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Research article

Assessment of national circular economy performance using super-efficiency dual data envelopment analysis and Malmquist productivity index: Case study of 27 European countries

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A B S T R A C T

The global commitment toward carbon neutrality and net zero emissions has substantially pressed the needs for all countries to accelerate the adoption of the circular economy paradigm. Tracking the national progress in terms of circular economy performance would provide valuable insights that could aid the effective design of improvement strategies toward sustainability. The current research proposes the combination of super-efficiency dual Data Envelopment Analysis and Malmquist productivity index to provide a full ranking and measure productivity changes in terms of circular economy of 27 European countries. The assessment involved six circular economy indicators encompassing waste generation per capita, waste intensity of the economy, recycling rate of waste in both overall and specific types of waste, i.e., packaging waste and biowaste, and circular material use rate. Our study indicates about one-half of the European countries were efficient in terms of circularity in 2018, where Netherlands, Germany, Austria, and Belgium were the front runner. The proposed approach suggests the European countries enhance their overall circular economy performance by prioritizing improvements strategies through promoting the recycling of biowaste and the circular material use rate. The MPI results over 2012–2018 indicate that Luxembourg exhibited the highest circularity advancement by 6%. Overall, the European countries have slightly enhanced their progression towards circular economy around 0.2% improvement. This suggests the European countries strengthen their policy and regulatory frameworks in support of the transition towards circular economy and encourage progressive movements in such a collaborative manner with the relevant stakeholders to build the momentum for change.

1. Introduction

The exponential growth of world population in contrast with the scarcity of non-renewable resources has led to a critical imbalance between production and consumption. Natural resources have been extensively exploited while tremendous amounts of waste have also been generated. Global waste generated annually has significantly increased from 635 million tonnes in 1965 to 2 billion tonnes in 2015 and is expected to reach at 3.5 billion tonnes by 2050 [1]. This gigantic amount of waste has caused detrimental environmental burdens to ecosystems, e.g., greenhouse gas emissions, air pollution, and plastic accumulation in water reservoirs. In light of this, there

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is an urgent need to develop methods or strategies that could foster active environmental and social responsibility along with the progressive development of economic perspective, which could finally lead to sustainability.

The "Circular Economy" paradigm has emerged as a potential and effective solution inaugurating the transition towards sustainable development. The concept has been proposed as a paradigm shift aiming at retaining the materials in the circularity of extraction, manufacturing, utilization, recycling, and reusing processes as long as possible [2]. This implies the implementation of closed-loop systems that create the unceasingly recycling process to minimize the resulting waste, while diminishing the exploitation of primary resources and utilizing the secondary raw materials instead [3]. This concept has received much attention among public, business sector, government, and especially in academic where recent extensive research has been explored [4,5]. The circular economy (CE) concept has considerable benefits that could promote economic gains while relieving environmental pressure; it, therefore, has been successfully implemented in various scales from organizational level through country or regional level.

The CE concept has been widely applied for the improvements in production/distribution as well as consumption section, which operate at three different spatial levels, i.e., micro level (e.g., companies, products, customers), meso level (e.g., industrial symbiosis) and macro level (e.g., city, region, country) [6]. Tracking the progress on how successful the CE paradigm has been implemented at the macro or national level necessarily requires a set of performance measures that thoroughly reflect their "circularity's evolution". There have been various national and intergovernmental initiatives attempting to measure and monitor the advancement of CE implementation [7–10]; nevertheless, no common measuring scheme arises [11–13]. This research, therefore, aims to utilize official CE indicators proposed by the European Commission, which are publicly available on the Eurostat website [14]. Our analysis particularly draws attention to the indicators that directly capture diverse aspects of materials circularity in the economy, including those relevant to raw materials and wastes, but excluding those measuring indirect effects regarding environmental and social aspects. We have included the most common CE indicators presented in the previous literature as summarized in Table 1, i.e., generation of municipal waste per capita, recycling rate of municipal waste and circular material uses rate. The assessment also aims to measure the performance regarding the management of specific wastes; therefore, the recycling rate of packaging waste and biowaste were also included. Lastly, the indicator of the generation of waste excluding major mineral wastes per GDP was incorporated to capture how the countries gain more economic growth while at the same time generating less waste [15].

The assessment of circularity performance at the national level often involves various indicators covering the key areas of circularity. Performing this task is, in practice, not straightforward due to the fact that it is rare to find such a single country performing well across the full range of indicators, as inherent trade-offs naturally arise. One of the potential tools that can consider multiple criteria simultaneously and gives in turn the quantitative score representing the performance of each assessed entity is called a multi-criteria decision-making (MCDM) tool. The use of MCDM tools for the efficiency assessment considering multiple circularity indicators has been prevalent among researchers as systematically reviewed by dos Santos Gonçalves and Campos (2022) [16] and Sassanelli et al. (2019) . However, most of the traditional MCDM techniques are derived from weighted sum basis that the decision-makers must subjectively define the weights expressing the relative importance of each criterion. This situation would be problematic and

Table 1
Comparison of DEA models along with the CE indicators and countries assessed of the previous studies and current study.

Publications	DEA model	Inputs	Outputs	Countries
Halkos and Petrou (2019)	DEA VRS CRS model	- Labor force - Investment - Population density - Waste	- GDP - NOx emissions - SOx emissions - GHG emissions	28 European Countries
Giannakitsidou et al. (2020)	DEA with weight restriction	- MSW generated - Basic human needs - Foundations of wellbeing opportunity	- Recycling rate of MSW - Circular material use rate	26 European Countries
Huang and Hu (2021)	Cooperative Game Network DEA	- Labor force - Capital - Energy consumption - Total wastes generated	- GDP per capita - Volume of recycled solid waste - Volume of backfill - Energy recovery	28 European Countries
Lacko et al. (2021)	DEA VRS CRS model	- Waste generated per capita - Gross capital formation	- Recycling rate of MSW - Circular material use rate	Visegrád Group countries
Temerbulatova et al. (2021)	DEA VRS CRS model	- Generation of municipal waste per capita - Water exploitation index - Final energy consumption - Social Progress Index	- Recycling rate of municipal waste - Circular material uses rate	27 European Countries
Current study	DEA Super-efficiency dual VRS with MPI	- Generation of municipal waste per capita - Generation of waste excluding major mineral wastes per GDP	- Recycling rate of municipal waste - Recycling rate of packaging waste - Recycling of biowaste per capita - Circular material uses rate	27 European Countries

controversial among different decision-makers since they might come up with different sets of weights which finally lead to the different analysis results.

Among the available MCDM tools, Data Envelopment Analysis (DEA) is a useful and distinct linear programming technique that offers an un-biased approach to quantify the efficiency of entities according to multiple criteria. In essence, DEA can avoid the subjectivity in the determination of weights attached to each indicator by optimizing them such that the assessed entity can achieve its greatest possible score as compared to the others. With its non-parametric nature, DEA does not require any assumptions on the production function as often the case in parametric techniques. In contrast, DEA creates the best-practice frontier or "Pareto frontier" and uses it as a benchmark for measuring the efficiency scores of the entities. The most fundamental model of DEA is called a CCR model [17]. A BCC or a dual model [18] is another DEA model that offers additional benefits over the CCR model in that it can suggest useful insights into how the inefficient DMUs can be improved and calculate quantitative performance targets for each indicator being assessed. Both models have been utilized by several researchers to determine the CE performance at the national level [19–21]. However, none of these publications addressed the insightful interpretations of the dual model through the identification of improvements for specific CE measures.

Despite its considerable benefits when applying to multi-criteria assessment problems, the traditional DEA model still has a limitation in that it cannot distinguish the differences among the efficient entities since their efficiency scores are given the same as unity. To obtain the full ranking of the European countries with respect to the environmental and CE performance, DEA with weight restriction model was proposed to impose common weights attached to each indicator [12]. However, this approach requires an articulation of preferential weights, thereby raising the question of common weights choice among different policy makers. Grey Relational Analysis is another technique proposed by the previous literature to construct the ranking of European countries with respect to CE performance [22]. Although this method can provide the full ranking of countries, it cannot suggest potential improvements of each CE indicator for individual countries. This research, therefore, proposes the super-efficiency dual DEA model that not only preserves the distinguishing feature of the dual DEA (i.e., capable of identifying quantitative targets and prioritizing the areas of improvements for individual entities), but also can provide the full ranking of entities based on the super-efficiency concept. In essence, the super-efficiency model differentiates the score of the efficient entities according to how superiority of such an entity behaves against the Pareto fronts, thereby giving score larger than one.

Furthermore, to investigate the dynamic development of CE performance, one potential tool is Malmquist Productivity Index (MPI), a time-series analysis technique that can measure productivity changes over time. MPI has several advantages over other time-series techniques such as Window analysis in that it can capture both technical efficiency (the efficiency of production processes) and technological changes (the adoption of new technologies). Moreover, its principle focuses on the production frontier representing the best performing units against which different units can be benchmarked. In light of this, MPI can be effectively facilitated by the super-efficiency dual DEA model to provide better discrimination of efficiency change among the efficient entities through the provision of distinguishable score given by the DEA. The integration of DEA and MPI has recently been employed to investigate countries' performance in terms of eco-efficiency changes [23], as well as energy and environmental changes [24]. However, its application to capture changes in the national CE performance still has been scarce.

This research, therefore, proposes to use the super-efficiency dual DEA model to benchmark and provide the full ranking of countries according to their circularity performance, and, for the ones found to be inefficient, identifying the indicators to be improved through the establishment of improvement targets that can be used to guide the transition efforts towards CE. The combination of the super-efficiency dual DEA model and MPI was explored to monitor the changes of national CE performance through time. The capability of the proposed approach was demonstrated through a circular economy assessment of 27 European countries according to six CE indicators, considering diverse perspectives of production and consumption, waste management, and circular materials aspects simultaneously. The rationale behind the selection of European countries as the case study is that they have adopted analogous rules, and regulations due to the legislation enforced by the European Union, thereby enabling their practices to be comparable.

The contribution of this research is threefold. First, to the best of our knowledge, this is the first paper proposes the integration of the super-efficiency dual DEA model in combination with MPI to measure and monitor the progress towards the national CE. Second, in addition to providing the full ranking of countries based upon their circularity performance which are the primary focus of the existing literatures, this paper has put special emphasis on the potential interpretation of using super-efficiency dual DEA model to highlight the source of inefficiency and establish the quantitative targets of each CE perspective for individual countries. Third, the performance measures chosen in this study also comprehensively capture different perspectives of circularity, particularly in terms of the level of waste generation, the recycling rate of waste in both overall and specific types of waste, and the use of secondary raw materials. This could allow the policy makers to extensively examine each aspect of circularity and provide breakdown details for performance improvements that are useful for further policy development. Our ultimate goal with this research is to emphasize the contribution of DEA as an alternative data analytics tool that could extract beneficial insights to enable appropriate data-driven decisions towards sustainable development.

The rest of the paper is constructed as follows. Section 2 describes the details of methods employed in this paper. Section 3 introduces the case study based on the CE assessment of European countries to express the capability of the proposed approach. In Section 4, the analysis results are put forward and discussed. Finally, the conclusions and key findings are drawn at the end of the paper.

2. Methods

This section provides detailed information regarding the relevant mathematical tools used in this study.

2.1. Fundamentals of DEA

Data Envelopment Analysis is a linear programming-based technique to measure the relative efficiency of the entities, also known as decision-making units (DMUs), according to various inputs and outputs. It makes use of the non-dominated front principle to establish the best-practice frontier from the given data, which represents the relationship between inputs and outputs. This frontier is then used as a benchmark against which the efficiency score of other entities is measured. In this sense, DEA is deliberately utilized as an MCDM tool for performance benchmarking considering a wide range of performance measures simultaneously, which are further categorized as inputs or outputs. Here, the inputs and outputs may not truly represent the resources and outcomes as is normally the case relating to the production theory. The inputs and outputs, however, are referred to the "less-the-better" and the "more-the-better" type of performance measures, respectively [25].

The DEA efficiency is originally determined from the ratio of weighted-sum outputs over weighted-sum inputs. The mathematical algorithm is calculated for each DMU while attempting to maximize its efficiency such that the efficiency of the other DMUs is restricted by unity. This is the original definition of the most fundamental DEA model, so-called a primal problem or CCR model. This model is formulated based on the concept of CRS which means that the ratio of the change in outputs to the change in inputs is constantly proportionate. The dual problem is another DEA model that is equivalent to the primal one but offers additional benefits in that it can suggest useful insights on how the inefficient DMUs can be improved by benchmarking against the best-practice frontier. The efficiency score obtained by solving the dual model are in the range between 0 and 1 where the highest score as of 1 implies that such DMUs are deemed efficient, while those with the score less than 1 are regarded as inefficient. However, giving an identical score of 1 for all efficient DMUs is one major limitation of the traditional DEA model.

2.2. Super-efficiency dual DEA model

The super-efficiency dual DEA model has emerged as one of potential tools capable of overcoming the aforementioned limitation of the conventional dual model as it can further differentiate the most efficient DMUs above all. The super-efficiency model was firstly introduced by Banker and Gifford (1988) [26], and Andersen and Petersen (1993) [27], where the model excludes the DMU under evaluation from the reference set. In essence, the model measures how superior the assessed DMU is against the Pareto frontier constructed from the remaining DMUs. The super-efficiency dual DEA model, however, might experience infeasibility when the assumption of VRS is made. The current study, therefore, chose a two-stage super-efficiency dual DEA model from Lee et al. (2011) [28] which can handle the infeasibility issues in the original super-efficiency dual VRS DEA model where the corresponding mathematical formulation is shown in Eq. (1) below.

$$\min_{\lambda_j, S_r} \sum_{r=1}^{s} s_r \tag{1}$$

$$\text{subjected to}: \sum_{j=1, j\neq o}^{n} \lambda_j y_{rj} + s_r y_{ro} \geq y_{ro} \; ; \forall r$$

$$\sum_{j=1}^{n} \lambda_j = 1$$

$$\lambda_j \geq 0, s_r \geq 0, r = 1, \ldots, s$$

Eq. (1) is calculated for individual DMU_o. Let a symbol '*' refers to the optimal decision variable obtained from the model. The optimal solutions (s_r^*) obtained by solving Eq. (1) will be further used in Eq. (2) as follows.

$$\min_{\lambda_j} \widehat{\theta}_o \tag{2}$$

$$\text{subjected to}: \sum_{j=1, j\neq o}^{n} \lambda_j x_{ij} \leq \widehat{\theta}_o x_{io} \; ; \forall i$$

$$\sum_{j=1, j\neq o}^{n} \lambda_j y_{rj} + s_r^* y_{ro} \geq y_{ro} \; ; \forall r$$

$$\sum_{j=1}^{n} \lambda_j = 1$$

$$\lambda_j \geq 0, i = 1, \ldots, m, r = 1, \ldots, s$$

where n is the number of DMUs involving in the assessment; o is an index for the assessed DMU for $o = 1, \ldots, n$; j is an index for other DMUs for $j = 1, \ldots, n$; m is the number of inputs consumed by DMU_j; x_{ij} is the amount of input i (for $i = 1, \ldots, m$) consumed by DMU_j; s is the number of outputs produced by DMU_j; and y_{rj} is the amount of output r (for $r = 1, \ldots, s$) produced by DMU_j. The variables obtained by solving the optimization problem in Model (2) are as follows: $\widehat{\theta}_o$ is the super-efficiency score of DMU_o; and λ_j is a linear weight attached to every single DMU_j (for $j = 1, \ldots, n$).

The final super-efficiency score (θ_o^{SE}) can then be computed by Eq. (3) following the associated conditions.

$$\theta_o^{SE} = \begin{cases} \dfrac{\sum_{r\in R}\left(\dfrac{y_{ro}}{y_{ro} - S_r^* y_{ro}}\right)}{|R|} + \widehat{\theta}_o^*, \, if \; R \neq \varnothing \\ \widehat{\theta}_o^*, \, if \; R = \varnothing \end{cases} \tag{3}$$

where $R = \{r | s_r^* > 0\}$ based on Model (1) and $|R|$ is the cardinality of the set R.

The super-efficiency score (θ_o^{SE}) of the efficient DMUs is always greater than or equal to 1 so that they can be discriminated for further analysis. The super-efficiency dual model is mathematically analogous to the conventional dual model, but one important condition that has been imposed is that the DMU being assessed must be excluded from the reference set that establishes the frontier. For the inefficient DMUs, the super-efficiency dual model will give identical efficiency results as the dual model. However, the super-efficiency dual model will give distinctive super-efficiency scores to each of the efficient DMUs so that they can be further differentiated and ranked.

In addition, the super-efficiency dual model can suggest the improvement pathway of every DMU deemed inefficient through its projection onto the Pareto frontier. Considering a single-input (X-axis) single-output (Y-axis) problem as shown in Fig. 1, the DMUs A, B, C and D are considered as efficient and form a Pareto frontier (A-B-C-D; the blue solid line). This production frontier has a piecewise linear characteristic imposed by the convexity constraints $\sum_{j=1}^{N} \lambda_j = 1$, which leads to a VRS assumption [29].

Each inefficient entity can be improved by moving towards the projected target on the frontier. The inefficient DMUs (E and F; the yellow circles) can become efficient by projecting a dashed line that is parallel to the X-axis onto the frontier. This approach of improving projection is called input-oriented which aims at minimizing inputs while retaining at least a certain level of outputs. The target point is contributed by the efficient DMU_j and the extent to which DMU_j have contributed is represented by their corresponding linear weights (λ_j^*) obtained by solving the model (2). For example, the improvement target of DMU *E* is essentially the projected point *e* which is formed by the linear combination between the efficient DMU *B* and *C* ($e = \lambda_B^* B + \lambda_C^* C$). The DMU *B* and *C* can be called an efficient peer group that is referenced by the DMU *E*. In a general term, the improvement target can be calculated by a summation of the multiplication between the raw data of the efficient DMUs and their corresponding linear weights obtained by solving the model. The improvement target for each input and output of any DMU_o is expressed as shown in the following Eq. (4).

$$T_{io}^* = \sum\nolimits_{j=1}^{n} \lambda_j^* x_{ij} \tag{4}$$

$$T_{ro}^* = \sum\nolimits_{j=1}^{n} \lambda_j^* y_{rj}$$

where T_{io}^* is a target of input *i* for DMU_o; T_{ro}^* is a target of output *r* for DMU_o; and λ_j^* is a linear weight attached to DMU_j. The symbol '*' refers to the optimal decision variable obtained from the model.

The improvement target for inputs and outputs is always lower and higher than the original value, respectively, in order to approach efficiency. After the target has been determined, the next step is to compute the improvement percentage (i.e., the amount required to become efficient) for each input and output of such an inefficient DMU_o. The improvement percentage is calculated on the basis of the projecting distance from the inefficient DMU_o onto the front as shown in Eq. (5).

$$\%IMP_i^* = \frac{x_{io} - \left(\sum_{j=1}^{n} \lambda_j^* x_{ij}\right)}{x_{io}} \times 100 \tag{5}$$

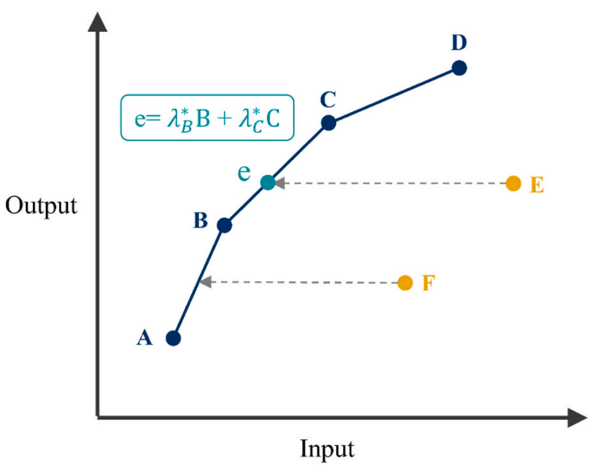

Fig. 1. An improvement of an inefficient DMU by input-oriented projection.

$$\%IMP_r^* = \frac{y_{ro} - \left(\sum_{j=1}^{n} \lambda_j^* y_{rj}\right)}{y_{ro}} \times 100$$

where the improvement percentage ($\%IMP^*$) for each indicator is computed by the difference between the attribute value and the target value divided by the attribute value.

2.3. Malmquist productivity index

The traditional DEA model can perform the efficiency assessment only at a particular period of time. Investigating the evolution of CE performance over time, therefore, requires other tools that can appropriately capture overall efficiency changes. One of the most favorable methods is Malmquist Productivity Index (MPI) which can be used to compare the changes in performance of the DMUs over time through the consideration of two essential changes, namely efficiency change (EC) and technological change (TC) [30]. The measure of $\mathrm{MPI_o}$ of any $\mathrm{DMU_o}$ from time period t to time period t+1 can be mathematically expressed as shown in Eq. (6).

$$MPI_o = \left[\frac{\mathrm{D_o^t}\left(\mathrm{x_o^{t+1}}, \mathrm{y_o^{t+1}}\right)}{\mathrm{D_o^t}\left(\mathrm{x_o^t}, \mathrm{y_o^t}\right)} \cdot \frac{\mathrm{D_o^{t+1}}\left(\mathrm{x_o^{t+1}}, \mathrm{y_o^{t+1}}\right)}{\mathrm{D_o^{t+1}}\left(\mathrm{x_o^t}, \mathrm{y_o^t}\right)}\right]^{\frac{1}{2}} \tag{6}$$

$$MPI_o = EC_o \times TC_o$$

where

$$EC_o = \frac{\mathrm{D_o^{t+1}}\left(\mathrm{x_o^{t+1}}, \mathrm{y_o^{t+1}}\right)}{\mathrm{D_o^t}\left(\mathrm{x_o^t}, \mathrm{y_o^t}\right)}$$

$$TC_o = \left[\frac{\mathrm{D_o^t}\left(\mathrm{x_o^t}, \mathrm{y_o^t}\right)}{\mathrm{D_o^{t+1}}\left(\mathrm{x_o^t}, \mathrm{y_o^t}\right)} \cdot \frac{\mathrm{D_o^t}\left(\mathrm{x_o^{t+1}}, \mathrm{y_o^{t+1}}\right)}{\mathrm{D_o^{t+1}}\left(\mathrm{x_o^{t+1}}, \mathrm{y_o^{t+1}}\right)}\right]^{\frac{1}{2}}$$

From the above equation, $\mathrm{D_o^t}(\mathrm{x_o^t}, \mathrm{y_o^t})$ and $\mathrm{D_o^{t+1}}(\mathrm{x_o^{t+1}}, \mathrm{y_o^{t+1}})$ denote the efficiency of $\mathrm{DMU_o}$ at time period t and t+1, respectively. $\mathrm{D_o^{t+1}}(\mathrm{x_o^t}, \mathrm{y_o^t})$ refers to the efficiency of $\mathrm{DMU_o}$ at time period t+1 by using the production possibility set of time period t (i.e., the data of time period t) and $\mathrm{D_o^t}(\mathrm{x_o^{t+1}}, \mathrm{y_o^{t+1}})$ refers to the efficiency of $\mathrm{DMU_o}$ at time period t by using the production possibility set of time period t+1 (i.e., the data of time period t+1) [31]. In other words, the calculation of MPI can be decomposed into two essential elements, which are efficiency change (EC) and technological change (TC) [32]. The efficiency change (EC) measures the change in the relative efficiency score between period t and t+1. The technological change (TC) represented by the geometric mean of the multiplication of two ratios measures the shift in technology, or in other words, the shift in best-practice frontier between period t and t+1.

The interpretation of the MPI value can provide useful insights on how such a $\mathrm{DMU_o}$ has evolved over time. If $\mathrm{MPI_o} > 1$, it means that the $\mathrm{DMU_o}$ has improved their productivity. If $\mathrm{MPI_o} < 1$, it means that the productivity of the $\mathrm{DMU_o}$ has worsened. If $\mathrm{MPI_o} = 1$, it means that there is no change in the productivity of the $\mathrm{DMU_o}$ over a period of t to t+1.

2.4. Data analytics approach for national circular economy assessment

In this section, we introduce a data analytics approach based on the combined use of the super-efficiency dual DEA and MPI to measure the CE performance of the countries using following steps:

1. *Problem definition and classification of indicators:* This step defines the essential DEA components, i.e., defining the countries whose performance are of interest as DMUs and specifying the assessment criteria as inputs or outputs. Specifically, the CE indicators to be minimized were considered as inputs and those to be maximized as outputs. Note that there is a suggested guideline for choosing the number of DMUs and the number of indicators following this relationship: $n \geq max\{m \times s, 3 \times (m + s)\}$, where n is the number of DMUs, m and s are the number of inputs and outputs, respectively [33]. However, this is just a recommendation to ensure proper discriminatory power of DEA.
2. *Data collection:* This step requires the collection of the attribute values expressing individual aspects of circularity for each DMU from reliable sources. Calculating the super-efficiency score requires a matrix of the attribute values for all DMUs at a particular time period. However, measuring the MPI requires a time series of attribute values.
3. *Application of super-efficiency dual DEA:* The use of super-efficiency dual DEA model aims at measuring the circularity performance of the countries at a particular period. This step comprises of sub-steps as follows: (1) solve the super-efficiency dual model by using a matrix of the attribute values as the model parameters, while solving the model for every country will give in turn its best-possible super-efficiency score (θ_o^{SE} from Eq. (3)) and the linear weights attached to the peer group (λ_j^* from Model (2)). All these optimal variables will be used for further useful interpretation in the following steps, (2) perform efficiency assessment where the countries will be categorized into the efficient and inefficient countries, and then further discriminated according to their super-efficiency score, and (3) perform inefficiency assessment where each inefficient country will be provided with its improvement target, a

list of peer group members it uses as references, how much each member of the peer group contributes to the target and how much effort it needs to become efficient.

4. *Application of MPI:* This step is to compute the MPI of each country to examine its progress in terms of CE over time. There are the sub-steps as follows: (1) set up the evaluated period of t and $t+1$ to calculate the MPI over that period, (2) calculate the super-efficiency score at the specific time period t and $t+1$ by benchmarking with the frontier derived from their own period, (3) calculate the super-efficiency score at the time period t by benchmarking with the frontier derived from period $t+1$ and calculate the super-efficiency score at the time period $t+1$ by benchmarking with the frontier derived from period t, (4) compute the terms of EC, TC and MPI for each DMU.

3. Case studies – circular economy performance of European countries

In this research, the assessment of CE performance of 27 European countries was divided into two small case studies. First, the capabilities of the super-efficiency dual DEA model in measuring the national circularity performance at a specific time was demonstrated by using the data in 2018 as an illustrative case. Second, the combined approach of the super-efficiency dual DEA model and MPI for monitoring the national circularity progress overtime was exemplified over the year of 2012–2018. The data source of this research relies on EUROSTAT database which provides high-quality and trustworthy European statistics available to the public [34].

3.1. Assessed European countries

The countries involved in the assessment were carefully chosen on the basis of the availability and the completion of the attribute values over the entire period being evaluated. The list of the assessed European countries is presented in Table 2.

3.2. Selected EUROSTAT circular economy indicators

European commission has launched the monitoring framework on the circular economy through four thematic areas and ten indicators encompassing different elements of circularity as detailed in Eurostat (2020) [35]. This research aims to use the official circular economy indicators classified by the European Commission; however, the list of indicators entails only some variables that can be compared over the entire European countries and the entire period being evaluated. It is still encouraging to incorporate any other circular economy performance indicator in the DEA analysis as long as the data is available in order to provide insight into how to improve the inefficient countries so as to make them optimal in terms of circular economy.

The following six sub-indicators considered in this research were from three thematic areas to comprehensively capture different perspectives of circularity as follows.

3.2.1. Production and consumption

Production and consumption sectors are significant drivers of the economy. The industrial and household sectors should take key roles in reducing the amount of waste generated through the production and consumption processes, which could ultimately promote self-sufficiency of raw materials. Due to data availability, two indicators from this area were used in this research as shown below.

- *Generation of municipal waste per capita (GMW)* considers the amount of waste collected by municipality and treated by the waste management system, expressing in *kg per capita.* Municipal waste includes mainly household waste and also analogous waste from merchants, offices, and public institutions. Reduction in municipal waste generation by households is a good signal of successful implementation of waste prevention policies and effective shift in consumption patterns responded by the population.
- *Generation of waste excluding major mineral wastes per GDP unit (GWG)* measures the waste intensity of the economy in *kg per thousand euro.* It considers the waste generated from both households and industrial sectors, including secondary waste. However, this indicator excludes major mineral wastes to improve comparability across countries since an inclusion of them could underrate some countries whose total generated waste is predominantly driven by the mineral wastes from construction/demolition and from mining activities.

Table 2
List of the European countries involved in this study.

European Countries				
Belgium (BE)	Ireland (IE)	Cyprus (CY)	Austria (AT)	Finland (FI)
Bulgaria (BG)	Greece (EL)	Latvia (LV)	Poland (PL)	Sweden (SE)
Czechia (CZ)	Spain (ES)	Lithuania (LT)	Portugal (PT)	United Kingdom (UK)
Denmark (DK)	France (FR)	Luxembourg (LU)	Romania (RO)	
Germany (DE)	Croatia (HR)	Hungary (HU)	Slovenia (SI)	
Estonia (EE)	Italy (IT)	Netherlands (NL)	Slovakia (SK)	

3.2.2. Waste management

- The waste management area puts emphasis on the share of recycled waste that is recirculated back to the economic system. The indicators fall into this area consider both overall recycling rate and recycling rates for specific waste streams, e.g., packaging waste, biowaste, electronic waste, etc. Due to data availability, three indicators from this area were included. *Recycling rate of municipal waste (RM)* is the ratio of the amount of municipal waste recycled through material recycling, composting and anaerobic digestion processes over the total municipal waste generated, measured in percentage of total waste generated.
- *Recycling rate of packaging waste (RP)* is the ratio of recycled packaging waste over the total generated packaging waste, expressing as percentage of total packaging waste generated. Packaging waste can be categorized according to types of materials used, i.e., paper and cardboard, plastic, wooden, metallic, and glass.
- *Recycling of biowaste (RB)* is indirectly estimated as the ratio of municipal waste that is composted/methanized through composting/anaerobic digestion processes over the total population, expressing in *kg per capita.* Biowaste is particularly crucial as it often ends in mixed municipal waste and if being improperly treated such landfilled, it will create significant environmental impacts. This indicator is, therefore, useful for monitoring progress of the implementation of composting and anaerobic digestion that contributes towards circular economy of municipal wastes.

3.2.3. Secondary raw materials

Secondary raw materials are the reutilization of materials from recycling stages instead of/or in combination with the virgin raw materials. The use of secondary raw materials can reduce the material and energy use, reduce the environmental impacts during the production and consumption stages, as well as enhance the security of materials supply. Due to data availability, only a single indicator from this category was included.

- *Circular material uses rate (CMU)* is expressed as the ratio of the circular use of materials over the overall material use, measured in percentage of total material use as shown in the following Eq. (7).

$$\mathrm{CMU} = \frac{\mathrm{RCV} - \mathrm{IMP_w} + \mathrm{EXP_w}}{\mathrm{DMU} + (\mathrm{RCV} - \mathrm{IMP_w} + \mathrm{EXP_w})} \tag{7}$$

The overall material use is defined as the summation of domestic material consumption (DMC) and the circular use of materials. DMC measures the total amount of materials used domestically by an economy obtained from material flow accounts [14]. The circular use of materials can be estimated as the amount of waste recycled by domestic recovery plants (RCV) minus imported waste bound for recovery ($\mathrm{IMP_W}$) plus exported waste bound for recovery abroad ($\mathrm{EXP_W}$). This indicator captures the proportion of materials that are recycled and returned to the economy, thereby minimizing the extraction of virgin materials, the total material use and resulting environment burdens.

4. Results and discussion

The investigation was conducted thoroughly by following the assessment procedure as aforementioned in Section 2.4 and the corresponding results are discussed next.

<u>*Step1:*</u> According to the DEA terminology, all of the assessed countries were defined as DMUs and the selected circular economy indicators were clearly labelled into inputs and outputs on the basis of how they contribute to the circularity efficiency as presented in Table 3. Two CE indicators were regarded as inputs since they should be minimized to enhance the efficiency: generation of municipal waste per capita (−), and generation of waste excluding major mineral wastes per GDP unit (−). The other four indicators were specified as outputs since they should be maximized to promote efficiency: recycling rate of municipal waste (+), recycling rate of packaging waste (+), recycling of biowaste (+) and circular material uses rate (+). The number of DMUs and indicators also follow the aforementioned guideline thereby ensuring reliable assessment.

<u>*Step2:*</u> The attribute values of 27 European countries over the year of 2012–2018 were retrieved from the EUROSTAT database [14]. Table 4 below shows the data in 2018 along with its descriptive statistics as an example and the data for the other periods were provided in the supplementary materials. A heatmap of Pearson correlation coefficients (r) of all indicators is depicted in Fig. 2. It shows that the correlation between the majority of indicators is very low to moderate with $r \leq |0.6|$. There is a strong positive relationship between recycling rate of municipal waste (RM) and recycling of biowaste (RB) with $r = 0.8$. This is because these two indicators are partially contributed from the same element, that is the recycling amount of biowaste. However, they still distinctively capture different angles of circularity, while RM focuses on the overall recycling rate of municipal waste, RB specifically measures the

Table 3
CE indicators as inputs and outputs of DEA assessment.

Inputs	Outputs
Generation of municipal waste per capita (GMW)	Recycling rate of municipal waste (RM)
Generation of waste excluding major mineral wastes per GDP (GWG)	Recycling rate of packaging waste (RP)
	Recycling of biowaste (RB)
	Circular material uses rate (CMU)

Table 4
DEA inputs and outputs data in terms of CE of European Countries in 2018.

Country	Inputs		Outputs			
	GM	GWG	RM	RP	RB	CMU
Belgium	409 (7)	99 (21)	54.4 (5)	85.3 (1)	82 (10)	19.9 (2)
Bulgaria	407 (5)	473 (26)	31.5 (20)	60.4 (20)	7 (27)	2.5 (24)
Czechia	494 (15)	86 (19)	32.2 (19)	69.6 (8)	50 (16)	8 (14)
Denmark	814 (27)	37 (3)	49.9 (7)	70.1 (6)	143 (4)	8.1 (13)
Germany	606 (24)	52 (8)	67.1 (1)	68.5 (10)	109 (6)	11.7 (7)
Estonia	405 (4)	650 (27)	28 (22)	60.4 (21)	15 (23)	13.5 (6)
Ireland	598 (23)	28 (2)	37.6 (14)	63.9 (16)	50 (17)	1.6 (26)
Greece	515 (19)	85 (18)	20.1 (25)	63.6 (17)	26 (21)	3.3 (22)
Spain	475 (13)	62 (11)	34.8 (17)	68.8 (9)	80 (11)	9.3 (12)
France	535 (20)	46 (5)	45.1 (11)	65.7 (14)	108 (7)	19.5 (3)
Croatia	432 (9)	77 (17)	25.3 (23)	58.4 (23)	12 (24)	5 (18)
Italy	499 (16)	69 (13)	49.8 (8)	68.3 (11)	105 (8)	18.8 (4)
Cyprus	646 (25)	39 (4)	16.5 (26)	70.2 (5)	11 (25)	2.8 (23)
Latvia	407 (6)	58 (9)	25.2 (24)	55.8 (26)	25 (22)	4.7 (20)
Lithuania	464 (12)	105 (23)	52.5 (6)	60.7 (19)	131 (5)	4.3 (21)
Luxembourg	803 (26)	27 (1)	49 (9)	70.9 (3)	154 (2)	10.8 (9)
Hungary	381 (3)	87 (20)	37.4 (15)	46.1 (27)	32 (19)	7 (15)
Netherlands	511 (18)	63 (12)	55.9 (4)	77.4 (2)	147 (3)	28.9 (1)
Austria	579 (22)	50 (7)	57.7 (3)	65.5 (15)	187 (1)	11.1 (8)
Poland	329 (2)	168 (25)	34.3 (18)	58.7 (22)	27 (20)	9.8 (11)
Portugal	507 (17)	72 (15)	29.1 (21)	57.6 (25)	86 (9)	2.2 (25)
Romania	272 (1)	128 (24)	11.1 (27)	57.9 (24)	9 (26)	1.5 (27)
Slovenia	486 (14)	73 (16)	58.9 (2)	68 (12)	79 (12)	10 (10)
Slovakia	414 (8)	102 (22)	36.3 (16)	66.6 (13)	39 (18)	4.9 (19)
Finland	551 (21)	70 (14)	42.3 (13)	70.2 (4)	72 (14)	5.9 (17)
Sweden	434 (10)	49 (6)	45.8 (10)	70.1 (7)	69 (15)	6.6 (16)
United Kingdom	463 (11)	58 (10)	44.1 (12)	62.1 (18)	78 (13)	16 (5)
Minimum	272	27	11.1	46.1	7	1.5
Maximum	814	650	67.1	85.3	187	28.9
Average	498	108	39.7	65.0	72	9.2
Standard Deviation	123	137	14.0	7.3	51	6.7

Remark The number shown in the parenthesis is the ranking of countries in each indicator.

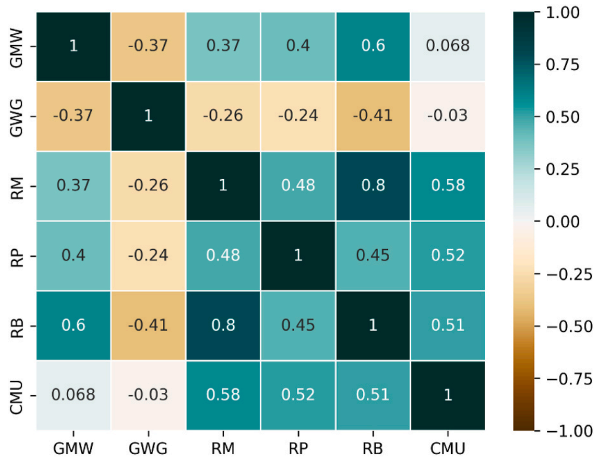

Fig. 2. Pearson correlation coefficients of DEA inputs and outputs.

recycling of biowaste per capita. Therefore, both indicators are included in the assessment as they will provide different insights for such an overall perspective as well as specific types of waste.

Step3: The super-efficiency dual DEA model features 35 variables and 7 constraints. It was implemented in GAMS 36.2.0 and solved with CPLEX 20.1.0.1 on an Intel® Core™ i7-11370H processor operating at 3.30 GHz. It took around 0.01 CPU seconds to solve every instance to global optimality.

4.1. Efficiency assessment

The results of super-efficiency score indicate 13 out of 27 European countries were efficient in terms of CE in 2018 (i.e., the super-efficiency score is larger than 1) as depicted by green bars in Fig. 3. The ranking of the efficient European countries according to their circularity from the top of the table is as follows: Netherlands, Germany, Austria, Belgium, Luxembourg, Romania, Ireland, Sweden, France, Poland, Lithuania, Slovenia, and Latvia. The efficient countries account for approximately 48% of the European countries assessed in this research. Netherlands was found to be the best performer in terms of CE with the highest score of 2.620. Netherlands, Germany, Austria, Belgium, and Luxembourg were ranked as the top five of the table since they were the best countries with respect to CMU, RM, RB, RP, and GWG, respectively. Although, Romania performed poorly in the areas of RM, RB, and CMU, it is the best performer in terms of GMW, thereby coming at the rank 6th.

The other 14 countries were deemed inefficient according to the efficiency score that is less than 1 as depicted by yellow bars in Fig. 3. The inefficient countries consist of United Kingdom, Hungary, Cyprus, Italy, Spain, Croatia, Slovakia, Denmark, Estonia, Portugal, Czechia, Bulgaria, Finland, and Greece. The inefficient countries show high efficiency values (ranges between 0.772 and 0.995), which indicates that they performed close to the efficient frontier. Greece was indicated as the worst performer in terms of CE with the lowest efficiency score of 0.772 since its performance was relatively poor in all CE indicators. This was followed by Finland and Bulgaria with the scores of 0.783 and 0.797, respectively. The results obtained here were in good agreement with the work done by Lacko et al. (2021) in that the Visegrád group countries (i.e., Poland, Czechia, Slovakia, and Hungary) did not perform well in terms of CE implementation when compared to the EU average. Even though these countries were inefficient in terms of CE, they can improve by approaching towards the efficient frontier constructed from efficient countries. It is worth pointing out here that some countries might have performed poorly in our assessment while they appeared at the top-ranked in other studies. This might be because of the different choice of indicators and the data retrieved from different periods which will alter the analysis results. Therefore, the results are valid only for specific CE indicators at specific time.

4.2. Inefficiency assessment

4.2.1. Interpretation of improvement percentage

Solving the super-efficiency dual model for each inefficient country provides in turn its improvement targets for each indicator calculated by Eq. (4). These targets are numerical goals that each inefficient country should aim to achieve in order to become efficient in CE through a decrease (or an increase) in its input (or output) values. Approaching these targets enables us to compute the

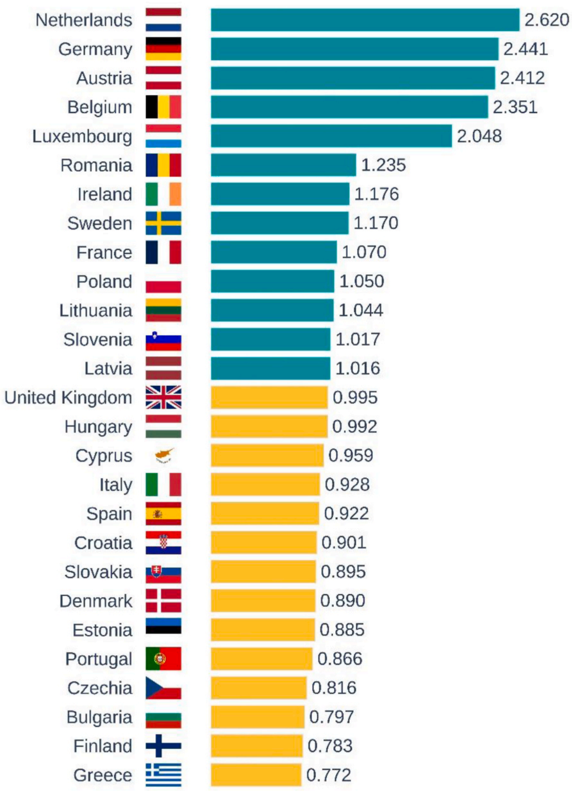

Fig. 3. Super-efficiency score of 27 European countries in terms of CE in 2018.

corresponding improvement percentage for each indicator by using Eq. (5). Fig. 4 shows an average improvement percentage across all inefficient countries for each indicator where inputs are presented by blue bar graphs indicating the decrease in the values and the outputs are displayed by green bar graphs indicating the increase in the values. Considering an input category, GWG was found to be the worst indicator needed to decrease (−) by 19.5% on average. Meanwhile, the worst output was the RB needed to increase by 124.7% on average, followed by CMU, which requires an 84.1% increase on average. These two outputs can be regarded as primary sources of CE inefficiency causing those inefficient countries to obtain an efficiency score of less than 1. This can be implied that, overall, the inefficient European countries performed deficiently in these two indicators and were greatly distant from their best practice. They should also be the first two indicators worth prioritizing to enhance the CE performance of the poorly performing countries, thereby narrowing the gap between the poorest players and the best practices, which will ultimately foster the CE performance of the EU as a whole.

To promote the recycling of biowaste of the inefficient countries, it might be useful to follow the practices of best performer, Austria, who has implemented several regulatory frameworks in supporting the recycling of biowaste. These include an increase of Landfill tax to reduce landfilled waste, the development of composting and anaerobic digestion infrastructure to encourage decentralized biowaste management, and the provision of incentives to encourage the separate collection of biowaste from other types of waste streams [36]. Meanwhile, the circular material uses rate of the countries can also be enhanced through several successful policies, e.g., the implementation of Extended Producer Responsibility (EPR) schemes, the provision of incentives to promote eco-design practices that encourage the design of products that use less material or incorporate recycled materials, and the development of a market for secondary raw materials.

The CE assessment by using DEA can provide the preliminary information of the CE efficiency score for each country. In addition, more comprehensive analysis on detailed improvements of each country would allow us to gain more valuable insight through the focus on individual indicators which could be used as a guideline for improvement strategies towards CE efficiency. A heatmap displaying the improvement percentage in each indicator for all the inefficient countries is shown in Fig. 5. A more intense blue/green color reflects a stronger improvement percentage for minimizing/maximizing the corresponding inputs/outputs to become efficient in the CE. For example, Bulgaria had two outputs shown in the green zone including RB and CMU that need to increase by 293.7% and 260%, respectively. For input indicators, Bulgaria needed to decrease GWG by 67% and decrease GMW by 20.3%. Improving these indicators could potentially enable Bulgaria to become efficient in terms of CE. This could be done through several policy recommendations such as encouraging product longevity and repairability, setting waste reduction targets, and increasing public awareness and education about the importance of reducing waste generation and the benefits of sustainable consumption.

4.2.2. Practical improvements through contribution analysis

To strategically implement the circularity improvement approaches in practice, it might be worthwhile to place emphasis on the primary factors that predominantly contribute to the values of circularity indicators. For clearer illustration, Greece, with the poorest performance in Europe in 2018, had several output values that are considered relatively low compared with the other European countries. For example, CMU of Greece was only about 3.3%, comparing with the best performer as Netherlands at 28.9%. This indicator is calculated through Eq. (4) using the following terms: DMC, RCV, IMP_{w} and EXP_{w}. To obtain high values in this attribute, RCV and EXP_{w} should be large while DMC and IMP_{w} should be small. However, the DMC and RCV are the key elements that play vital role on this indicator since the values of IMP_{w} and EXP_{w} are often comparatively small. Let us investigate the breakdown of elements contributing to the overall material use for 27 European countries in 2018 which was sorted by CMU values in descending order as depicted in Fig. 6. It is interesting to note that even though the IMP_{w} contribution was relatively trivial, most of the European countries (i.e., 23 of 27) had imported waste for recovery. Greece as the worst performer exhibited a very small proportion of RCV only 3.7% in contrast to the high-performance countries in this indicator, i.e., Netherlands, Belgium, and France, whose RCV accounted for 28%, 20%, and 19% of the overall material use, respectively. That is, an increase of the RCV proportion will increase the value of CMU indicator, which potentially lead to higher efficiency score.

Another example of detailed improvements in the circularity indicator is the recycling of packaging waste. Fig. 7 shows the

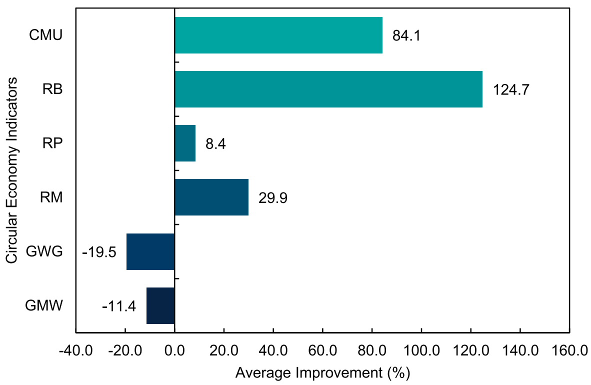

Fig. 4. An average improvement percentage for each CE indicator.

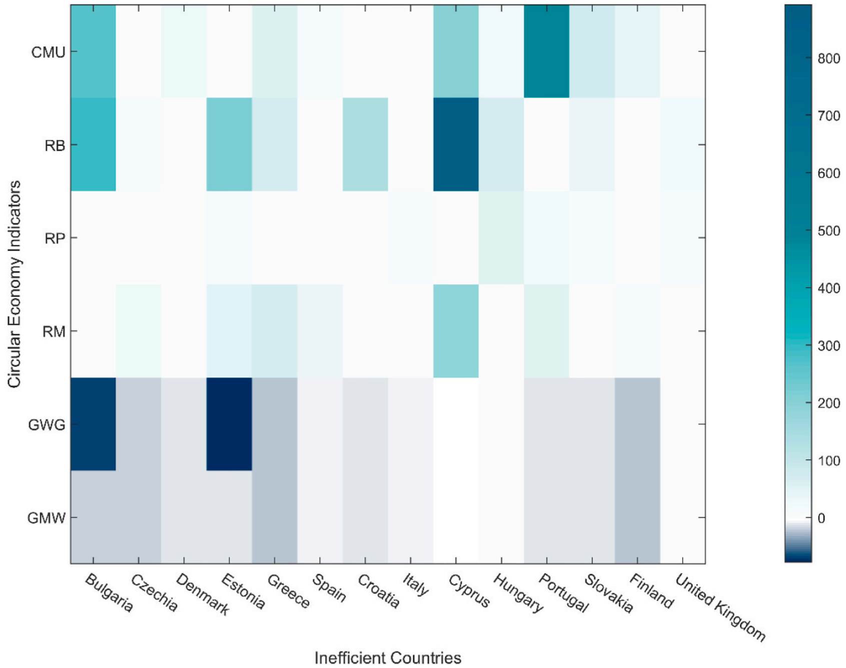

Fig. 5. Heatmap of improvement percentage for each inefficient country.

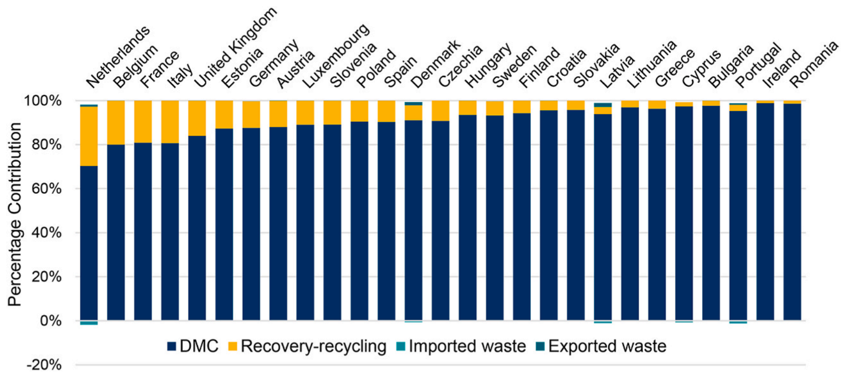

Fig. 6. Percentage contribution of each element constituting the overall material use for 27 European Countries in 2018.

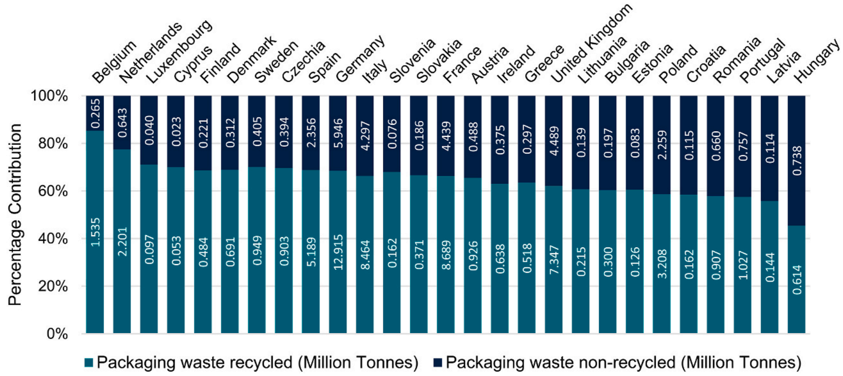

Fig. 7. Percentage contribution of packaging waste recycle to the overall packaging waste and the breakdown of recycled and non-recycled packaging waste in million tonnes for 27 European countries in 2018.

breakdown comparison of the recycled packaging waste for 27 European countries in 2018 which was sorted by RP values in descending order. Let us investigate in detail of Portugal and Netherland, it was observed that even both countries performed quite well in general since their percentage of recycled packaging waste were more than 50%; however, Portugal still had low proportion of recycled packaging waste in contrast with Netherland whose accounts for 77.4%. In essence, Portugal has recycled 1.027 million tonnes of the packaging waste which constitutes 57.6% of overall packaging waste [37]. If Portugal can increase the amount of recycled packaging waste while retaining or minimizing the overall packaging waste generated, this would benefits Portugal to become closer to the efficiency in CE. This could be done through the promotion of separate collection and sorting of packaging waste, the implementation of a deposit-return system, and the implementation of EPR scheme for packaging producers.

Reducing packaging waste generated could support Portugal to become closer to the CE efficiency frontier. Deeper insights on material types of packaging waste in 2018 of Portugal indicated paper and cardboard materials constituting the largest proportion of packaging waste at 803,769 tonnes which accounts for approximately 45% of all packaging waste [37] as shown in Fig. 8. Prioritizing the reduction in this type of waste while promoting its recycling would help Portugal enhance the attribute value in this indicator and eventually approach the efficiency in a CE.

4.2.3. Interpretation of linear weights

The projection of the inefficient countries onto the efficient frontier creates such an improvement target which is essentially established from the linear combination of the efficient countries. Every inefficient country uses the efficient countries as references through the linear weights (computed by DEA) assigned to them which represent how much they have contributed to such target. Fig. 9 displays heatmap of linear weights attached to each efficient country referenced by the inefficient countries for improvements, where Y-axis represents 13 efficient countries, X-axis refers to the rest 14 inefficient countries and color range reflects different value of linear weights. For such an illustrative case, the interpretation of Croatia's column indicates that the improvement target of Croatia was constituted from the linear combination of Belgium, Latvia, Romania, and Sweden with linear weight values of 0.042, 0.736, 0.148, and 0.074, respectively. This might be implied that in order to become efficient, Croatia should try to mimic the circularity characteristics of Latvia at 73.6%, followed by Romania at 14.76% and so on. On the other hand, the interpretation of Netherland's row means that Netherland contributes to the improvement targets of Spain, Italy, Portugal, Finland, and UK with the linear weight values of 0.194, 0.490, 0.306, 0.067 and 0.445, respectively.

The linear coefficients of the efficient countries that were referenced by the inefficient ones are presented in each row of the heat map in Fig. 9, and they were summed up (across each row) and displayed as a bar chart of the efficient countries in Fig. 10. It was observed that Sweden was used as references by 12 inefficient countries with the summation of linear weights at 6.58, followed by Netherlands and Romania at 5.92 and 2.82, respectively. Let us revisit the attributes data of Sweden in 2018, it was found that all of them were neither the best nor the worst in every way. In other words, its attribute values were balanced in all indicators, thereby making Sweden as the best compromise country that usually forms a convex hyperplane on which the inefficient countries radially project. Sweden was also the reference that requires much less efforts to mimic in order to reach the circularity efficiency, and, therefore, was rather more approachable to be referenced by most of the inefficient countries.

Step4: We next investigate the advancement in CE implementation of the European countries over the period of 2012–2018 by using the combination of super-efficiency dual DEA and MPI, which allows us to monitor the development in the aspects of efficiency change and technological progress. In this study, the evaluated period was divided into three intervals, i.e., 2012–2014, 2014–2016, and 2016–2018, since the data was available biannually. The computed super-efficiency scores of each country in 2012, 2014, 2016, and 2018 were provided in the supplementary materials. These scores were essentially used to compute different terms in Eq. (6) constituting an MPI score of every country for each time interval. In this study, the interpretation of MPI was categorized according to the values as follows: (1) $MPI_o < 1$ means that the circularity productivity of such DMU_o has deteriorated and is represented by down right arrows (↘), (2) $MPI_o = 1$ means that the DMU_o has no progress and is represented by right arrows (→), (3) $MPI_o > 1$ means that the circularity advancement of the DMU_o has improved and is represented by up right arrows (↗).

The overall MPI of the European countries over the period of 2012–2018 as shown in Table 5 and Fig. 11 revealed a slight progress of circularity productivity as a whole with MPI of 1.002, implying that the European countries have progressed towards CE by 0.2%. The increase in productivity was contributed by an increase in overall technological changes (or frontier shift) of 0.4% and a decrease in overall efficiency changes of 0.2% over the entire period. The biannual CE progress of the European countries captured by MPI shows 3.5% regression, 0.1% growth, and 3.0% growth during 2012–2014, 2014–2016, and 2016–2018, respectively. The highest CE productivity was in 2016–2018 which is mainly due to technological progress which increased by 7.4% and a decline in efficiency

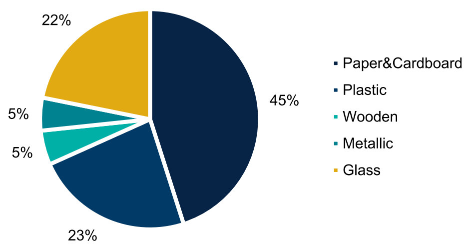

Fig. 8. Breakdown contribution of packaging waste according to material types of Portugal in 2018.

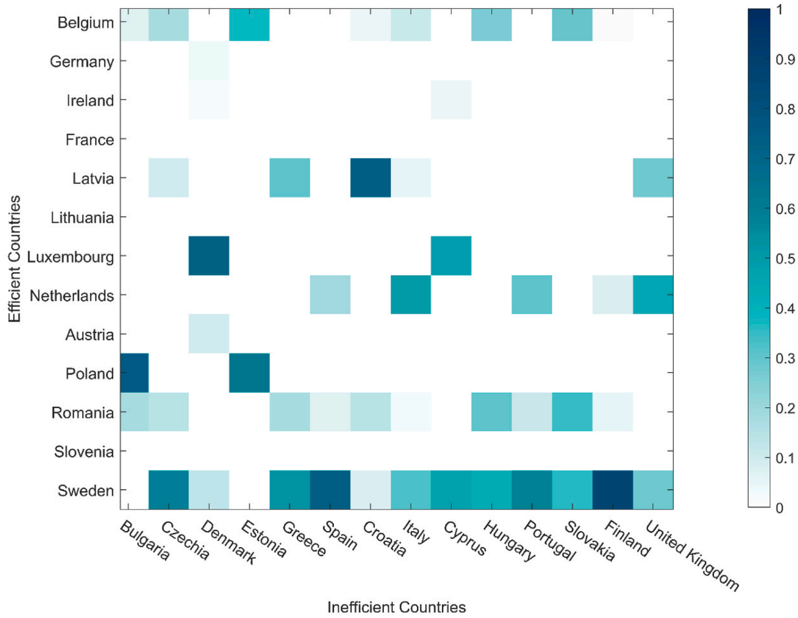

Fig. 9. Heatmap of linear weights.

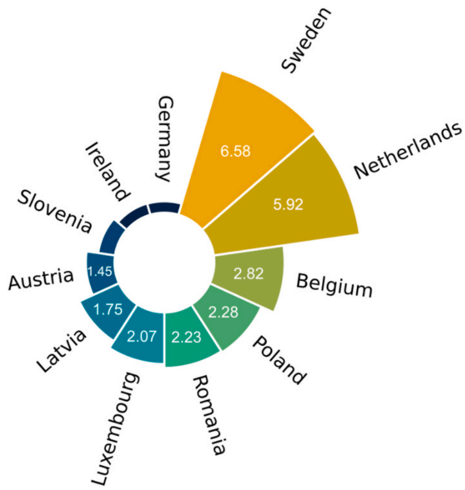

Fig. 10. Summation of linear weights for the efficient countries.

change of 4.1%.

We investigated further the MPI for individual European countries over the period of 2012–2018 to track the circularity productivity. The result of an average MPI across the evaluated period for each country suggests that 13 European countries have advanced their circularity productivity. While the other countries have slightly improved by 0.1–2.4%, Luxembourg exhibited the highest circularity advancement of 6.0%, contributing by an increase in efficiency change of 4.8% and an increase in technological changes of 1.2%. Slovakia came after with 2.4% CE productivity, resulting from an increase in technological changes of 6.1% and a decline in efficiency change of 3.5%. Germany was the only country continuously enhancing its productivity over the evaluated period of 2012–2018 with 2.3% advancement in CE. However, Denmark showed the largest deteriorating change in circularity performance at 8.8%, which is mainly due to a decline in technological changes of 12.1%, while the other 14 countries exhibited slight regression between 0.3 and 3.2%.

Over the period of 2012–2014, Netherlands and Germany were only two countries whose circularity performance have enhanced by 3.7% and 2.3%, respectively, while the others have recessed. Cyprus showed the lowest MPI of 0.899 and had regressed CE productivity by of 10.1%, resulting from the deteriorating changes in both technical efficiency of 5.9% and technological advancements by 4.4%. Estonia and Ireland also had comparatively low MPI of 0.902 and 0.904, respectively; however, these were primarily due to

Table 5
Malmquist Productivity Index for circularity development of European Countries over the period of 2012–2018.

No.	European countries	2012–2014				2014–2016				2016–2018				2012–2018			
		EC	TC	MPI	Change	EC	TC	MPI	Change	EC	TC	MPI	Change	EC	TC	MPI	Change
1	Belgium	0.992	0.968	0.960	↘	1.106	0.989	1.094	↗	0.879	0.983	0.864	↘	0.988	0.980	0.968	↘
2	Bulgaria	0.957	1.012	0.968	↘	1.243	0.820	1.019	↗	1.007	1.046	1.053	↗	1.062	0.954	1.013	↗
3	Czechia	1.083	0.901	0.977	↘	0.999	1.016	1.016	↗	0.677	1.491	1.009	↗	0.901	1.110	1.000	→
4	Denmark	1.643	0.579	0.951	↘	1.743	0.423	0.737	↘	0.390	2.776	1.083	↗	1.038	0.879	0.912	↘
5	Germany	1.010	1.013	1.023	↗	1.007	0.997	1.004	↗	1.039	1.002	1.041	↗	1.019	1.004	1.023	↗
6	Estonia	0.525	1.716	0.902	↘	1.024	1.078	1.104	↗	1.029	1.020	1.049	↗	0.821	1.236	1.015	↗
7	Ireland	0.679	1.331	0.904	↘	1.239	0.919	1.139	↗	1.062	0.896	0.952	↘	0.963	1.031	0.993	↘
8	Greece	1.004	0.978	0.982	↘	1.212	0.865	1.048	↗	0.983	1.050	1.032	↗	1.062	0.961	1.021	↗
9	Spain	0.989	0.983	0.972	↘	1.023	0.995	1.018	↗	0.992	1.003	0.995	↘	1.001	0.994	0.995	↘
10	France	1.020	0.952	0.971	↘	1.093	0.940	1.027	↗	0.938	1.035	0.971	↘	1.015	0.975	0.990	↘
11	Croatia	0.902	1.069	0.964	↘	0.980	1.069	1.047	↗	1.010	1.044	1.055	↗	0.963	1.060	1.021	↗
12	Italy	0.998	0.970	0.968	↘	1.006	0.984	0.991	↘	1.016	0.983	0.999	↘	1.007	0.979	0.986	↘
13	Cyprus	0.941	0.956	0.899	↘	1.041	1.040	1.083	↗	1.036	0.939	0.973	↘	1.005	0.977	0.982	↘
14	Latvia	0.914	1.075	0.983	↘	1.095	0.943	1.033	↗	1.080	0.952	1.028	↗	1.026	0.988	1.014	↗
15	Lithuania	1.064	0.916	0.975	↘	1.224	0.820	1.004	↗	1.058	0.939	0.993	↘	1.113	0.890	0.990	↘
16	Luxembourg	1.240	0.746	0.925	↘	0.656	1.005	0.659	↘	1.412	1.383	1.953	↗	1.048	1.012	1.060	↗
17	Hungary	1.068	0.916	0.978	↘	1.071	0.931	0.997	↘	1.101	0.971	1.068	↗	1.080	0.939	1.014	↗
18	Netherlands	1.079	0.962	1.037	↗	1.021	1.022	1.043	↗	0.826	1.156	0.955	↘	0.969	1.043	1.011	↗
19	Austria	0.902	1.097	0.990	↘	0.992	0.988	0.980	↘	0.955	0.983	0.939	↘	0.949	1.021	0.969	↘
20	Poland	1.314	0.732	0.962	↘	0.831	1.195	0.993	↘	0.933	1.099	1.025	↗	1.006	0.987	0.993	↘
21	Portugal	0.973	1.008	0.980	↘	1.022	0.994	1.016	↗	0.955	1.055	1.007	↗	0.983	1.019	1.001	↗
22	Romania	0.896	1.065	0.955	↘	1.039	0.996	1.036	↗	1.034	1.028	1.064	↗	0.988	1.030	1.017	↗
23	Slovenia	0.769	1.251	0.962	↘	1.244	0.801	0.996	↘	0.991	0.981	0.971	↘	0.982	0.994	0.977	↘
24	Slovakia	0.973	1.009	0.981	↘	0.956	1.080	1.032	↗	0.966	1.097	1.060	↗	0.965	1.061	1.024	↗
25	Finland	1.047	0.923	0.967	↘	0.973	1.042	1.013	↗	0.950	1.045	0.992	↘	0.989	1.002	0.990	↘
26	Sweden	1.006	0.946	0.952	↘	0.954	1.094	1.044	↗	1.047	0.953	0.997	↘	1.002	0.995	0.997	↘
27	UK	0.972	1.001	0.973	↘	1.005	0.994	1.000	→	1.024	0.971	0.995	↘	1.000	0.989	0.989	↘
	Average	**0.980**	**0.985**	**0.965**	↘	**1.052**	**0.951**	**1.001**	↗	**0.959**	**1.074**	**1.030**	↗	**0.998**	**1.004**	**1.002**	↗

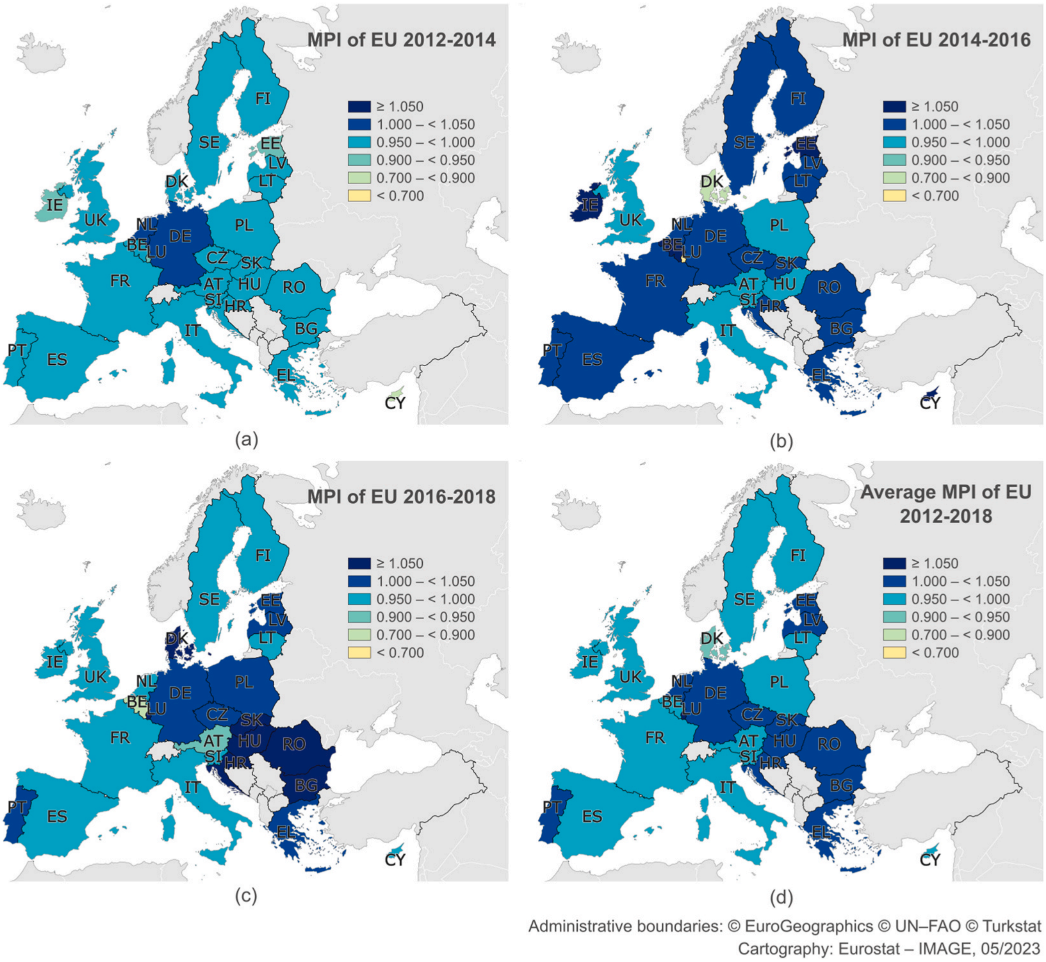

Fig. 11. MPI expressing circularity development of 27 European countries over the period of 2012–2018, (a) MPI over 2012–2014, (b) MPI over 2014–2016, (c) MPI over 2016–2018, and (d) an average MPI over 2012–2018. (Spatial maps was created by using IMAGE Interactive map generator platform [38]).

the substantial regression in efficiency changes of 47.5% and 32.1%, respectively.

From 2014 to 2016, approximately 70% or 19 of the 27 European countries had a progressive productivity. This developing trend also corresponded to the implementation of the First Circular Economy Action Plan in 2015. The action plan has encouraged every member of the EU to realize the importance and benefits of adopting the CE paradigm, and, as a result, brought about the practical implementation and the continuous development towards CE of most of the European countries. Ireland was the first rank in circularity progression with the productivity of 13.9%, which comes from a substantial growth in efficiency change of 23.9% and a decrease in technological change of 8.1%. Luxembourg was at the bottom of the table in terms of circularity evolution during 2014–2016 with the lowest MPI of 0.659, mostly due to the worsening change in efficiency change of 34.4% even though it was deemed efficient by the super-efficiency dual model in both periods.

Later in the period of 2016–2018, the improvement trends seemed to slightly drop since the lower number of countries, that was 14, compared to the period of 2014–2016 had enhanced the CE efficiency. Luxembourg has progressively developed in terms of CE with the highest MPI of 1.953 due to the considerable growth both in efficiency change of 41.2% and in technological change of 38.3%. Meanwhile, Belgium has recessed its circularity productivity with the smallest MPI of 0.864 which came from declining changes both in efficiency change of 12.1% and in technological change of 1.7%.

5. Conclusions

This research proposes an integration of the super-efficiency dual DEA and MPI to measure the CE performance and track the circularity progress of 27 European countries. The results of our study show that in 2018 Netherlands, Germany, Austria, and Belgium exhibited an excellent overall CE performance, particularly in terms of the recycling of municipal waste, packaging waste, biowaste and the use of secondary materials which corresponds to their well-recognized strong environmental policies and initiatives. The majority of Southern Europe like Greece and Bulgaria were among the worst CE performers. The inefficiency assessment pinpoints the most critical CE aspects that need urgent and serious mitigations, i.e., an engagement of the recycling of biowaste, followed by the circular material uses rate to enhance the overall CE performance of the European countries. For those countries deemed inefficient, the approach can suggest country-specific improvements pathway through the identification of primary sources of inefficiency and the establishment of quantitative improvement targets that can be used to guide the transition efforts towards CE.

The MPI results unveils that Luxembourg had the highest circularity advancement, mainly due to an increase in efficiency change, while Denmark showed the largest deteriorating change as a result from a decline in technological changes. Overall, the European countries have slightly advanced their circularity performance by 0.2% over the period of 2012–2018, which contributed by an increase in overall technological changes of 0.4% and a decrease in overall efficiency changes of 0.2%. This suggests the European countries strengthen their policy and regulatory frameworks in support of the transition towards circular economy and encourage progressive movements in such a collaborative manner with the relevant stakeholders to build the momentum for change. Some of the limitations of this study include the unavailability of data which limits the number of CE indicators and not all European countries can be included in the assessment for the sake of comparability. In addition, the DEA results are sensitive to the choice of inputs and outputs as well as the modelling choices, and therefore, this case study might not be compared to the others using different sets of CE indicators.

It will be worthful for potential future research to investigate the key influential factors affecting efficiency and inefficiency in terms of CE via some regression analysis to obtain more insights for improving the CE performance. Other possibilities could be an extension of our analysis to incorporate other countries either those with better CE performance to establish the superior efficient frontier for more effective benchmarking practices, or those with the poor CE performance to provide recommendations for CE improvements by benchmarking with the European's best practices.

Author contribution statement

Adithep Banjerdpaiboon: performed the experiments; analyzed and interpreted the data; wrote the paper.

Phantisa Limleamthong: conceived and designed the experiments; analyzed and interpreted the data; contributed reagents, materials, analysis tools or data; wrote the paper.

Data availability statement

Data included in article/supp. material/referenced in article.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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