ISSN: 2634 - 8853

Journal of Engineering and Applied Sciences Technology

SCIENTIFIC Research and Community

Review Article

Open Access

Circular Economy – Comparative Study Within the EU of Five Countries on The Spectrum Based on Eurostat and Artificial Intelligence Methods. Case study: Germany, Holland, France, Romania and Poland

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ABSTRACT

This paper is a short presentation of concepts related to a circular economy, such as those depicted by Paul Ekins, the butterfly model introduced by Ellen Mac Arthur, the 9 R's introduced by European Union in 2017, to denote the strategies for a circular economy, the indicators of a circular economy proposed by Teresa Domenech such as the consumption material use, recycling, energy use, consumption, renewable energy, air quality, water consumption; well-being – health, social cohesion, as well as the indicators of a circular economy proposed by Peterborough such as the amount of renewable electricity available to each household, CO_2 emissions per capita, percentage household waste recycled, percentage circular jobs, and so on. North America and Europe, as well as Japan are the first promoters of this kind of economy throughout the globe. Inside Europe, the differences situate themselves between western Europe, more advanced on the implementation of the roadmap for a circular economy, while the Eastern Europe is designing its roadmap and moving towards its implementation. A brief presentation is made on three major western European countries – Germany, Netherlands and France, by considering them as role models into the future circular economy. Additionally, it is presented how far they are onto this path, the programs they have implemented, and what they still need to achieve. On the other hand, is also made a short study on eastern and central European strategy plan for a circular economy and bio- economy. Special focus is given to Romania and Poland, considering their efforts involved in some programs such as recycling electronics, and construction materials and also highlighting a lack of initiative for other programs, such as recycling municipal wastes, reinserting back into the economy raw materials and the production of renewable biological resources for the conversion into food by innovative and efficient technologies. The research paper is based on EUROSTAT charts, graphs, roadmap and tables. It uses two artificial intelligence deep learning methods, a Multi-Layer Perceptron and a Long Term Short Memory, to estimate and forecast three-time series based on the data set collected from 2013 to 2022 for 2023-2027.

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Received: November 05, 2024; **Accepted:** November 07, 2024; **Published:** December 02, 2024

Keywords: Butterfly Model, Circular Economy, Recycle, Key Indicators, Roadmap, Policies, MATLAB Simulink Software Package, Multi Layer Perceptron (MLP), Long Term Short Memory (LSTM)

Introduction

"In 2015, the UE commission adopted the first *Circular Economy Action Plan (CEAP)* of the UE, which includes measures tightly linked to the key priorities of the UE, such as occupying labor force, economy growth, the agenda related to investments, the efforts involved in climate and energy changes, social agenda and industrial innovation, as well as tight efforts registered at the national and international level for sustainable development [1].

Addressing actions with regards to circular economy, which were first taking place in 2015, the UE commission adopted a new CEAP in 2020 to achieve the goal towards a Europe cleaner and more competitive, in cooperation with economical actors, consumers, citizens and organizations, civil societies. The CEAP announced initiatives throughout the life cycle of products, addressed to consumers, and producers, which concentrate on designing products, on the production processes, on consumption, but also on preventing waste and pollution, making sure that the resources that were used will stay in UE economy for as long as possible. The main value chains associated to products, which were put onto focus throughout the CAEP, include electronic products, telecommunications, batteries and vehicles, plastic, packaging, textile materials, constructions and buildings, as well as food, water and nutrients [2].

The main objectives of Circular Economy are also included in the action plan of the UE, i.e. *"Zero Pollution"*, which states that wastes should be reduced significantly, the municipal wastes should be lessened by 50% until 2030. These are part of a list of objectives that contribute to "vision pollution 0 for 2050". CAEP announced different strategies and initiatives: an initiative regarding circular electronic products, a *strategy of UE for textile* and a *Strategy UE for Plastic for 2020*. In the last segment relating to circular economy, in 2022, CE adopted an initiative for sustainable products including the proposition of *An Act of Regulations for eco designing sustainable products*. This Initiative would have as main objective to ensure that products, which are introduced on the UE market are more life long resistant, are successfully passing the test of circularity, making production and the consumption more ecological, reducing to the minimum waste and pollution. The *European Ecological Pact* is the new European agenda for sustainable growth, hoping that the extension of circular economy will contribute to achieving climate neutrality till 2050, to realizing ODD and the decoupling of economic growth from the use of resources. Until now, 17 state members of the UE elaborated strategies, in general terms, regarding circular economy. In this narrative, we will go through the main concepts related to Circular Economy (such as *Butterfly Model* and the *9 R's*), we will see the *key indicators* which quantify the progress that is made in different countries in implementing different aspects of circularity (section 2). The remainder of this paper consists of the following sections. In section 3, we will compare through values and graphs, five countries, N*etherlands, France, Germany, Poland and Romania.* A rigorous analysis is performed in section 3, regarding the quantity and quality measures of circularity, by quantifying the score associated to different indicators for each of the studied countries, and comparing them to each other. These key indicators will teach us about the progress that is taking place in different countries, towards an economical framework encompassing circularity concepts. Section 4 is dedicated to the different policies currently implemented in those countries, with relevant results and impact. Section 5 is dedicated to an analysis from an engineering point of view. We will describe the different methods taken from Artificial Intelligence algorithms, and implemented in a software engineering platform such as MATLAB – SIMULINK, to make an analysis of three other indicators of circular economy for the same five countries we have studied so far.

Concepts Related to Circular Economy

The definition of the Ellen MacArthur Foundation is "A circular economy is an industrial system that is restorative or regenerative by intention and design. It replaces the "end-of-life" concept with restauration, shifts towards the use of renewable energy, eliminates the use of toxic chemicals, which impair reuse, and aims for the elimination of waste through the superior design of materials, products, systems, and within this, business models" [3].

Butterfly Model

Ellen MacArthur is famous for breaking the world record time for sailing solo non-stop round the world in 2005. She set up the Ellen MacArthur Foundation (EMF) in 2010. Partnering with a number of large companies and the McKinsey consultancy, EMF produced in 2013 three publications 'Towards Circular Economy", the first of which containing the celebrated "butterfly diagram". The four people credited in the first volume of this publication are Baumgart, Stahel, Benyus and Roland Clift. The Foreword of the volume is by Janez Potocnik, then European Commissioner for the Environment [3].

This model shown in Figure 1 emphasises environment sustainability and its focus is overwhelmingly on making circular use of natural resources and reducing environmental impacts.

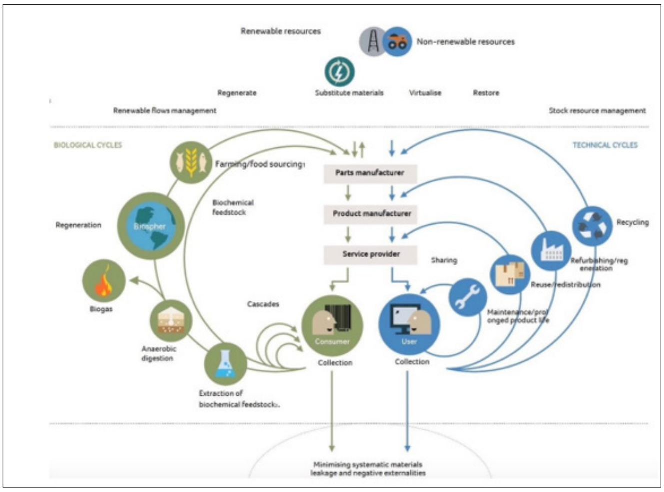


Figure 1: T*he Butterfly Model* proposed by Ellen MacArthur Foundation to Describe Circular Economy, (*source* [3]).

The 9 R's Concept

Recycling is a key element in circular economy. As time has gone on the number of R's has multiplied. The Japanese Government's 3 R Initiative' (*reduce, reuse, recycle*) started from 2004.

By 2017, nine separate R's contributing to circular economy have been identified, namely *Refuse (0), Rethink, Reduce, Re-use, Repair, Refurbish, Remanufacture, Repurpose, Recycle and Recover* (see Annex 1, Diagram 1).

Key Indicators

In order to quantify the progress that is taking place towards an economical framework encompassing circularity concepts, in different countries, there are many indicators that are in handy. Amongst these indicators, the most important are: *Domestic Material Consumption, Resource Productivity, Eco-Labels, Number of Industrial and Territorial Ecology Projects, Car- Sharing, Food Waste, Expenditure on Product Repair and Maintenance, Quantities of Waste sent to Landfill, Use of Recycled Raw Materials in Production Process, Employment in the Circular Economy*. Different agencies at the national and European level (such as *EIONET - the European Environment Information Observation Network, or EEA – European Environment Agency*), gather economic data, computes the values of indicators and releases reports on a regular basis, containing the relevant information [4-9]. Netherlands is one of the front runners in Europe at designing and achieving policy actions in sustainability and working towards a complete framework of economic circularity [6]. In this sense, the Institute of Circular Economy (ICER) in Netherlands released a report (ICER 21) containing data about more than 30 indicators to measure the progress in circular framework. These indicators are more refined compared to the regular indicators and show more precise information. As examples of these indicators can be highlighted the *Material resource footprint on the economy, Share of recycled waste in processed waste, and Biodiversity footprint of production,* etc.

Material footprint (Raw Material Consumption)

The *Material footprint* presented in Figure 2, which is also called raw material consumption (RMC), represents the global demand for the extraction of materials (minerals, metal ores, biomass, and fossil energy materials) induced by consumption of goods and services within a geographical reference area.

They are divided into following Different Categories:

- *domestic extraction of materials* measured in tonnes of gross material, for example, gross ore or gross harvest
- *imports* and *exports* measured by estimates of raw material equivalents of the products traded while domestic and abroad extraction require to produce the traded products. RMC measures the amount of extraction needed to produce the goods demanded by final users in the geographical reference area.

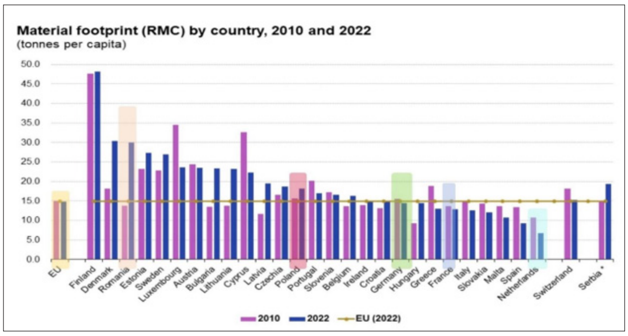


Figure 2: *Material footprint (RMC)*, per countries (focus on the *five* selected countries) reported to EU rate, *source* [10]

Domestic Material Consumption by Selected Category

The *Domestic Material Consumption (DMC)* depicted in Figure 3 measures the total amount, in tons, of material directly used in an economy, i.e. by resident businesses, governments and other institutions for economic production or by households. The DMC equals the domestic extractions of materials plus imports minus exports. At the same time, the DMC is the number of materials that become part of the material stock within the economy or are released back to the environment in form of e.g., emissions to air. It also illustrates the absolute level of the use of resources, and shows the difference between the consumption driven by domestic demand from consumption driven by the export market [11-12].

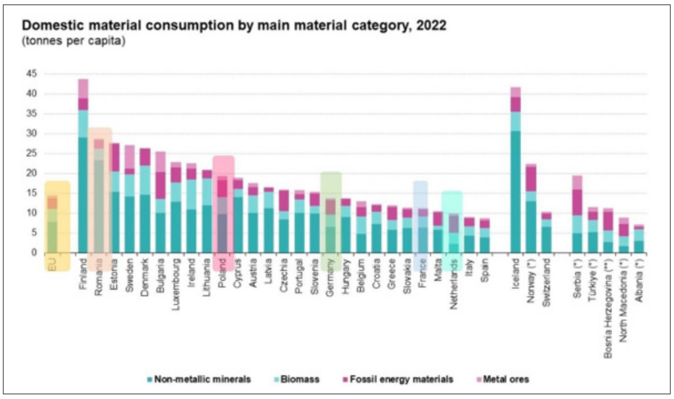


Figure 3: *Domestic consumption* by main category per countries (focus on the *five* selected countries) reported to EU, 2022, (source [11-12]).

Resource Productivity (Gross Domestic Product / Domestic Material Consumption)

The *Resource Productivity* shown in Figure 4 is defined here as GDP divided by DMC. It is noteworthy to mention that the GDP is expressed in different measurement units, of which the following are used to calculate two different resource productivity ratios. An appropriate choice depends on the context of the analysis:

- *euro per kilogram* using chain-linked volume data for the GDP, to be used for analyzing developments in real terms over time
- PPS *per kilogram* using current price data for the GDP expressed in purchasing power standards (PPS)

Also, PPS are artificial currency units that remove differences in purchasing power between economies by taking account of price level differences; these can be used when comparing across different economies at one point in time (for one particular year). The following graph illustrates the importance of Resource Productivity in different countries of EU (see also *Table 1* from *the Annex 1*). It shows that in western countries, the resource productivity is higher than in eastern European countries, where Netherland is situated on the first place compared to Romania which is on the last place amongst the countries in the focus for the present study.

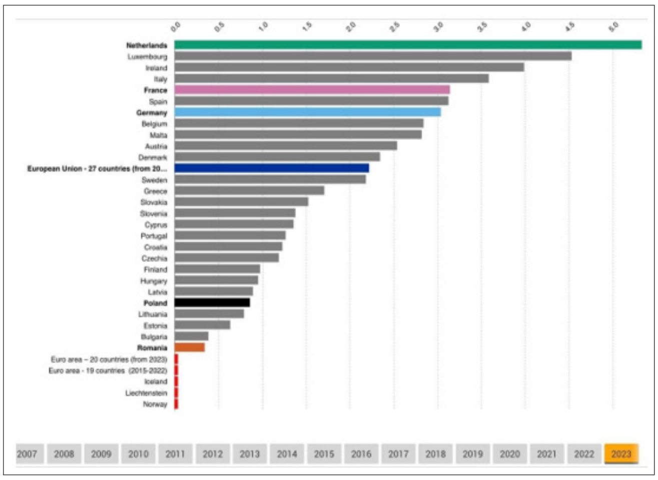


Figure 4: *Resource Productivity (euro/Kg)* measured in the countries of EU (focus on the *five* selected countries), in 2023, *source* [13].

This indicator is a measure of the total amount of material directly used by an economy (measured as domestic material consumption, so the DMC is in relation to GDP). Resource productivity (GDP/DMC) illustrated in Figure 5 is the European Union sustainable development indicator for policy evaluation which indicates the amount of GDP generated per unit of direct material consumed.

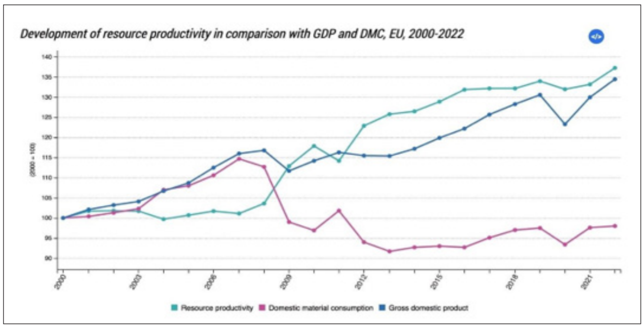


Figure 5: Evolution of three indicators *(Resource Productivity, Domestic Material Consumption* and *Gross Domestic Product)* from 2000 to 2021 through the countries of EU, *source* [12]

The long-term changes rates of DMC and GDP instruct on the degree of decoupling between DMC (pressure on the environment) and GDP (economic growth). In Figure 6 it can be seen that different countries in EU spread above and below the diagonal line, which represents the case when the DMC and GDP rates meet, i.e., they have the same rate of growth. The countries which find themselves above this diagonal line, have a higher DMC growth compared to GDP growth and both are not de-couple. It is the particular situation of Romania amongst the countries from this case study. Below the diagonal line are all countries whose GDP increased faster than their DMC and achieve relative decoupling, which is the case of Poland. Absolute decoupling was achieved when the DMC registered a decrease, which the GDP had a high rate of increase. It is the case of Netherlands, Germany and France. EU average is at the limit between relative and absolute decoupling.

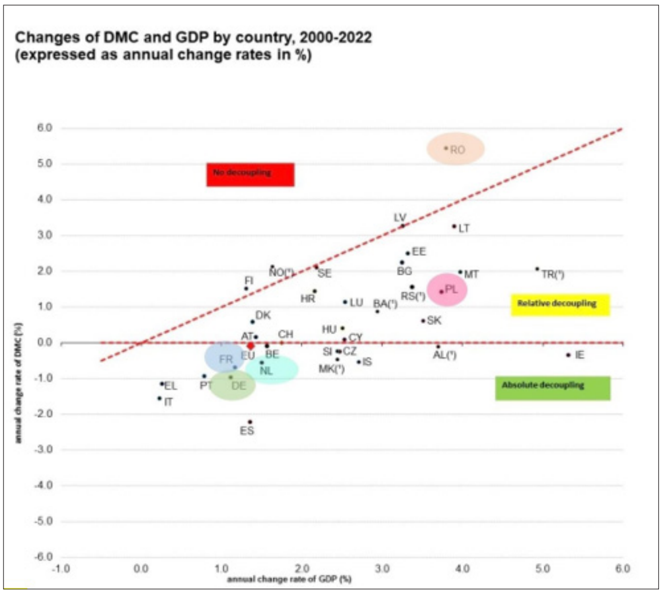


Figure 6: Different degrees of *decoupling DMC and GDP* amongst countries of Europe (focus on the *five* selected countries), 2020-2022, (*source* [12])

Circular Material Use Rate (CMU)
This indicator measures the contribution of recycled materials towards the overall use of materials. The circularity rate is the share of material resources used in the EU which came from recycled waste materials, thus saving primary raw materials from being extracted. A higher circularity rate means that more secondary materials replace primary raw materials, thus reducing the environmental burden that comes with extracting new materials [9].

It is computed by using following the formula:

$$CMU = \frac{M}{U} \qquad (1)$$

where U is the circular use of Material, and M is an indicator of the overall material use.

Also,

$$U = RCV_R - IMP_w + EXP_w \qquad (2)$$

where,
- RCV_R is designated for the amount of waste recycled in domestic recovery plants,
- IMP_W denotes the amount of imported waste bound for recovery, and
- EXP_W represents the amount of exported waste bound for recovery abroad.

The graph from Figure 7 illustrates the circularity rates for different countries in EU, with a focus on the five countries included into the present study. A high circularity rate is registered for Netherlands and France, which proves them as front stage actors in the programs of recycling and treatment of wastes, that return to the production process. Germany and Poland are quite close to the average of EU [14]. And Romania is far behind, which means it has a long way to go before reaching the right status in circularity terms. Romania will need to find the means to implement programs to recycle more and use less raw material resources.

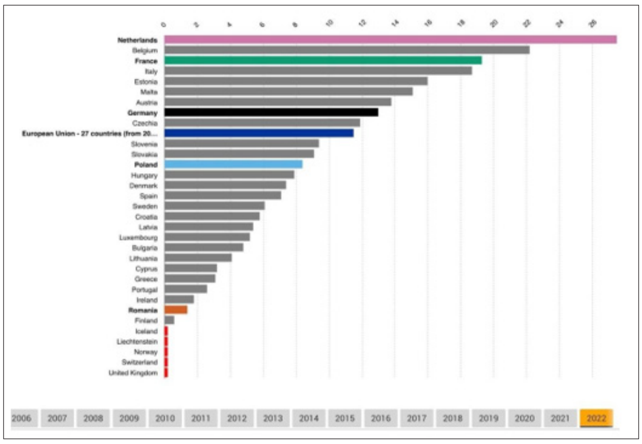


Figure 7: *Circularity use rate* among countries in EU (focus on *five* countries), *source* [13]

The graph in *Annexe 1, Diagram 2*, shows that throughout the period 2015-2022, the average circularity rate is stable for the main types of materials used in production process, a bit of increase tendency being for *metal* ores and *biomass.*

Policy Implementation
Zero waste policy, taking place in France, has set up as a "Nothing New" campaign to challenge society to question its consumption habits and, if possible, to purchase nothing new [5,16-20]. In 2018, 14000 participants committed to avoiding the purchase of new products and finding alternatives to consumption. The campaign has been extended in 2019 and is aiming to reach 100 000 participants by the end of the year.

Repairability Index of Electric and Electronic Products
Since 1st January 2021, a reparability index is compulsory in France for five categories of electronic products and home appliances [4]. This tool is meant to provide information to the consumer about the degree of reparability of purchases. An index is displayed, which could vary from 1 to 10, which informs customers about the reparability score for that product. The following categories of items are featuring the index: washing machines, smart phones, laptops, TV monitors, electric lawn mowers, and recently vacuum cleaners and dishwashers.

The "Green Deal" Programme - Netherlands
It is a joint initiative of the Ministry of Economic Affairs and Climate Policy, the Ministry of Infrastructure and Water Management and the Ministry of Interior and Kingdom Relations [6,15]. By means of this programme, the government enables organizations and businesses, on their own initiative, to identify existing barriers to green growth or the implementation of CE activities and to submit a request for review. By providing advice on regulation, administration or funding, and in some cases on amending regulations, the government has managed to stimulate the economic activity of the circular business ideas from scratch without providing further financial incentives [6].

Nederland Circulair and Versnellingshuis
In 2018, there were more then 100 000 circular businesses in Netherlands. A circular business is any business that applies one or several R-strategies in practice. The entrepreneurs involved in activities related to circularity can make use of various programmes, aimed at supporting and promoting entrepreneurship, such as Nederland Circulair, the business support organisation Versnellingshuis, and the instruments implemented by Netherlands Entreprise Agency (RVO).

City Deal Circular and Conceptual Construction
Cities and businesses in the Netherlands share cooperation in the construction field, on knowledge and expertise, expanding the Circular Economy knowledge of the participants and ensuring it is made widely available.

Re-Use Berlin Initiative -Germany
It is an initiative of the Berlin Senate's Department for the Environment, Transport and Climate Protection, which aims to strengthen the market for second-hand goods, including electronic equipment, in Berlin. The city of Berlin established three centers for re-use: the *NochMall* and *Re-use SuperStore*, which act like huge second-hand warehouses, and the *Re-Use Centre* for climate-friendly resource use. This last one offers shopping for second hand goods, sharing, repairing, and upcycling, together with bicycle repairs, open workshops for repair and upcycle textiles. In addition, it proposes a construction and creative market, where someone could get second – hand battens, fabrics, hardware, sheet metal, beams, felts and fleeces, paints, decorations. This project offers an online experience, an informative website where citizens could find easily where they can drop off or purchase second-hand goods, through the bundling of existing second- hand shops in Berlin in a network.

Repair Bonus - Thuringia
It is an initiative taking place in the German Federal State of Thuringia. It is dedicated to the repair of electrical and electronic devices. Local people who repaired a broken household electrical appliance are reimbursed half of the repair costs – up to a maximum of 100 euros per person and calendar year.

My Water Programme - Poland
It is an initiative taking place in Poland, by which it is meant to preserve water resource, by collecting rain water to be later used for domestic or farming purposes [8]. Financial support is given for purchase, assembly and launching of installations for the collection of rainwater from impermeable surfaces, such as roofs, pavements, and driveways; the retention of rainwater in the ground and in the drainage layer of green roofs.

Re-Use of Wood - Divadlo Brand
The Divadlo Brand operates in the area of environmentally friendly technologies in the construction and interior design sectors. It is part of the current drive for zero/less waste, upcycling and return to craftsmanship [8]. Divadlo recovers old wooden material and reuses it in modern architecture – in the form of façade, wall panelling or furniture fronts made from old wood. It minimises the environmental footprint of construction and reducing the use of new wood.

Re-Use of Asphalt
The Minister of Climate and Environment defined a regulation for making asphalt recyclable. It drew the conditions by which asphalt should be considered an essential component with documented properties to be reused for the construction of roads and highways. This way, it complies with the circular economy views of minimising waste as much as possible and keeping materials in the economy for a longer time.

Green Group - Romania
It has two branches – one is ***Green Fiber*,** the only producer of synthetic polyester fibers in Romania and the largest producer of fibers in Europe made from 100% recycled pets flakes [9].

The second branch is ***GreenWEEE***, which focuses on the collection, treatment, and recycling of waste electrical and electronic equipment (WEEE), cables, batteries, and car components.

LanaTerm
It is a thermal Insulation solution, which is based on sheep's wool to create thermal insulation for buildings.

ecoHORNET
It develops multi-system burners with ecological combustion producers to create gas, oil, and biochar through pyrolysis [9]. Pyrolysis plants treat all types of industrial biomass which cannot be recycled and stored in ways that avoid biological degradation, including household wastes and sewage sludge, unrecycled plastic and rubber wastes, deteriorated soils with hydrocarbons, coal, waste oil.

Artificial Intelligence Methods for Data Estimation and Forecasting Time Series – Load Forecasting and Fitting using Neural Networks in MATLAB
The circular economy indicators mentioned in the previous sections are provided by Eurostat statistics for each country and for European Union (EU), as average. They provide valuable information regarding the level of circularity in different countries and showcase the importance for countries to work harder to implement different programmes for achieving more circularity. In this section, we will try another type of analysis for three other types of circular economy indicators then the ones analysed in section 3 of this article. We are using two Artificial Intelligence (AI) Deep Learning methods, such as a *Multi Layer Perceptron* (MLP) and *Long Short Time Memory (LSTM)*. Both methods can be used for forecasting and estimation of three time series indicators, namely *Eco Innovation Index (EII)* chosen as a reference value of 100% in EU, for the year 2013 and *Circular Material Use Rate (CMUR)* measured in annual percentage – these two are taken as two main independent factors (input variable) that have a strong impact on the *Greenhouse Gas Air Emission (GGE)*, selected as a dependent output variable. The evaluation period is starting with the year 2013 and ending by 2022. We have enough data for "proof concept" and for the implementation of both algorithmic methods, in an attractive MATLAB Simulink R2024a simulation environment. Both AI methods could also be implemented in Python; this has the advantage of being an open-source software package and is compatible with MATLAB. In order to forecast the values of future time steps of a sequence, we need to specify the targets as the training sequences with values shifted by one time step. At each time step of the input sequence, the LSTM neural network learns to predict the value of the next time step. Since the results obtained are encouraging, and both methods are performing well, the same investigations could be extended for analysis in each country in the EU community, or to countries worldwide. The three main indicators were selected because recording greenhouse gas emissions rates in the air is of great importance for its impact on the environment; therefore, it needs not to be disregarded if we want to ensure a clean environment for future generations.

MLP Method For Estimation and Forecasting Time Series

This study is limited to building an MLP neural network that can estimate the **Greenhouse gases in air emission (GEE)** described only by two attributes (features), namely **Circular material use rate (CMUR)** and **Eco Innovation Index (EII)** at the EU level, considered the most representative impact factors on **GGE** [21].

The features of the measurement input dataset are represented by two attributes called **predictors**, which are designated by two vectors:

P1= EII, P2= CMUR.

The measurement output dataset is represented by a single feature called **target** and designated by the vector:

T = GGE

We make a rigorous analysis of the combined impact of both predictors on the target, considering the two row vectors P = [P1 ; P2];

This is an example of a ***fitting problem***, where inputs (P) are matched up to associated target output (T), and we would like to create a neural network which not only estimates the known target given known inputs, but can also generalize to accurately estimate outputs for inputs that were not used to design the solution. Neural networks are very attractive by their two features to fitting (estimation) and prediction of the future values of target (output) evolution. A ***neural network*** with enough elements (called ***neurons)*** can fit any data with arbitrary accuracy. They are particularly well suited for addressing nonlinear problems. Given the nonlinear nature of real- world phenomena, neural networks are the most suitable candidate for solving the fitting and prediction problems.

The two input attributes will act as inputs to a neural network, and the estimated and predicted output GGE will be the target. The network will be designed by using the two predictors independently or in combination to train it to produce the target estimations and predictions as time series

Step 1: Preparing the Data

Data for function fitting problems are set up for a neural network by organizing the data in supervised mode into two matrices, the input matrix P and the target matrix T.

Here such a dataset is loaded.

P1= [100 103.52 105.33 106.16 107.94 109.44 111.05 112.39 115.84 121.47];

P2= [11.2 11.1 11.2 11.4 11.5 11.6 11.3 11.6 11.4 11.5];

T= [7493.98 7234.8 7299.14 7269.87 7365.31 7224.86 6878.76 6197.54 6553.27 6475.77];

P= [P1;P2];

T=GGE;

Step 2: Neural Network Architecture

The next step is to create a neural network that will learn to estimate the target value of GGE, as the impact of the input predictors P1, P2 independently or their combination P = [P1 ; P2].

Two-layer (i.e., one-hidden-layer) feed forward neural networks can fit any input-output relationship given enough neurons in the hidden layer. Layers which are not output layers are called hidden layers.

In this study are selected three hidden layers of 25, 5 and 5 neurons. In general, more difficult problems require more neurons, and perhaps more layers. Simpler problems require fewer neurons. The input and output have sizes of 0 because the network has not yet been configured to match our input and target data. This will happen when the network is trained.

net = fitnet (25,15,5); *view(net)*

Step 3: Training the NN

Now the network is ready to be trained. The samples are automatically divided into training, validation and test sets. The training set is used to teach the network. Training continues as long as the network continues improving on the validation set. The test set provides a completely independent measure of network accuracy.

The Neural Network Training Tool (see *Figure 8.e*) shows the network being trained and the algorithms used to train it. It also displays the training state during training and the criteria which stopped training will be highlighted in green.

The buttons at the bottom open useful plots which can be opened during and after training.

[net, tr] = train(net,P,T);

To see how the network's performance improved during training, either click the "Performance" button in the training tool, or call PLOTPERFORM.

Performance is measured in terms of mean squared error, and shown in log scale. It rapidly decreased as the network was trained.

Performance is shown for each of the training, validation, and test sets. The final network is the network that performed best on the validation set.

figure; plotperform(tr)

Step 4: Testing the Neural Network

The mean squared error (mse) of the trained neural network can now be measured with respect to the testing samples. This will give us a sense of how well the network will do when applied to data from the real world.

testP = P(: , tr.testInd);testT = net(testP);perf = mse(net, testT, testP)

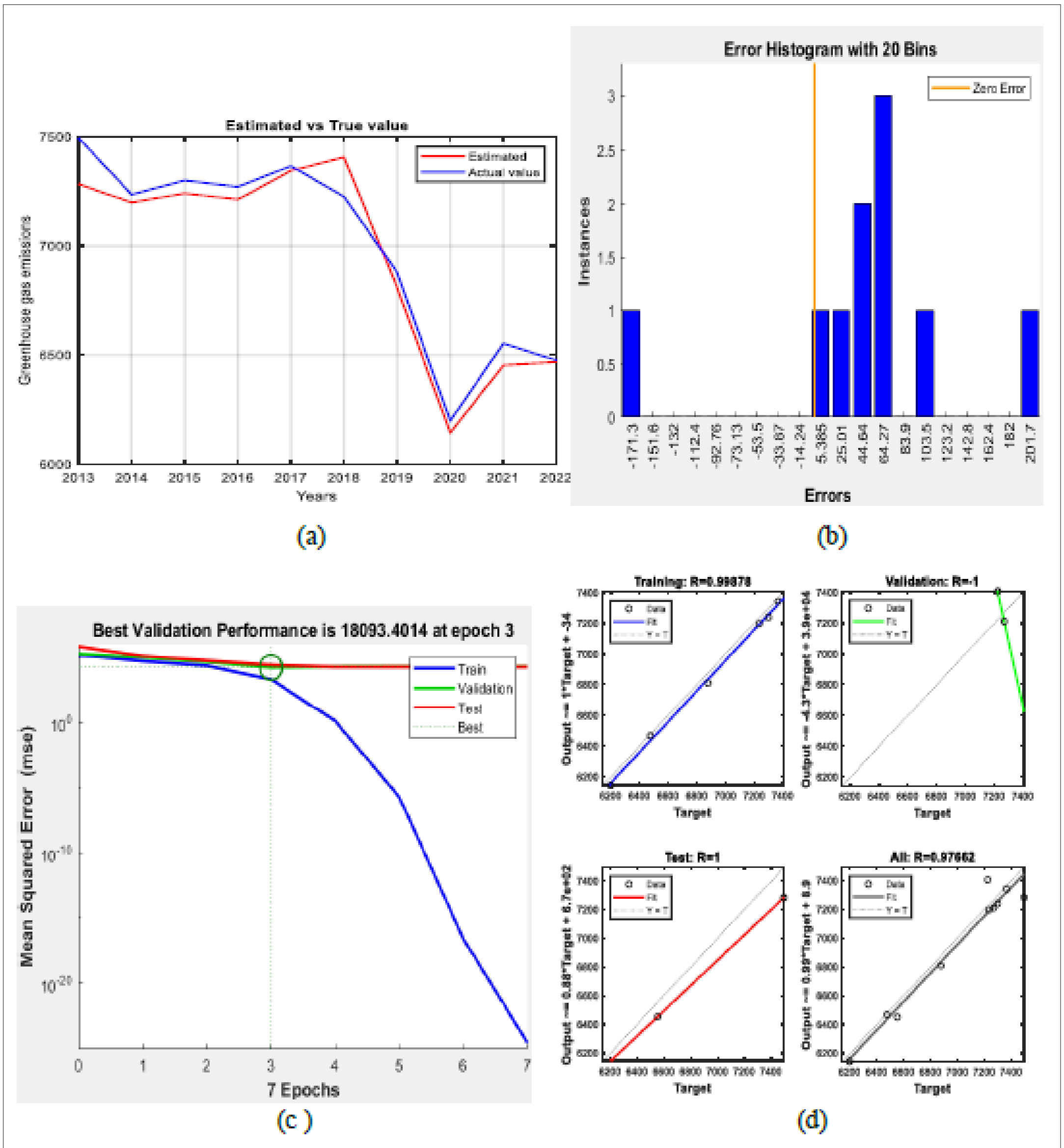
Another measure of how well the neural network has fit the data is the regression plot across all samples. The regression plot shows the actual network outputs plotted in terms of the associated target values. If the network has learned to fit the data well, the linear fit to this output-target relationship should closely intersect the bottom-left and top-right corners of the plot. If this is not the case then further training, or training a network with more hidden neurons, would be recommended.

Y = net(P);figure; plotregression (T,Y)

The third measure of how well the neural network has fit data is the error histogram (see Figure 8.b). This shows how the error sizes are distributed. Typically, most errors are near zero, with very few errors far from that.

e = T - Y; figure; ploterrhist (e)

The complete MATLAB simulation results are shown in Figure 8



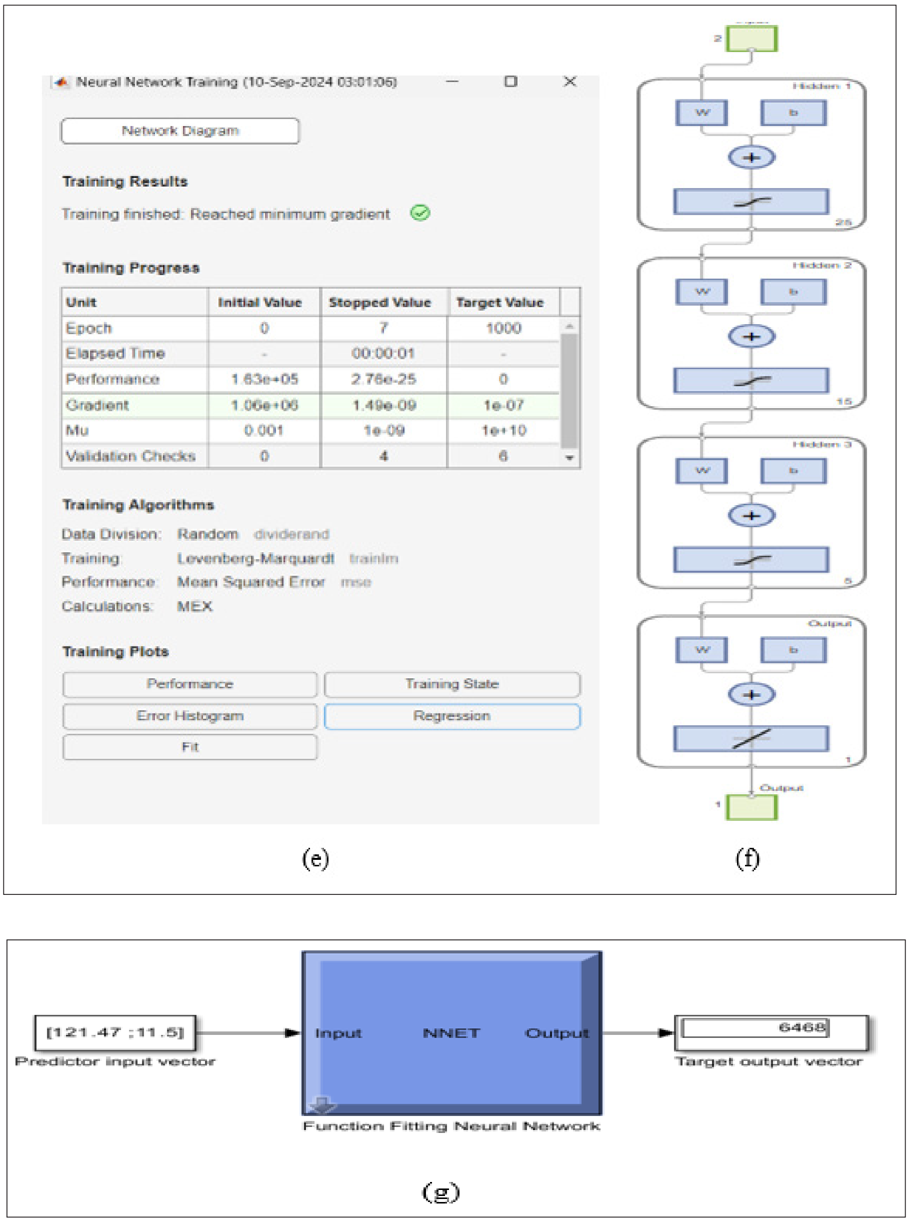


Figure 8: MATLAB Simulation Results – MLP Simple Method: (a) Estimation Performance versus True Value, (b) Histogram Performance, (c) Training Phase Progress, (d) Regression Performance, (e) Training Results, (f) NN Architecture, (g) Simulink Function Fitting Neural Network

The times series forecasting has the output target Y selected directly; this is a times series vector starting at time instance *t = 2* (*year : 2014*) and ending to the time instance *t = 10* (*year : 2022*) and as predictor input is same vector Y starting at time instance *t = 1* (*year : 2013*) and ending to the time instance *t = 9* (*year : 2021*, *i.e. t-1*). The complete MATLAB simulation results in this case are shown in Figure 9, for same set of diagrams as in Figure 8.

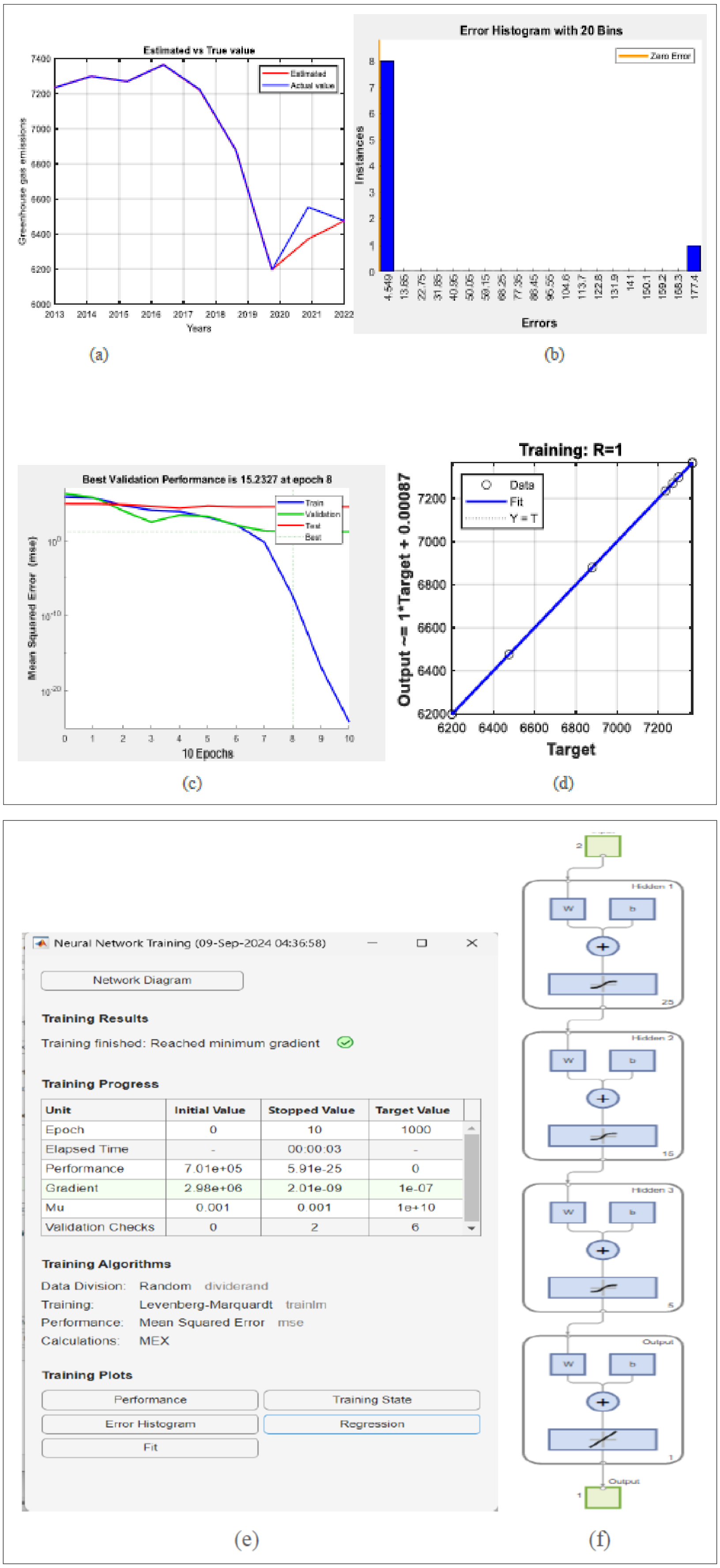


Figure 9: MATLAB Simulation Results - MLP Times Series Forecasting Method: (a) Estimation Performance Versus True Value, (b) Histogram Performance, (c) Training Phase Progress, (d) Regression Performance, (e) Training Results, (f) NN Architecture.

We conducted the same simulation tests on the data set of the *five* selected countries: France, Netherlands, Germany, Poland and Romania. The results in MATLAB can be visible in the *Annexes – Figure 2 – Figure 6*.

In Simulink, the results of training and prediction are stored in a **Simulink Function Fitting Neural Network** block that can be useful to predict the future values for greenhouse gas emissions for EU and all other five countries, forecasting on 2023-2027 years period. The cascade architectures of these blocs at the EU level, and for each of the *five* selected countries are shown in *Figure 10*, and the *forecasts values* versus *observed values* are shown also in *Figure 11*.

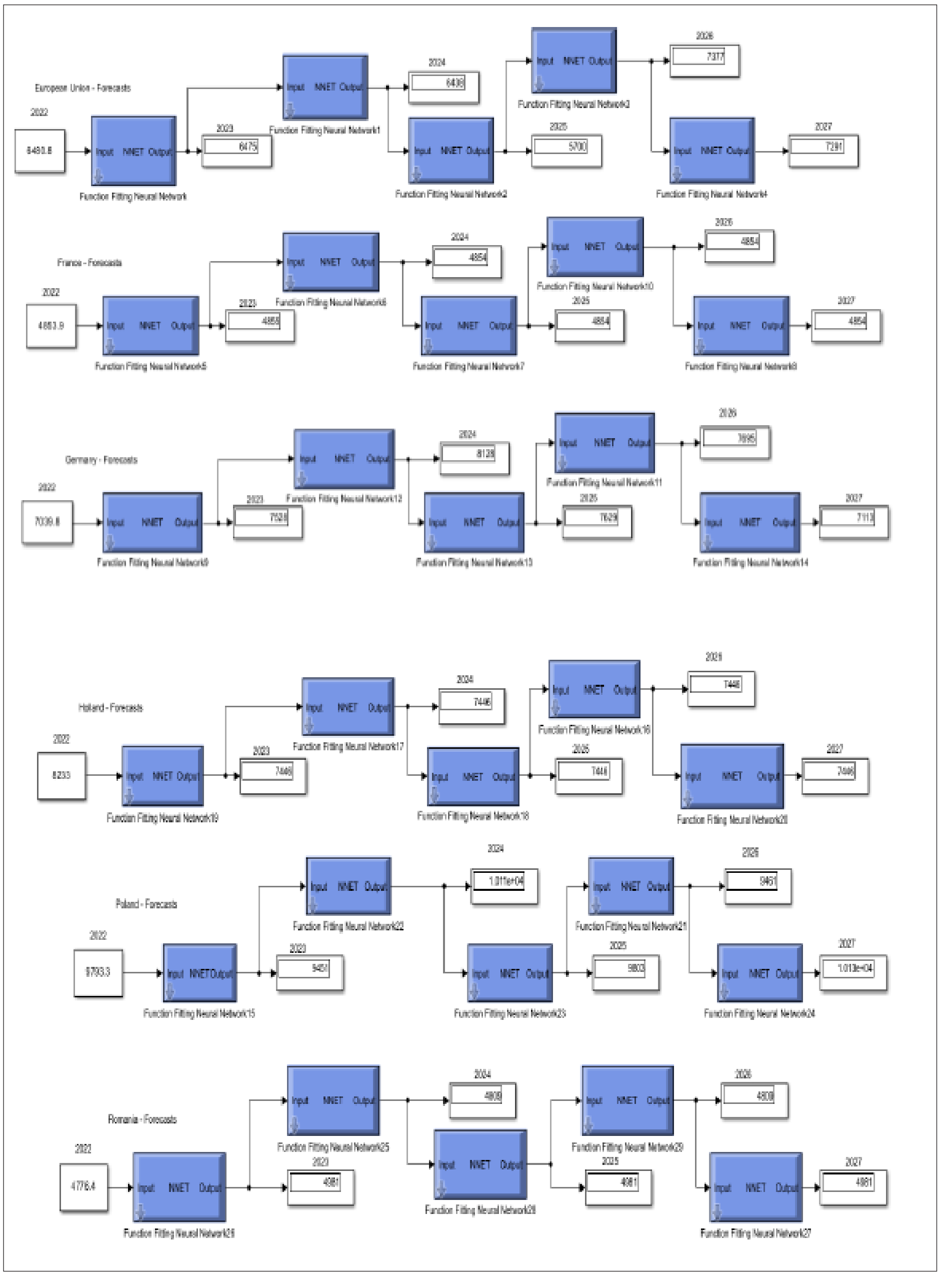


Figure 10: Simulink Function Fitting Neural Network blocks cascade architectures - forecasting times series on 2023-2027 years period. The countries are shown from top to bottom in the following order: EU, FRA, GER, HOL, POL and RO.

An overall perspective on the greenhouse gas emissions in air is presented at the *European Union level* and for each of the *five* selected countries members of EU in *Figure 11*, with detailed diagrams for each country, and for the EU, shown in *Figure 6 (Annexes)*.

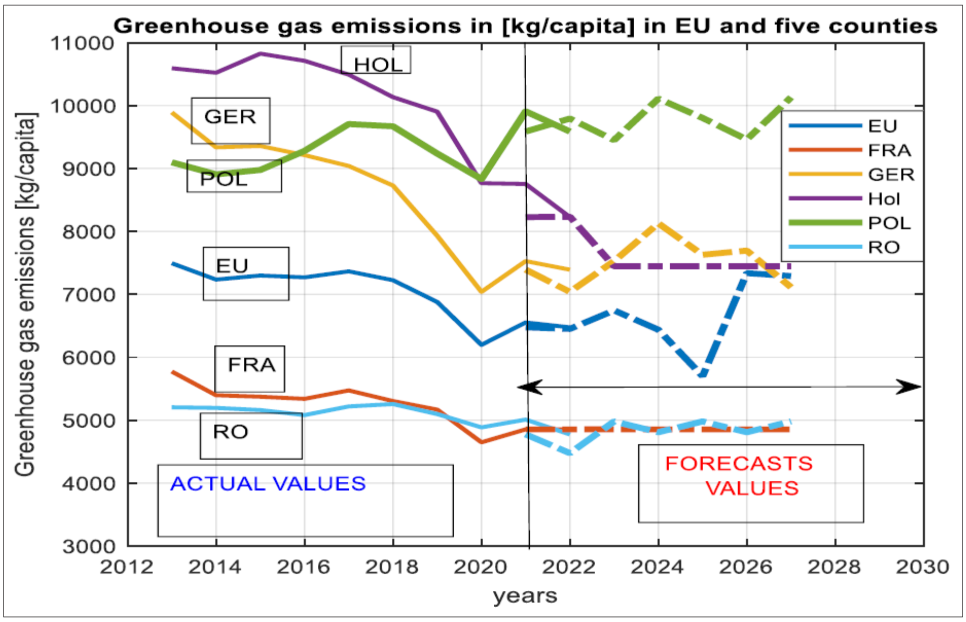


Figure 11: Comparative diagrams of the GGE in the air at *EU level* and per countries (focus on the *five* selected countries), with *actual data* through 2013-2022 years period, and with *forecasted data* through 2022-2028 years period.

The *individual diagrams* for European Union, and for the *five* selected countries with *the actual data* through 2013-2022 years period, followed by *the forecasted data* through 2022-2028 are attached in the Annexes, *Figure 7.(a.-f.)*

LSTM Method For Estimation and Forecasting Time Series
This method of forecasting times series is using a long short-term memory (LSTM) network [22-23]. An **LSTM network** is a recurrent neural network (**RNN**) that processes input data by looping over time steps and updating the RNN state. The RNN state contains information remembered over all previous time steps. You can use an LSTM neural network to forecast subsequent values of a time series or sequence using previous time steps as input. To train an LSTM neural network for time series forecasting, train a regression LSTM neural network with sequence output, where the responses (targets) are the training sequences with values shifted by one time step, as is shown in *Figure 12 (a)*. In other words, at each time step of the input sequence, the LSTM neural network learns to predict the value of the next time step.

There are two methods of forecasting: ***open loop*** and ***closed loop forecasting***.

Open Loop Forecasting
It predicts the next time step in a sequence using only the input data. When making predictions for subsequent time steps, the true values are collected from data source (*Eurostat statistics*) used as input. Thus, for example, say you want to predict the value for time step ***t*** of a sequence; in this case, you will be using data collected in time steps 1 through (***t-1***). In order to make predictions for time step (***t+1***), you will wait until the true value is recorded for time step ***t*** ; this value will be used as input to make the next prediction, as is shown in *Figure 12 (b)*. We use open loop forecasting when we have true values to provide to the recurrent neural network (RNN) before making the next prediction. The reader interested in the details of this method is referred to [22- 23].

Closed Loop Forecasting
It predicts subsequent time steps in a sequence by using the previous predictions as input. In this case, the model does not require the true values to make the prediction. For example, say you want to predict the values for time ***steps t*** through (**t+k**), of the sequence using data collected in time ***steps 1*** through (***t-1***) only. In order to make predictions for time ***step i***, we use the predicted value for time ***step*** (***i-1***) as input. We use closed loop forecasting to forecast multiple subsequent time steps or when you do not have the true values to provide to the RNN before making the next prediction.

Figure 12 (c) shows the predictors (***channels 1*** and ***2***) and target (***channel 3***) sequences with forecasted values using closed loop prediction.

We conducted a simulation test using *an open loop forecasting* followed by a *closed loop forecasting* with a *LSTM network*. The three indicators EII, CMUR and GGE are involved in this simulation, with real data provided for 10 years (2013 - 2022) as average values at the *EU level*. The forecasted data is over 30 years, starting with the year 2013.

The complete MATLAB simulation results are depicted in *Figure 12 (a-c)*.

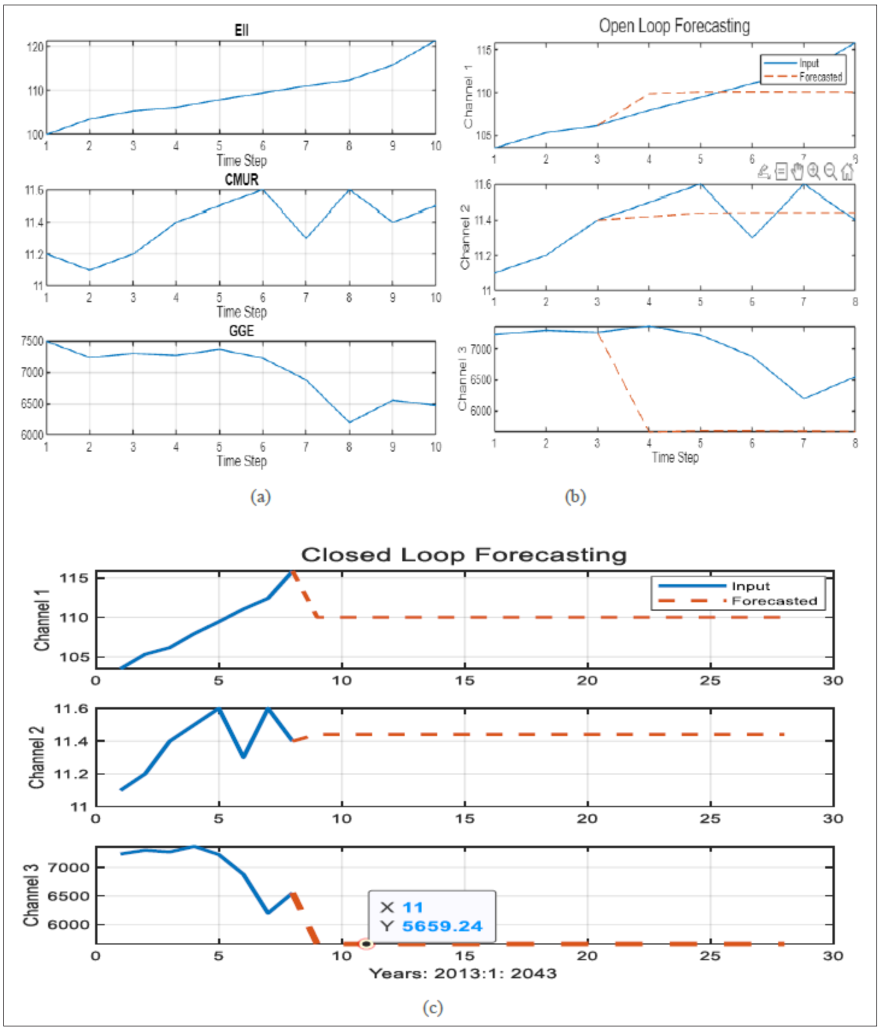


Figure 12: MATLAB Simulation results – LSTM Deep Learning forecasting time series method, (a) The training sequences of predictor and target vectors in all three channels, (b) open-loop forecasting, (c) closed loop forecasting.

Performance Analysis and Comparison of MLP-NN and LSTM Deep Learning Models for Time Series Forecasting

Time series forecasting is a critical task in various domains, including finance, economics, and supply chain management. Accurate forecasting allows organizations to make informed decisions, optimize resources, and plan for future trends. The forecasting performance depends significantly of the quality and the amount of enough data under investigation for each time series. A rigorous analysis of the MATLAB and Simulink simulation test results presented in *Figure 11*, and detailed in *Figure 6 (Annexes)*, at the average *EU level* and each of the *five* European countries selected for this study, reveal a decreasing tendency of the greenhouse gas emissions for Netherlands, Germany, France, Romania, and Poland, while for the EU average, it is still an increasing trend. These results showcase the importance of implementing urgent policies in many countries in the EU, for lowering the Green Gas Emissions. It seems that both NN forecasting time series models as regression methods are the most appropriate for this study. The LSTM method was used for average values registered over the countries in EU, for three indicators IIE, CMUR and GGE; it was conducted as an alternative method to MLP NN forecasting method, for the purpose of comparison of the methods. The results presented in *Figure 12*, are not conclusive for this research, since this method does not perform well enough, the data set of values being too small. We plan to use data sets with many more data to illustrate the effectiveness of this method in future work, in other applications in the economics and finance areas.

Conclusions

Concluding, this short review is focused on *five* countries from EU that are on their way to achieving circularity, with the mention that *Netherlands* and *France*, throughout well-established programs of recycling materials and informative platforms towards population, are well set on this road. On the other side, *Poland* and *Romania*, need to reduce consumption and find programs to treat wastes. Poland is a huge actor in mine extraction, and therefore needs to reduce the use of raw materials. *Germany* has long been pioneering for reducing pollution related to industrial activities, through the car manufacturing of electric vehicles, and eco-innovation; still, it has not yet implemented a thorough circular economy framework, involving all possible stakeholders, business, research, education, policy makers, because it has already a very stable and outstanding industrial, social infrastructure; pushing the economy towards circularity, is the ultimate goal; it implies reconfiguring the existing models, changing the mentalities. It takes a sure pace, while doing so, which does not shake the whole structure into place and but maintains it cohesiveness, and still drives it towards excellency. Lastly, we have investigated different AI techniques to forecast circular economy indicators beyond the measured set of values, for the years to come; these techniques are Multilayer Perceptron (MLPs) Neural Networks with predicators and using time series forecasting, with software tools such as MATLAB and Simulink. Both forecasting methods perform very well and are most suitable for applications in economics and finance fields.

Annex 1

Table 1: *Resource Productivity* measured in different countries of EU, (*source*: [13])

Table | Line | Bar | Map

GEO ↓ / TIME	2019	2020	2021	2022	2023
European Union - 27 countries (from 2020)	2.0675 (s)	2.0377	2.0707	2.1624	2.2232 (s)
Finland	0.9278	0.9013	0.9414	0.9084	0.9787 (s)
France	2.9471	2.9948	2.8931	3.1293	3.1465 (s)
Germany	2.7055	2.684	2.6899	2.8645	3.0421 (s)
Greece	1.4765	1.5231	1.6194 (b)	1.6783	1.7108 (s)
Hungary	0.8274	0.9142	0.9867	1.0917	0.9564 (s)
Iceland	2.8368	3.0548	2.8511	2.7797	:
Ireland	2.6351	2.9775	3.4341	3.6805	3.9913 (s)
Italy	3.4612	3.4286	3.3724	3.4595	3.5887 (s)
Latvia	0.9684	0.931	0.9216	0.9431	0.8965 (s)
Liechtenstein	:	:	:	:	:
Lithuania	0.8205	0.7756	0.7947	0.8309	0.7949 (s)
Luxembourg	4.2288	4.0843	4.0327	4.3123	4.5348
Malta	2.2004	1.8367	2.3394	2.7351	2.8235 (s)
Montenegro	:	:	:	:	:
Netherlands	4.0546 (e)	4.27	4.768	4.5626	5.336 (s)
North Macedonia	0.4514	0.4371	0.5042	0.5134	:
Norway	2.6686	2.8642	3.1751	3.2176	:
Poland	0.7711	0.7649	0.7992	0.8453	0.863 (s)
Portugal	1.1741	1.1984	1.0694	1.2758	1.2699 (s)
Romania	0.3684 (s)	0.3448	0.3559	0.3748	0.3461 (s)

Table 2: *Resource Productivity (in PPS)* per countries of Europe (focus on *five* selected countries), (*source*: [13])

	GDP_{PPS} per capita	DMC per capita	Resource productivity (GDP_{PPS}/DMC)	
	(PPS per capita)	(tonnes per capita)	(PPS per kilogram)	(Index EU = 100)
EU	35 428	14.4	2.4	100.0
Belgium	42 239	13.0	3.3	132.9
Bulgaria	21 844	25.5	0.9	35.0
Czechia	32 000	16.0	2.0	81.7
Denmark	48 718	26.4	1.8	75.2
Germany	41 245	13.8	3.0	121.9
Estonia	30 283	27.7	1.1	44.7
Ireland	82 503	22.5	3.6	148.5
Greece	24 281	12.0	2.0	82.9
Spain	29 706	8.8	3.4	137.6
France	36 028	11.2	3.2	131.3
Croatia	26 074	12.3	2.1	86.7
Italy	33 689	9.1	3.7	151.6
Cyprus	32 349	18.9	1.7	70.1
Latvia	26 033	16.5	1.6	64.4
Lithuania	31 496	20.9	1.5	61.5
Luxembourg	92 176	22.9	4.0	164.4
Hungary	27 373	13.8	2.0	81.2
Malta	35 963	10.6	3.4	138.7
Netherlands	46 098	10.0	4.6	189.1
Austria	44 122	17.6	2.5	102.1
Poland	28 809	19.4	1.5	60.8
Portugal	26 882	15.8	1.7	69.5
Romania	27 066	28.8	0.9	38.4
Slovenia	32 494	15.4	2.1	86.2
Slovakia	24 366	11.5	2.1	86.9
Finland	38 684	43.7	0.9	36.1
Sweden	42 264	27.1	1.6	63.6
Iceland	44 923	41.6	1.1	44.1
Norway(*)	54 267	22.4	2.4	99.0
Switzerland(**)	47 933	10.5	4.5	185.7
North Macedonia(*)	12 858	8.9	1.4	59.2
Albania(*)	10 296	7.2	1.4	58.5
Serbia(*)	14 349	19.4	0.7	30.2
Turkey(*)	20 336	11.5	1.8	72.1
Bosnia and Herzegovina(***)	10 235	11.2	0.9	37.2

Note: GDP in current prices, Purchasing Power Standards (PPS)

GEO \ TIME	2015	2016	2017	2018	2019	2020	2021	2022
European Union - 27 countries (from 2020)	11.2	11.4	11.5	11.6	11.3	11.6	11.4	11.5 (s)
Belgium	18.2	18.2	19.1	20.8	20.7	23	23.7	22.2 (e)
Bulgaria	3.1	4.4	3.5	2.5	4.1	5.9	4.8	4.8 (s)
Czechia	6.9	7.5	9.1	10.4	10.5	11.5	11.4	11.9 (s)
Denmark	8.3	8	7.9	8	7.6	7.6	8	7.4 (s)
Germany	11.7	11.8	11.7	12.1	12.5	12.9	12.7	13 (s)
Estonia	11.7	12.1	12.7	13.9	15.4	16.5	15.9	16 (s)
Ireland	1.9	1.8	1.7	1.7	1.6	1.7	1.9	1.8 (s)
Greece	1.8	2.1	2.5	3	3.4	4.2	3.5	3.1 (s)
Spain	7.5	8.2	8.8	8.9	9	9.2	6.9	7.1 (s)
France	18.7	19.3	18.7	19.5	18.1	18.7	18.7	19.3 (s)
Croatia	4.6	4.6	5.1	5	5.3	5.5	5.7	5.8 (s)
Italy	17.2	17.8	18.4	18.8	18.8	20.6	19	18.7 (s)
Cyprus	2.4	2.4	2.4	2.7	3.1	3.8	2.8	3.2 (s)
Latvia	5.3	6.5	5.4	4.7	4.7	5.2	5.6	5.4 (s)
Lithuania	4.1	4.6	4.5	4.3	3.9	4	4.2	4.1 (s)
Luxembourg	9.5	7	10.4	10.7	9	9.6	4.1	5.2
Hungary	5.8	6.4	6.8	7	5.6	5.2	7.3	7.9 (s)
Malta	4.6	4.2	6.6	8.3	12.8	16.5	12.8	15.1 (s)
Netherlands	26.6	29	26.8	25.8	25.6	27.2	28.5	27.5 (s)
Austria	11.2	12	12.1	11.9	11.6	11.5	12.8	13.8 (s)
Poland	11.9	10.6	10.4	10.5	9.2	7.3	9.1	8.4 (s)
Portugal	2.1	2.1	2	2.2	2.3	2.5	2.6	2.6 (s)
Romania	1.7	1.7	1.8	1.6	1.4	1.5	1.4	1.4 (s)

Table 3: *Circularity use rate*, among countries of EU, (focus on *five* countries), (*source*: [13])

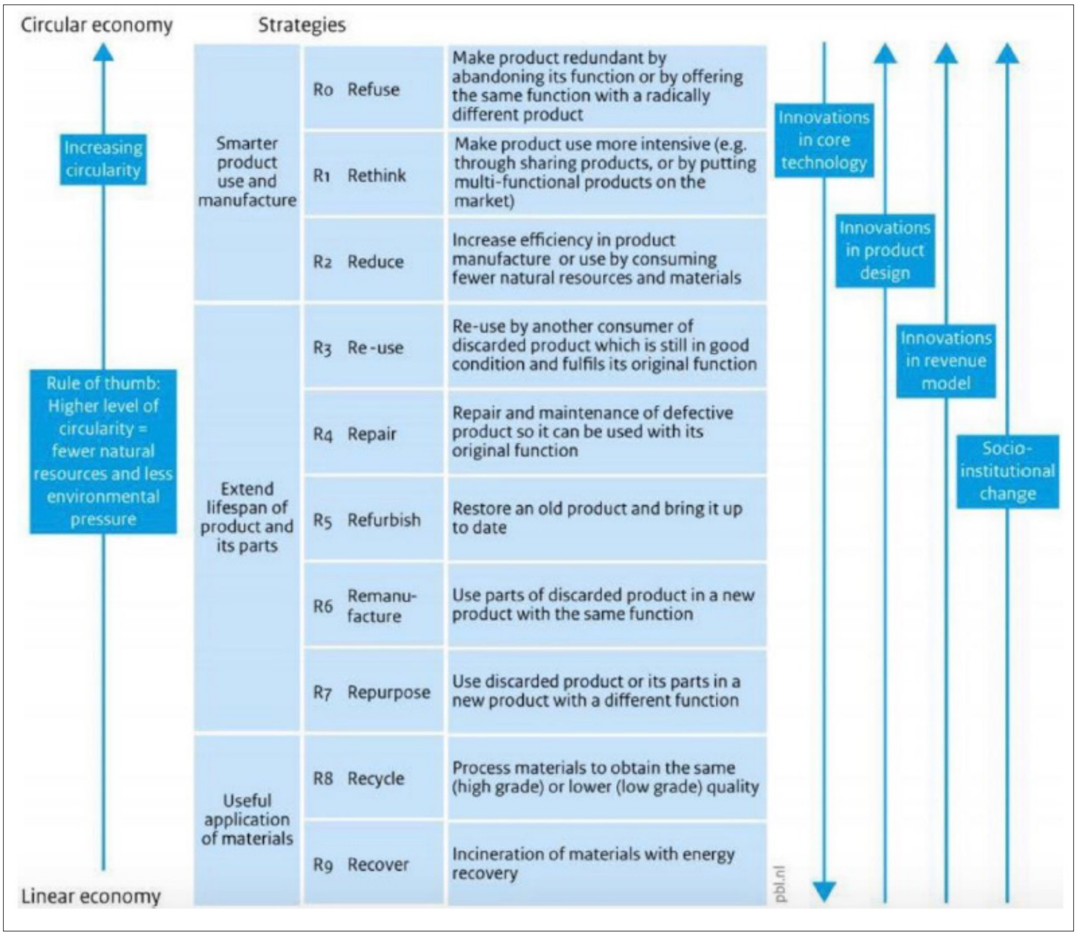


Diagram 1: *The nine R's* in Circular Economy, (*source*: [3])

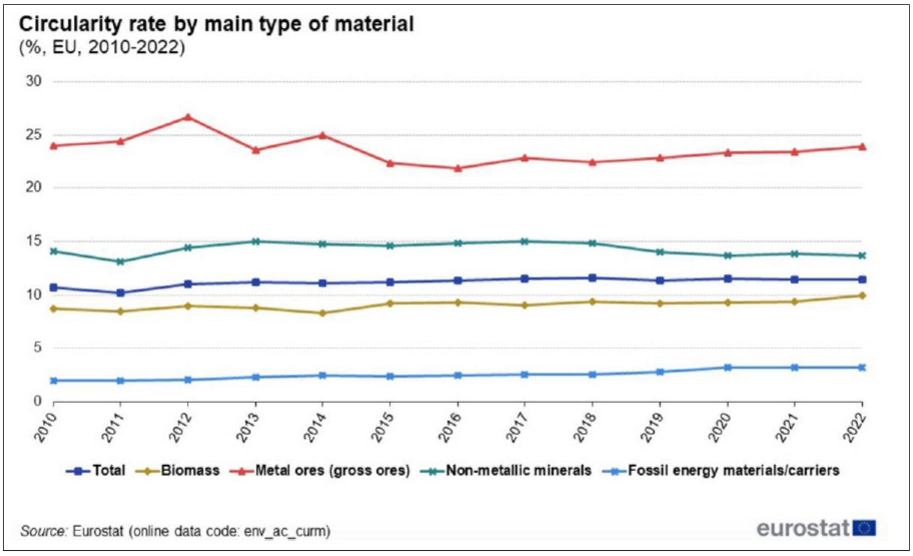


Figure 1: Circularity rate by main type of material (source: Eurostat, [10-13])

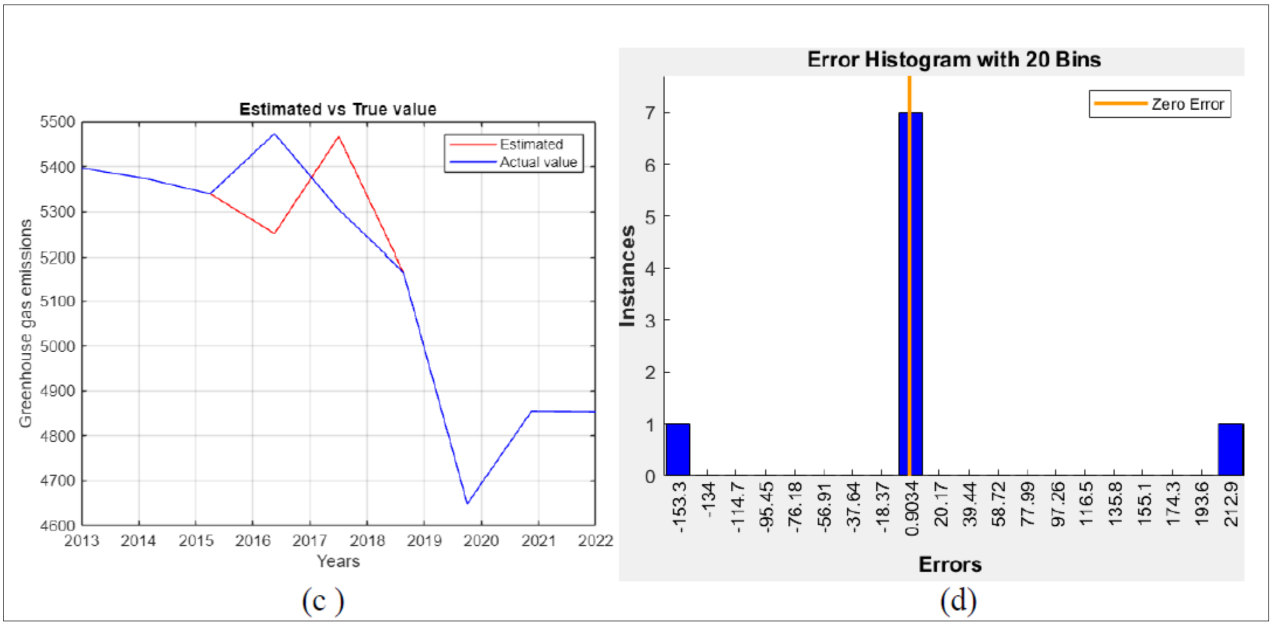


Figure 2: France Greenhouse Gas Emission in Air MLP - NN Model – MATLAB Simulation Results, (a) Training Progress – Best Validation Performance, (b) Regression Performance, (c) Estimated Values Versus Actual Values, (d) Error Histogram Performance

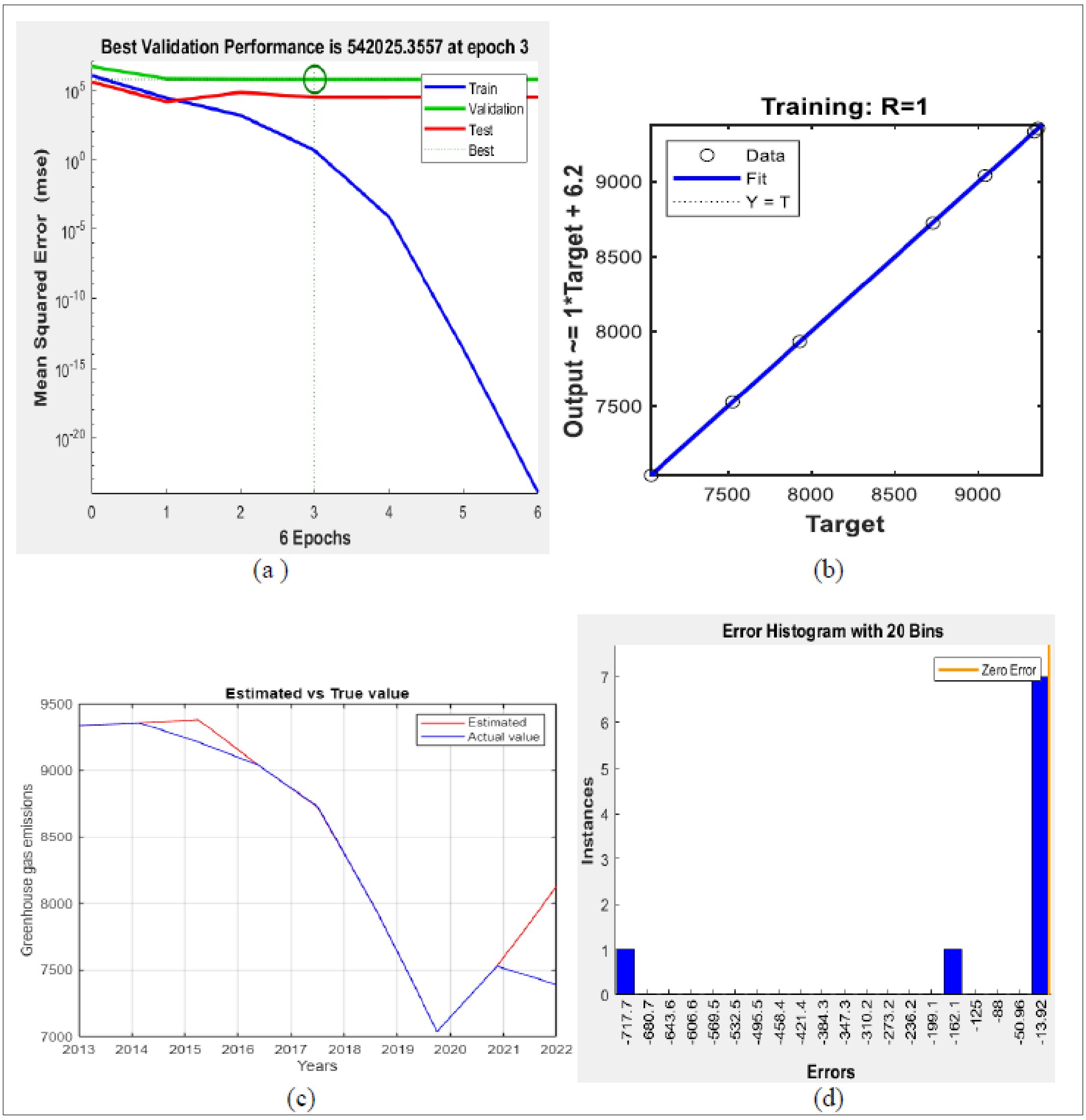


Figure 3: Germany Greenhouse Gas Emission in Air MLP - NN model – MATLAB Simulation Results, (a) Training Progress – Best Validation Performance, (b) Regression Performance, (c) Estimated Values Versus Actual Values, (d) Error Histogram Performance

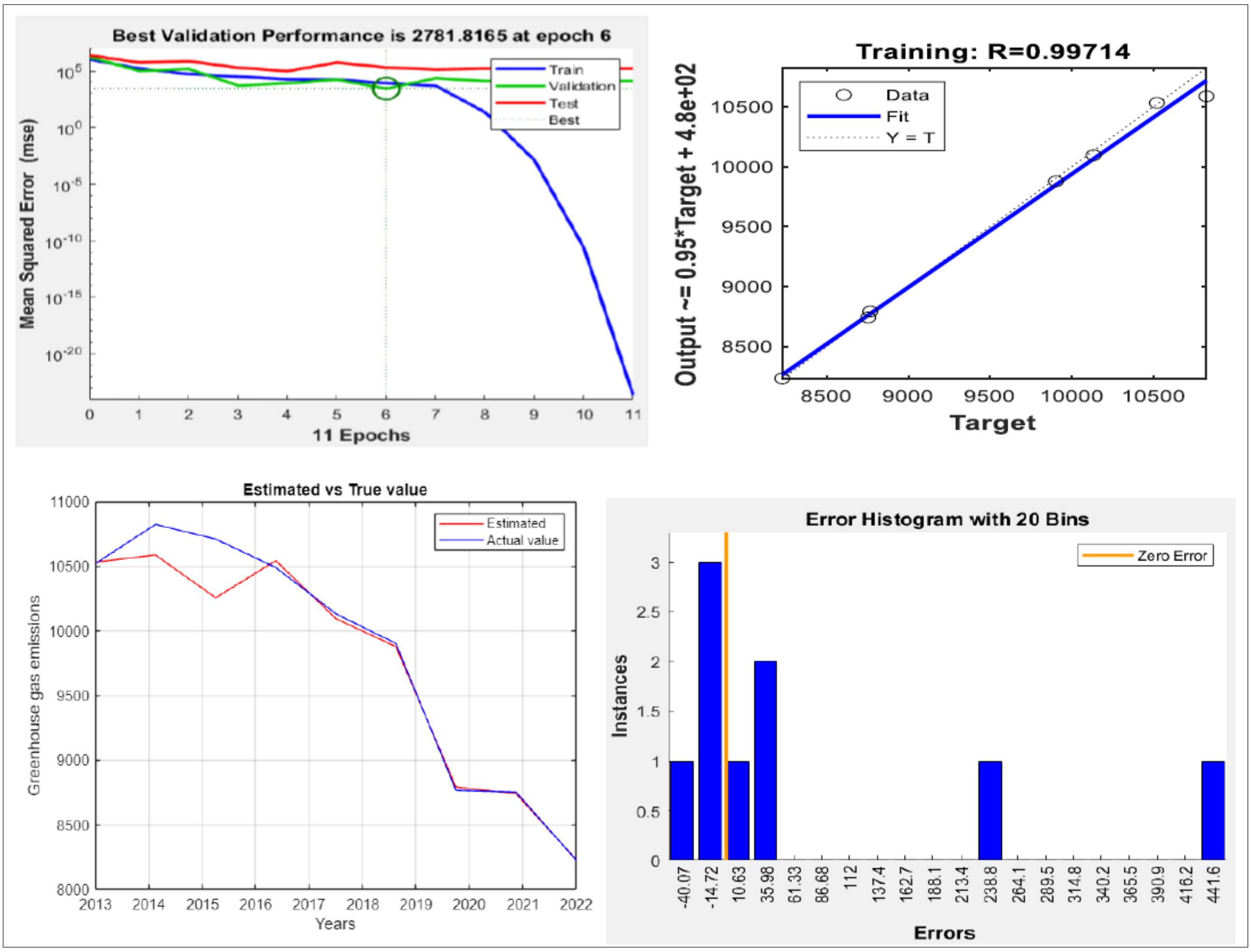


Figure 4: Netherlands Greenhouse Gas Emission in Air MLP - NN Model – MATLAB Simulation Results, (a) Training progress – Best validation Performance, (b) Regression Performance, (c) Estimated Values Versus Actual Values, (d) Error Histogram Performance

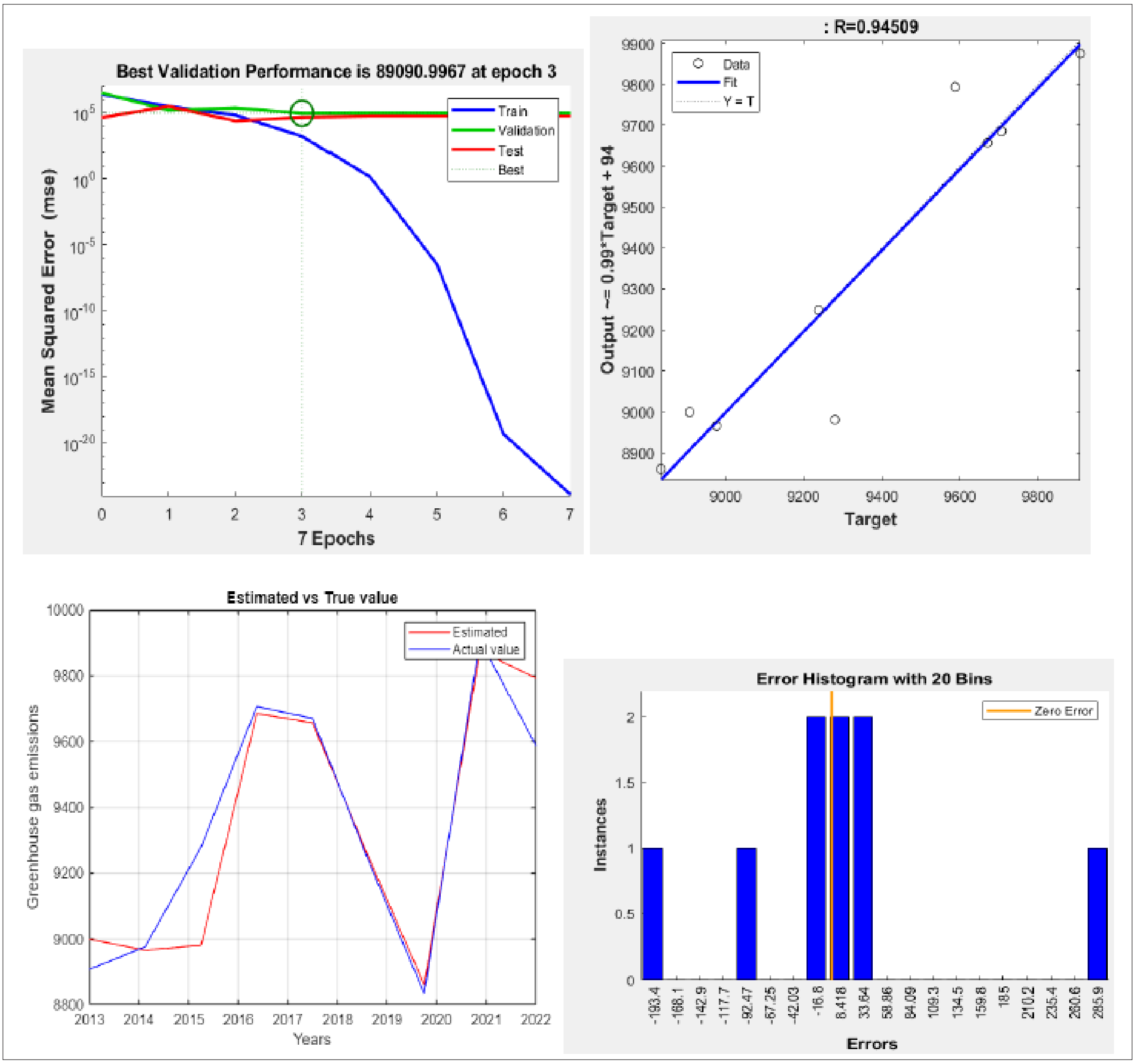


Figure 5: Poland Greenhouse Gas Emission in Air MLP - NN Model – MATLAB Simulation results; (a) Training Progress – Best Validation Performance, (b) Regression Performance, (c) Estimated Values Versus Actual Values, (d) Error Histogram Performance

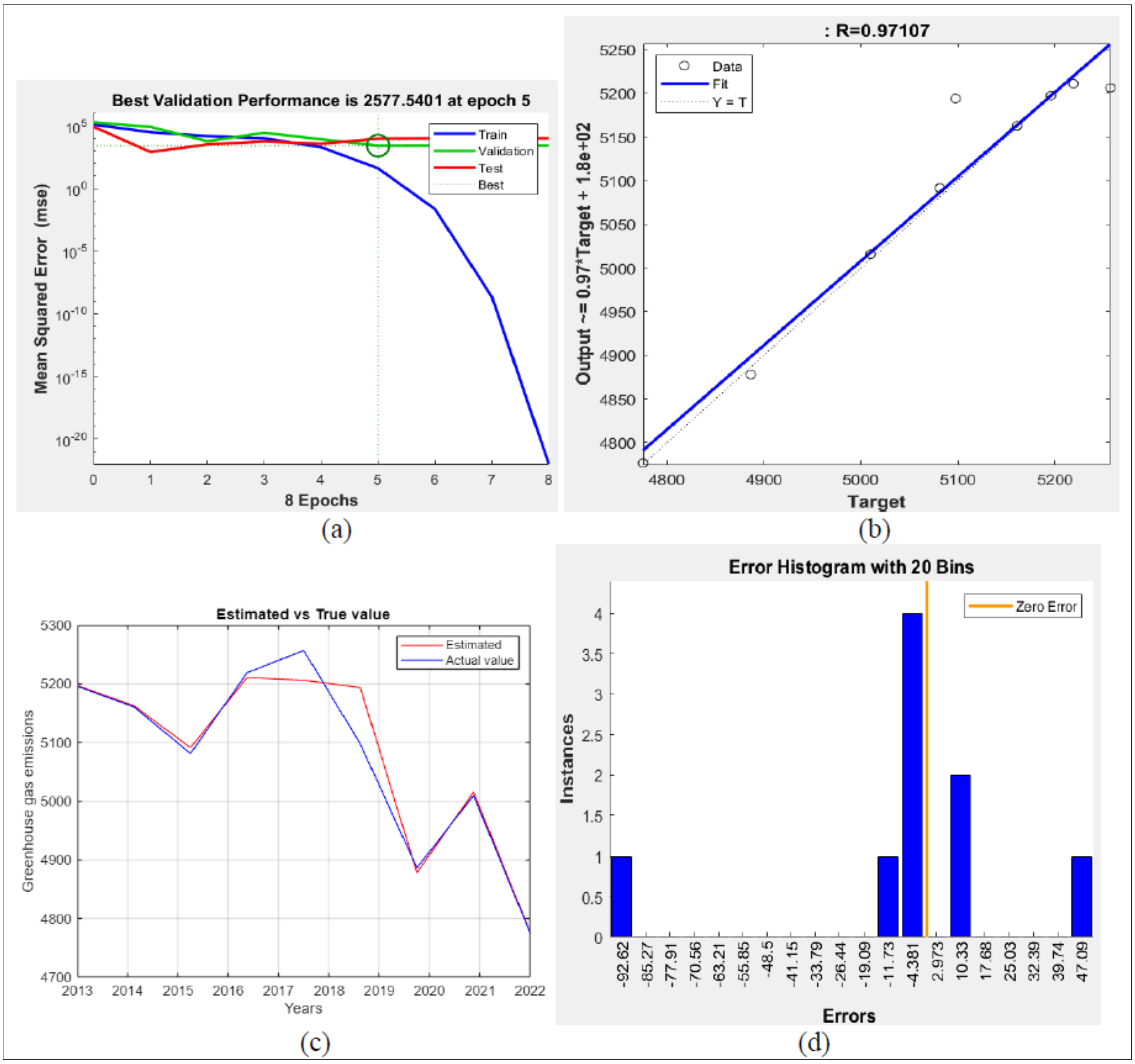
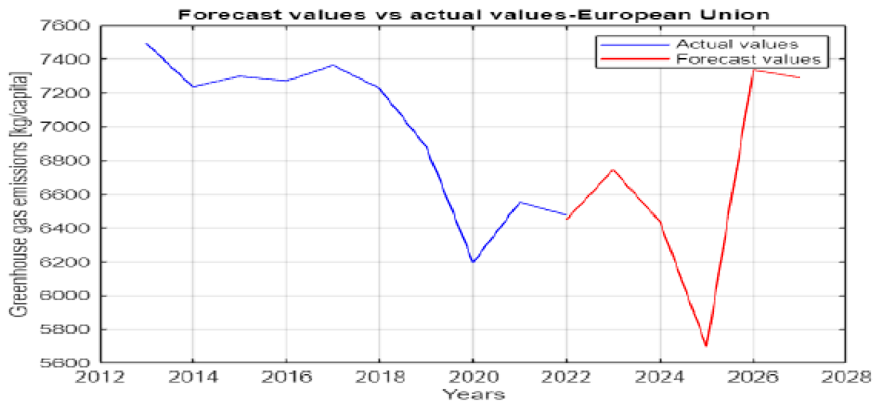


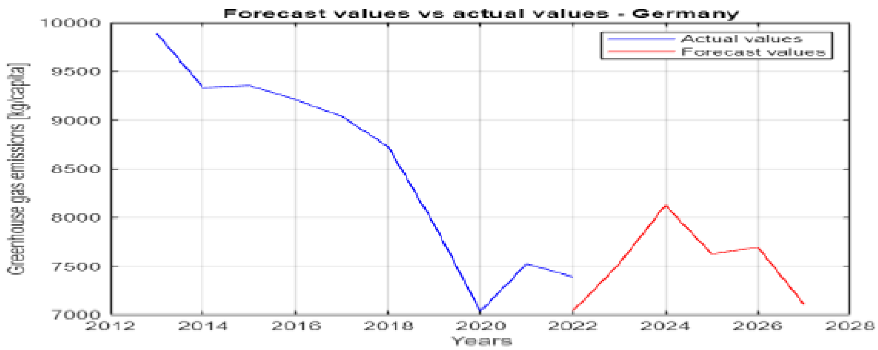
Figure 6: Romania Greenhouse Gas Emission in Air MLP - NN Model – MATLAB Simulation Results, (a) Training Progress – Best Validation Performance, (b) Regression Performance, (c) Estimated Values Versus Actual Values, (d) Error Histogram Performance


Forecast values vs actual values-European Union
Actual values
Forecast values
Greenhouse gas emissions [kg/capita]
Years

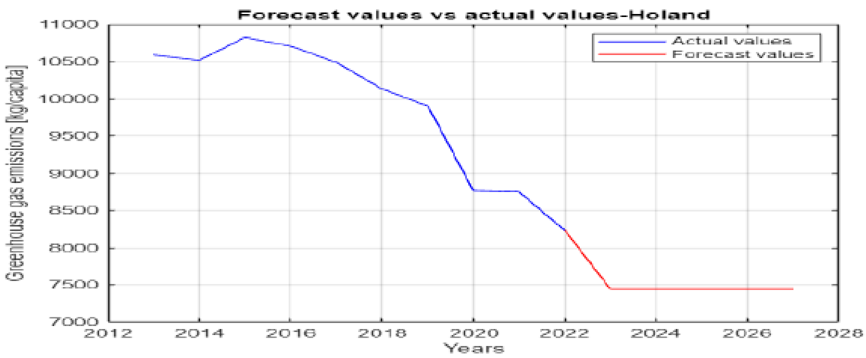
(a)


Forecast values vs actual values-France
Actual values
Forecast values
Greenhouse gas emissions [kg/capita]
Years

(b)


Forecast values vs actual values - Germany
Actual values
Forecast values
Greenhouse gas emissions [kg/capita]
Years

(c)


Forecast values vs actual values-Holand
Actual values
Forecast values
Greenhouse gas emissions [kg/capita]
Years

(d)

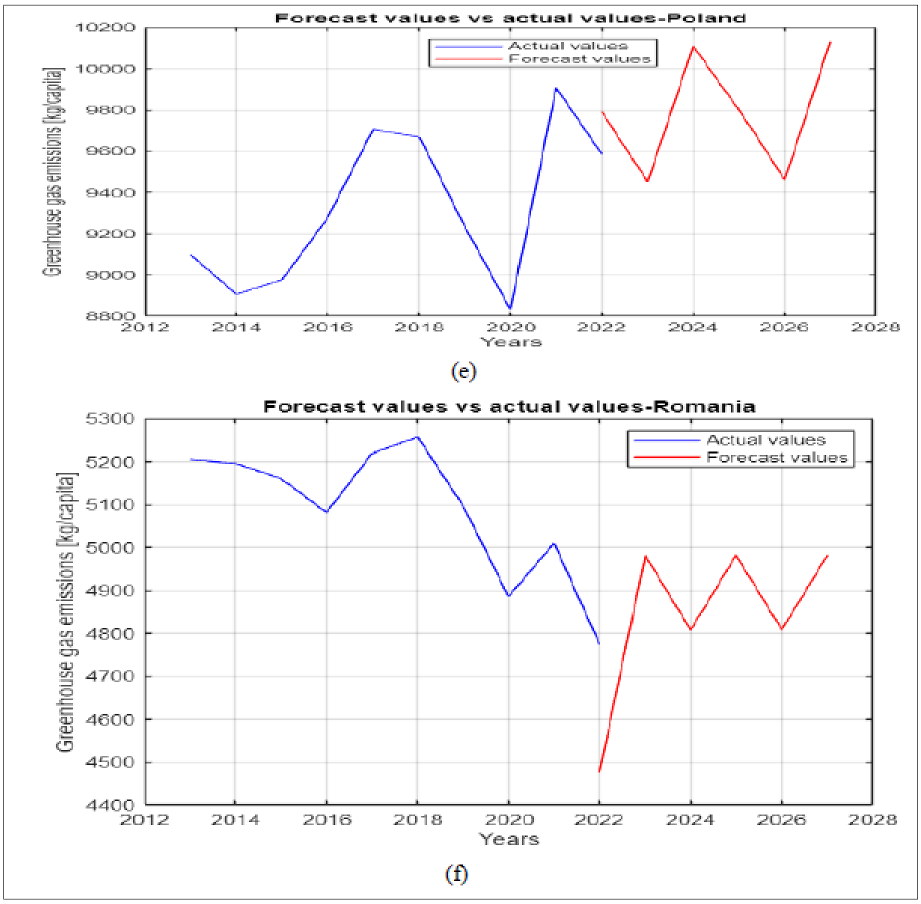


Figure 7: Details on the greenhouse gas emissions in air at the EU level and per countries (focus on the *five* selected countries). The *actual data* (2013-2022) followed by the *forecasted data* (2022-2028). (a) EU, (b) France, (c) Germany, (d) Netherlands, (e) Poland, (f) Romania

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