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COMPARATIVE ANALYSIS OF CIRCULAR ECONOMY PERFORMANCE: EVIDENCE FROM EUROPE

Abstract

The transition towards the circular economy (CE) model has gained recognition as a critical component in envisioning a sustainable future for humanity, owing to the inherent unsustainability of the current linear economic model of production and consumption. By repurposing resources and goods at the end of their useful lives, CE seeks to minimize waste creation while extending the life of these materials and products in the manufacturing cycle. The European Commission (EC) has backed switching from linear to CE to decrease undesirable interactions between the economy and the environment. Performance indicators developed under the CE monitoring framework are the best instruments for monitoring progress towards CE. The purpose of the current research is to examine the CE performance of the European Union (EU) countries – the Netherlands, France, and Germany. The analysis demonstrates strong relationships between important environmental parameters and the way they affect CE performance through a neural network procedure. The insights gained from this study, along with the broader research context provided by related studies, enhance the understanding of the difficulties and complexities in implementing and monitoring CE progress in different contexts.

Key words: *circular economy, performance indicators, comparative analysis, neural networks, EU countries*

JEL classification: *Q51, Q56, Q57*

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КОМПАРАТИВНА АНАЛИЗА ПЕРФОРМАНСИ ЦИРКУЛАРНЕ ЕКОНОМИЈЕ: ЕМПИРИЈСКА АНАЛИЗА НА ПРИМЕРУ ЕВРОПЕ

Апстракт

Транзиција ка моделу циркуларне економије (ЦЕ) препозната је као кључна компонента у обликовању одрживе будућности човечанства, с обзиром на инхерентну неодрживост тренутног линеарног економског модела производње и потрошње. Циркуларна економија настоји да минимизира стварање отпада кроз поновну употребу ресурса и производа на крају њиховог животног циклуса, продужавајући тако век трајања материјала и производа у производном процесу. Европска комисија (ЕК) подржала је прелазак са линеарног на циркуларни модел како би се смањиле негативне интеракције између економије и животне средине. Индикатори перформанси садржани у Оквиру за мониторинг ЦЕ представљају најбоље инструменте за праћење напретка ка циркуларној економији. Циљ овог истраживања је испитивање перформанси ЦЕ у земљама Европске уније (ЕУ) – Холандији, Француској и Немачкој. Анализа показује снажну повезаност између кључних еколошких параметара и њиховог утицаја на перформансе ЦЕ путем поступка неуронске мреже. Увиди стечени овим истраживањем, заједно са ширим истраживачким контекстом сродних студија, доприносе бољем разумевању изазова и сложености у имплементацији и праћењу напретка ЦЕ у различитим контекстима.

Кључне речи: циркуларна економија, индикатори перформанси, компаративна анализа, неуронске мреже, земље ЕУ

Introduction

With the focus on recycling, reusing, and cutting waste in order to create a more sustainable future, CE has become an important strategy for the advancement of sustainability. Ezeudu et al. (2022) state that CE encourages social justice, economic prosperity, and environmental quality – the fundamental principles of sustainable development. This concept advocates for a transformation from the traditional linear model of ‘take-make-dispose’ to a more sustainable, closed-loop system where resource use is optimized, and waste is minimized (Marković et al., 2020; Rađenović & Živković, 2023; Radivojević et al., 2024). Currently, just 7.2% of the world economy is circular, and this percentage is falling yearly as a result of rising material extraction and consumption (Circle Economy, 2024). Due to fast industrialization and population growth, there is an alarming trend in the rising exploitation and use of resources worldwide. Hence, a change in society’s attitudes from materialism to more environmentally friendly production and consumption practices is needed.

Fostering CE and combining technology into various industrial strategies and regulations to ensure competitive, sustainable, low-carbon, and resource-efficient economies has particularly been the focus of the EU (Korhonen et al., 2018). In 2015, EC adopted the “Closing the Loop - An EU Action Plan for the Circular Economy” announcing the transition to a CE as a strategic move towards sustainability. The Action Plan envisaged CE to offer significant benefits to EU countries, including improved competitiveness by safeguarding businesses from resource scarcity and volatile prices, creating new business opportunities, introducing innovative production and consumption methods, and creating local jobs across various skill levels (EC, 2015). Additionally, CE contributes to energy saving, biodiversity preservation, and pollution reduction, aligning with key EU priorities like job growth, climate and energy, social agenda, and industrial innovation (EC, 2015). The EU's role is recognized as pivotal in enabling this transition through regulatory frameworks, investment stimulation, and other supportive mechanisms. Accordingly, to evaluate the success of initiatives aimed at promoting the CE in the EU, the "Measuring Progress Towards Circular Economy in the European Union - Key Indicators for a Monitoring Framework" was adopted in 2018 (EC, 2018). This was followed by the adoption of "A new Circular Economy Action Plan For a cleaner and more competitive Europe", which projected that implementing CE principles throughout the EU economy could boost GDP by an additional 0.5% by 2030 and generate about 700.000 new jobs (EC, 2020). Further, the plan aims to accelerate the transformational change required by the European Green Deal to reach climate neutrality by 2050 (European Council, 2023), while decoupling economic growth from resource use and building on CE actions implemented since 2015 (EC, 2020). Finally, the plan emphasizes EU-level action with added value, calling for long-term engagement from Member States, regions, and global cooperation, aligning with the United Nations "The 2030 Agenda for Sustainable Development" (UN, 2015) and achieving sustainable development goals (SDGs), particularly Goal 12 on ensuring sustainable consumption and production patterns.

However, the implementation and progress in adopting CE models vary significantly across regions, necessitating a comparative analysis to understand these disparities better. The relevance of CE is particularly pronounced in the EU countries, given their diverse economic landscapes and environmental challenges. Thus, the current research aims to provide a comparative analysis of CE indicators across EU nations, namely the Netherlands, France, and Germany. It focuses on evaluating and critically analysing the adoption and effectiveness of CE practices across these countries by employing a neural networks approach. Through this analysis, the paper will contribute to the understanding of the dynamics and complexities involved in transitioning to a CE, offering insights into the successes and challenges faced by selected EU countries. The findings will not only aid in policy formulation but also provide a framework for other regions looking to implement or enhance their CE strategies.

The manuscript is structured in the following way. Firstly, the introduction is followed by a section covering the theoretical background and literature review on CE performance indicators. Then, the data and methods section come next. Finally, the report concludes with a discussion of the research findings and their implications on CE performance in the selected EU countries using Neural Designer-Machine Learning Software.

Theoretical backgrounds and Literature review

Resource extraction, production, transportation, and storage activities in the conventional linear economy model are major contributors to greenhouse gas emissions

(Smol et al., 2020). However, switching to a CE can help reduce emissions, mainly from resource exploitation and production processes. By adopting strategies such as waste reduction, energy-efficient production, and using renewable resources, carbon footprint can be reduced and climate resilience enhanced (Yang et al., 2023). Additionally, through particular strategies like recycling, re-manufacturing, and reuse, a CE helps mitigate resource scarcity, ensuring that valuable materials are kept in productive use for longer periods, thereby reducing the need for extraction of virgin resources (Payet, 2021). CE fosters innovation and economic growth by creating new business opportunities, stimulating investment in sustainable technologies, and driving efficiency gains across value chains. By redesigning products and processes to minimize waste and maximize resource use, diverse economic entities can unlock cost savings, enhance competitiveness, and tap into emerging markets for green products and services (Caldera et al., 2022). Furthermore, the change to a CE facilitates research and development in fields such as sustainable transportation, renewable energy, and eco-materials science, among others, spurring technological innovation (Jinqiao et al., 2022; Anttonen et al., 2018). With no less importance is the fact that CE promotes different kinds of economic and social resilience by diversifying supply sources, reducing dependability on virgin resources, and creating closed-loop systems that minimize supply chain vulnerabilities. By localizing production, adopting modular designs, and implementing reverse logistics, businesses can enhance their resilience to external shocks and uncertainties, ensuring continuity of operations and supply (Islam et al., 2022). Moreover, by prioritizing sustainable practices and resource-friendly considerations, a CE promotes fair labour practices, human rights, and social justice, contributing to a more equitable and inclusive society. The process of transition to a CE is vital and essentially sustainable observed from a global perspective if it addresses pressing challenges such as resource scarcity, climate change, environmental pollution, economic growth, natural hazards resilience, etc.

Recent studies have underscored the importance of developing and analysing CE indicators to gauge the progress of different regions towards SDGs. For instance, Geng et al. (2012) emphasized the role of national CE indicators, particularly in the context of China, highlighting their importance in policy-making and achieving CE outcomes. The knowledge gained from Chinese efforts on CE indicators, emphasizing the need for a comprehensive set of sustainability indicators including social and business indicators, is valuable to both developed and developing countries seeking to implement CE principles within their regulatory policies.

Similarly, Korhonen et al. (2018) critically examined the concept of CE and its limitations, emphasizing the need for scientific rigor in defining and operationalizing CE indicators. According to Gregson et al. (2015), EU policies often overlook global recycling networks, focusing instead on transforming waste into resources within the EU, which poses challenges to CE effectiveness. CE has limited enactment in the EU due to political and moral concerns. Mhatre et al. (2021) argue that infrastructure, laws, and technology availability contribute to the CE in the EU, with recycling being the most popular option. Mazur-Wierzbicka (2021) points to the fact that different countries within the EU have adopted varying strategies, as well as the variations in the extent to which these have been effective in meeting the challenges of a CE.

Silvestri et al. (2020) explore the adoption of the CE at the regional level within the EU, by developing the CE Static Index (CESI) and the CE Dynamic Index (CEDI), which permitted both a static and a dynamic evaluation of the CE performance of EU regions. Garcia-Bernabeu et al. (2020) created a composite indicator called CE, using TOPSIS approach and a unique aggregation methodology, to evaluate EU nations' performance and highlight areas for improvement. They highlighted the need for a comprehensive monitoring framework at the national level to aggregate various CE dimensions. The study by Robaina et al. (2020) revealed that the efficiency of resource productivity and the determinants for a CE in Europe vary widely. They highlighted that there are noticeable differences in CE advancement between European countries, influenced by different policies and socio-economic development levels.

Vranjanac et al. (2023) used SmartPLS to study how CE innovation affects performance in EU nations. They found that supportive environments and financing are crucial for innovation to boost performance. The authors discussed the necessity of investments in research and innovations to improve recycling efficiency and support the secondary raw materials market. The findings contribute to understanding the dynamics of CE innovations and their effects on performance within the EU context. Radivojević et al. (2024) investigated the relationship between CE practices and economic growth by analysing data from 27 EU countries over 2000-2021. They specifically examined the impact of three CE indicators – Resource Productivity (RP), Generation of municipal waste per capita (MWpc), and Recycling rate of municipal waste (RRMW) – on GDP per capita. The findings revealed that CE practices not only enhance environmental sustainability but also significantly contribute to economic growth in EU countries. This reinforces the need for integrated policies to promote CE principles as part of sustainable development strategies.

However, notwithstanding the increasing volume of scholarly work on CE, there is a gap in comparative studies specifically focusing on the selected EU countries – the Netherlands, France, and Germany. By adopting CE principles and practices, countries, regions and inter-countries entities can unlock environmental, economic, and social benefits, securing a more sustainable and resilient future for generations to come. The selection of France, Germany, and the Netherlands for the research tasks in this study was influenced by their pioneering efforts in networking and collaborating with the Indo-Pacific region. The Indo-Pacific region has gained widespread acknowledgement as the preeminent geo-economic and geostrategic focal point globally. In economic terms, these nations account for a large part of the world's population, GDP, and marine trade. They present a unique context due to their varied stages of economic development, regulatory environments, and cultural perspectives on sustainability.

Initially, France was the country that initiated the focus on this region, mostly because of its significant historical-colonial legacy. Following France, Germany, and the Netherlands have joined cooperation programs with the Indo-Pacific region, creating national guidelines. In the context of the EU as a supranational entity, despite the undeniable importance of the Indo-Pacific region, scholarly literature addressing the burgeoning interest of the EU in the region remains relatively sparse (Weiqing & Yang, 2024). Nonetheless, Europe possesses significant interests, broadly categorized into economic, environmental, and normative domains, as delineated in recent academic publications (Abbondanza & Wilkins, 2023). Economically, the Indo-Pacific stands as the second-largest export destination for the EU, with the combined trade between the EU and the Indo-Pacific constituting approximately 70% of global trade. Moreover, their economies frequently exhibit complementary attributes.

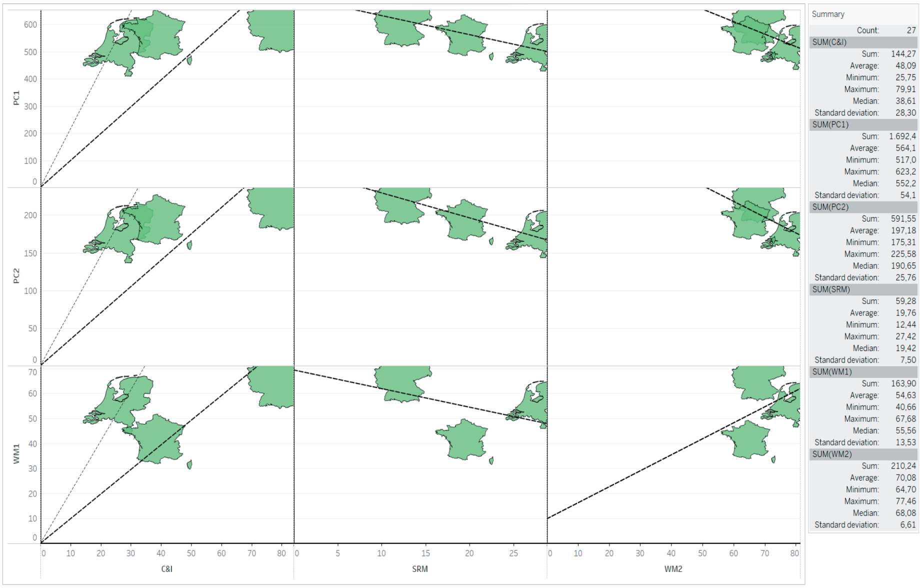
Having this in mind, the conclusions and Joint Communication on the EU Strategy for cooperation in the Indo-Pacific were adopted in 2021 (EC, 2021). Among other things, this Strategy focuses on the fulfilment of specific activities, such as: partnerships and cooperation agreements, value chains, trade negotiations, green alliances, ocean governance, research and innovation, connectivity partnerships, and others. The EU's engagement in the region includes initiatives to promote sustainable resource management practices, enhance environmental governance frameworks, and address transboundary environmental challenges through regional cooperation mechanisms. In the end, The EU's Indo-Pacific strategy includes initiatives to promote research collaboration, capacity-building, and knowledge exchange on environmental issues, leveraging scientific expertise and technological innovations to support SDGs achievements and environmental protection efforts. (EC, 2024).

This paper fills the gap by providing a comparative evaluation of CE indicators across these countries, drawing insights from the latest research and policy developments. This study analysis is grounded in the understanding that CE is not just an environmental or economic strategy, but a comprehensive approach that intersects with technological, cultural, and policy dimensions. As highlighted by Kirchherr et al. (2018), cultural and market barriers play a significant role in adopting CE practices across the EU, pointing to the complexity of implementing CE strategies. This paper, therefore, adopts a multi-dimensional approach to analyse the CE indicators, considering the interplay of these diverse factors through a neural network approach.

Methodology and Data

Following a neural network software solution, this research methodology examines three EU countries: the Netherlands, Germany, and France. The objective is to determine the relationship between inputs and outputs as a target variable in the context of a comparative study and a CE paradigm. Neural network applications have become more popular in the CE because of their functional features, reduced data needs, and ability to predict the future over the long term (Nema et al., 2017). There are several benefits over conventional analytical techniques. To construct the best neural network architecture for certain CE performance metrics, the Neural Designer-Machine Learning Software solution was applied. This is because it takes some intelligence to read the obtained data and analyse them effectively. This software offers applied comparative analysis that can predict trends, establish correlations, and identify patterns between inputs and outputs using a variety of effective neural network algorithms (Lopez, 2023). The approach involves starting with a small number of neurons and gradually increasing complexity until certain halting conditions are met. Additionally, this predictive model's expanding inputs approach is used in selecting inputs. By determining the correlation between each input and each output in the data set, this approach constructs a neural network that only includes the inputs that are most closely connected with the correct outputs (Hennemann Hilario da Silva & Sehnem, 2022). The neural network approach was used to evaluate which indication had the greatest influence and the most significant relationship between the input and output variables. Specifically, the study focuses on certain selected countries that have made progress in implementing the CE, particularly from an environmental point of view.

Figure 1: Descriptive statistics map chart with trend lines for average values of selected indicators 2016-2020



Source: Author's visualization according to available data from Eurostat Database

The most effective tools for monitoring progress toward the realization of CE principles are CE performance indicators. These indicators are part of the CE Monitoring Framework (Eurostat, 2023) and were chosen based on the most recent average values of the indicators for the countries selected from the Eurostat Database, for the five years 2016-2020 (Figure 1):

- Generation of municipal waste per capita (PC1) – indicator measures (Kg/capita) the waste collected by or on behalf of municipal authorities and disposed of through the waste management system. (Eurostat 2020a)
- Generation of packaging waste per capita (PC2) – indicator measures (Kg/capita) the packaging waste quantity in EU Member States. Packaging waste means any packaging or packaging material covered by the definition of waste in the Waste Framework Directive (EC, 2008), excluding production residues. (Eurostat 2020b)
- Recycling rate of municipal waste (WM1) – indicator measures (%) the share of recycled municipal waste in the total municipal waste generation. (Eurostat 2020c)
- Recycling rate of packaging waste by type of packaging (WM2) – indicator is defined as the share of recycled packaging waste in all generated packaging waste (%). (Eurostat 2020d)
- Circular material use rate (SRM) – the indicator calculates the percentage of material that is recycled and repurposed into the economy, hence reducing the amount of basic raw materials extracted during material consumption. The ratio of the circular material usage to the total material use is called the circularity

rate, or circular material use. More secondary resources replace primary raw materials, lowering the environmental effects of primary material extraction, is indicated by a greater circularity rate (%) value. (Eurostat 2020e)

- Patents related to waste management and recycling (C&I) – the patent indicator keeps a count of the number of patents related to secondary raw materials and recycling. This count is based on the Cooperative Patent Classification (CPC) codes used to attribute recyclables and secondary raw materials. However, it is important to note that this indicator only illuminates the latest recycling technology and does not cover all waste management technologies or other circular economy services and business models. (Eurostat 2020f).

Research results and Discussion

An analysis of the input variables' correlations was conducted using the Neural Designer software to identify the variables with the strongest correlation. Table 1 reveals that the generation of municipal trash per capita (PC1) and the generation of packaging waste per capita (PC2) have the highest correlation, with a coefficient value of 0.99 indicating their joint contribution to the output variable. Moreover, their positive correlation suggests that the three EU nations followed a similar approach in developing their output variable. On the other hand, the highest negative correlation, which is -0.99, has variables Generation of packaging waste per capita (PC2) and Circular material use rate (SRM), which means that these variables have a diametrically opposite effect on the output variable and are not dependent on each other.

Table 1 Correlation coefficient of the analysed CE indicators

Indicators	PC1	PC2	WM1	WM2	SRM	C&I
Generation of municipal waste per capita (PC1)*	1	0.99	0.61	-0.58	-0.99	0.98
Generation of packaging waste per capita (PC2)		1	0.63	-0.56	-0.99	0.99
Recycling rate of municipal waste (WM1)			1	0.39	-0.51	0.68
Recycling rate of packaging waste by type of packaging (WM2)				1	0.73	-0.58
Circular material use rate (SRM)					1	-0.99
Patents related to waste management and recycling (C&I)						1

*Note: PC1 indicator and PC2 indicator are inversed proportional

Source: Author's calculation

The chart below illustrates the impact of input variables on the output variable GERMANY, based on their respective values. A positive value for an input variable results in an increase in the output variable. Conversely, when an input variable is increased and the output variable is decreased, it produces a negative value. In case the output variable is close to zero, it indicates that changes in the input variable do not have any significant effect on it. Based on the Figure 2 below, the three most relevant inputs of this model are:

- PC1 with a value of -0.286.
- WM1 with a value of 0.232.
- PC2 with a value of -0.054.

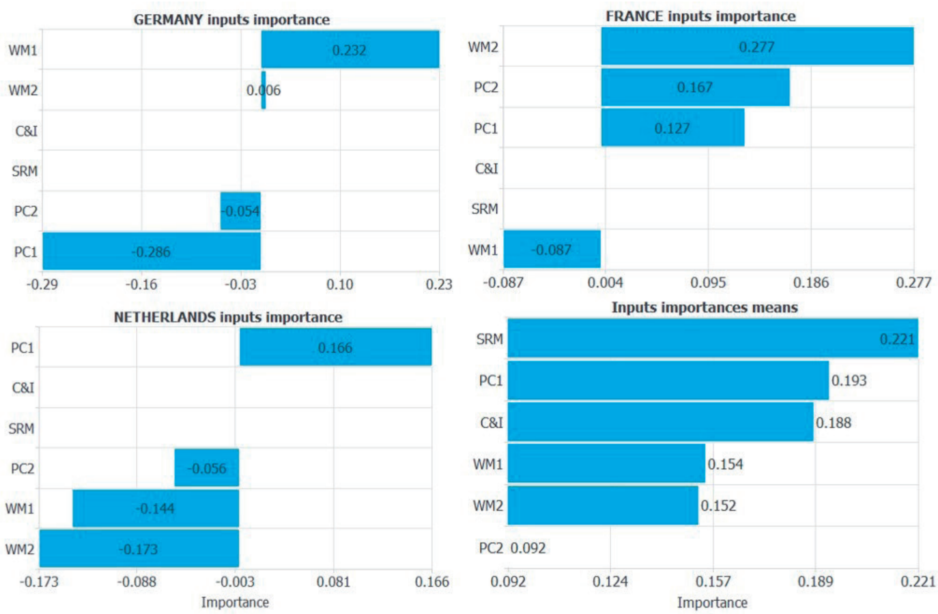
Germany has effectively increased its recycling rates over the past ten years, with almost two-thirds of its municipal solid waste (MSW) going through the processes of digestion, composting, and recycling. The recycling rate, inclusive of material recycling and composting/digestion, has maintained a consistent level of 67% over the past five years. France has witnessed a gradual rise in its recycling rate (Figure 2), climbing from 42.9% in 2016 to 45.1% in 2018, but experiencing a decline thereafter. By 2020, the recycling rate has reached 42.7%. Simultaneously, the proportion of waste sent to landfills has decreased, dropping from 22.4% in 2016 to 18.1% in 2020:

- WM2 with a value of 0.277.
- PC2 with a value of 0.167.
- PC1 with a value of 0.127.

Between 2016 and 2019, the Netherlands produced around 9 million tonnes of municipal garbage, a consistent level. But in 2020, the total climbed to 9.3 million tonnes, a 5.8% rise. According to Figure 2 the three most relevant inputs of this model are:

- WM2 with a value of -0.173.
- PC1 with a value of 0.166.
- WM1 with a value of -0.144.

Figure 2: Inputs importance across the countries and Overall importance 2016-2020



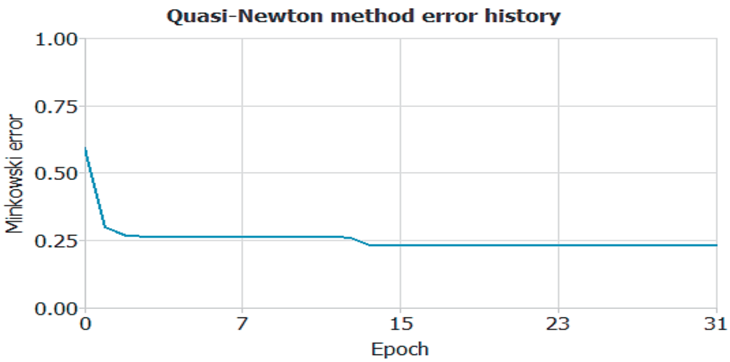
Source: Authors' elaboration from the Neural Designer

The selected EU countries exhibit substantial variations in SRMs, with percentages ranging from 27.5% in the Netherlands to 12% in Germany. France, during the analysed period, maintained a mean SRM of 19%. These disparities highlight notable distinctions in recycling capabilities and material consumption levels among analysed nations. In the analysed context, Germany produced a considerable 620 kilograms of municipal waste per capita, surpassing the EU average of 527 kilograms (Perestrello, 2022). Meanwhile, the Netherlands consistently generated around 9 million tonnes of municipal waste between 2016 and 2019. However, in 2020, there was a notable 5.8% increase, resulting in a total of 9.3 million tonnes. On a per capita basis, the Netherlands averaged 517 kilograms of municipal waste. France is in the middle with an average poverty indicator of municipal waste generation per capita, with a mean value of 552 kg/capita. Based on the highest number of patents, Germany leads in waste management and recycling innovations with 80 patents. This positions it as the innovation leader among analysed countries, significantly surpassing others. Following closely are France with 39 patents and the Netherlands with 26 patents. It can be concluded OVERALL inputs importances means of this model are (Figure 2):

- SRM with a value of 0.221.
- PC1 with a value of 0.193.
- C&I with a value of 0.188.

The training strategy is the process that is used to train a neural network. During training, the neural network is taught to minimize loss by adjusting its parameters. The type of training provided is determined by how these parameters are adjusted. In this case, the quasi-Newton approach is used for training. Unlike Newton's approach, it does not require the computation of second derivatives. Instead, the quasi-Newton approach uses gradient information to approximate the inverse Hessian at each iteration of the algorithm (Song, 2018). The following chart shows how the error decreases with the epochs during the training process.

Figure 3: Quasi-Newton method of error history



Source: Authors' elaboration from the Neural Designer

This model's accuracy is based on the Minkowski error (R), where 2 is the reference value. In this model (Figure 3), the Minkowski error starts at 0.59 and decreases to 0.23 after 31 epochs, indicating that the model is accurate.

$$E = \frac{1}{R}\sum_{n}\sum_{k=1}^{c}|y_k(x_n;W) - t_{kn}|^R$$

where E is error function, R is number 2, y_k is the output layer, x_n is the input layer, W is weights array, t is time (Christiansen et al., 2014)

Another one model validity checker is the root mean square error, a statistic that indicates the average difference between the model's predicted values and the dataset's actual values, can be used to evaluate how well a neural network model fits a dataset. A model's ability to "fit" a dataset improves with a decreased root mean square error (RMSE). The root mean square error, or RMSE for brief, can be calculated using the following formula:

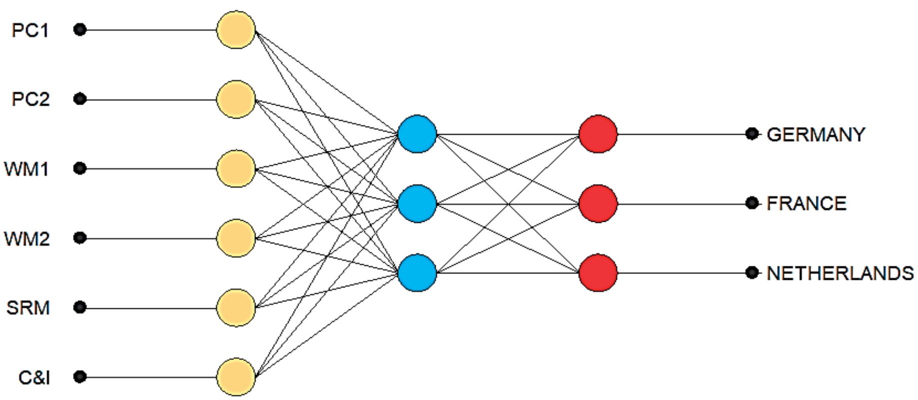
$$\mathrm{RMSE} = \sqrt{\frac{\sum(P_i - O_i)^2}{n}}$$

where Σ is a fancy symbol that means "sum", P_i is the predicted value for the i^{th} observation in the dataset, O_i is the observed value for the i^{th} observation in the dataset and n is the sample size. RMSE value in this model is 0.68 which indicates the satisfactory validity (very-good (0-0.50), good (0.50-0.60), satisfactory (0.60-0.70), or unsatisfactory (>0.70)) following Moriasi et al. (2007).

Lastly, Figure 4 displays the graphical depiction of the deep architecture that was produced as a result of the in-depth comparison analysis of a few chosen circular economy indicators. A neural network, an unscaling layer, and a scaling layer are all present. Yellow circles stand for scaling neurons, blue circles for perceptron neurons, and red circles for unscaling neurons. For every six inputs, there are three outputs generated. The neural network architecture's three levels of complexity are indicated by the quantity of hidden neurons. The network architecture is shown graphically in the following diagram. It contains the subsequent layers:

- Scaling layer with 6 neurons (yellow).
- Perceptron layer with 3 neurons (blue).
- Probabilistic layer with 3 neurons (red).

Figure 4 Neural network architecture for the input/output comparative analysis of the selected EU countries



Source: Authors' calculation in the Neural Designer-Machine Learning Software

The following listing presents the mathematical equation represented by neural network Box 1. This equation generates the outputs GERMANY, FRANCE, and NETHERLANDS based on the inputs PC1, PC2, WM1, WM2, SRM, and C&I. In classification models, the neural network spreads information in a feed-forward manner across the scaling, perceptron, and probabilistic layers.

Box 1: Mathematical expression of the neural network comparative analysis

```
scaled_PC_one_ = (PC_one_-564.1329956)/38.25189972;
scaled_PC_two_ = (PC_two_-197.1820068)/18.2159996;
scaled_WM_one_ = (WM_one_-54.63330078)/9.569849968;
scaled_WM_two_ = (WM_two_-70.08000183)/4.674630165;
scaled_SRM = (SRM-19.76000023)/5.300320148;
scaled_C_amprsn_I = (C_amprsn_I-48.08929825)/20.00769997;

perceptron_layer_1_output_0 = tanh (-0.0260498 + (scaled_PC_one_*-0.150281)
+ (scaled_PC_two_*0.0269897) + (scaled_WM_one_*0.126636) + (scaled_WM_
two_*0.108936) + (scaled_SRM*0.191541) + (scaled_C_amprsn_I*-0.164575));
perceptron_layer_1_output_1 = tanh (0.1125 + (scaled_PC_one_*0.184082) + (scaled_
PC_two_*-0.129688) + (scaled_WM_one_*0.096521) + (scaled_WM_two_*-0.0174927)
+ (scaled_SRM*-0.0272949) + (scaled_C_amprsn_I*0.0316406));
perceptron_layer_1_output_2 = tanh (-0.0515625 + (scaled_PC_one_*-0.169043) +
(scaled_PC_two_*-0.0744629) + (scaled_WM_one_*0.0323364) + (scaled_WM_two_*-
0.196545) + (scaled_SRM*-0.173767) + (scaled_C_amprsn_I*-0.0827881));

probabilistic_layer_combinations_0 = 0.139343 +0.0166138*perceptron_layer_1_
output_0 -0.0495239*perceptron_layer_1_output_1 -0.101257*perceptron_layer_1_
output_2
probabilistic_layer_combinations_1 = -0.177722 -0.0802124*perceptron_layer_1_
output_0 -0.0871948*perceptron_layer_1_output_1 -0.195862*perceptron_layer_1_
output_2
probabilistic_layer_combinations_2 = 0.0154907 -0.197656*perceptron_layer_1_output_0
-0.059082*perceptron_layer_1_output_1 -0.123779*perceptron_layer_1_output_2
sum = exp(probabilistic_layer_combinations_0) + exp(probabilistic_layer_combinations_1)
+ exp(probabilistic_layer_combinations_2);

GERMANY = exp(probabilistic_layer_combinations_0)/sum;
FRANCE_ = exp(probabilistic_layer_combinations_1)/sum;
NETHERLANDS = exp(probabilistic_layer_combinations_2)/sum
```

Conclusion

The efficacy of the CE paradigm can be assessed through multiple functional lenses, including economic, social, and ecological dimensions. Its performance can be spatially evaluated across various territorial scales, ranging from regional to global levels, utilizing diverse modelling techniques ranging from rudimentary numerical methods to sophisticated artificial intelligence approaches such as neural networks. In that sense, this scientific paper uniquely contributes by examining the CE performance within the context of three distinct EU countries, highlighting the novel selection of these entities for performed analysis.

Given the diverse economic landscapes and environmental challenges across EU countries, the CE is particularly relevant in the selected EU countries – the Netherlands, Germany, and France. The Netherlands was the third member of the EU to adopt an Indo-Pacific strategy, after Germany and France. To protect and advance Dutch political and economic interests, the Dutch government initiated an unambiguous choice in November 2020 towards a more active Dutch and EU posture in the Indo-Pacific. The German Policy guidelines for the Indo-Pacific are very extensive, begging the question of whose goals are to take precedence if difficult decisions need to be taken. The largest obstacle is allocating the required funds and personnel to meet the expectations that have been established among Indo-Pacific countries. Overall, the EU's efforts to optimize and adapt circular infrastructure are demonstrated by the umbrella strategy covering the entire EU.

Consequently, this study aims to add to the body of knowledge about evaluating CE performance in this area. Moreover, the study employs an advanced methodological framework incorporating optimized neural network architectures tailored to specific CE performance metrics. The study utilizes a neural network software solution to explore relationships between various input and output variables in CE performance across three Indo-Pacific EU countries. Six key indicators from the EU CE monitoring framework were analysed: Generation of municipal waste per capita, Generation of packaging waste per capita, Recycling rate of municipal waste, Recycling rate of packaging waste by type, Circular material use rate, and Patents related to waste management and recycling. The applied optimization process uses a mathematical model to find the ideal operating conditions in comparing the above-mentioned EU countries. This predictive model enables authors to reproduce various operating scenarios and modify control variables to increase efficiency. Particularly, performance circularity optimization means finding the rules that, by the CE concepts, minimize or maximize the performance variables for a specific set of countries participating in the Indo-Pacific Agreement.

A notable finding from this analysis is the strong correlation between the generation of municipal waste per capita and the generation of packaging waste per capita, highlighting the joint contribution of these input variables in the formation of output variables in CE. The importance of input variables on the output variable for Germany, as an example, demonstrates the influence of these indicators on national CE performance. By accelerating the procedures for product sorting and breakdowns, component refurbishment, and material recycling, machine learning can assist in the development and enhancement of the reverse logistics infrastructure needed to "close the loop" on goods and materials. To support efforts to fundamentally reshape the economy into one that is resilient, regenerative, and long-term fit, integrating the power of machine learning with a vision for a CE represents a significant, and currently unexplored opportunity to harness one of the outstanding technological developments of stakeholders' energy.

While acknowledging the imperfections of the model, it signifies a significant advancement in the analytical capabilities concerning CE performance within the selected entities. Furthermore, the model's adaptable architecture offers flexibility, enabling modification of existing CE performance indicators and integration of new ones. Future research endeavours should focus on refining composite indicator structures, expanding the scope of input variables, and devising additional relevant metrics, such as the virtual material use rate, to further enhance analytical depth and accuracy.

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References

Abbondanza G., Wilkins T., (2023). Europe in the Indo-Pacific: Economic, security, and normative engagement. *International Political Science Review*. https://doi.org/10.1177/01925121231202694

Anttonen M., Lammi M., Mykkänen J., Repo P., (2018). Circular economy in the triple helix of innovation systems. *Sustainability.* https://doi.org/10.3390/su10082646

Caldera S., Jayasinghe R., Desha C., Dawes L., Ferguson S., (2022). Evaluating Barriers, Enablers and Opportunities for Closing the Loop through 'Waste Upcycling': A Systematic Literature Review. *Journal of Sustainable Development of Energy, Water and Environment Systems,* 10(1):1–20. https://doi.org/10.13044/j.sdewes.d8.0367

Christiansen N.H., Voi P., Winther O., Høgsberg J., (2014). Comparison of Neural Network Error Measures for Simulation of Slender Marine Structures. *Journal of Applied Mathematics*, 1-11. https://doi.org/10.1155/2014/759834

Circle Economy, (2024). *The circularity gap report 2024, https://www.circularity-gap.world/2024#download*, (30.01.2024).

EC, (2008). *Directive 2008/98/EC of the European Parliament and of the Council of 19 November 2008 on waste and repealing certain Directives (text with EEA relevance). https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:32008L0098.* (10.01.2024).

EC, (2015). *Closing the Loop - an EU Action Plan for the Circular Economy. https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:52015DC0614* (20.12.2023).

EC, (2018). *Measuring Progress Towards Circular Economy in the European Union – Key Indicators for a Monitoring Framework. https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=SWD%3A2018%3A17%3AFIN* (20.12.2023).

EC, (2020). *A new Circular Economy Action Plan For a cleaner and more competitive Europe. https://eur-lex.europa.eu/legal-content/EN/TXT/?qid=1583933814386&uri=COM:2020:98:FIN* (20.12.2023).

EC, (2021). *The EU strategy for cooperation in the Indo-Pacific. https://www.eeas.europa.eu/eeas/joint-communication-indo-pacific_en.* (20.12.2023).

EC, (2024). *EU Indo-Pacific Strategy. https://www.eeas.europa.eu/sites/default/files/documents/2024/EU%20Indo-pacific%20FS-01-24-V3.pdf.* (10.01.2024).

European Council, (2023). *European Green Deal, https://www.consilium.europa.eu/en/policies/green-deal/* (10.01.2024).

Eurostat, (2020a). *Generation of municipal waste per capita (cei_pc031). https://ec.europa.eu/eurostat/cache/metadata/en/cei_pc031_esmsip2.htm.* (20.12.2023).

Eurostat, (2020b). *Generation of packaging waste per capita (cei_pc040) https://ec.europa.eu/eurostat/cache/metadata/en/cei_pc040_esmsip2.htm.* (20.12.2023).

Eurostat, (2020c). *Recycling rate of municipal waste (cei_wm011). https://ec.europa.eu/eurostat/cache/metadata/en/cei_wm011_esmsip2.htm* (20.12.2023).

Eurostat, (2020d). *Recycling rate of packaging waste by type of packaging (cei_wm020). https://ec.europa.eu/eurostat/cache/metadata/en/cei_wm020_esmsip2.htm* (20.12.2023).

Eurostat, (2020e). *Circular material use rate (cei_srm030) https://ec.europa.eu/eurostat/cache/metadata/en/cei_srm030_esmsip2.htm.* (20.12.2023).

Eurostat, (2020f). *Patents related to waste management and recycling (cei_cie020) https://ec.europa.eu/eurostat/cache/metadata/en/cei_cie020_esmsip2.htm* (20.12.2023).

Eurostat, (2023). *Circular economy monitoring framework. https://ec.europa.eu/eurostat/web/circular-economy/monitoring-framework.* (20.12.2023).

Ezeudu O.B., Agunwamba J.C., Ugochukwu U.C., Oraelosi T.C., (2022). Circular economy and frugal innovation: a conceptual nexus. *Environmental Science and Pollution Research* 29:29719–29734. https://doi.org/10.1007/s11356-022-18522-6

Garcia-Bernabeu A., Hilario-Caballero A., Plà-Santamaria D., Salas-Molina F., (2020). A Process Oriented MCDM Approach to Construct a Circular Economy Composite Index. *Sustainability.* https://doi.org/10.3390/su12020618

Geng Y., Fu J., Sarkis J., Xue B., (2012). Towards a national circular economy indicator system in China: an evaluation and critical analysis. *Journal of Cleaner Production* 23(1):216–224. https://doi.org/10.1016/j.jclepro.2011.07.005

Gregson N., Crang M., Fuller S., Holmes H., (2015). Interrogating the circular economy: the moral economy of resource recovery in the EU. *Economy and Society*, 44:218–243. https://doi.org/10.1080/03085147.2015.1013353

Hennemann Hilario da Silva T., Sehnem S., (2022). The circular economy and Industry 4.0: synergies and challenges, *Revista de Gestão*, 29(3):300–313. https://doi.org/10.1108/REGE-07-2021-0121

Islam M.T., Iyer-Raniga U., Trewick S., (2022). Recycling Perspectives of Circular Business Models: A Review. *Recycling,* 7, 79. https://doi.org/10.3390/recycling7050079

Jinqiao L., Maneengam A., Saleem F., Mukarram S.S., (2022). Investigating the role of financial development and technology innovation in climate change: evidence from emerging seven countries. *Economic research* 35(1):3940–3960. https://doi.org/10.1080/1331677X.2021.2007152

Kirchherr J., Piscicelli L., Bour R., Kostense-Smit E., Muller J., Huibrechtse-Truijens A., Hekkert M., (2018). Barriers to the circular economy: Evidence from the European Union (EU). *Ecological Economics* 150:264–272. https://doi.org/10.1016/J.ECOLECON.2018.04.028.

Korhonen J., Honkasalo A., Seppälä J., (2018). Circular Economy: The Concept and its Limitations. *Ecological Economics*, 143:37–46. https://doi.org/10.1016/J.ECOLECON.2017.06.041.

Lopez R., (2023). *What is Neural Designer? https://www.neuraldesigner.com/learning/user-guide/what-is-neural-designer/* (20.12.2023).

Marković M., Krstić B., Rađenović T., (2020). Circular economy and sustainable development. *Economics of sustainable development* 4(1):1–9. https://doi.org/10.5937/ESD2001001M

Mazur-Wierzbicka E., (2021). Circular economy: advancement of European Union countries. *Environmental Sciences Europe*, 33:1–15. https://doi.org/10.1186/s12302-021-00549-0

Mhatre P., Panchal R., Singh A., Bibyan S., (2021). A systematic literature review on the circular economy initiatives in the European Union. *Sustainable Production and Consumption*, 26. https://doi.org/10.1016/J.SPC.2020.09.008.

Moriasi D.N., Wilson B.N., Douglas-Mankin K.R., Arnold J.G., Gowda P.H., (2012). Hydrologic and Water Quality Models: Use, Calibration, and Validation. *Transactions of the ASABE*, 55:1241–1247. http://dx.doi.org/10.13031/2013.23153

Nema M.K., Khare D., Chandniha S.K., (2017). Application of artificial intelligence to estimate the reference evapotranspiration in sub-humid Doon valley. *Applied Water Science,* 7(7):3903–3910. doi: https://doi.org/10.1007/s13201-017- 0543-3

Payet J., (2021). Assessment of Carbon Footprint for the Textile Sector in France. *Sustainability,* 13, 2422. https://doi.org/10.3390/su13052422

Perestrello M., (2022). *Nato and the Indo-Pacific Region - Report https://www.nato-pa.int/document/2022-nato-and-indo-pacific-region-report-krimi-021-pcnp* (10.12.2023).

Radivojević, V., Rađenović, T., & Dimovski, J. (2024). The Role of Circular Economy in Driving Economic Growth: Evidence from EU Countries. *SAGE Open, 14*(4), 21582440241240624.

Rađenović T., Živković S., (2023). The Importance of Circular Economy for Sustainable Development. *Economic and Social Development: Book of Proceedings*, 186-198.

Robaina M., Villar J., Pereira E.T., (2020). The determinants for a circular economy in Europe. *Environmental Science and Pollution Research* 27:12566–12578. https://doi.org/10.1007/s11356-020-07847-9

Silvestri F., Spigarelli F., Tassinari M., (2020). Regional development of Circular Economy in the European Union: A multidimensional analysis. *Journal of Cleaner Production*, 255:120218–120260. https://doi.org/10.1016/j.jclepro.2020.120218

Smol M., Marcinek P., Duda J., Szołdrowska D., (2020). Importance of Sustainable Mineral Resource Management in Implementing the Circular Economy (CE) Model and the European Green Deal Strategy. *Resources.* 9(5):55. https://doi.org/10.3390/resources9050055

Song H., (2018). *Nature-Inspired VLSI Circuits - From Concept to Implementation*. Lulu.com, USA.

UN, (2015). *Transforming our World: The 2030 Agenda for Sustainable Development, https://sdgs.un.org/sites/default/files/publications/21252030%20Agenda%20for%20Sustainable%20Development%20web.pdf.* (10.01.2024).

Vranjanac Ž., Rađenović Ž., Rađenović T., Živković S., (2023). Modeling circular economy innovation and performance indicators in European Union countries. *Environmental Science and Pollution Research.* 30(34):81573–81584. https://doi.org/10.1007/s11356-023-26431-5

Weiqing S., Ziqing Y., (2024). Unpacking the EU's Indo-Pacific strategy: a testing case of strategic autonomy, *Australian Journal of International Affairs,* https://doi.org/10.1080/10357718.2024.2305650

Yang M., Chen L., Wang J., Msingwa G., Osman A., Fawzy S., Rooney D.W., Yap P.S., (2023). Circular economy strategies for combating climate change and other environmental issues. *Environmental Chemistry Letters* 21:55–80. https://doi.org/10.1007/s10311-022-01499-6