frac{2}{8(8+1)} \\
 &= \left( \left( 8 \cdot \frac{0.2018 \cdot (1 + 0.155)}{0.2018 \cdot (1 + 0.155) + 0.1534 \cdot (1 + 0.130) + 0.1541 \cdot (1 + 0.295) + \dots + 0.156 \cdot (1 + 0.106)} \right)^{0.112} \right)^{\frac{1}{1+1}} + \\
 &\quad \left( 8 \cdot \frac{0.2018 \cdot (1 + 0.155)}{0.2018 \cdot (1 + 0.155) + 0.1534 \cdot (1 + 0.130) + 0.1541 \cdot (1 + 0.295) + \dots + 0.156 \cdot (1 + 0.106)} \right)^{0.112} \right)^{\frac{1}{1+1}} + \\
 &\quad \left( 8 \cdot \frac{0.2018 \cdot (1 + 0.155)}{0.2018 \cdot (1 + 0.155) + 0.1534 \cdot (1 + 0.130) + 0.1541 \cdot (1 + 0.295) + \dots + 0.156 \cdot (1 + 0.106)} \right)^{0.112} \right)^{\frac{1}{1+1}} + \\
 &\quad \left( 8 \cdot \frac{0.1534 \cdot (1 + 0.130)}{0.2018 \cdot (1 + 0.155) + 0.1534 \cdot (1 + 0.130) + 0.1541 \cdot (1 + 0.295) + \dots + 0.156 \cdot (1 + 0.106)} \right)^{0.118} \right)^{\frac{1}{1+1}} \\
 &\quad + \dots + \\
 &\quad \left( 8 \cdot \frac{0.156 \cdot (1 + 0.106)}{0.2018 \cdot (1 + 0.155) + 0.1534 \cdot (1 + 0.130) + 0.1541 \cdot (1 + 0.295) + \dots + 0.156 \cdot (1 + 0.106)} \right)^{0.132} \right)^{\frac{1}{1+1}} + \\
 &\quad \left( 8 \cdot \frac{0.156 \cdot (1 + 0.106)}{0.2018 \cdot (1 + 0.155) + 0.1534 \cdot (1 + 0.130) + 0.1541 \cdot (1 + 0.295) + \dots + 0.156 \cdot (1 + 0.106)} \right)^{0.132} \right)^{\frac{1}{1+1}} \\
 &= 0.820
 \end{aligned}$$

Similarly, the Power Heronian weighted functions of the remaining alternatives were obtained.

(2) Then, by applying expressions (6) and (7), we get the utility degrees of alternative A1 (Austria) in relation to IA and AIA:

$$\begin{aligned}
 \mathfrak{S}_1^- &= \frac{PHWF_1^{\varpi_1, \varpi_2}}{PHWF_{AIA}^{\varpi_1, \varpi_2}} = \frac{0.820}{0.598} = 1.371; \\
 \mathfrak{S}_1^+ &= \frac{PHWF_1^{\varpi_1, \varpi_2}}{PHWF_{IA}^{\varpi_1, \varpi_2}} = \frac{0.820}{1.008} = 0.813.
 \end{aligned}$$

Steps 5 and 6 The ranking of alternatives is done based on the utility function, expression (9). The utility functions of the alternatives are shown in Table 10.

The alternative should have the highest possible value of the utility function  $\mathfrak{S}_i$ . Based on the obtained values  $\mathfrak{S}_i$ , the ranking of alternatives within the cluster was performed.

In order to calculate the initial results using the Power Heronian MARCOS methodology, it is necessary to define two stabilization parameters  $\varpi_1, \varpi_2 \geq 0$ ;  $\varpi_1, \varpi_2 \in \mathfrak{R}$ , where  $\mathfrak{R}$  represent a set of real numbers. For the calculation of the initial results, the values of the parameters  $\varpi_1 = \varpi_2 = 1$  were adopted. It is observed that the change in the values of the parameters  $\varpi_1$  and  $\varpi_2$  affects the mathematical transformation of expression (8). From this, we can assume that the change of the parameters and can also affect the change of the initial results. Therefore, in the following section, the dependence of the obtained results (Table 10) on the parameters' values ( $\varpi_1$  and  $\varpi_2$ ) is analyzed. Through the experiment, which is presented in the next part, the change of parameter values in the interval  $1 \leq \varpi_1, \varpi_2 \leq 100$  was simulated. Figure 5 shows the effect of changing the parameters  $\varpi_1$  and  $\varpi_2$  on the change of the utility function  $\mathfrak{S}_i$  alternative A1 (Croatia) in cluster 2.

Figure 5 indicates a significant dependence of the utility function  $\mathfrak{S}_i$  on the values of the parameters  $\varpi_1$  and  $\varpi_2$ . A similar dependence exists for the utility function of the remaining alternatives in all three considered clusters. Changing the parameters  $\varpi_1$  and  $\varpi_2$  through 100 scenarios simulates an increase in uncertainty and risk in information when making a decision. Thus, the initial scenario in which the value of

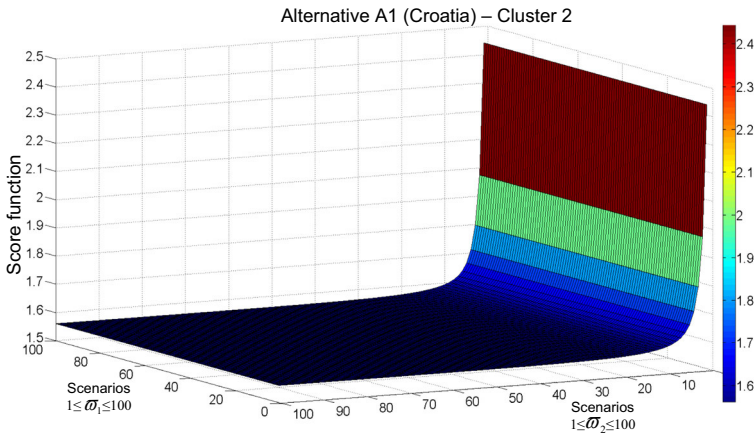
**Table 10** The utility functions and ranking of the alternatives

Country		Rank
<i>Cluster 1</i>		
Austria	0.666	8
Belgium	0.631	10
Cyprus	0.573	18
Czechia	0.679	6
Denmark	0.687	4
Estonia	0.575	16
Finland	0.701	2
France	0.606	13
Germany	0.660	9
Hungary	0.572	19
Ireland	0.692	3
Luxembourg	0.626	11
Malta	0.603	14
Netherlands	0.743	1
Poland	0.574	17
Portugal	0.577	15
Slovakia	0.610	12
Slovenia	0.673	7
Sweden	0.679	5
<i>Cluster 2</i>		
Croatia	0.701	1
Greece	0.649	3
Italy	0.606	4
Spain	0.678	2
<i>Cluster 3</i>		
Bulgaria	0.612	4
Latvia	0.713	1
Lithuania	0.712	2
Romania	0.623	3

$\varpi_1 = \varpi_2 = 1$  is adopted represents an optimistic scenario, while the scenario in which the value of  $\varpi_1 = \varpi_2 = 100$  is adopted represents a pessimistic scenario. Figure 6 shows the impact of changing the parameters  $\varpi_1$  and  $\varpi_2$  changing the utility function of alternatives in all three clusters.

Figure 6a-c shows the change in the utility functions of the alternatives in clusters 1, 2, and 3. Figure 6a shows that the scenarios show significant changes in the utility functions of the alternatives within cluster 1. However, the utility functions of the three first-ranked alternatives retained their dominance over the considered set of alternatives within cluster 1. Through the considered 100 scenarios, the initial rank of the first three alternatives was retained as follows Netherlands > Finland > Ireland. Also,





**Fig. 5** Dependence of utility function of alternatives A1 (Croatia) on parameters  $w_1$  and  $w_2$  change

the worst four alternatives within cluster 1 did not change rankings through the scenarios, i.e., it was confirmed that Hungary, Cyprus, Poland, and Estonia are the worst alternatives in cluster 1. The remaining alternatives change rankings through scenarios; however, these changes are not drastic, as confirmed by Spearman's correlation coefficient (SCC). SCC was used to determine the statistical correlation between the initial solution and the solutions obtained through the scenarios. The average value of SCC through scenarios is 0.864, which indicates a high correlation between the obtained solution and the obtained solutions through scenarios.

Figures 6b and c simulate the change in utility functions of alternatives in clusters 2 and 3, respectively. The results show that for cluster 2, the initial rank was confirmed through all scenarios. In cluster 3 (Fig. 6c), the initial rank of the two first-ranked alternatives (Latvia and Lithuania) was confirmed. For the values of parameters  $1 \leq w_1, w_2 \leq 13$ , the initial rank of the third-ranked and fourth-ranked alternative (Romania and Bulgaria) was confirmed, while for the values of parameters  $14 \leq w_1, w_2 \leq 100$ , the third-ranked and fourth-ranked alternatives replaced their places. The results from Fig. 6 indicate that the value of  $w_1$  and  $w_2$  should not be small, so it is recommended to recommend the value  $4 \leq w_1, w_2 \leq 8$  to obtain effective results. The presented experiment showed that the range of dominant alternatives was confirmed through the considered scenarios and that the initial solution was credible.

## 7 Comparison of the power heronian MARCOS model with other MCDM models

The following section compares the Power Heronian MARCOS model with other MCDM techniques to validate the obtained results. Numerous studies (Pamucar and Cirovic 2015; Zolfani et al. 2020; Pamucar 2020; Ali et al. 2021) indicate that normalization techniques can lead to distortion results. Therefore, in this study, multi-criteria techniques were used, which use linear normalization (like MARCOS methodology)

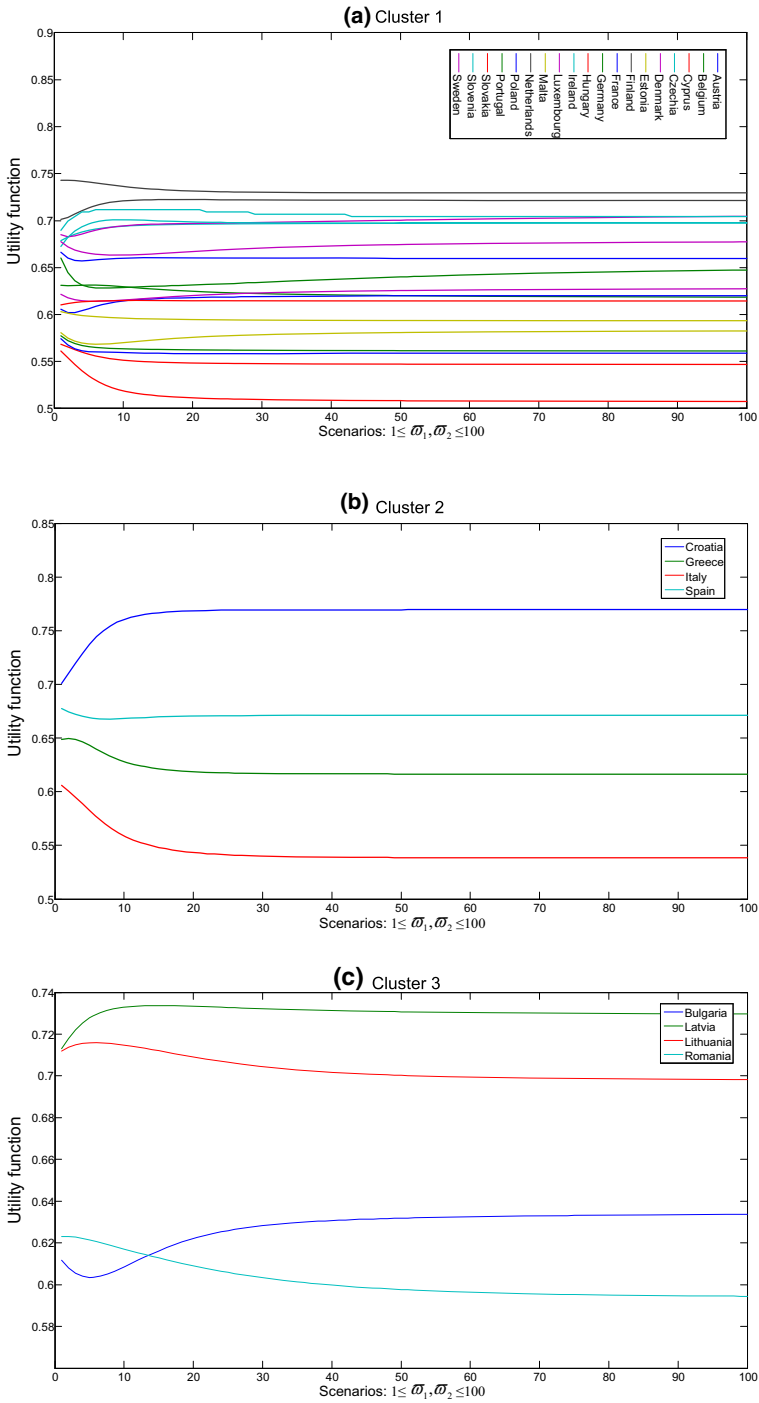


Fig. 6 Dependence of utility function alternatives on parameter  $\varpi_1$  and  $\varpi_2$  changes

to standardize the elements of the initial decision matrix. The following multi-criteria models were chosen for comparison: conventional MARCOS method (Stevic et al. 2020), MABAC (Multi-Attributive Border Approximation Area Comparison) method (Pamucar 2015), and WASPAS (Weighted Aggregated Sum Product Assessment) method (Zavadskas et al. 2012). Table 11 shows the results of the application of these multi-criteria techniques.

Based on the results from Table 11, we can initially conclude that all multi-criteria techniques propose an identical rank in clusters 2 and 3. In cluster 1, there were minor

**Table 11** Ranks of alternatives based on different MCDM techniques

Alternative	PH-MARCOS	MARCOS	MABAC	WASPAS
<i>Cluster 1</i>				
Austria	8	8	8	8
Belgium	10	10	10	10
Cyprus	18	17	17	19
Czechia	6	6	6	6
Denmark	4	3	3	4
Estonia	16	16	16	17
Finland	2	2	2	2
France	13	13	13	13
Germany	9	9	9	9
Hungary	19	15	15	18
Ireland	3	4	4	3
Luxembourg	11	11	11	11
Malta	14	14	14	14
Netherlands	1	1	1	1
Poland	17	18	18	16
Portugal	15	19	19	15
Slovakia	12	12	12	12
Slovenia	7	7	7	7
Sweden	5	5	5	5
<i>Cluster 2</i>				
Croatia	1	1	1	1
Greece	3	3	3	3
Italy	4	4	4	4
Spain	2	2	2	2
<i>Cluster 3</i>				
Bulgaria	4	4	4	4
Latvia	1	1	1	1
Lithuania	2	2	2	2
Romania	3	3	3	3

**Table 12** Statistical correlation between applied multi-criteria cluster techniques 1

	PH-MARCOS	MARCOS	MABAC	WASPAS
SCC	1.000	0.968	0.968	0.996

differences in the ranks of the considered multi-criteria methods. Such deviations in ranks are expected since it is a large set of alternatives, and the differences between the individual criterion functions of the alternatives are minimal. Spearman's coefficient shows a high correlation between the presented results, which is confirmed by the values from Table 12.

The values of Spearman's coefficient indicate negligible differences in ranks between multi-criteria techniques, so we can conclude that alternative 14 (Netherlands) is the best solution in cluster 1. To see the characteristics of applied multi-criteria techniques, Table 13 compares them through seven defined criteria.

**Table 13** Comparisons of different methods

Characteristics	PH MARCOS (proposed)	MARCOS (Stevic et al. 2020)	MABAC (Pamucar and Cirovic 2015)	WASPAS (Zavadskas et al. 2012)
Flexible decision making due to decision makers' risk attitude	Yes	No	No	No
Allows input parameters supporting each other	Yes	No	No	No
Eliminates the influence of extreme values from the decision-making matrix	Yes	No	No	No
Characteristics of functions for defining weighted sequences	Nonlinear form	Linear form	Linear form	Linear form
Ability to process complex information	Yes	No	No	No
Clearly defined range of alternatives	Yes	Yes	Yes	Yes
Algorithm complexity	Partially	No	No	No

The results show that the Power Heronian MARCOS methodology is a powerful tool for rational and objective decision-making. Based on the results presented in the previous section, it is evident that all applied multi-criteria techniques suggest similar solutions, i.e., that in cluster 1 it stands out as the dominant alternative 14 (Netherlands). On the other hand, in clusters 2 and 3, alternative 1 (Croatia) and alternative 2 (Latvia) stand out as the dominant alternatives, respectively. However, besides analysing prevalent solutions, it is necessary to single out other characteristics of the MCDM techniques used.

MARCOS, MABAC, and WASPAS methods for weighted averaging of matrix elements use the traditional linear weighted function. On the other hand, the PH-MARCOS model uses the nonlinear hybrid Power Heronian function to eliminate the influence of extreme values from the decision-making matrix. One of the consequences of applying different aggregation functions is reflected in their limited ability to rationally process extreme and unreasonable information in the initial decision matrix. The occurrence of extreme and unreasonable parameters in the decision matrix can result from an error in data entry, incorrect measurement, etc. Therefore, this characteristic of the aggregation function is extremely important. Processing such data using a conventional linear weighted function applied to MARCOS, MABAC and WASPAS methods can lead to distortions of the criterion functions of the alternatives. Namely, in some situations, a linear weighted function can cause a disproportionate increase in the utility functions of alternatives and lead to biased reasoning. The application of the hybrid Power Heronian function eliminates such anomalies, which objectifies the decision-making process. In addition to the above PH-MARCOS model enables flexible decision making due to decision-makers risk attitude, while MARCOS, MABAC, and WASPAS techniques do not have this ability.

## 8 Managerial insights and practical implication

The utility of proposed decision-making tool is evident but acceptance by management could be a concern. Most of managers and decision makers will find acceptance in tools and models that can be easily understood. The proposed MCDM framework may not readily fall into the easily understood category. This situation is true for most mathematically complex approaches. The utilization of this tool as part of the toolset of a decision support system will make it more acceptable to management. This tool will be more acceptable to managers who have to deal with greater magnitudes of uncertainties and imprecision in circular economy. At this time, tables for ranking scheme are provided, but graphical representation of the cluster relations may enhance managerial acceptance.

The methodology's flexibility in selection and weighting of performance measures to be used is also valuable. This flexibility will allow management to perform sensitivity analyses at many levels and thus obtain more robust and relevant solutions. This technique can also provide strategic guidance for decision making in EU countries. The methodology helps decision makers and politicians to select the most appropriate set of measures for achieving the strategic goals.

The EU adopted a Circular Economy action plan to facilitate the transition to the CE, with the intention of establishing new employment, fostering sustainable economic development, protecting the environment and increasing the EU's economic competitiveness (European Commission 2015). Actually, the CE model is closely linked to social enterprise activities in the EU to benefit society, business, and environment (Robinson 2021). The joint advantages of supporting the green transition and inclusivity, particularly under the European Action Plan, will further leverage potential of the social business activity, which is a pioneer in employment creation related to the circular economy (European Commission 2015). Furthermore, CE's social effect is linked to topics like "gender equalities," "decent work and economic growth," "reduced inequalities," increased service quality, and so on (Social Circular Economy 2018). In this paper, social indicators such as poverty risk, income distribution, uneducated and untrained young people, employment rate, life expectancy, corruption rate and employment rate among young people were analyzed within the framework of the CE strategies in EU. These social indicators allow assessing the degree of transition achieved by the EU countries in the implementation of circular economy. This case study helps managers and policy makers understand whether the social effect of the CE is proceeding as planned or adjustments are necessary.

## 9 Conclusions

The paradigm of a CE is promoted as a sustainable approach to the predominant linear economic model in the context of resource shortages and global warming. While the environmental and economic aspects have been received much attention, the social implications of CE are still lacking studies by practitioners and scholars. This paper presented a combination of clustering and decision making models to investigate the social development levels of EU countries in the framework of the CE. In this study, poverty risk, income distribution, uneducated and untrained young people, employment rate, life expectancy, corruption rate and employment rate among young people were identified as the important social indicators within the scope of the CE. EU countries have a significant differences in terms of social development levels. EU countries are classified according to their similar social development levels within the CE idea using the k means clustering method, which is one of the most prominent classification algorithms in machine learning approaches. Then, weight coefficients of indicators obtained from MEREC and CRITIC methods were integrated with the help of an aggregation operator thereby reducing the potential bias of a single objective weight. In the last step, the extended MARCOS method powered by the Power Heronian function was applied to each cluster individually to identify the ranks of EU countries.

Thus, the main results of this study are as follows:

1. This paper is the introduction of the k-means cluster based MCDM framework that provides objective evaluation. The present methodology enables the flexible evaluation of alternative solutions despite dilemmas in the decision-making process.

2. Clustering analysis results show that EU countries are divided into 3 different clusters in terms of their similarity rates. Thus, it was ensured that countries with homogeneous characteristics are evaluated together.
3. Findings of the case study demonstrated that “the risk of poverty rate” and “young people neither in employment nor education and training” are the most prominent criteria for determining the social level of the countries for each cluster, respectively. Further, it is evident that all applied MCDM methods suggest similar solutions for all clusters. The Netherlands, Croatia, and Latvia are the best alternatives in clusters 1, 2 and 3, respectively.
4. The proposed methodology is an effort to ensure a reliable decision support system to evaluate the social capability of countries in terms of CE. The outcomes of the case study can give policymakers and authorities an idea of how to improve social level within the CE considering weaknesses of EU countries. Put it differently, social capabilities can be increased by focusing on the weaknesses of these countries.

The proposed methods with its empirical study has also some limitations. Firstly, two different objective weighting methods such MEREC and CRITIC were used to determine the relative importance weights. However, objective evaluation methods were not used in the criteria weighting in this study. Therefore, it is possible to develop an integrated subjective–objective methodology to obtain the importance weights of the criteria. Additionally, future studies relates to the merging of uncertainty theory, such as fuzzy sets and rough sets, grey numbers, as well as the integration of subjective–objective models. Second limitation is that the interrelationship among criteria is not considered in this proposed model. Therefore, the relative importance weights and their influence on each criterion can be obtained from the integrated subjective methods to make up for the equal weighting assumption. Another limitation of this study, only silhouette index was used to determine the optimal number of clusters in the k-average method. On the other hand, different clustering technique such as Elbow, Gap statistics could be used in determining the number of clusters. In further study, using hybrid or innovative clustering algorithms, the clustering efficiency can be accelerated to perform better than suggested and current clustering schemes. In addition, further research should be directed towards considering the possibility of applying Einstein and Hamacher norms in the Power Heronian MARCOS model. An interesting direction for further research is the implementation of rough sets in combination with D numbers in order to address uncertainties in group models for decision making and their application in the field of medical waste treatment (Lotfi et al. 2021a), supply chain management (Lotfi et al. 2021b, c, d).

## 10 Appendix A1

### 10.1 Proof for Theorem 1

The expression (2) is divided into segments to the gradual derivation of the expression (8).

From the expression (2) and (3) can be obtained:

$$nw_i \psi_i = n \frac{n \widehat{w}_i w_i}{\sum_{t=1}^n \widehat{w}_t w_t} \psi_i \text{ respectively } nw_j \psi_j = n \frac{n \widehat{w}_j w_j}{\sum_{t=1}^n \widehat{w}_t w_t} \psi_j;$$

Further, can be obtained.

$$(nw_i \psi_i)^{\varpi_1} \cdot (n \psi_j)^{\varpi_2} = \left( n \frac{n \widehat{w}_i w_i}{\sum_{t=1}^n \widehat{w}_t w_t} \psi_i \right)^{\varpi_1} \cdot \left( n \frac{n \widehat{w}_j w_j}{\sum_{t=1}^n \widehat{w}_t w_t} \psi_j \right)^{\varpi_2};$$

Respectively, it is obtained.

$$\begin{aligned} & \frac{2}{n(n+1)} \sum_{x=1}^n (nw_i \psi_i^{(x)})^{\varpi_1} \sum_{y=x}^n (nw_j \psi_j^{(y)})^{\varpi_2} \\ &= \frac{2}{n(n+1)} \sum_{x=1}^n \left( n \frac{n \widehat{w}_i w_i}{\sum_{t=1}^n \widehat{w}_t w_t} \psi_i^{(x)} \right)^{\varpi_1} \sum_{y=x}^n \left( n \frac{n \widehat{w}_j w_j}{\sum_{t=1}^n \widehat{w}_t w_t} \psi_j^{(y)} \right)^{\varpi_2}; \end{aligned}$$

Finally, it is obtained the expression for weight rough Power Heronian operator ( $PHWF_i^{\varpi_1, \varpi_2}$ ):

$$\begin{aligned} & PHWF_i^{\varpi_1, \varpi_2} \\ &= \left( \frac{2}{n(n+1)} \sum_{x=1}^n \left( n \frac{n \widehat{w}_i w_i}{\sum_{t=1}^n \widehat{w}_t w_t} \psi_i^{(x)} \right)^{\varpi_1} \sum_{y=x}^n \left( n \frac{n \widehat{w}_j w_j}{\sum_{t=1}^n \widehat{w}_t w_t} \psi_j^{(y)} \right)^{\varpi_2} \right)^{\frac{1}{\varpi_1 + \varpi_2}} \end{aligned}$$

### Appendix A2

Decision matrix.

Country/Criterion	C1	C2	C3	C4	C5	C6	C7	C8
	min	min	min	max	max	max	max	max
Austria	13.3	4.17	9.5	78.3	89	81.8	77	37.7
Belgium	14.8	3.61	12	71.8	83.5	81.7	75	33.6
Bulgaria	22.6	8.10	18.1	75	80.7	75	43	34
Croatia	18.3	4.76	14.6	66.8	75.8	78.2	47	32.6
Cyprus	14.7	4.58	15.3	75.8	81.7	82.9	58	37.4
Czechia	10.1	3.34	11	80.2	87.3	79.1	56	36.3
Denmark	12.5	4.09	10.2	79.4	85.1	81	87	40.1
Estonia	21.7	5.08	11.2	81.2	83.3	78.5	74	39.1
Finland	11.6	3.69	10.3	77.9	84.4	81.8	86	38.9
France	13.6	4.27	14	79	75.7	82.8	69	35.4
Germany	14.8	4.89	8.6	82.7	92.7	81	80	39.1
Greece	17.9	5.11	18.7	61.5	59.4	81.9	48	33.2
Hungary	12.3	4.23	14.7	75.3	85.6	76.2	44	34.5
Ireland	13.1	4.03	7	75	84.5	82.2	74	37.5



Country/Criterion	C1	C2	C3	C4	C5	C6	C7	C8
	min	min	min	max	max	max	max	max
Italy	20.1	6.01	23.3	63.4	58.7	83.4	53	32
Latvia	22.9	6.54	11.9	78.6	84.1	75.1	56	37
Lithuania	20.6	6.44	13	78.2	80.1	76	60	37.2
Luxembourg	17.5	5.34	7.7	70.1	89.4	82.3	80	33.9
Malta	17.1	4.18	9.4	76.1	93.4	82.5	54	36.3
Netherlands	13.2	3.94	5.7	81	91.9	81.9	82	41
Poland	15.4	4.37	12.9	73	84	77.7	58	33.6
Portugal	17.2	5.16	11	76.2	80.3	81.5	62	38.3
Romania	23.8	7.08	16.6	70.9	76.1	75.3	44	33.8
Slovakia	11.9	3.34	15.2	73.4	83.9	77.4	50	34.2
Slovenia	12	3.39	9.2	76.6	86	81.5	60	35.9
Spain	20.7	5.94	17.3	68.7	73	83.5	62	35.4
Sweden	17.1	4.33	7.2	84.5	87.9	82.6	85	42

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## Declarations

**Competing interest** The authors declare no conflict of interest.

## References

- Abdel-Basset M, Mohamed R (2020) A novel Plithogenic TOPSIS-CRITIC model for sustainable supply chain risk management. *J Clean Prod* 247:119586
- Ali Z, Mahmood T, Ullah K, Khan Q (2021) Einstein geometric aggregation operators using a novel complex interval-valued pythagorean fuzzy setting with application in green supplier chain management. *Rep Mech Eng* 2(1):105–134
- Alliance G (2015) The social benefits of a circular economy: lessons from the UK. Green Alliance, London
- Arsu T, Ayçin E (2021) Evaluation of OECD countries with multi-criteria decision-making methods in terms of economic, social and environmental aspects. *Oper Res Eng Sci Theory Appl* 4(2):55–78
- Ayçin E (2020) Using CRITIC and MAIRCA methods in personnel selection process. *Bus J* 1(1):1–12
- Aytaç E (2020) Unsupervised learning approach in defining the similarity of catchments: hydrological response unit-based k-means clustering, a demonstration on Western Black Sea Region of Turkey. *Int Soil Water Conserv Res* 8:321–331. <https://doi.org/10.1016/j.iswcr.2020.05.002>
- Badi I, Pamucar D (2020) Supplier selection for steelmaking company by using combined Grey-MARCOS methods. *Decis Mak Appl Manag Eng* 3(2):37–48
- Bain KK, Firlı I, Tri S (2016) Genetic algorithm for optimized initial centers K-means clustering in SMEs. *J Theoret Appl Inf Technol (JATIT)* 90:23
- Bakır M, Akan Ş, Özdemir E (2021) Regional aircraft selection with fuzzy PIPRECIA and fuzzy MARCOS: A case study of the turkish airline industry. *Facta Universitatis Ser Mech Eng* 19(3):423–445
- Chakraborty S, Chattopadhyay R, Chakraborty S (2020) An integrated D-MARCOS method for supplier selection in an iron and steel industry. *Decis Mak Appl Manag Eng* 3(2):49–69
- Della Spina L (2019) Multidimensional assessment for “culture-led” and “community-driven” urban regeneration as driver for trigger economic vitality in urban historic centers. *Sustainability* 11(24):7237

- Diakoulaki D, Mavrotas G, Papayannakis L (1995) Determining objective weights in multiple criteria problems: The critic method. *Comput Oper Res* 22(7):763–770
- Djordjevic D, Stojic G, Stevic Z, Pamucar D, Vulevic A, Mistic V (2019) A new model for defining the criteria of service quality in rail transport: the full consistency method based on a rough power heronian aggregator. *Symmetry* 11(8):992. <https://doi.org/10.3390/sym11080992>
- Ecer F, Pamucar D (2021) MARCOS technique under intuitionistic fuzzy environment for determining the COVID-19 pandemic performance of insurance companies in terms of healthcare services. *Appl Soft Comput* 104:107199. <https://doi.org/10.1016/j.asoc.2021.107199>
- European Commission (2015) Commission adopts ambitious new Circular Economy Package. [https://ec.europa.eu/commission/presscorner/detail/en/IP\\_15\\_6203](https://ec.europa.eu/commission/presscorner/detail/en/IP_15_6203)
- Eurostat (2021) <https://ec.europa.eu/eurostat/data/database>. Accessed 9.26.21
- Geissdoerfer M, Savaget P, Bocken NMP, Hultink EJ (2017) The circular economy – a new sustainability paradigm? *J Clean Prod* 143:757–768. <https://doi.org/10.1016/j.jclepro.2016.12.048>
- Ghisellini P, Cialani C, Ulgiati S (2016) A review on circular economy: the expected transition to a balanced interplay of environmental and economic systems. *J Clea Prod* 114:11–32. <https://doi.org/10.1016/j.jclepro.2015.09.007>
- Goswami SS, Mohanty SK, Behera DK (2021) Selection of a green renewable energy source in India with the help of MEREC integrated PIV MCDM tool. In: *Materials today: proceedings*.
- Hadi A (2022) Web application system to find best urban hospital location for COVID-19 patients based on internet of things. *Bull Electr Eng Inform* 11(1):386–395
- ILO (2015) Gender equality and green jobs, green jobs Programme, international labour organization). [https://www.ilo.org/wcmsp5/groups/public/---ed\\_emp/---emp\\_ent/documents/publication/wcms\\_360572.pdf](https://www.ilo.org/wcmsp5/groups/public/---ed_emp/---emp_ent/documents/publication/wcms_360572.pdf).
- Kayapinar Kaya S, Aycin E (2021) An integrated interval type 2 fuzzy AHP and COPRAS-G methodologies for supplier selection in the era of Industry 4.0. *Neural Comput Appl* 33:10515–10535. <https://doi.org/10.1007/s00521-021-05809-x>
- Keshavarz Ghorabae M, Amiri M, Kazimieras Zavadskas E, Antuchevičienė J (2017) Assessment of third-party logistics providers using a CRITIC–WASPAS approach with interval type-2 fuzzy sets. *Transport* 32(1):66–78. <https://doi.org/10.3846/16484142.2017.1282381>
- Keshavarz Ghorabae M, Amiri M, Zavadskas EK, Antucheviciene J (2018) A new hybrid fuzzy MCDM approach for evaluation of construction equipment with sustainability considerations. *Arch Civil Mech Eng* 18:32–49. <https://doi.org/10.1016/j.acme.2017.04.011>
- Keshavarz-Ghorabae M (2021) Assessment of distribution center locations using a multi-expert subjective objective decision-making approach. *Sci Rep*. <https://doi.org/10.1038/s41598-021-98698-y>
- Korhonen J, Honkasalo A, Seppälä J (2018) Circular economy: the concept and its limitations. *Ecol Econ* 143:37–46
- Kou G, Peng Y, Wang G (2014) Evaluation of clustering algorithms for financial risk analysis using MCDM methods. *Inf Sci* 275:1–12
- Ljubljana BL (2021) University of, 2021. Data mining. <https://orangedatamining.com/>
- Lleti R, Ortiz MC, Sarabia LA, Sánchez MS (2004) Selecting variables for k-means cluster analysis by using a genetic algorithm that optimises the silhouettes. *Anal Chim Acta* 515(1):87–100
- Lotfi R, Kargar B, Gharehbaghi A, Weber GW (2021a) Viable medical waste chain network design by considering risk and robustness. *Environ Sci Pollut Res* 1–16
- Lotfi R, Kargar B, Hoseini SH, Nazari S, Safavi S, Weber GW, Lotfi R, Kargar B, Hoseini SH, Nazari S, Safavi S, Weber GW (2021b) Resilience and sustainable supply chain network design by considering renewable energy. *Int J Energy Res* 45(12):17749–17766
- Lotfi R, Mostafaeipour A, Mardani N, Mardani S (2018) Investigation of wind farm location planning by considering budget constraints. *Int J Sustain Energ* 37(8):799–817
- Lotfi R, Safavi S, Gharehbaghi A, Ghaboulia Zare S, Hazrati R, Weber GW (2021c) Viable supply chain network design by considering blockchain technology and cryptocurrency. *Math Prob Eng*. <https://doi.org/10.1155/2021/7347389>
- Lotfi R, Sheikhi Z, Amra M, AliBakhshi M, Weber GW (2021b) Robust optimization of risk-aware, resilient and sustainable closed-loop supply chain network design with Lagrange relaxation and fix-and-optimize. *Int J Logist Res Appl* pp 1–41
- MacQueen J (1967) Some methods for classification and analysis of multivariate observations. In: *Proceedings of the fifth Berkeley symposium on mathematical statistics and probability*. Oakland, CA, USA, 281–297

- Milosevic T, Pamucar D, Chatterjee P (2021) Model for selecting a route for the transport of hazardous materials using a fuzzy logic system. *Military Tech Courier* 69(2):355–390
- Milovanovic VR, Aleksic AV, Sokolovic VS, Milenkovic MA (2021) Uncertainty modeling using intuitionistic fuzzy numbers. *Military Tech Courier* 69(4):905–929
- Mukhamezzyanov I (2021) Specific character of objective methods for determining weights of criteria in MCDM problems: entropy, CRITIC and SD. *Decis Mak Appl Manag Eng* 4(2):76–105
- Murray A, Skene K, Haynes K (2017) The circular economy: an interdisciplinary exploration of the concept and application in a global context. *J Bus Ethics* 140(3):369–380
- Nikonorova M, Imoniana JO, Stankeviciene J (2020) Analysis of social dimension and well-being in the context of circular economy. *Int J Glob Warm* 21:299–316. <https://doi.org/10.1504/IJGW.2020.108678>
- Orhan M, Aytekin M (2020) Comparing The R&D performance of turkey and last members countries of EU using critic weighted maut and saw methods. *Bus Manag Stud Int J* 8(1):754–778
- Özdağoğlu A, Keleş MK, Işıldak B (2021a) Cabin crew selection in civil aviation with fuzzy SWARA and fuzzy MARCOS methods. *Gümüşhane Univ J Soc Sci Inst* 12(2):284–302
- Özdağoğlu A, Keleş MK, Işıldak B (2021b) Evaluation of the world's busiest airports with Piprecia-E, smart and marcos methods. *Erciyes Univ J Fac Econ Admin Sci* 58:333–352
- Padilla-Rivera A, do Carmo, B.B.T., Arcese, G., Merveille, N., (2021) Social circular economy indicators: selection through fuzzy delphi method. *Sustain Prod Consump* 26:101–110
- Padilla-Rivera A, Russo-Garrido S, Merveille N (2020) Addressing the social aspects of a circular economy: a systematic literature review. *Sustainability* 12:7912
- Pamucar D (2020) Normalized weighted geometric Dombi Bonferroni mean operator with interval grey numbers: application in multicriteria decision making. *Rep Mech Eng* 1(1):44–52
- Panchal D, Chatterjee P, Sharma R, Garg RK (2021) Sustainable oil selection for cleaner production in Indian foundry industries: A three phase integrated decision-making framework. *J Cleaner Prod* 313:127827
- Peng X, Krishankumar R, Ravichandran KS (2021) A novel interval-valued fuzzy soft decision-making method based on CoCoSo and CRITIC for intelligent healthcare management evaluation. *Soft Comput* 25(6):4213–4241
- Pitkänen K, Karppinen TKM, Kautto P, Turunen S, Judl J, Myllymaa T (2020) Sex, drugs and the circular economy: the social impacts of the circular economy and how to measure them. *Handb Circ Econ*
- Puška A, Stojanović I, Maksimović A, Osmanović N (2020) Evaluation software of project management used measurement of alternatives and ranking according to compromise solution (MARCOS) method. *Oper Res Eng Sci Theory Appl* 3(1):89–102
- Rani P, Mishra AR, Saha A, Hezam IM, Pamucar D (2021) Fermatean fuzzy Heronian mean operators and MEREC-based additive ratio assessment method: an application to food waste treatment technology selection. *Int J Intell Syst* 37(3):2612–2647. <https://doi.org/10.1002/int.22787>
- Robinson S (2021) Social circular economy. [http://www.socialcirculareconomy.com/uploads/7/3/5/2/73522419/social\\_circular\\_economy.pdf](http://www.socialcirculareconomy.com/uploads/7/3/5/2/73522419/social_circular_economy.pdf)
- Rousseuw PJ (1987) Silhouettes: a graphical aid to the interpretation and validation of cluster analysis. *J Comput Appl Math* 20:53–65. [https://doi.org/10.1016/0377-0427\(87\)90125-7](https://doi.org/10.1016/0377-0427(87)90125-7)
- Sabaghian K, Khamforoosh K, Ghaderzadeh A (2021) Presentation of a new method based on modern multivariate approaches for big data replication in distributed environments. *PLoS ONE* 16(7):e0254210. <https://doi.org/10.1371/journal.pone.0254210>
- Schroeder P, Anggraeni K, Weber U (2019) The relevance of circular economy practices to the sustainable development goals. *J Ind Ecol* 23:77–95. <https://doi.org/10.1111/jiec.12732>
- Simic V, Gokasar I, Deveci M, Karakurt A (2021) An integrated CRITIC and MABAC based Type-2 neutrosophic model for public transportation pricing system selection. *Soc Econ Plann Sci*, 101157
- Skvarciany V, Lapinskaitė I, Volskytė G (2021) Circular economy as assistance for sustainable development in OECD countries. *Oeconomia Copernicana* 12(1):11–34
- Social Circular Economy (2018) The frank Jackson foundation. <https://circulareconomy.europa.eu/platform/en/knowledge/social-circular-economy-opportunities-people-planet-and-profit>
- Stević Ž, Pamučar D, Puška A, Chatterjee P (2020) Sustainable supplier selection in healthcare industries using a new MCDM method: measurement of alternatives and ranking according to COMPromise solution (MARCOS). *Comput Ind Eng* 140:106231. <https://doi.org/10.1016/j.cie.2019.106231>
- Tinsley HE, Brown SD (2000) Handbook of applied multivariate statistics and mathematical modeling. Academic Press, Cambridge
- Trung DD, Thinh HX (2021) A multi-criteria decision-making in turning process using the MAIRCA, EAMR, MARCOS and TOPSIS methods: a comparative study. *Adv Prod Eng Manag* 16(4):443–456

- Ulutaş A, Karabasevic D, Popovic G, Stanujkic D, Nguyen PT, Karaköy Ç (2020) Development of a novel integrated CCSD-ITARA-MARCOS decision-making approach for stackers selection in a logistics system. *Mathematics* 8(10):1672
- Vujičić MD, Papić MZ, Blagojević MD (2017) Comparative analysis of objective techniques for criteria weighing in two MCDM methods on example of an air conditioner selection. *Tehnika* 72(3):422–429. <https://doi.org/10.5937/tehnika1703422V>
- Walker AM, Opferkuch K, Roos Lindgreen E, Simboli A, Vermeulen WJV, Raggi A (2021) Assessing the social sustainability of circular economy practices: industry perspectives from Italy and the Netherlands. *Sustain Prod Consump* 27:831–844. <https://doi.org/10.1016/j.spc.2021.01.030>
- Wang F, Franco-Penya HH, Kelleher JD, Pugh J, Ross R (2017) An analysis of the application of simplified silhouette to the evaluation of k-means clustering validity. In: International conference on machine learning and data mining in pattern recognition, Springer, Cham, pp 291–305
- Wang Q, Wang C, Feng Z, Ye J (2012) Review of K-means clustering algorithm. *Electron Des Eng* 20:21–24
- Wei G, Lei F, Lin R, Wang R, Wei Y, Wu J, Wei C (2020) Algorithms for probabilistic uncertain linguistic multiple attribute group decision making based on the GRA and CRITIC method: application to location planning of electric vehicle charging stations. *Econ Res-Ekonomika Istraživanja* 33(1):828–846
- WESO (2018) World employment and social outlook 2018: greening with jobs. [https://www.ilo.org/weso-greening/documents/WESO\\_Greening\\_EN\\_web2.pdf](https://www.ilo.org/weso-greening/documents/WESO_Greening_EN_web2.pdf).
- Yager RR (2001) The power average operator. *IEEE Trans Syst Man Cybernet Part Syst Hum* 31(6):724–731
- Yu D (2013) Intuitionistic fuzzy geometric Heronian mean aggregation operators. *Appl Soft Comput* 13:1235–1246. <https://doi.org/10.1109/3468.983429>
- Zavadskas EK, Turskis Z, Antucheviciene J, Zakarevicius A (2012) Optimization of weighted aggregated sum product assessment. *Elektronika Ir Elektrotechnika* 122(6):3–6. <https://doi.org/10.5755/fj01.eee.122.6.1810>
- Zhao H, Zhao H, Guo S (2017) Evaluating the comprehensive benefit of eco-industrial parks by employing multi criteria decision-making approach for circular economy. *J Clean Prod* 142:2262–2276
- Zhao S, Wang D, Liang C, Leng Y, Xu J (2019) Some Single-valued neutrosophic power heronian aggregation operators and their application to multiple-attribute group decision-making. *Symmetry* 11(5):653. <https://doi.org/10.3390/sym11050653>
- Zolfani SF, Yazdani M, Pamucar D, Zarate P (2020) A VIKOR and TOPSIS focused reanalysis of the MADM methods based on logarithmic normalization. *Facta Univ Ser Mech Eng* 18(3):341–355

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