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# The Role of Energy Consumption and Economic Growth on Carbon Emission: Application of Artificial Neural Network

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#### **ABSTRACT**

This paper examines the influence of gross domestic product (GDP) and energy consumption (renewable energy and non-renewable energy) on carbon emissions in European Union (EU) Countries use of panel data from 2000 to 2020. By using Artificial Neural Network (ANN) machine learning computational technique, variables are categorized into input and output parameters. The result from the analyses shows that RMSE values of all variables are significant. Further, the normalized importance obtained from the multilayer perception ANN algorithm highlights the importance of variables and their association. The finding suggests that EU countries should adopt a clean energy strategy and policy for environmental protection without compromising economic growth.

Keywords: GDP growth, Energy Consumption, Carbon Emission, Artificial Neural Network

JEL Classifications: F43, K32, O13, P18, C63

#### 1. INTRODUCTION

Climate change has become debatable issue due to carbon emission and other greenhouse gas (GHG) concentration in the environment which is primarily influenced by globalization and economic development (Ahmad et al., 2016). Since the midtwentieth century, the research and technological development, transportation, foreign investment, and international market access has resulted in growth of the world economy. The growing trend of economic activities has influenced the consumption of energy that has become a key concern in the twenty-first century (Akram et al., 2022). Energy is a vital factor and necessary input along with land, labour, capital and entrepreneurship (Salari et al., 2021). It is widely seen that rising energy demand and environmental pollution especially, carbon emission is increasing all over the world and have become a serious concern among policymakers, government, and stakeholders.

Carbon emission is generated by the product, events, organisations or individuals either directly or indirectly (Akadiri et al., 2019). World events such as war, electricity production, air conditioning, transportation, industrial heating, maritime seaports, and the oil and gas industry have influenced the carbon emission which has recognized by the economic, social and political importance which is required to mitigate climate change. Thus, carbon emission is linked with energy uses and economic prosperity. Moreover, the indicators of carbon dioxide emission are growth level, energy uses (both conventional and non-conventional sources), financial growth, technological innovation, trade liberalization and urbanization supported by the studies along with globalization and its influencing factors (Wen et al., 2021).

The studies in different countries with global and regional perspectives differ in method, time-period and selected variables (Debone et al., 2021). The relationship between gross domestic

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product (GDP), energy consumption and carbon emission are explained by applied econometric methods. Moreover, authors have used various modelling approaches such as Artificial Neural Network, STIRPAT model and causality test in their study to examine the influence of different factors.

An empirical study by Le et al., (2020) analysed the association between GDP, energy consumption and carbon emission during 1996 to 2012 with the use of yearly data. The result of their study exhibits that, energy uses leads to economic development in the region. The consumption of Non-renewable energy sources raises carbon emissions but clean energy (renewable sources of energy) adoption help to curb emissions only in developed countries whereas, developing countries do not gain such benefit. Kais and Ben Mbarek, (2017) examined the causality in North African countries during 1980-2012 by using panel data model. The granger causality result confirms the existence of association ship among economic growth, energy consumption and carbon emission both short and long run respectively. Magazzino (2016) also explored the nexus between energy consumption, GDP growth and carbon emission in Italy by using the yearly data of 1970-2006. The result from Toda and Yamamoto shows the existence of bidirectional causality from carbon emission to energy consumption and economic growth. Further, same variable used in the study of Abdel-Gadir, (2020) to examine the nexus in the period of 1980-2018 in Oman. The finding from ARDL bound approach confirms that carbon emission is influenced with economic development and energy consumption. Awodumi, and Adewuyi, (2020) studied the linkage of non-renewable energy consumption to GDP growth and carbon emission in African top oil producing countries during 1980-2015. The result from NDRL exhibits that energy uses promotes economic growth that further leads to carbon emissions.

Omri (2013) extended study in 14 MENA regions in the period of 1990-2011. The estimation and result from the simultaneous equation model (GMM technique) show the existence of causal relationship among energy consumption to economic growth and carbon emission and, economic growth to carbon emission. The bidirectional causality is found from energy consumption to economic growth and economic growth to carbon emission. Moreover, uni-directional causality also being observed from energy consumption to carbon dioxide emission.

Pradhan et al., (2020) analysed the nexus between renewable energy consumption with gross domestic product, carbon emissions along with globalization and price in OECD (Organisation for Economic Co-operation and Development) countries during 1970-2015. The result from Machado and Silva Panel Quantile Regression shows the occurrence of long run relationship within variables.

Vo et al., (2019) study examined the relationship within energy uses, GDP growth, carbon emission and population growth in five Asian countries during 1971-2014. Their result shows heterogenous result where long and short run association occurs between variables in some countries, whereas the influence of economic growth to carbon emission and energy consumption is absent in few countries. Saboori and Sulaiman, (2013) studied

the causality between economic growth, energy consumption and carbon dioxide emissions in the ASEAN countries during 1971 to 2009. By the application of Autoregressive Distributed Lag (ARDL) and Granger causality methods, finding confirms positive and statistically significant relationship both in the short and long run. Further, Sulaiman and Abdul, (2017) used same variables and examined the relationships in the Malaysia during 1975-2015. Finding from ARDL approach shows the dependency of carbon emission on energy consumption as well as on economic growth. Sun et al., (2020) analysed causality among carbon emission, energy uses, output growth and trade from 1992 to 2015 in OECD countries. Their finding shows a long run influence of carbon emission from the variables. Also, Zhu et al., (2016) investigated the influence of GDP growth, energy consumption and foreign investment on carbon emissions in the ASEAN five1 countries during 1981 to 2011. The result from the panel quantile regression method shows that effect of carbon emission is heterogeneous in the low and high-emission countries.

The objective of this study is to apply ANN to explore the association among energy consumption, GDP growth and carbon emission in EU member countries. The focus on EU countries is due to multiple causes such as, high energy consumption, environmental concern and policy measure to mitigate carbon emission with pre-determined targets.

The remainder flow of this paper is as follows- section 2 highlights the related studies along with information about the ANN model used in disciplines. Section 3 explains the ANN methodology. Section 4 reports result and discussion. Section 5 conclude, recommend related policy measures and provides limitation of the study.

#### 2. ARTIFICIAL NEURAL NETWORK

Machine learning is a discipline of artificial intelligence (AI) that has gained wider attention with the evolution of digital platforms (Kethmi and Perera, 2021). It is a computer-based algorithm that is designed to used automatically data to achieve specific objectives. The capability of data preparation, automation and the iterative process has made machine learning a popular statistical analysis tool among researchers with its ability to save time.

The Development of artificial intelligence has made Artificial Neural Network (ANN) widely accepted topic in past three decades (Wu and Feng, 2018). Primarily the ability to learn and analyse the association among nonlinear variables makes it more acceptable among (Janková, 2021). It is superior to statistical regression models that analyses large data sets which has become a dominant modeling field/paradigm which does not requires computer programming to a solution like other numerical results (Ghritlahre and Prasad, 2018). It is considered a key technological revolution in the computer-based data processing method which analyzed algorithms and signals in advanced ways (Vogl et al., 2022; Burton, 2016). It consists of self-learning capacities, a feedback network and high-speed data processing to finding an optimal solution. ANN

Indonesia, Malaysia, Philippines, Singapore and Thailand.

is a machine-learning data processing system that works like a human brain (Boateng et al., 2018). It sets with neurons that process the data with forward layers. The model characterizes with a network of an input, hidden layer and output. ANN works like a replica of human brain. The development of AI has motivated researchers to study and apply in the field of business and manufacturing, infrastructure design, security, automobile, aviation, engineering (nuclear, thermal and chemical), electrical and electronics, ergonomics, pharmacy bio-medical, etc. (Paturi and Cheruku, 2021). Moreover, future event and risk is important for researcher due to multiple variables and its association, which requires study and analysis to build a suitable model for prediction (Baareh, 2013). However, the application of ANN model in EU member countries to examine multiple variable analyses is not enough.

## 3. DATA AND METHODOLOGICAL **FRAMEWORK**

This study considers yearly data from Twenty-four European Union Countries<sup>2</sup> from 2000 to 2020. The study uses variables such as, energy consumption (kg of oil equivalent per capita), economic growth (gross domestic product (GDP), constant \$ 2010), renewable energy consumption (% of total electricity output) and carbon emission (metric tons per capita). Energy consumption is of two kinds-renewable and non-renewable (oil). All data are extracted from World Bank Database. Artificial Neural Network model is used to explain the relationship. Carbon emission is dependent variable whereas energy consumption, GDP and renewable energy consumption is an independent variable respectively. The basic equation model is

#### CEM=f (ENG, GDP, REN)

Where CEM represents carbon emission; ENG is energy consumption; GDP is gross domestic product as a proxy of economic growth and REN is renewable energy consumption respectively.

#### 3.1. Analysing Procedure

The basic procedure for ANN modelling is that we followed is - Step-1: Data collection: Initially we collect data for the analyses. Step-2: Categorisation of data: We categorise data into two parts: input variables (ENG, GDP, REN) and output variable (CEM). Step-3: Splitting data into 80:20 ratio: In this stage, we split all input and output variable into 80:20 ratio for Training and Testing purpose. Step-4: Architecture: We set an automatic architecture to decide hidden layers and epoch. Step-5: By observing output data, we calculate RMSE values.

The methodological flow of ANN model is seen in the Figure 1 below;

#### 4. RESULTS AND DISCUSSION

#### 4.1. Results

The structure of ANN model is shown on Figure 2. The ANN analyses are conducted through IBM SPSS Neural Network Computer Package version 26. While beginning the analyses, data is set in the multilayer neural network perception through SPSS command side. The algorithm is used by the software to rescale and standardize the data. We set automatic architecture for the activation function. Accordingly, the algorithm is efficiently run by the software and provides an output that is later run by 10 times (Leong et al., 2020; Liébana-Cabanillas et al., 2017) to minimize the error. While doing multiple validation testing, we obtain root mean square error (RMSE) values. Table 1 shows average RMSE value of training and testing procedure that is 0.235 and 0.236 respectively. Figure 1 shows the relative graph of RMSE values used in training and testing procedures.

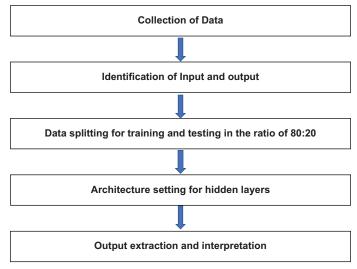
Later, to check the strength of variables, sensitivity analyses is conducted to get normalized importance (Table 2). The result

Figure 1: Artificial neural network diagram

Bias ENG H(1:2)

Synaptic Weight > 0 Synaptic Weight < 0 GDP REN H(1:4) Hidden layer activation function: Hyperbolic tangent Output layer activation function: Identity Input data Hidden layer Output data

Figure 2: Methodological flow of ANN model



Portugal, Malta, Hungary, Luxembourg, Poland, Austria, Belgium, United Kingdom, Sweden, Finland, Slovak Republic, Slovenia, Romania, Latvia, Cyprus, Italy, France, Spain, Bulgaria, Czech Republic, Denmark, Estonia, Germany and Ireland.

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Figure 3: The RMSE of training and testing data for intention. RMSE: The root mean square of errors

**Table 1: RMSE values** 

Training			<b>Testing</b>			<b>Total samples</b>
N	SSE	RMSE	N	SSE	RMSE	
400	12.306	0.175	104	3.106	0.173	504
408	16.316	0.200	96	3.496	0.191	504
400	23.148	0.241	104	6.722	0.254	504
389	20.152	0.228	115	5.692	0.222	504
393	29.021	0.272	111	9.867	0.298	504
397	27.755	0.264	107	6.163	0.240	504
398	36.789	0.304	106	6.972	0.256	504
401	26.426	0.257	103	7.104	0.263	504
394	13.798	0.187	110	4.468	0.202	504
405	20.041	0.222	99	6.59	0.258	504
mean	22.575	0.235	mean	6.018	0.236	
Standard deviation	7.597769	0.040503	Standard deviation	1.974761	0.038332	

SSE: Sum of square errors, RMSE: The root mean square of errors, N: Sample size

**Table 2: Sensitivity analyses** 

Neural networks (NN)	ENG	GDP	REN
NN1	1	0.367479	0.369808
NN2	1	0.350338	0.287775
NN3	1	0.194769	0.440524
NN4	1	0.372991	0.310669
NN5	1	0.221317	0.225948
NN6	1	0.339106	0.693021
NN7	1	0.266624	0.237705
NN8	1	0.200258	0.41452
NN9	1	0.344838	0.280087
NN10	1	0.260128	0.275578
Mean importance	1	0.291785	0.353563
Normalised importance	100%	29%	35%

ENG: Energy consumption, GDP: Gross domestic product, REN: Renewable energy consumption

shows the importance of variables are energy consumption (100%), renewable energy consumption (35%) and gross domestic product (29%) with their respective weight.

Figure 3 shows the RMSE of training and testing data for intention. The highest accuracy is seen in the ANN number-1 with lowest RMSE for testing. The highest value of RMSE for training and testing data records are 0.304 and 0.298 respectively. Thus, it recognizes an acceptable association between dependent and independent variables.

#### 4.2. Discussion

This study carried out to analyses the association between among energy consumption, economic growth and renewable energy consumption with carbon in the EU countries. The finding of study shows that used variables are significantly related to carbon emission with their respective weights. The possible reason for carbon emission with energy consumption is the overlapping nature of energy uses which is further linked with economic growth (Bianco et al., 2019). Economic structure of a country and energy mix could lead to inequality. Energy consumption, real income and trade are observed as the possible determinant of carbon emission (Dogan and Seker, 2016). The influence of GDP growth and carbon emission is positive in low-income countries and becomes negative when a country moves to a high-income level. Rising economic growth after a certain level decrease due to the achievement of a certain threshold level. Additionally, uses of renewable energy mitigate carbon emission and improve environmental conditions. The energy mix criteria provide a way to promote clean energy sources for consumption and get the projected target of EU to increase renewable energy up-to 27% by 2030 which is significantly rational. To achieve the target, financial support to scientific and academic institutions as well as researchers is foremost consideration to facilitate clean energy production at the least cost. further, sound regulatory policy and norms are required to increase public awareness of clean energy consumption and uses. In addition, trade openness provides a good insight that technological spillover and composition effect where, energy intensive and polluting industries basically move to develop and less developed countries due to minor and liberal environmental lows.

Additionally, industrialization is another important result of economic prosperity and carbon emission in EU countries (Lee, 2019). The industrialized-led economic growth is primarily supported by manufacturing, logistics and transport industries which are key determinants of carbon emission. to continue as a global supply chain the emission level is reduced with conservation schemes with the participation of the international level. Fossil fuel consumption and economic growth widely promote carbon emission, a way out is to check the energy mix in the country. An alternative way to add and use of wood biomass in EU countries is recommended that significantly reduced carbon emissions (Sulaiman et al., 2020). The authoritarian efforts to the improvement wood biomass sources with their efficiency and sustainability can provide a way to use energy and reduce carbon emissions. Investment in the wood biomass industry can positively replace fossil fuels and help to achieve energy security with a proper energy strategy.

#### 5. CONCLUSION

This study examines the influence of economic growth and energy consumption on carbon emissions in Twenty-Four European Union member states from 2000 to 2020. With the application of artificial neural network model, this research explores the variables of interest and contribution in environmental emission. The finding of study exhibits that energy consumption and GDP are the prime determinants of carbon emissions in EU countries. This implies that rising economic activities require enough energy for consumption and production activities. The development stages widely depend upon the industrial activities that provide both employment, income and finished goods. Manufacturing units are key areas in the industrialized economy that provide sufficient goods to the masses at any time. Energy is an important input for economic activities which helps to run industrial activity without compromising the market demand. Most industries run by fossil fuel negatively impact the environment. The shifting from fossil fuel-based economy to clean sources of energy provides a way to maintain both environmental quality and economic activities. This is further promoted with efficient regulatory and institutional norms. Government plays a crucial role to facilitate clean energy production and consumption to all sectors. The target to achieve a sustainable future by 2030 motivates the adoption and uses of renewable sources of energy is considerable. While doing so, financial constraint is a key focus area to work and provision of tax rebates, incentives, tariff schemes etc. are to attract energy producers that further accelerate clean energy production.

This study has several limitations. Initially, we apply ANN model solely without the addition of structural equation model, regression model, smart pls etc. Further, this study checks the association between economic growth, energy consumption and carbon emission but left some components that lead to raise energy demand. Urbanization and trade are an important determinant of carbon emission which is not added here with this study. Additionally, the role of research and development and technological advancement in the energy sector is not examined. Moreover, the effect of financial sector in the energy transition is not considered. Besides, the rising activity of digital marketing and online transaction further accelerate energy consumption related carbon emission. Moreover, the popularity of crypto currency

market in the world especially in developed region is also not considered, which is a key focus area of energy consumption. Thus, moving from traditional to modern energy sources reduce the burden of import bills, facilitates a clean environment to promote sustainable future, and helps to reduce climate change adversities in the European region as well as in the world.

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