



**TÜRKİYE CUMHURİYETİ
ADANA ALPARSLAN TÜRKER SCIENCE AND TECHNOLOGY
UNIVERSITY**

**GRADUATE SCHOOL
BUSINESS ADMINISTRATION DEPARTMENT**

**ESTIMATING ECOLOGICAL FOOTPRINTS OF OECD COUNTRIES
WITH PANEL DATA ANALYSIS AND NEURAL NETWORKS**

SEVİM GÜLİN DEMİRBAY

Ph.D.



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**THESIS ADVISOR
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ADANA, 2025

DECLARATION OF CONFORMITY

In this thesis study, which was prepared following the thesis writing rules of Adana Alparslan Türkeş Science and Technology University Institute of Graduate School, I declare that I provide all the information, documents, evaluations and results in accordance with scientific ethics and moral codes without resorting to any means or assistance that would be contrary to scientific ethics and traditions. I also declare that I refer to all of the articles I used in this study with appropriate references and accept all moral and legal consequences of a situation is found contrary to my statement regarding my work.

06/02/2025

[Signature]

Sevim Gülin DEMİRBAY

ÖZET

PANEL VERİ ANALİZİ VE YAPAY SİNİR AĞLARI İLE OECD ÜLKELERİNİN EKOLOJİK AYAK İZLERİNİN TAHMİN EDİLMESİ

Sevim Gülin DEMİRBAY

Doktora, İşletme Anabilim Dalı

Danışman: Doç. Dr. Selim GÜNDÜZ

Şubat 2025, 224 sayfa

Hızla artan nüfus, sanayileşme, kentleşme ve tüketim alışkanlıklarındaki artış, dünyamızın ekolojik denge üzerinde ciddi baskılar oluşturmaya neden olmaktadır. Bu durum, doğal kaynakların kontrolsüz ve sürdürülemez bir şekilde talep edilmesine yol açmıştır. Ekolojik tahribatın giderek daha görünür bir hale gelmesi, sürdürülebilir kalkınma hedefleri doğrultusunda "Ekolojik Ayak İzi" kavramının ortaya çıkmasını sağlamıştır.

Araştırmada, yenilenebilir enerji tüketimi, küreselleşme ve ekonomik büyümenin ekolojik ayak izi üzerindeki etkileri analiz edilmiştir. Çalışma kapsamında, 1995-2021 yılları arasında elde edilen veriler kullanılarak panel veri analizi ve yapay sinir ağı yöntemleri ile tahminleme yapılmıştır. Panel veri analizi ile bağımsız değişkenlerin bağımlı değişken üzerindeki etkileri detaylı bir şekilde incelenmiş ve bu değişkenler, yapay sinir ağı modeli için girdi olarak kullanılmıştır. Böylece, ekolojik ayak izinin tahmin edilmesine yönelik yüksek doğruluklu bir model geliştirilmiştir.

Araştırma sonucunda, modelde yer alan bağımsız değişkenlerin, ekolojik ayak izi üzerindeki etkilerinin anlamlı ve farklılık gösterdiği tespit edilmiştir. Özellikle gayrisafi yurt içi hasıla ve KOF küreselleşme endeksi, ekolojik ayak izini pozitif yönde etkileyen önemli faktörler olarak öne çıkmıştır. Diğer yandan, yenilenebilir enerji tüketiminin ekolojik ayak izini azaltan önemli bir değişken olduğu belirlenmiştir. Elde edilen sonuçlar doğrultusunda, ekolojik ayak izinin artışının kontrol altına alınabilmesi için yenilenebilir enerji yatırımlarının artırılması gerektiği sonucuna ulaşılmıştır.

Modelleme sürecinde ileri beslemeli yapay sinir ağı yöntemi tercih edilmiş ve modelin eğitimi için Levenberg-Marquardt algoritması kullanılmıştır. Yapay sinir ağı modeli, her bir OECD ülkesi için yüksek güvenilirlikle tahminleme yaptığı sonucuna ulaşmıştır.

Literatürde ekolojik ayak izlerinin tahmin edilmesinde panel veri analizi ve yapay sinir ağı yöntemlerinin eş zamanlı olarak kullanılmasına yönelik çalışmaların sınırlı sayıda olması, bu araştırmanın motivasyonunu oluşturmuştur. Dolayısıyla, bu tez çalışması, hem yöntemsel hem de içerik açısından literatüre önemli bir katkı sağlamayı hedeflemektedir.

Anahtar Kelimeler: Ekolojik Ayak İzi, Panel Veri Analizi, Yapay Sinir Ağları, Yenilenebilir Enerji, Küreselleşme, OECD Ülkeleri, Sürdürülebilirlik.



ABSTRACT

ESTIMATING ECOLOGICAL FOOTPRINTS OF OECD COUNTRIES WITH PANEL DATA ANALYSIS AND NEURAL NETWORKS

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Supervisor: Assoc. Prof. Dr. Selim GÜNDÜZ

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The rapid increase in population, industrialization, urbanization, and changing consumption patterns has placed significant pressure on the ecological balance of our planet. This situation has led to the uncontrolled and unsustainable demand for natural resources. As ecological degradation becomes increasingly evident, the concept of the "Ecological Footprint" has emerged in line with the goals of sustainable development.

This study analyzes the effects of renewable energy consumption, globalization, and economic growth on the ecological footprint. Using data from the period 1995–2021, estimations were conducted through panel data analysis and artificial neural network methods. Panel data analysis was employed to examine the impact of independent variables on the dependent variable in detail, and these variables were then used as inputs for the artificial neural network model. Consequently, a high-accuracy model was developed for predicting the ecological footprint.

The findings indicate that the independent variables included in the model have significant and varying effects on the ecological footprint. In particular, Gross Domestic Product (GDP) and the KOF Globalization Index have been identified as key factors that positively influence the ecological footprint. On the other hand, renewable energy consumption has been determined as a crucial variable in reducing the ecological footprint. Based on the results, it has been concluded that increasing investments in renewable energy is essential for controlling the rise in the ecological footprint.

During the modeling process, a feedforward artificial neural network approach was adopted, and the Levenberg-Marquardt algorithm was utilized for model training. The artificial neural network model demonstrated high reliability in forecasting ecological footprints for each OECD country.

The limited number of studies in the literature that simultaneously employ panel data analysis and artificial neural network methods for predicting ecological footprints served as a primary motivation for this research. Therefore, this dissertation aims to contribute significantly to the literature both methodologically and in terms of content.

Keywords: Ecological Footprint, Panel Data Analysis, Artificial Neural Networks, Renewable Energy, Globalization, OECD Countries, Sustainability.

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LIST OF ABBREVIATIONS

ANN	: Artificial Neural Networks
ARDL	: Autoregressive Distributed Lag
CADF	: Cross-sectional Augmented Dickey-Fuller
CD	: Cross-Sectional Dependence Test
CIPS	: Cross-Sectionally Augmented Im, Pesaran, and Shin
DOLS	: Dynamic Ordinary Least Squares
EBA	: Extreme Bound Analysis
EF	: Ecological Footprint
FMOLS	: Fully Modified Ordinary Least Squares
GDP	: Gross Domestic Product
GI	: Globalization Index
LM	: Lagrange Multiplier
ML	: Multilayer Perceptrons
MSE	: Mean Square Error
NFA	: National Footprint Account
OECD	: Organization for Economic Cooperation and Development
REC	: Renewable Energy Consumption
ReLU	: Rectified Linear Unit
SELU	: Scaled Exponential Linear Unit
SLP	: Single Layer Perceptrons
SPSS	: Statistical Package for the Social Sciences
WWF	: World Wide Fund for Nature

LIST OF SYMBOLS

$\hat{\rho}_{ij}$	: Correlation Coefficient
CO_2	: Carbon Dioxide
w_n	: Weight Values
gha	: Global Hectar
R^2	: Coefficient of Determination



1. INTRODUCTION

Due to swift population increase, industrialization, technological advancement, and urbanization, individuals' consumption patterns have commenced to evolve. The alteration in consumption patterns leads to the depletion of natural resources, subsequently resulting in environmental issues that jeopardize the survival of organisms worldwide (Özsoy and Dinç, 2016).

The rising global consumer demands have led to environmental issues, hence enhancing humanity's environmental consciousness and highlighting the notion of sustainability (Tunç, Ömür and Düren, 2012). Sustainability is the fulfillment of present human needs and expectations without surpassing natural resource limits or jeopardizing future generations' capacity to satisfy their fundamental requirements (Global Footprint Network, 2010). In this context, the idea of ecological footprint has arisen to ascertain the extent to which sustainability is being compromised. The ecological footprint has gained prominence in recent years as an indicator of environmental degradation (Tosunoğlu, 2014; Bello and Solarin, 2018; Karaman, 2024). The Ecological Footprint integrates science, policy, and economics to revolutionize global natural resource management and secure a sustainable future (Global Footprint Network, 2024).

The ecological footprint quantifies the biological water and arable land necessary to generate all resources utilized by an individual, community, or specific activities, as well as to assimilate the waste they generate (Cordero, Todd and Abellera, 2008; Global Footprint Network, 2010; Rudolph and Figge, 2017). It is quantified in global hectares (gha). In summary, it is characterized as renewable natural resources utilized for the creation of goods consumed by a community or individual (World Wide Fund for Nature, 2012). The increasing ecological demand, coupled with human use of natural resources surpassing nature's capacity for regeneration, poses a significant threat to the welfare of individuals and societies. Ecological Footprint studies indicate that humanity consumes about 75% of the planet's resources, equating to 1.75 times the Earth's capacity (World Wide Fund for Nature, 2022; Wackernagel, Hanscom, Jayasinghe, Lin, Murthy, Neill and Rayen, 2021). The overexploitation of Earth's resources threatens the ecological equilibrium and the long-term survival of humanity. To avert this catastrophe, enhancing individuals' awareness of their ecological footprint is crucial for

attaining a sustainable ecosystem (Birand, 2016). The use of global resources exceeds their production, indicating that the Earth's biological capacity is inadequate to satisfy human wants and requirements, resulting in an escalating ecological footprint and a widening ecological deficit. Figure 1 illustrates the variation in the global ecological footprint and biocapacity throughout time.

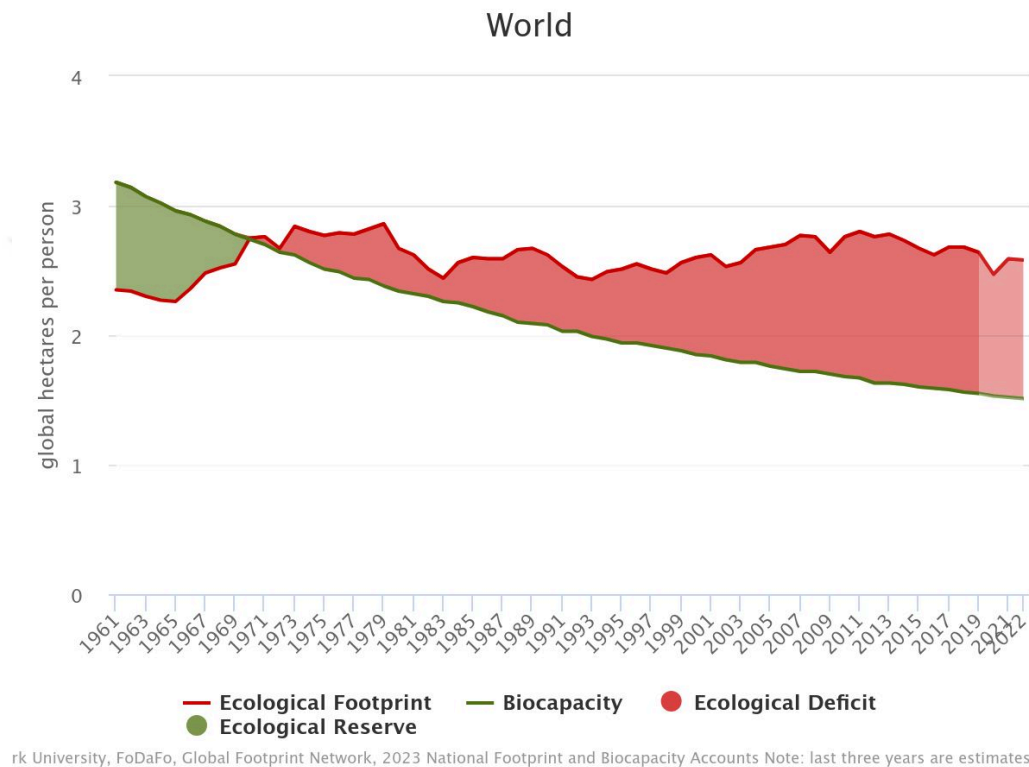


Figure 1.1. Variations in Ecological Footprint and Biological Capacity Over Time

Source: Global Footprint Network (2024)

Globally, ecological footprint values exceed biological capacity. Residents of these countries must recognize their ecological footprint levels, examine their origins, and implement strategies to mitigate the problems associated with ecological deficits (Tosunoğlu, 2014).

Research conducted by the World Wide Fund for Nature (WWF) in 2008 indicates that of economic development and energy consumption persist at an accelerated pace, carbon dioxide emissions are projected to quadruple by the mid-21st century relative to current levels. The inference made from this is that mankind requires two other planets with an identical biological environment to Earth to fulfill its needs and eliminate its trash. Significant forecasts indicate

that the prolonged degradation of the environment by humanity may result in production and enduring productivity issues, potentially culminating in a full collapse of the ecosystem.

The choices made by decision-making units vary based on anticipated future conditions. The efficacy of foresight performance is crucial for decision-making entities to adopt appropriate policies (Altan, 2020). The idea of foresight is described as the estimation of potential future values of a variable of interest based on specific assumptions (Ataseven,2013). In recent years, Artificial Neural Networks (ANN) have been extensively employed for predictive purposes. This study employed the ANN approach to forecast future ecological footprints.

In our investigation, the correlation between the dependent variable and the independent factors was analyzed using panel data analysis. Research has demonstrated that renewable energy usage, globalization, and economic expansion, analyzed as independent variables, exert distinct influences on the ecological footprint, the dependent variable. The independent variables demonstrated to influence the dependent variable through panel data analysis were incorporated into the model as input variables in the ANN methodology. ANN's are frameworks designed to enhance the influence on the dependent variable by assessing the effect strength of each parameter and amplifying the coefficient of the parameter with the greatest effect strength.

2. THEORETICAL FOUNDATIONS AND LITERATURE REVIEW

Our research utilized the variables of globalization, economic growth, and renewable energy consumption, encompassing both economic and environmental dimensions, to analyze their link with the ecological footprint. This section of the thesis elucidates the literature review for each variable and the analytical methodologies employed.

2.1. Parameters Utilized in Analysis

2.1.1. Ecological Footprint

Humans inherently engage in continuous connection with their environment. Since prehistoric eras, humanity has utilized nature to fulfill its fundamental requirements. Over time, thanks to advancements in agriculture and the industrial revolution, humanity has increasingly exploited nature for its own advantage, reaching perilous levels. The continuous nature of this process has resulted in irreversible disturbances in the equilibrium of environmental systems (Öztürk, 2010). Concerns regarding the future of the globe are escalating due to causes such as population expansion and economic advancement. The Ecological Footprint idea has arisen to quantify environmental degradation, mitigate identified harms, and promote the long-term sustainability of a habitable world (Ayhan, 2024). The Ecological Footprint (EF) integrates science, politics, and economics to revolutionize global natural resource management and secure a sustainable future. The area of water and arable land necessary to assess ecological balances adversely impacted by human activities and to rehabilitate them within the ecosystem is delineated (WWF, 2012). This approach evaluates our reliance on the natural environment. The EF starkly illustrates the accelerated depletion of our planet's resources. Regrettably, nations frequently overlook the pressing necessity to diminish their ecological footprint, as such actions are likely to impede economic progress across various sectors (Tosunoğlu, 2014). If these nations persist in their existing consumption patterns, our earth will be unable to sustain this burden (Akıllı, Kemahlı, Okudan and Polat, 2008).

Biological capacity refers to the biological productivity of a region's or country's land and water regions (Özsoy and Dinç, 2016). Various factors influence the biocapacity of a region. This

encompasses the expanse of agricultural land, pastures, fisheries, and woods within defined bounds, together with the fertility of the land or water (WWF, 2010)

Ecological openness is the disparity between the Earth's biocapacity and the ecological footprint necessary for nature to manage the waste produced by the consumption of natural resources (Mızık and Avdan, 2020). In other words, ecological deficit arises when the ecological footprint surpasses the biological capacity threshold. The biospheric component that generates resources for human consumption is termed biocapacity.

Assessing the ecological footprint of countries is crucial for evaluating human impact on the environment. The ecological footprint of countries differs due to variations in consumption, population, fossil fuel utilization, and economic levels. Given the negative relationship between consumption and income, it is established that high-income nations typically own greater ecological footprints (Tosunoğlu, 2014; Dinç, 2016; Hüdavendigar, 2024). Research on ecological footprints indicates that industrialized nations, specifically, possess a greater ecological footprint compared to other countries and exploit more ecologically productive regions (Akıllı et al., 2008).

For sustainable living, humanity's ecological footprint must not exceed the planet's biocapacity of 1.6 global hectares per capita. An Ecological Footprint of 6.4 global hectares per capita indicates that the demands of a country's population for food, fiber, urban space, and carbon sequestration surpass the Earth's per capita capacity by a factor of four (WWF, 2022). It is crucial to reassess our lifestyle and the planet's ecological potential, particularly regarding the ecological footprint.

Table 2.1. Values for OECD Countries in 2022

OECD Countries	Biocapacity	Ecological Footprint	Limit Exceeding	Number of World
Australia	11,02	5,78	+5,24	3,83
Austria	2,89	5,63	-2,74	3,73
Belgium	1,16	6,69	-5,53	4,43
Canada	14,24	7,42	+6,82	4,91
Chile	3,23	3,84	-0,61	2,54
Colombia	3,59	1,98	+1,61	1,31
Costa Rica	1,62	2,6	-0,98	1,72
Czech Republic	2,52	5,08	-2,56	3,37
Denmark	4,22	7,29	-5,07	4,82
Estonia	9,81	8,12	+1,69	5,38
Finland	11,75	5,36	+6,39	3,55
France	2,46	4,31	-1,85	2,86
Germany	1,61	4,5	-2,89	2,98
Greece	1,6	3,78	-2,18	2,5
Hungary	2,57	3,79	-1,22	2,51
Ireland	3,11	4,51	-1,4	2,98
Israel	0,24	4,16	-3,92	2,76
Italy	0,97	3,95	-2,98	2,62
Japan	0,63	4,04	-3,41	2,68
Korea, Rep	0,65	5,82	-5,17	3,85
Latvia	9,93	7,72	+2,21	5,11
Lithuania	5,97	6,43	-0,46	4,26
Luxembourg	1,23	10,96	-9,73	7,26
Mexico	1,2	2,29	-1,09	1,51
Netherlands	1,11	6,02	-4,91	3,99
New Zealand	8,45	5,43	+3,02	3,59
Norway	6,75	5,4	+1,35	3,57
Poland	2,02	4,65	-2,63	3,08
Portugal	1,48	3,72	-2,24	2,46
Slovak Republic	2,67	4,16	-1,49	2,75
Slovenia	2,49	4,78	-2,29	3,17
Spain	1,72	3,92	-2,2	2,59
Sweden	8,52	4,94	3,58	3,27
Switzerland	1,13	3,74	-2,61	2,47
Turkey	1,48	3,39	-1,91	2,25
United Kingdom	1,02	3,57	-2,55	2,36
United States	3,72	7,46	-3,74	4,94

Table 2.1 presents the per capita biocapacity, ecological footprint, overshoot, and requisite number of worlds for each OECD nation in 2022. It is feasible to compare ecosystems across different worldwide regions and their respective biological production areas using global hectare assessments. Ecological footprint levels that surpass the nation's existing biological capacity result in the threshold being limit exceeded. As the consumption of fossil fuels escalates, individuals' ecological footprints enlarge. Countries exhibit disparate ecological footprints based on their wealth levels, indicating an unequal distribution of responsibility and biocapacity. The global ecological footprint unfortunately increase due to human activities that cause increased damage to the ecosystem. Investments in biocapacity should be directed towards contries, and the efficiency of production zones should be enhanced. The ecological footprint concept distinctly illustrates the rapid depletion of global resources. Regrettably, as this entails decelerating economic growth in several sectors, nations largely neglect efforts to mitigate the increase of their ecological imprint (Tosunoğlu, 2014).

2.1.1.1. Components of the Ecological Footprint

The ecological footprint is composed of six primary components, each representing a distinct aspect of resource consumption and environmental impact. These categories include the carbon footprint, grazing land footprint, forest land footprint, fishing ground footprint, cropland footprint, and built-up land footprint. Together, these elements provide a comprehensive framework for evaluating the pressure human activities exert on natural ecosystems (Wackernagel, Onisto and Bello, 1997).

Carbon Footprint

Global initiatives are underway to attain an environmentally sustainable future, foster economic growth, and create low-carbon economies. Consequently, the notion of carbon footprint was established to mitigate anthropogenic greenhouse gas emissions and counteract their adverse environmental effects (Binboğa and Aylin, 2018). The carbon footprint denotes the quantity of carbon dioxide emissions (CO₂) generated at every phase of the product life cycle, encompassing manufacture, transportation, and utilization. Carbon footprints are typically categorized into two distinct types: primary (direct) and secondary (indirect) footprints. The primary carbon footprint represents the quantification of direct CO₂ emissions stemming from the combustion of fossil fuels. This category includes emissions associated with household energy consumption and various modes of transportation, such as automobiles and air travel.

The secondary footprint measures indirect CO₂ emissions across the whole life cycle of the things we utilize, encompassing their manufacture and eventual decay (Republic of Turkey Ministry of Health, 2024; Kumaş, Akyüz, Zaman and Güngör, 2019)

Carbon emissions released into the atmosphere due to the destruction of natural ecosystems exceed the storage capacity of these ecosystems. Carbon dioxide (CO₂), a prominent greenhouse gas, accumulates in the atmosphere, resulting in ecological issues such as climate change and ocean acidification, which have historically posed significant environmental challenges (Özsoy, 2015).

Grazing Land Footprint

Grazing lands, which include rangelands and pastures, play a critical role in supporting global livestock production systems by providing essential resources for meat, milk, and fiber production (Derner, Hunt, Filho, Ritten, Capper and Han, 2017). In addition to their agricultural significance, these lands serve as crucial habitats, fostering wildlife conservation and supporting biodiversity (Fuhlendorf and Engle, 2001; West, 1993). The grazing land footprint quantifies the area of grazing land utilized to satisfy human demand for animal products (Sivrikaya, 2018). The degradation or erosion of designated grazing areas and grass utilization by animals, resulting from excessive and improper practices, the conversion of traditionally managed pastures into agricultural land, and the allowance of construction or afforestation in these regions, can result in the destruction of biodiversity within pasture ecosystems (WWF, 2012; Özsoy and Dinç, 2016).

Forest Land Footprint

Forest areas encompass regions allocated for timber production or signify natural forests. These regions require effective management to safeguard against erosion, uphold climate stability, preserve the hydrological cycle, and restore biodiversity (Wackernagel et al., 1997). Forested regions are crucial for the maintenance of environmental sustainability. Forested regions alleviate the impacts of climatic abnormalities and rejuvenate the biological system. Forested regions substantially influence environmental pollutants (Waheed, Chang, Sarwar and Chen, 2018). Unaccounted variables in footprint calculations, including forest land degradation, neglect of biodiversity conservation, climate change, and selective designation of forest areas for timber extraction, diminish forests' capacity to provide ecological services (WWF, 2012).

To enhance the beneficial effects of forest areas on environmental quality, it is essential to safeguard these regions (Özbek and Oğul, 2023).

Fishing Ground Footprint

Overfishing, the depletion of fisheries, and the exploitation of low-trophic species jeopardize numerous marine ecosystems (Crowder, Hazen, Avissar, Bjorkland, Latanich and Ogburn, 2008). There is a broad acknowledgment that fisheries significantly affect marine ecosystems and the species contained within them (Jackson, Kirby, Berger, Bjorndal, Botsford, Bourque, Bradbury, Cooke, Erlandson, Estes, Hughes, Kidwell, Lange, Lenihan, Pandolfi, Peterson, Steneck, Tegner, Warner, 2001). The fishing area footprint is established by calculating the entire marine and freshwater area necessary to support the fish and seafood that are produced and consumed (WWF, 2012; Özsoy and Dinç, 2016). The ecological footprint of fishing was primarily concentrated in the oceans of industrialized nations in North America, Europe, and Japan in 1950, but by 2005, it had extended to encompass most of the world's productive waterways (Swartz, Sala, Tracey, Watson and Pauly, 2010). Exploring the Ecological Footprint is crucial for obtaining a sustainability indicator and establishing a framework to enhance the eco-efficiency of fishing activities, aiming to generate greater income with fewer resources (Olivas and Dagostino, 2020).

Crop Land Footprint

Agriculture is the primary economic activity directly associated with food supply. The swift expansion of the world population is exacerbating the disparity between food demand and supply (Ghosh and Chakma, 2018). The correlation between agricultural management and the overexploitation of natural resources is frequently a topic of discourse in environmental sciences (Passeri, Borucke, Blasi, Franco and Lazarus, 2013). The agricultural land footprint denotes the entire land area allocated for the cultivation of food, fiber, animal feed, oil crops, and rubber for human consumption (Tosunoğlu, 2014). Inadequate global data sets, unsustainable farming practices, and activities that lead to long-term declines in soil fertility, including soil degradation, erosion, and salinization, are omitted from the assessment of the agricultural land footprint (Kitzes, Peller, Goldfinger and Wackernagel, 2007).

Built-Up Land Footprint

Research on urbanization's impact on biodiversity loss emphasizes water, soil, and overall ecosystems, underscoring the dangers urbanization presents to biodiversity. Built-up land footprints allow for the assessment of urbanization's effect on land scarcity in cities, as increased urban population densities correlate with a heightened demand for biologically productive areas for urban infrastructure (Kassouri, 2021). Built-up land regions encompass 0.3 billion hectares of the global geographical surface. Housing, transportation, industrial production, and water supply infrastructures occupy a substantial percentage of environmentally productive land (Akıllı et al., 2008). The built-up land footprint refers to the land area occupied by infrastructure and structures essential for human requirements, including residential properties, transportation systems (roads, bridges), industrial facilities, and power plants. Estimates of the built-up area footprint encompass hydroelectric dams and reservoirs utilized for hydroelectric power generation (WWF, 2012; Özsoy and Dinç, 2016).

2.1.1.2. Calculation of Ecological Footprint

The Ecological Footprint is calculated using the National Footprint Account (NFA) formula, a methodology applied at the national level. The NFA formula is delineated below (Van den Bergh and Verbruggen, 1999; Tosunoğlu, 2014).

$$\text{Ecological footprint (gha *)} = \text{Consumption} \times \text{Population} \times \text{Production Area} \quad (2.1.)$$

Ecological footprint assessments are articulated using a standardized unit known as the global hectare. Consumption is defined as the extent or frequency of product utilization. Population is a notion that quantifies the number of individuals residing in a specific area during a designated time frame. The production area denotes the biologically productive space necessary to sustainably satisfy a portion of consumption (Akıllı et al., 2008).

Rudolph and Figge (2017) assert that consumption can be evaluated by a methodology that considers many sectors of activity, including manufacturing, importation, and exportation.

$$EF_{consumption} = EF_{production} + EF_{imports} - EF_{exports} \quad (2.2.)$$

Elevations in the ecological footprint of an individual, community, or activity signify heightened demand for biologically productive regions, whereas biocapacity denotes the availability of such areas (Apaydin, 2020). The calculation of the ecological footprint rests on two fundamental pillars: the capacity to track resource consumption and waste generation, and the capability to quantify the biological production area necessary for fulfilling needs and managing waste disposal. Ecological footprints derived from these foundations indicate the extent of biologically productive land utilized by individuals for production and consumption (Akillı et al., 2008). In Turkey, the ecological footprint assessed in 2011 was 2.66 gha/person, of which approximately 47%, or 1.7 gha/person, constituted the carbon footprint. Consequently, utilizing renewable energy sources in lieu of non-renewable energy sources is essential for mitigating carbon emissions (Dinç, 2016).

2.1.1.3. Methods for Mitigating Ecological Footprint

It is imperative to diminish our ecological footprint for the sustainable future of our planet. To cease surpassing ecological boundaries, investments in biocapacity should be undertaken, and the efficiency of producing sectors should be enhanced. Conscious consumption practices must be adopted, domestic renewable energy sources should be utilized in lieu of external supplies, and energy waste must be curtailed (Eren, Aygün, Chabanov and Akman, 2016; Kurtuldu, 2019). Development plans must incorporate quantitative evaluations of the ecological footprint. International commitments regarding climate change, biodiversity, and protected areas must be fulfilled. Resource efficiency must be enhanced, and supplementary protected areas should be created. Choices regarding lifestyle, including modes of transportation (e.g., walking, cycling, utilizing public transit instead of driving), shopping preferences (e.g., purchasing from local or farmers' markets), and product selection (e.g., opting for organic over non-organic produce), alongside more efficient utilization of natural resources like energy, can mitigate emissions. In the same way that we manage our infrastructure and other manufactured capital assets, we must opt to more effectively manage and protect our ecological assets. Both the corporate sector and the public must significantly contribute to mitigating ecological harm (WWF, 2012).

Numerous strategies are available for individuals seeking to reduce their ecological footprint. A key approach involves minimizing the use of private vehicles, which can be effectively substituted by walking, cycling, carpooling, or utilizing public transportation. Additionally,

choosing organic and locally sourced products not only supports sustainable agriculture but also reduces the carbon footprint associated with long-distance food transportation.

Another critical area for reducing ecological impact is the adoption of innovative technologies aimed at improving energy efficiency in both residential and workplace settings. This includes exploring renewable energy options, such as solar or wind power, which can replace traditional, non-renewable energy sources. Individuals can further contribute to sustainability by sourcing "green" energy from local power utilities that emphasize renewable resources.

In terms of transportation, selecting vehicles with lower fuel consumption and reduced emissions can significantly contribute to a decrease in overall environmental harm. Moreover, choosing to live near one's workplace helps reduce commuting time and reliance on fuel-burning vehicles. Lastly, reducing the consumption of animal-based foods is another impactful strategy, as livestock farming is one of the primary contributors to greenhouse gas emissions and environmental degradation.

These actions, individually or in combination, form a robust framework for significantly reducing one's ecological footprint, promoting sustainability, and mitigating the effects of climate change (Wilson and Anielski, 2005; Palmer, 1998).

The computation of ecological footprints enables the comparison of various entities, including countries, individuals, cities, villages, workplaces, and institutions. If a person's footprint size is below the country's average, it is presumed that the individual does not exert pressure on natural resources; conversely, if it exceeds the average, it is believed that natural resources are being depleted. Furthermore, juxtaposing each nation's ecological footprint with its biological potential is beneficial for assessing remaining resources. An ecological deficit arises when a country consumes significantly more natural resources than it possesses. If a country's biocapacity exceeds its ecological footprint, it possesses an ecological reserve.

2.1.2. Globalization

Globalization exerts a direct influence on economic growth and an indirect impact on the environment. Numerous literary research demonstrate the favorable correlation between ecological footprint and globalization.

Rudolph and Figge (2017) investigated the influence of globalization on the ecological footprint in their analysis of 146 countries. The study employed the "Extreme Bound Analysis (EBA)" technique, concluding that the KOF globalization index exhibits a significant and positive correlation with ecological footprints. Although social globalization positively influences imports and exports, it has been demonstrated to adversely impact the ecological footprint of manufacturing and consumption. A study investigating the essential connection between globalization and ecological footprint was carried out by Sharif, Afshan and Qureshi (2019). The research sample encompassed data from the first 15 globalized countries spanning the years 1970 to 2016. The research indicated that the relationship between globalization and ecological footprint varied based on the distinct environmental and trade policies of the countries. In the same way, Apaydin (2020) examined the effects of globalization on the ecological footprint in his research. The research examined data from the KOF Globalization Index from 1980 to 2014. The ARDL, DOLS, and FMOLS models were employed as distinctive research methodologies. They determined that globalization and ecological footprint are positively correlated, and the relationship is significant. Kirikkaleli, Adebayo, Khan ve Ali (2021) analyzed the effects of globalization on Turkey's ecological footprint. The research employed a dual compliance strategy to regulate energy consumption, economic growth, and trade liberalization. The research revealed that globalization positively impacts the ecological footprint in the long term, negatively affects trade openness in the short term, and adversely influences GDP growth in both the short and long term. The study by Erkut, Günay, and Yenilmez (2024) sought to investigate the correlation between globalization and ecological footprint within the MIKTA countries: Mexico, Indonesia, South Korea, Turkey, and Australia. The investigation encompassed panel data from 1970 to 2018. The research determined that economic globalization diminishes the ecological footprint in Mexico and Indonesia.

Our research utilized the KOF globalization index data, encompassing economic, political, and social dimensions, like as employed in the study by Gygli, Haelg, Potrafke and Sturm (2019), to examine the globalization parameter. KOFGI is a composite index that quantifies globalization for nearly every country worldwide, rated on a scale from 1 to 100. The data is annually updated with the addition of a new year (Haelg, 2020).

2.1.3. Economic Growth

While economic growth and development are crucial for all nations, they are particularly paramount objectives in emerging ones. Economic growth often denotes the augmentation of national income throughout time (Demircan, 2003). A favorable correlation is anticipated with GDP, the primary metric of national economic growth. Economic growth typically escalates alongside the rise in GDP inside nations. The GDP variable was utilized to analyze the correlation between economic growth and ecological footprint. The financial measure of goods and services generated inside a country over a specified period is known as GDP (Costanza, Kubiszewski, Giovannini, Lovins, McGlade, Picketti Ragnarsdóttir, Roberts, Vogli and Wilkinson, 2014). Akıllı et al. (2008) conducted a study targeting students and staff from the Faculty of Economics and Administrative Sciences at Akdeniz University to evaluate individual ecological footprints. The research involved 241 participants, selected from a total population of 1,886 individuals. The analysis focused on footprints related to food, waste, housing, and transportation, examining variations across gender, age, income level, occupation, and consumption patterns. Statistical methods, including the T-Test and Kruskal-Wallis H Test, were employed to analyze the data. The analyses revealed that ecological footprint rates were consistent across genders, that total footprints escalated with increased consumption corresponding to higher income, and that individuals possessing property and vehicles, as well as academic personnel, exhibited greater income levels compared to other professional categories.

Figure 2.1. GDP Trends of OECD Members: 1995-2021 (Current US Dollars)

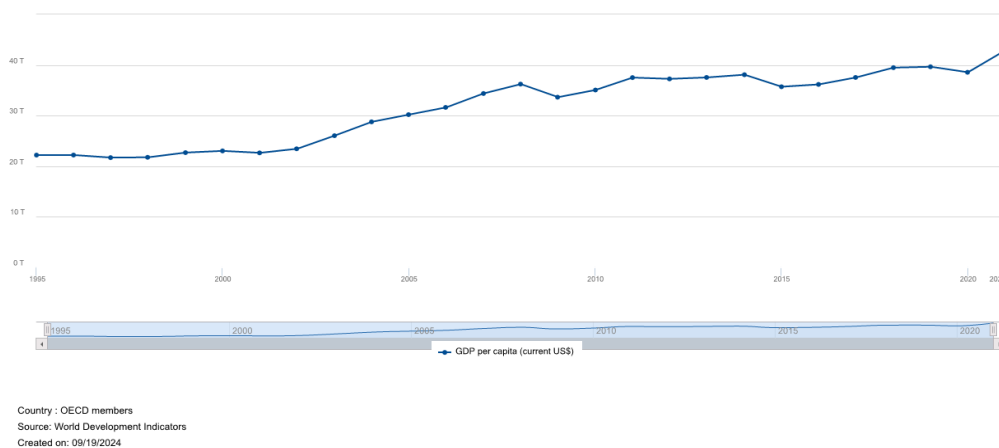


Figure 2.1 illustrates the trajectory of the Gross Domestic Product (GDP) of OECD nations in current US dollars from 1991 to 2021. A discernible rising trajectory in gross domestic product is evident over the years. The Covid-19 pandemic precipitated a substantial decrease in gross domestic product values during the crisis and towards the conclusion of 2019. It is evident that it surpasses the gross domestic product figures of the 1980s and 1990s (Bucak and Saygılı, 2022).

The short-term objectives established to sustain the global economy are leading to the daily depletion of our natural capital. Rather than fretting over our economic deficits, we must establish long-term objectives to address the ecological deficiencies that jeopardize our economic sustainability (Brown, 2002; Johnson and Lewis, 2007). Brown (2002) contends that: “Economic deficits represent what we borrow from one another, whereas ecological deficits signify what we appropriate from future generations.”

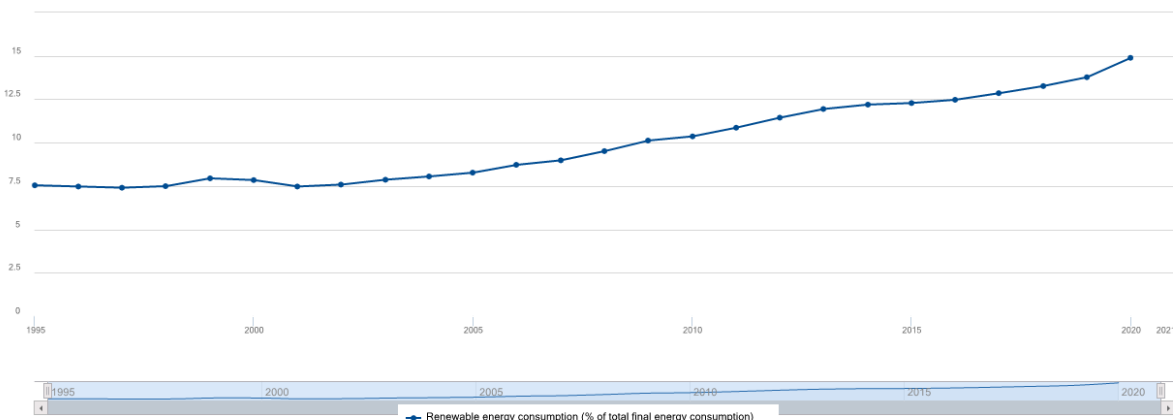
2.1.4. Renewable Energy Consumption

Renewable energy sources possess an indefinite existence and can be utilized repeatedly. This is critically significant for energy sustainability. Literature studies have established a statistically significant correlation between renewable energy utilization and ecological footprint (Kapçak, 2024). Pata, Aydin and Haouas (2021) conducted an analysis of the effects of globalization, renewable energy consumption, natural resource abundance, and the human development index on environmental deterioration in the ten countries with the greatest ecological footprints. The findings from the panel estimator indicate that the increase in the human development index and renewable energy use negatively and statistically significantly affects the ecological footprint. Simultaneously, they determined that while the availability of natural resources diminishes environmental quality, globalization exerts little influence on environmental pressure. Although non-renewable energy sources facilitate the attainment of national growth objectives, they also contribute to environmental degradation, heighten ecological damage, and intensify global warming by diminishing the planet's biological carrying capacity. Utilizing renewable energy sources rather than non-renewable ones is crucial for enhancing environmental quality and mitigating global warming by reducing ecological effect (Koçak, 2024). The utilization of renewable energy enhances environmental quality by diminishing the ecological footprint, thereby indicating that renewable energy usage adversely affects the ecological footprint (Yavuz, 2022). Topçu (2021) examined the impact of imports,

exports, and renewable energy utilization on Turkey's ecological footprint from 1990 to 2015. The study employed the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests. The investigation revealed that the consumption rate of natural resources exceeded the production rate, signifying an increasing ecological deficit. He contended that renewable energy should supersede fossil fuel energy to circumvent this impasse.

Koçak (2024) analyzed how renewable energy developments influence Turkey's ecological footprint during the period from 2000 to 2020. The relationship between the variables was assessed using the ARDL bounds testing approach and the Toda-Yamamoto causality analysis. The results reveal that an increase in Turkey's GDP is associated with a growth in the ecological footprint, whereas greater reliance on renewable energy resources is linked to a decrease in ecological footprint levels.

Figure 2.2. Renewable Energy Consumption in OECD Member Countries



Country : OECD members
Source: World Development Indicators
Created on: 09/19/2024

Source: World Development Indicators

Figure 2.2 depicts the trend in the proportion of renewable energy utilization relative to total final energy consumption among member countries of the Organisation for Economic Co-operation and Development (OECD) over the period from 1995 to 2021.

2.2. Analytical Methods Employed

2.2.1. Panel Data Analysis

The collection of data on variables is a crucial phase in economic research. The dependability of estimates hinges on the diligent collection of data from credible sources, adhering strictly to the established model. Three categories of data are frequently utilized in econometric analysis. The types are time series data, cross-sectional data, and panel data. Time series data denotes information that records variations in variables across time, typically quantified in intervals such as days, months, or seasons. Cross-sectional data refers to information gathered from many units at particular time points. Panel data refers to the aggregation of cross-sectional observations of entities, including persons, nations, corporations, and households, across a designated timeframe. The panel data analysis methodology has lately attained prominence. Panel data analysis encompasses two dimensions: cross-sectional and temporal. In panel data analysis, cross-sectional data is combined with time series data (Kiral and Çelik, 2018). A larger volume of significant data, , reduced linear dependence among parameters, enhanced efficiency, augment the reliability of parameter estimation (Ari and Zeren, 2011; Gujarati, 2021). It has the benefit of analyzing both the disparities among units and the variations in units over time (Baltagi, 2008; Hsiao, 2022). Panel data has many units, each represented at least twice (Stock and Watson, 2020). It comprises N sections (countries, firms, persons, etc.) and T time periods (annual, quarterly, monthly, etc.) of observations for each unit (Tatoğlu, 2021; Asteriou ve Hall, 2021; Karlılar, 2019; Çelik, 2019; Baltagi, 2008).

Panel data is also known as long-section data (Alıcı and Işık, 2024). Panel data analysis is defined as the estimation of economic linkages utilizing panel data. Panel data analysis is a statistical method utilized to investigate two-dimensional panel data, often comprising cross-sectional and longitudinal data (Maddala, 2001). Panel data, also known as cross-sectional data with a temporal component, refers to data collected over more than one time period (Tatoğlu, 2021). In panel data representation, subscripts denote time and unit. The panel data model is typically represented by the subsequent equation (Kiral and Çelik, 2018).

$$Y_{it} = \alpha + \sum_{k=1}^q \beta_k X_{kit} + u_{it} \quad i = 1, \dots, N; t = 1, \dots, T; k = 1, \dots, q \quad (2.3)$$

The model posits that the error terms u_{it} are identically and independently normally distributed throughout all time periods and units $[INN(0, \sigma_u^2)]$, exhibiting a mean of zero and constant variance. In the model, the subscript i denotes units such as family, individual, firm, or city, whereas t signifies time intervals such as day, month, or year. β_k denotes the constant term, X_{kit} signifies the value of the k th explanatory variable for the i th unit at time t , and Y_{it} indicates the value of the dependent variable for the i th unit at time t . The incorporation of the i and t indices in the model parameters indicates their dependence on both units and time (Özer and Biçerli, 2003; Kırıl and Çelik, 2018).

Static analysis rely on fixed effect and random effect regression methodologies. The fixed effect model posits that the initial value will remain constant across all cross-sectional units. In the fixed effect model, the slope parameters remain constant across all cross-sectional units, whereas the fixed parameter differs among units due to the unit-specific effect it incorporates. This indicates that the constant term assumes a distinct value for each cross-sectional unit (Kırıl and Çelik, 2018). A notable advantage of the fixed effects approach is its ability to mitigate bias issues stemming from missing factors that remain constant throughout time (Al-Mulali, Weng-Wai, Sheau-Ting and Mohammed, 2015; Tatoğlu, 2021).

Fixed effect models operate under the premise that the independent variables are uncorrelated with the error terms and correlated with the unit effect (Tatoğlu, 2021). A fixed effect model can be articulated using the equation provided below (Kaya and Yılmaz, 2006).

$$Y_{it} = \beta_{1i} + \beta_{2i}X_{2it} + \beta_{3i}X_{3it} + u_{it}, \beta_{1j} \neq \beta_{1i} \quad (2.4.)$$

Prior to assessing the validity of the fixed effects model, it is essential to determine the presence of fixed effects within the model. of the computed F statistic exceeds the F critical value, the fixed effects model is considered valid (Asteriou and Hall, 2021).

The random effects model establishes the initial value as a stochastic variable. The initial values are the sum of the constant β_1 and the zero-mean stochastic variable u_{it} . The random effects model is denoted by the equation provided below (Kırıl and Çelik, 2018).

$$Y_{it} = \beta_{1i} + \beta_{2i}X_{2it} + \beta_{3i}X_{3it} + u_{it}, \beta_{1j} \neq \beta_{1i} + \mu_i \quad (2.5.)$$

The words balanced and unbalanced panel denote the existence of absent observations in panel data. The balanced panel denotes a scenario in which variables are accessible for every time period and unit, whereas the unbalanced panel signifies a situation where at least one unit is unavailable for a specific time period (Stock and Watson, 2020; Wooldridge, 2010; Saraçoğlu, 2011; Tatoğlu, 2021; Alıcı and Işık, 2024).

Table 2.2. Advantages and Challenges of Panel Data Analysis

Advantages	Challenges
Facilitates more precise judgments concerning model parameters.	Panel data may be constrained by variations within the margin of error.
Mitigates the issue of multicollinearity.	Panel data may be constrained by issues in data acquisition.
Reduces forecast discrepancy.	Panel data may be constrained by the brevity of the time period
The influence of excluded factors can be managed.	

Source: Asteriou ve Hall, 2021; Karlılar, 2019; Tatoğlu, 2021; Hsiao, 2022

2.2.1.1. Cross-Sectional Dependence Test

Cross-sectional dependence denotes the association among the units constituting a series. The presence or absence of cross-sectional dependence among the series substantially influences the outcomes generated (Breusch and Pagan, 1980; Pesaran, 2004). Cross-sectional dependency tests are used to choose the suitable panel unit root test group for the study (Gençoğlu, Kuşkaya and Büyüknalbant, 2020). It is crucial to investigate the presence of cross-sectional dependency in the series and the cointegration equation. Cross-sectional dependence must be considered while choosing unit root and cointegration tests for further study (Göçer, 2013).

2.2.1.1.1. Breusch-Pagan Lagrange Multiplier (LM) Test

The Breusch-Pagan Lagrange Multiplier (LM) Test, introduced by Trevor Breusch and Adrian Pagan in 1980, is a statistical method used to evaluate cross-sectional dependence. The fundamental notion examined is the existence of a correlation between the components. The choice of cross-sectional dependence tests for the study is contingent upon the number of units and the duration of the time period. When the duration of the series surpasses the number of sections ($T > N$), the Lagrange multiplier is employed in the Breusch-Pagan test to identify the presence of interrelationships among the multiple variables of the model (Göçer, 2013; Koç, Koç and Gümüş, 2016; Topaloğlu, 2018; Djama, 2023). The CD-LM1 test by Breusch and Pagan (1980) may yield abnormal results when the group mean is presumed to be zero while the unit mean diverges from zero (Yalçınkaya, 2016). The subsequent equation delineates the Breusch-Pagan Lagrange Multiplier (LM) test statistic.

$$\lambda_{LM} = T \sum_{i=1}^{N-1} \sum_{j=i+1}^N \hat{\rho}_{ij}^2 \quad (2.6.)$$

The correlation coefficient, $\hat{\rho}_{ij}$, between the residues of units i and j is computed using the following equation (Tatoğlu, 2021; Baltagi, Feng and Kano, 2012).

$$\hat{\rho}_{ij} = \hat{\rho}_{ji} = \frac{\sum_{t=1}^T \hat{v}_{it} \hat{v}_{jt}}{(\sum_{t=1}^T v_{it}^2)^{1/2} (\sum_{t=1}^T v_{jt}^2)^{1/2}} \quad (2.7.)$$

The chi-square distribution for this test of cross-sectional dependency is defined by $\frac{N(N-1)}{2}$ degrees of freedom and includes two distinct hypotheses (Djama, 2023). The fundamental hypothesis of the test is defined as $H_0: \rho_{ij} = 0$ for $i \neq j$, indicating the absence of correlation among the residuals derived from each unit (Boğa, 2019). Rejection of the null hypothesis (H_0) at significance levels implies acceptance of the alternative hypothesis (H_1), signifying that the panel exhibits a horizontal dependency relationship among its components. (Djama, 2023).

2.2.1.1.2. Pesaran Test Statistics

The Pesaran (2004) test is designed to evaluate cross-sectional dependence in fixed and random effect panel data models (İmre, 2018). In contrast to the Breusch-Pagan (1980) test, the Pesaran CD test is intended to assess situations where the cross-sectional dimension surpasses the temporal dimension of the panel series. This test represents a more sophisticated version of the Breusch-Pagan LM test (1980) as it incorporates elements that are absent in the original (Djama, 2023).

$$CD = \sqrt{\frac{2T}{N(N-1)}} \left(\sum_{i=1}^{N-1} \sum_{j=i+1}^N \hat{\rho}_{ij} \right) \quad (2.8.)$$

The correlation coefficient of the residuals for units i and j is represented by $\hat{\rho}_{ij}$. The quantity of time series observations between units i and j is represented by T_{ij} . In instances of unbalanced panels, the Pesaran test identity is computed as follows (Djama, 2023).

$$CD = \sqrt{\frac{2}{N(N-1)}} \left(\sum_{i=1}^{N-1} \sum_{j=i+1}^N \hat{\rho}_{ij} \sqrt{T_{ij} \hat{\rho}_{ij}} \right) \quad (2.9.)$$

The test hypothesis is defined as ' $H_0: \rho_{ij} = 0$ ', indicating the absence of correlation between units and/or time periods. The alternative hypothesis is defined as, ' $H_1: \rho_{ij} \neq 0$ ' There exists a link between units and/or between time intervals (İmre, 2018). of the null hypothesis (H_0) is rejected at the significance thresholds, the alternative hypothesis (H_1), which indicates a horizontal dependency relationship among the panel sections, is accepted, hence suggesting the presence of correlation between the units (Gürel, 2015; Djama, 2023).

2.2.1.2. Panel Unit Root Test

Panel unit root tests including both temporal and cross-sectional data are seen statistically more robust than time series unit root tests that rely solely on temporal information. Incorporating

the cross-sectional dimension into the analysis enhances the variability of the data (Beyaert and Camacho, 2008; Göçer, 2013; Mercan, 2014).

In panel data analysis, unit root tests assessing the stationarity of series are categorized into two groups: first-generation and second-generation panel unit root tests, depending on the presence of cross-sectional dependence among the units comprising the panel. First-generation panel unit root tests presume that the components constituting the series are independent and that all units are uniformly influenced by a shock occurring in any unit within the series. Second-generation panel unit root tests operate under the premise that each unit reacts distinctly to a shock impacting one of the units within the panel (Çınar, 2011; Yalçınkaya and Kaya, 2017; Kızıltan, Golovko and Yereli, 2019).

Our research identified cross-sectional dependency among the countries in the panel, necessitating the application of second-generation unit root tests to assess the stationarity of the series, with the CADF test employed for calculations. The CADF test assumes that the error term consists of two distinct components: a common factor shared across all series and an idiosyncratic element specific to each individual series. This relationship is mathematically expressed in the following equation (Pesaran, 2007; Bucak and Saygılı, 2022).

$$CIPS(N, T) = N^{-1} \sum_{i=1}^N CADF_i \quad (2.10.)$$

2.2.1.3. Hausman Test

The Hausman test is conducted to ascertain the link between unit and temporal effects and independent variables, hence evaluating the appropriateness of fixed or random effects models (Tatoğlu, 2021). The Hausman test is based on the knowledge of whether the relationship between the unobserved random effects and the independent variables is significant. In the absence of a substantial relationship between the variables, it is determined that the random effects model is suitable (Kılıçkaya, 2022). The fundamental hypothesis of the Hausman test is articulated as ' H_0 : Parameter differences are not systematic (unit and/or temporal effects are

random)', ' H_1 : Parameter differences are systematic (unit and/or temporal effects are constant)' (Gürel, 2015; Tatoğlu, 2021).

$$H_0: E(\mu_i | X_{ijt}) = 0 \quad (2.11.)$$

$$H_1: E(\mu_i | X_{ijt}) \neq 0 \quad (2.12.)$$

The Hausman test statistic use the chi-square (χ^2) distribution. The test statistic result is compared to the tabulated χ^2 value. The Hausman test hypotheses indicate that the null hypothesis H_0 affirms the validity of the random effects model, whilst the alternative hypothesis H_1 contends that the random effects model is invalid (Wooldridge, 2010). of the Hausman test statistic surpasses the critical value ($W > \chi^2_{table}$), the fixed effects model is favored. of the P value is below 0.05, the fixed effects model is favored; otherwise, the random effects model is favored (Kılıçkaya, 2022). In the Hausman test, rejecting the null hypothesis that the coefficients from the random effects model are equivalent to those from the fixed effects model suggests that the random effects model yields superior results; failing to reject the null hypothesis implies that the fixed effects model is more efficacious (Bayraktutan and Demirtaş, 2011; Gürel, 2015). This decision-making process is crucial for ensuring the validity and reliability of the results derived from the econometric analysis. This statistical test is crucial for choosing between these two models, as it helps assess whether the assumptions underlying the random effects model are valid. Specifically, the Hausman test evaluates the consistency of the random effects estimators compared to the fixed effects estimators.

2.2.2. Artificial Neural Networks

Artificial intelligence, a notion that has gained prominence recently, has transcended science fiction and commenced its integration into our daily life (Durmuş and Erdem, 2023). Recently, artificial intelligence has been implemented across different domains, enhancing our daily experiences. Artificial intelligence is extensively utilized across multiple sectors, including health, transportation, trade, education, law, economy, information technology (for identifying and mitigating security threats, resolving technological issues, etc.), marketing (for analyzing social media feedback, forecasting consumer purchasing behavior, etc.), finance and

accounting, and customer service, and it also profoundly influences customs procedures (Çağlayan, 2021). The advent of artificial intelligence has resulted in the proliferation of numerous technical goods. A multitude of artificial intelligence technologies are employed and advanced in this domain. The foundational technologies of artificial intelligence algorithms include machine learning, ANNs, fuzzy logic, expert systems, and genetic algorithms (Fındıkcı and Kavacık, 2024).

ANN are algorithms patterned on the structure of human neurons and may be trained and simulated (Atik, Deniz and Yıldız., 2007). The brain's smallest unit, the biological nerve cell, comprises dendrites, soma, axon, nucleus, and synapses. Synapses are junctions that enable the transfer of electrical signals between cells. The soma processes the received impulses and generates an electrical signal in the nerve. The signals generated are conveyed to the dendrites through the axon. Dendrites convey these signals to the synapses and enable transmission to adjacent cells. The brain's smallest unit, the biological nerve cell, comprises dendrites, soma, axon, nucleus, and synapses. Synapses are connections that enable the transfer of electrical information between cells. Signals received by the soma are processed, resulting in the generation of an electrical signal by the nerve. The signals generated are conveyed to the dendrites through the axon. Dendrites convey these signals to the synapses and enable transmission to adjacent cells (Öztemel, 2006). ANNs are processors composed of neurons that function in a parallel and distributed manner to execute tasks, retain acquired data, and undergo training for their application (Ataseven, 2013). The network model comprises multiple layers of fundamental processing units referred to as neurons. A neuron has two primary functions: to gather input and to generate output (Dongare, Kharde and Kachare, 2012).

The architecture of the ANN model is widely utilized in addressing many issues, since it can be educated to enhance learning behavior and may be applied efficiently across diverse sectors (Kuvvetli, Dağsuyu and Oturakçı, 2015). Warren McCulloch and Walter Pitts (1943) pioneered ANNs by creating a computational model for neural networks utilizing threshold logic methods. Neural networks possess several key qualities, including the power to represent nonlinear problems, advanced computational and information-processing capabilities, a parallel distributed architecture, the ability to process incomplete information, fault tolerance, and the capacity to learn and generalize. These attributes illustrate the ability of neural networks to tackle intricate issues (Yetkin, 2014). ANNs are widely utilized across various domains,

including complex nonlinear function approximation, image analysis, pattern detection, and data classification (Dongare, Kharde and Kachare, 2012).

ANNs are computational frameworks modeled after the human brain. The illustration depicts the biological neuron, the fundamental functioning unit of the brain.

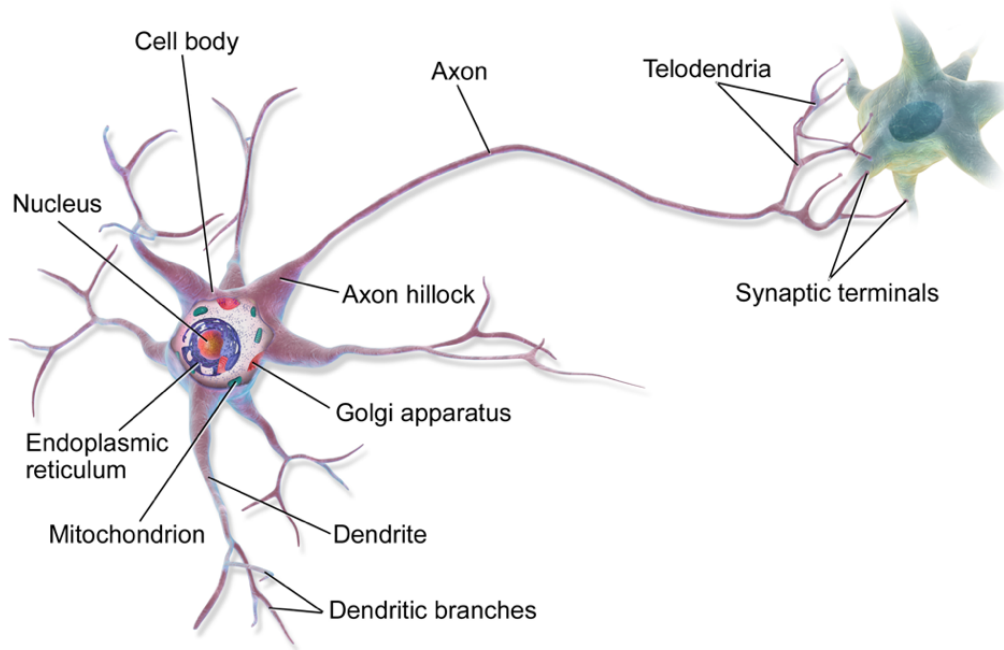


Figure 2.3. Biological Neuron (Blaus, 2013)

The artificial neuron, which simulates a nerve cell, comprises five fundamental components.

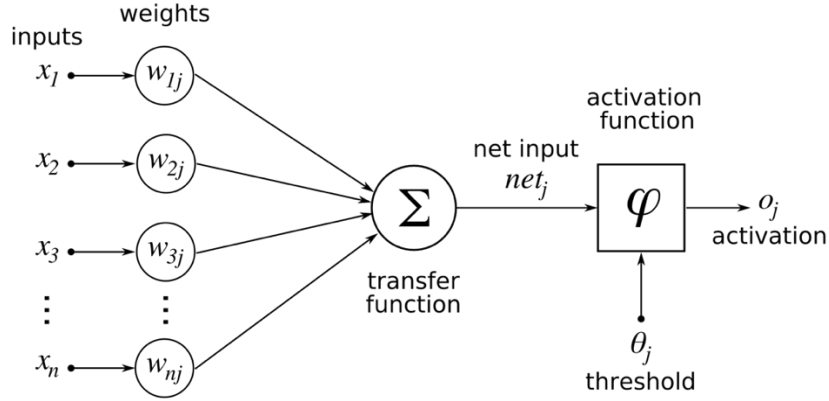


Figure 2.4. Artificial Neuron (Chrislb, 2005)

An artificial neuron consists of five fundamental components, each playing a critical role in its functionality. Inputs, represent the external data or signals received by the neuron, which serve as the initial information to be processed. Weights are numerical values assigned to each input, determining their relative importance in the computation. These weights are adjustable and are optimized during the training process to enhance the model's performance. The transfer function combines the weighted inputs into a single aggregated value, often through a summation process. Subsequently, the activation function applies a mathematical transformation to the output of the transfer function, introducing non-linearity to the model and enabling it to solve complex problems. Finally, the output represents the neuron's response, which is passed to subsequent layers in the network or used as the final prediction, depending on the architecture of the model (Dongare et al., 2012; Kas, 2024). The neuron in the biological nervous system parallels the processing element in the artificial nervous system; the dendrite in the biological nervous system corresponds to the collection function in the artificial nervous system; the cell body in the biological nervous system aligns with the activation function in the artificial nervous system; the axons in the biological nervous system equate to the artificial neuron output in the artificial nervous system; and the synapses in the biological nervous system correspond to the weights in the artificial nervous system (Kas, 2024). Each neuron is coupled to the neurons of the preceding layer through adjustable synaptic weights (Kalogirou, 2004).

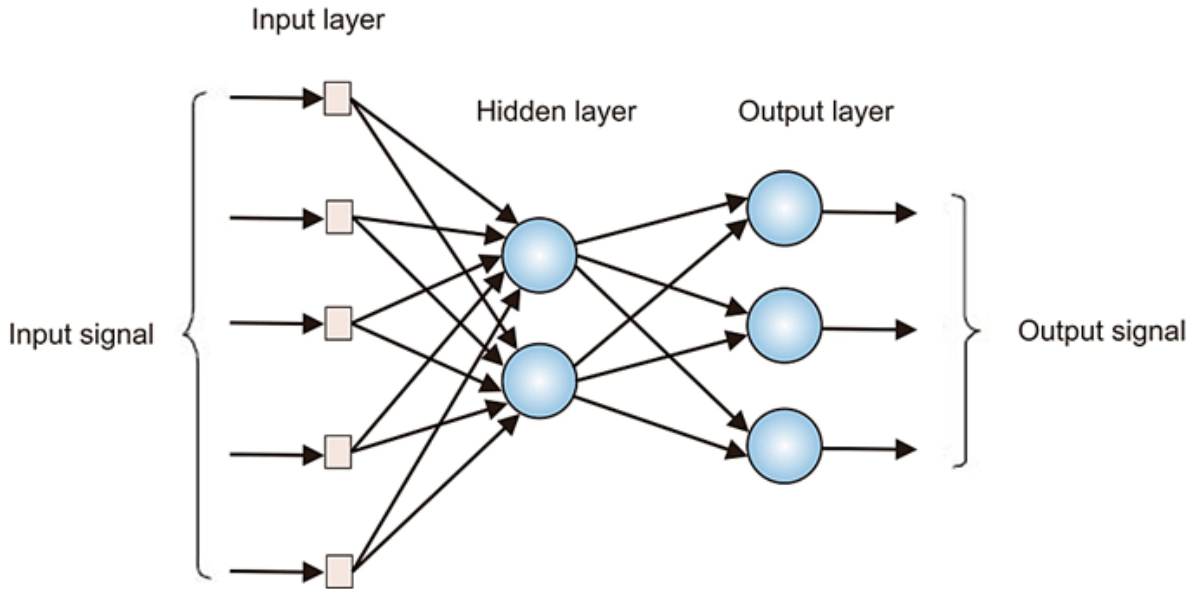


Figure 2.5. Artificial Neural Network (Aboodi, Abadi and Ibrahim, 2017)

The input layer is the phase in which data from the external world is conveyed to the cellular network. The input layer transmits data to the processing element along with the weights of the connections. The weights are assigned randomly and can be adjusted till the error is minimized. An ANN may comprise multiple intermediate layers (Yetkin, 2014). Increasing the quantity of intermediary layers and artificial neurons enhances computational complexity, however facilitates the resolution of increasingly intricate issues (Çayiroğlu, 2015). The processed data is conveyed from the intermediate layer to the output layer. Upon processing the data in the intermediate layer, the output layer conveys the processed information to the external environment, according to the inputs in the input layer (Kas, 2024).

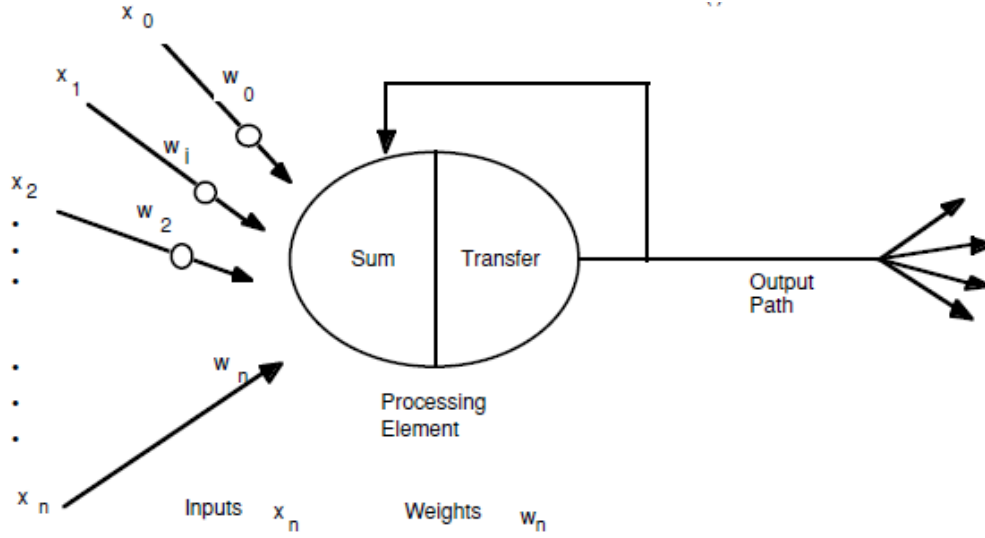


Figure 2.6. A Basic Artificial Neuron (Anderson and McNeil, 1992)

Figure 2.6. depicts the architecture of a conventional artificial neuron. x_n denotes the diverse inputs to the network. Each input is multiplied by the weight values (w_n) that denote the influence of the preceding layer on the specific input set or processing element. Subsequent to multiplication, it is integrated with the summation function (Σ), processed through a transfer function, and the output is then derived (Anderson and McNeil, 1992; Kaynar and Taştan, 2009).

Multiple aggregation functions are employed in the computation of net input. These are (Çayıroğlu, 2015);

1. Net input is determined by multiplying the weight values by the inputs and summing the resultant values. The formulation is expressed as

$$Net = \sum_{i=1}^N X_i * W_i \quad (2.12.)$$

2. The weight values are multiplied by the inputs, and the net input is determined by multiplying the resultant values. The formulation is expressed as

$$Net = \prod_{i=1}^N X_i * W_i \quad (2.13.)$$

3. The net input is defined as the maximum value achieved when the weights associated with N inputs are multiplied by the inputs. The formulation is expressed as

$$Net = Max(X_i * W_i) \quad (2.14.)$$

4. The net input is defined as the smallest value achieved when the weights associated with N inputs are multiplied by the inputs. The formulation is expressed as

$$Net = Min(X_i * W_i) \quad (2.15.)$$

5. The multiplication of input values by weights determines the quantities of positive and negative values. The greater value is designated as the cell's net input. The formulation is expressed as

$$Net = \sum_{i=1}^N Sgn(X_i * W_i) \quad (2.16)$$

6. The information received by the cell is aggregated by weighting. The net input of the cell is ascertained by summing the newly computed input values with the previously acquired information. The formula is expressed as

$$Net = Net(old) + \sum_{i=1}^N X_i * W_i \quad (2.17.)$$

Activation functions dictate the neuron's output based on the input and the network's weights. The output of the summing function that surpasses the designated bias (threshold) value is utilized as input for the activation function. The activation function assesses the net input to the cell, determining the output generated in response to that input (Kas, 2024). Numerous functions serve as activation functions. These are (Çayiroğlu, 2015; Sharma, Sharma and Athaiya, 2017; Rasamoelina, Adjailia and Sincak, 2020);

1. Linear Activation Function
2. Binary Step Function
3. Sigmoid / Logistic Activation Function

4. Tanh Function (Hyperbolic Tangent)
5. Rectified Linear Unit (ReLU)
6. Scaled Exponential Linear Unit (SELU)
7. Leaky ReLU
8. Parametrized ReLU
9. Exponential Linear Unit
10. Swish
11. SoftMax
12. Mish

ANNs comprise single layer perceptrons (SLP) and multilayer perceptrons (MLP). The single layer perceptron model, while initially constructed, is significant as it underpins the multilayer perceptron model. The single-layer model comprises solely input and output layers. The fundamental characteristic of the model is its ability to resolve linear occurrences. The perceptron model and the Adaline/Madaline model have significant importance among single-layer perceptron models (Kas, 2024).

The multilayer perceptron model was developed to investigate nonlinear interactions. Figure 2.7 illustrates a three-layer architecture with an input layer, an output layer, and an intermediate layer. The intermediate layer may comprise multiple hidden layers, each containing several processing elements (neurons). Likewise, many process elements may exist in the output layer. Process elements inside a layer are interconnected with all components of the preceding layer, and each process element produces an output. Although sigmoid and hyperbolic tangent functions are prevalent activation functions in multilayer perceptron models, the optimal function for a certain scenario is ascertained by the designer's practical experimentation (Öztemel, 2006).

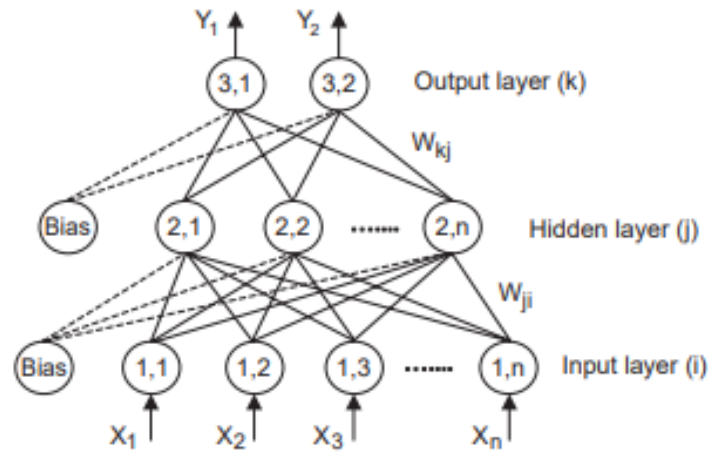


Figure 2.7. Multilayer Feedforward Neural Network (Kalogirou, 2004)

A six-step methodology is employed in the development of an ANN model. The target data and input data are initially supplied to the network as a model. Once the data in the model are classified as a training set or validation set, the hidden layer inside the network architecture is established, along with the quantity of neurons in that layer. Upon completion of the adjustments, the process of computing the output from the data and weights, known as training the data, commences. The evaluation process is conducted to ascertain if the network has acquired knowledge as a result of the training. The evaluation method entails intermittently halting the training to assess its performance until satisfactory results are obtained. Upon attaining an acceptable outcome, the ANN model is deemed completely trained and prepared for application (Ogwueleka et al., 2015).

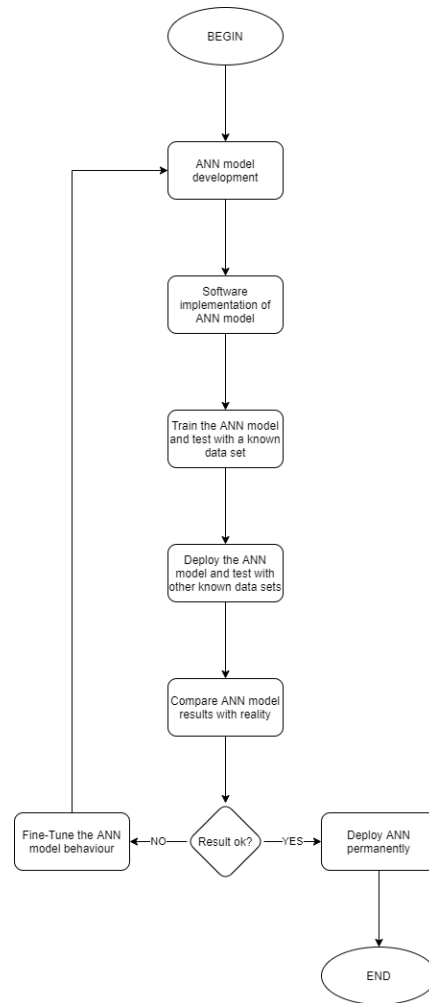


Figure 2.8. Phases in the construction of an ANN model (Ogwueleka, Misra, Colomo-Palacios and Fernandez, 2015)

2.2.2.1. Merits and Demerits of Artificial Neural Networks

2.2.2.1.1. Merits of Artificial Neural Networks

ANN have a unique advantage over other models by autonomously establishing data correlations through parameter adjustments during the training phase, hence obviating the necessity for a predefined model (Şeker, Yıldırım and Berkay, 2004). ANN can operate with incomplete data. They can swiftly acclimate to novel instances. They can be re-educated and utilized with updated data. Consequently, novel solutions appropriate for the system can be generated. The network does not necessitate a mathematical model. It refrains from making any conclusive assumptions before to formulating a solution to the issue. The network can persist in functioning despite damage to specific cells. The network's performance may deteriorate

based on the condition of the cells; yet, it can still identify the important cell (Yetkin, 2014). Nonlinear interactions can be represented by nonlinear activation functions in the context of an ANN. ANNs are capable of addressing nonlinear problems and exhibit superior predictive accuracy relative to alternative nonlinear models (Erturan and Merdivenci, 2022). They possess the capability to utilize numerous variables and factors, together with the ability to learn from exemplars (Öztemel, 2006). Conventional computer systems exhibit a pronounced susceptibility to faults that may arise within the system. A minor inaccuracy in the system can lead to the inability to attain the intended outcome or considerable inaccuracies in the results. Nonetheless, the malfunction of one or more neurons in ANNs exerts a diminished effect on the system relative to conventional information processing systems (Tolon and Tosunoğlu, 2008).

2.2.2.1.2. Demerits of Artificial Neural Networks

ANNs necessitate a duration for training. As the iterations in the network operation escalate, the solution time correspondingly extends. No definitive time schedule exists for the network to finalize training. It solely relies on the error tolerance defined by the user. This results in a squander of time and money resources. The determination of network parameters in an ANN relies on the user's expertise, as there are no concrete guidelines. As the network exclusively operates with numerical data, it is imperative to quantify the issues (Yetkin, 2014). The drawbacks of these models encompass the selection of activation functions, the quantity of hidden layers, the specification of neuron count within these layers, the absence of a conclusive criterion for concluding network training, and the necessity for iterative refinement of the network (Kızılkaya, 2017). A further drawback of ANNs is the potential for memorizing. Some Artificial Intelligence (AI) systems, intended for work with limited data sets, may retain knowledge from the training process. To resolve this issue, it may be essential to eliminate this data from the network architecture (Metlek and Çetiner, 2021). They may be unable to ascertain the ideal solution to an issue or may commit errors. This is due to the absence of a function to train the network. In certain instances, insufficient data may persist even after the function is established (Tolon and Tosunoğlu, 2008).

2.2.2.2. Learning Algorithms in Artificial Neural Networks

The primary benefit of ANNs is their capacity for learning. The learning process in ANNs commences with the training of the network. Training a neural network entails ascertaining the

weight values. The weight values are originally allocated randomly. Samples are input into the network, and the weight values are modified until the optimal values are established. Selecting the appropriate weight values guarantees that the network accurately interprets the indicated event (Yıldırım, 2024). Learning in ANNs involves comparing the anticipated outcome with the actual result generated by inputting data into the input layer and producing one or more output values through the activation function. Should the disparity between the actual and anticipated outcomes be correspondingly substantial, the algorithms are modified, and this procedure persists until the designated error rate is achieved. Modifications are initially applied to the network's weights. Training of the network concludes when the error rate attains the specified threshold. Most ANN learning algorithms are employed to develop process models. Three learning strategies are commonly employed in ANN. The methodologies employed in this study encompass supervised learning, unsupervised learning, and reinforcement learning, each of which offers distinct analytical frameworks tailored to the objectives of the research (Ahamed and Akthar, 2016; Kas, 2024).

2.2.2.2.1. Supervised Learning

It is one of the most often employed educational techniques. The input and output data for the event intended for instruction to the ANN are presented to the network. The objective is to elucidate the correlation between inputs and outputs (Kas, 2024). The anticipated output value of the neural network is juxtaposed with the actual output value of the network. An error is characterized as the disparity between the two outputs. During network creation, the weights are adjusted iteratively until the network's error is minimized, often initiated randomly (Anderson and McNeill 1992). In supervised learning, the neural network must undergo training prior to its application. Supervised learning is implemented subsequent to the presentation of input and output data to the neural network. The adviser possesses complete authority over the educational process. The adviser ascertains the duration of the training by choosing the training set and the false value. The fundamental characteristic of this method is the utilization of authentic input and output data throughout the training process (Ataseven, 2013). Envision an archaeologist unearthing a human skeleton. Historical male and female skeletal specimens assist in ascertaining the sex of the skeletal structure. Historical data allows for the determination of the skeletal structure's sex as male or female (Dongare et al., 2012).

The principles of supervised learning are as follows (Şen, 2004):

1. Perceptron Learning Rule
2. Delta Learning Rule
3. Extended Delta-Bar-Delta Learning Rule
4. Backpropagation Learning Rule

2.2.2.2.2. Unsupervised Learning

Unsupervised learning examines and categorizes unlabeled datasets through machine learning techniques. Even if the data cannot be classified, it is organized according to their similarities and differences. This algorithm identifies concealed patterns or clusters of data autonomously. The capacity to identify similarities and contrasts in information renders this strategy an optimal solution. It is a prevalent method of learning employed in categorization tasks (Yetkin, 2014; Kas, 2024). Unsupervised learning algorithms can execute more intricate computational tasks than supervised learning systems (Dike, Zhou, Deveerasetty and Wu, 2018, Sun, Yen and Yi, 2018). In contrast to supervised learning, the network is trained just using input values and is anticipated to learn independently. The system allocates weights according to the input values. The learning process concludes with the modification of the network link weights to differentiate between inputs exhibiting identical features (Kas, 2024).

2.2.2.2.3. Reinforced Learning

Reinforced Learning is a learning paradigm that serves as an intermediary between supervised and unsupervised learning. In this pedagogical approach, the teacher's involvement is confined to assessing the accuracy of the calculated result. The learning system assesses its efficacy based on environmental feedback, categorizing it as either effective (rewarding) or ineffective (punishable), and adjusts its parameters accordingly. Typically, parameter modifications are implemented until equilibrium is attained (Jha, 2007; Dongare et al., 2012).

2.2.2.3. Feed Forward Neural Networks

Feedforward neural networks are categorized as "single layer" or "multilayer" according to the quantity of layers. Input signals are transmitted to the output layer through weights, and output signals are computed by the neurons in the output layer. In this network, signals are permitted to traverse solely from input to output. There is an absence of feedback, indicating that the

output of one layer does not influence the output of another. Multilayer neural networks contain a minimum of one hidden neuron layer situated between the input and output layer (Sazlı, 2006; Senthilkumar, 2010; Öztürk and Şahin, 2018; Kuvvetli et al., 2015).

2.2.2.4. Backpropagation Algorithm

The backpropagation algorithm is the most common learning rule employed. The objective of learning algorithms is to ascertain the weights that yield the optimal alignment between input and output data (Yetkin,2014). Feedforward neural networks are trained using the backpropagation algorithm. The goal of the algorithm is to backpropagate the vector to update the weights of the networks. The divergence between the actual network output and the intended output is termed error. The backpropagation technique employs a supervised learning rule, as it analyzes the outputs during processing (Sazlı, 2006). The backpropagation method is advantageous because to its simplicity and efficacy in addressing intricate patterns (Kishore and Kaur, 2012).

2.2.2.5. Levenberg-Marquardt Algorithm

The Levenberg-Marquardt algorithm, independently developed by Kenneth Levenberg and Donald Marquardt, is a powerful numerical optimization technique used for minimizing nonlinear functions. This algorithm is particularly renowned for its efficiency and stable convergence properties, making it a widely preferred method in various fields, especially in training ANNs for small to medium-sized problems (Yu and Wilamowski, 2018).

The goal is to minimize an objective function that is defined as the sum of squared errors between the model's output and the observed data points. In this context, the objective is to adjust the parameters of the model to best represent the underlying relationship in the data, ensuring minimal discrepancies (Gavin, 2019).

The strength of the Levenberg-Marquardt algorithm lies in its ability to combine the advantages of two other well-known optimization techniques: the Gauss-Newton method and gradient descent. It dynamically adjusts the algorithm's behavior, switching between these two methods based on the current state of the optimization process. This allows the Levenberg-Marquardt algorithm to offer both the fast convergence of the Gauss-Newton method and the stability of gradient descent, making it an ideal choice for training neural networks and solving nonlinear optimization problems.

The application of the Levenberg-Marquardt algorithm in ANNs has proven highly effective, as it significantly improves training times and stability compared to other gradient-based optimization methods. It is particularly beneficial when dealing with complex, high-dimensional data sets where traditional optimization techniques may struggle to achieve convergence or efficiency. Furthermore, its stability ensures that the training process does not diverge, which is a crucial requirement for successfully training deep neural networks (Yu and Wilamowski, 2018).



3. RESEARCH METHODS

3.1. Research Model

In our research model framework, literature reviews constituted the foundation for identifying dependent and independent variables. The investigation highlighted economic growth, renewable energy utilization, and globalization as the variables exerting the most substantial influence on the ecological footprint. In the analysis; the ecological footprint per capita gha value was taken into account annually. The annual value of gross domestic product per capita in dollars was considered to assess economic growth. The percentages of annual total final energy consumption for renewable energy were considered. Annual statistics from the KOF Swiss Economic Institute, encompassing economic, political, and social globalization, were utilized for globalization index. The study examines the impact of renewable energy usage, globalization, and economic expansion on environmental degradation. The study utilized the annual ecological footprint as the dependent variable, while gross domestic product, renewable energy consumption, and the KOF globalization index were incorporated as independent variables.

Descriptive statistics for the dependent and independent variables of each country were input into the SPSS program as data. Table 3.1 presents the descriptive statistics of the variables utilized in the investigation.

Table 3.1. Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
Descriptive Statistics					
EF_AUS	27	5,65	8,80	7,5974	,94329
EF_AUT	27	5,39	6,65	6,0030	,34930
EF_BEL	27	6,51	8,71	7,8419	,59465
EF_CAN	27	7,01	9,75	8,5144	,63212
EF_CHE	27	3,72	5,89	5,1144	,69946
EF_CHL	27	3,40	4,30	3,8596	,23821
EF_COL	27	1,96	2,32	2,0826	,09749
EF_CRI	27	2,51	3,70	3,0281	,30526
EF_CZE	27	5,02	7,21	5,9026	,44550
EF_DEU	27	4,32	5,95	5,3770	,41543
EF_DNK	27	6,96	9,80	8,4415	,88712

Table 3.1. Descriptive Statistics (continued)

EF_ESP	27	3,76	6,16	4,9404	,83356
EF_EST	27	4,62	8,83	7,0544	1,01222
EF_FIN	27	4,98	7,64	6,1485	,69375
EF_FRA	27	4,20	6,33	5,5370	,58591
EF_GBR	27	3,46	6,32	5,0885	,82759
EF_GRC	27	3,67	6,63	5,1781	,85939
EF_HUN	27	3,06	4,76	3,8770	,37226
EF_IRL	27	4,31	7,77	6,0248	1,01499
EF_ISR	27	4,23	6,21	5,2274	,54067
EF_ITA	27	3,80	5,93	5,0519	,72695
EF_JPN	27	3,84	5,56	4,7978	,47057
EF_KOR	27	3,76	6,17	5,4704	,51977
EF_LTU	27	3,55	6,37	4,9189	,84331
EF_LUX	27	10,66	17,28	14,0152	1,50947
EF_LVA	27	3,14	7,75	5,4967	1,21770
EF_MEX	27	2,19	4,17	2,9444	,39563
EF_NLD	27	5,86	7,53	6,7507	,45906
F NOR	27	5,03	6,92	5,9507	,49563
EF_NZL	27	5,22	8,50	6,5293	,93998
EF_POL	27	4,22	4,93	4,5856	,18484
EF_PRT	27	3,71	5,03	4,3167	,40817
EF_SVK	27	3,76	5,49	4,4041	,39223
EF_SVN	27	4,57	7,26	5,4311	,71888
EF_SWE	27	4,89	8,14	5,9463	,66064
EF_TUR	27	2,41	3,48	3,0674	,29973
EF_USA	27	7,06	10,93	9,2696	1,19098
GDP_AUS	27	19695,73	68198,42	41795,8629	17145,67699
GDP_AUT	27	24558,76	53517,89	40835,5178	10310,27592
GDP_BEL	27	23015,07	51863,83	38187,5554	9587,82993
GDP_CAN	27	20679,63	52670,34	37969,1069	11753,63516
GDP_CHE	27	38865,02	93446,43	66699,3561	19303,25796
GDP_CHL	27	4477,19	16185,91	10216,1659	4428,26820
GDP_COL	27	2236,07	8263,64	4810,2561	2085,10653
GDP_CRI	27	3194,11	12669,34	7435,4164	3643,31850
GDP_CZE	27	5824,12	26822,51	15518,9373	6960,37465
GDP_DEU	27	23628,33	51426,75	38041,3528	8781,80547
GDP_DNK	27	30743,55	69268,65	50111,1958	12563,67314
GDP_ESP	27	14730,80	35510,72	24933,1560	6734,53988
GDP_EST	27	3134,39	27698,48	13488,8549	7638,80539
GDP_FIN	27	24345,91	53772,79	40217,1687	10669,69774
GDP_FRA	27	22416,43	45515,96	35138,1623	7774,78065
GDP_GBR	27	23168,95	50397,69	38153,8768	7951,90986
GDP_GRC	27	12072,93	32127,98	19752,2622	5650,30809
GDP_HUN	27	4494,71	18755,10	11145,2408	4579,34355
GDP_IRL	27	19158,46	102001,80	50743,1267	21514,80048
GDP_ISR	27	18916,67	52129,52	29691,7698	9961,23830
GDP_ITA	27	20137,59	40944,91	30537,6534	6523,61513
GDP_JPN	27	32423,76	49145,28	39057,5945	4141,46015
GDP_KOR	27	8281,72	35125,52	21595,6585	8184,16924
GDP_LTU	27	2167,79	23849,62	10929,8637	6557,39454
GDP_LUX	27	46641,64	133711,79	90249,2311	30504,76097

Table 3.1. Descriptive Statistics (continued)

GDP_LVA	27	2329,58	20930,40	10531,3522	6029,71679
GDP_MEX	27	4225,40	11490,02	8759,1609	2004,34501
GDP_NLD	27	26214,50	58727,87	43177,0906	11215,54915
GDP_NOR	27	34803,46	103553,84	68446,4896	24132,09388
GDP_NZL	27	13641,10	49624,18	30385,7110	11548,17518
GDP_POL	27	3686,85	18050,28	10098,0438	4600,43467
GDP_PRT	27	11526,37	24949,04	18681,3009	4815,32078
GDP_SVK	27	4819,13	21765,72	13349,6773	5892,94481
GDP_SVN	27	10201,30	29331,06	19456,9615	6432,37418
GDP_SWE	27	27247,86	61417,68	45917,5481	11793,73352
GDP_TUR	27	2855,04	12578,19	7867,1697	3338,92068
GDP_USA	27	28690,88	71055,88	47530,0100	11829,05630
KOF_AUS	27	73,00	81,00	78,3333	2,61652
KOF_AUT	27	81,00	89,00	86,4074	2,18842
KOF_BEL	27	85,00	90,00	88,1111	1,86740
KOF_CAN	27	76,00	84,00	81,7037	2,25004
KOF_CHE	27	82,00	91,00	87,8519	2,67040
KOF_CHL	27	59,00	77,00	72,0000	5,92258
KOF_COL	27	47,00	64,00	56,6667	5,90958
KOF_CRI	27	52,00	72,00	64,1481	5,43991
KOF_CZE	27	68,00	85,00	79,5556	5,48658
KOF_DEU	27	77,00	89,00	85,2963	3,60358
KOF_DNK	27	82,00	89,00	86,5185	2,02618
KOF_ESP	27	73,00	86,00	81,2593	3,91833
KOF_EST	27	61,00	83,00	75,9630	6,46578
KOF_FIN	27	78,00	88,00	84,6296	2,85749
KOF_FRA	27	78,00	88,00	84,6296	3,32991
KOF_GBR	27	82,00	89,00	86,9630	2,40962
KOF_GRC	27	67,00	84,00	77,5185	4,79880
KOF_HUN	27	69,00	85,00	80,7778	4,69315
KOF_IRL	27	76,00	86,00	83,0370	2,79397
KOF_ISR	27	62,00	79,00	73,2963	4,89753
KOF_ITA	27	73,00	83,00	79,9630	3,06947
KOF_JPN	27	58,00	78,00	71,1111	5,36609
KOF_KOR	27	57,00	79,00	71,2222	6,55353
KOF_LTU	27	53,00	82,00	71,9259	8,50758
KOF_LUX	27	77,00	87,00	82,5556	3,32049
KOF_LVA	27	51,00	80,00	68,7037	8,61936
KOF_MEX	27	53,00	73,00	63,3333	6,58086
KOF_NLD	27	82,00	91,00	87,5185	2,86048
KOF_NOR	27	79,00	86,00	83,4815	1,88864
KOF_NZL	27	69,00	77,00	74,5556	2,13638
KOF_POL	27	62,00	81,00	74,5926	6,48821
KOF_PRT	27	71,00	85,00	79,8148	4,09537
KOF_SVK	27	60,00	83,00	75,7778	8,21974
KOF_SVN	27	53,00	82,00	73,5556	8,24310
KOF_SWE	27	82,00	90,00	87,4815	2,32661
KOF_TUR	27	58,00	72,00	66,5185	4,56888
KOF_USA	27	74,00	82,00	79,2593	2,39539
REC_AUS	27	6,70	12,30	8,6259	1,39162
REC_AUT	27	22,60	36,00	29,6222	4,66322

Table 3.1. Descriptive Statistics (continued)

REC_BEL	27	1,10	12,30	5,3259	3,88038
REC_CAN	27	19,70	23,90	21,7778	1,02744
REC_CHE	27	16,70	27,70	20,6407	3,13409
REC_CHL	27	24,10	34,20	29,3222	3,05518
REC_COL	27	25,70	33,60	30,1778	2,00659
REC_CRI	27	28,90	42,40	36,1296	3,72763
REC_CZE	27	5,20	17,20	10,3111	4,09853
REC_DEU	27	2,20	18,50	9,7444	5,37167
REC_DNK	27	7,30	39,50	21,0222	10,83897
REC_ESP	27	7,30	19,30	12,2667	4,16939
REC_EST	27	17,20	40,40	23,6926	5,93859
REC_FIN	27	26,90	50,20	35,5259	6,87384
REC_FRA	27	8,50	16,80	11,5074	2,55206
REC_GBR	27	,80	13,60	4,2481	4,03374
REC_GRC	27	7,10	21,50	11,7815	4,77131
REC_HUN	27	4,60	17,20	10,2630	4,69960
REC_IRL	27	1,90	13,70	5,6741	3,89759
REC_ISR	27	2,90	9,10	5,8444	1,72946
REC_ITA	27	4,50	18,70	10,7593	5,26449
REC_JPN	27	3,50	8,80	5,0481	1,57855
REC_KOR	27	,40	3,60	1,5926	1,04731
REC_LTU	27	10,30	33,80	21,8222	7,54521
REC_LUX	27	1,30	20,80	7,0148	5,92054
REC_LVA	27	32,00	44,00	36,9926	3,58822
REC_MEX	27	9,00	13,30	10,6741	1,45406
REC_NLD	27	1,20	12,20	4,2704	2,89001
REC_NOR	27	55,80	61,40	58,2074	1,62479
REC_NZL	27	24,60	30,30	27,8185	1,41965
REC_POL	27	5,90	16,10	9,4815	3,18929
REC_PRT	27	18,10	32,30	24,7778	4,05276
REC_SVK	27	3,60	17,90	9,0111	4,49027
REC_SVN	27	10,20	23,40	18,0963	3,92864
REC_SWE	27	31,40	57,90	43,4556	7,75387
REC_TUR	27	11,40	21,90	15,3296	3,35718
REC_USA	27	4,50	11,00	7,2074	2,16118
Valid N (listwise)	27				

3.2. Research Sample

Considering that gross domestic product data for Lithuania and Latvia, both OECD nations, has been accessible since 1995, the survey was amended to commence in that year. The research closes with 2021 as the final data set, as KOF Globalization Index data is available only until that year. Iceland was excluded from the analysis because to insufficient ecological footprint data. The study encompassed a duration of 27 years and involved 37 nations from 1995 to 2021.

3.3. Data Analysis

3.3.1. Panel Data Analysis

This study first examined the effects of globalization, renewable energy use, and economic growth on the ecological footprints of OECD member countries by panel data analysis. Table 3.2 presents the range of changes and datasets for the variables utilized in the analysis of both dependent and independent variables within the OECD nation group.

Table 3.2. Variation Ranges of Variables and Parameters in the Study

Parameter Name	Unit	Data Frequency	Years	Change Range	Data base
Ecological Footprint	per person (gha)	Annual	1995-2021	1,96gha-17,28gha	Global Footprint Network
Economic Growth	GDP per capita current US\$	Annual	1995-2021	2167,79\$-133711,9\$	Data World Bank
Renewable Energy Consumption	% of total final energy consumption	Annual	1995-2021	0,4%-61,4%	Data World Bank
Globalization	KOF Swiss Economic Institute	Annual	1995-2021	47-91	ETHzürich

The economic model's equality is represented by the equation,

$$\ln EF_{it} = \beta_0 + \beta_1 \ln GI_{it} + \beta_2 \ln GDP_{it} + \beta_3 \ln REC_{it} + \varepsilon_{it} \quad (3.1.)$$

The model employs countries as $i=1,...,N$ cross-sectional units and to represent the time $t=1,...,T$ dimension. The model use $\ln EF$, representing the logarithm of the ecological footprint, as the dependent variable. The independent variables $\ln GI$, $\ln GDP$, and $\ln REC$ denote the natural logarithms of globalization, GDP per capita, and energy consumption, respectively. The panel data analysis method was employed to elucidate the impact of the independent variables on the ecological footprint.

Table 3.3. Descriptive Statistics of Dependent and Independent Variables

Variables	Mean	Median	Maximum	Minimum	Standard Deviation	Kolmogorov-Smirnov (KS) Test	KS Test p value	Skewness	Kurtosis
lnGDP	10,0234	10,1662	11,80	7,68	,85670	0.070	0.000	-,621	-,167
lnKOFGI	4,3493	4,3820	4,51	3,85	,12484	0.141	0.000	-1,279	1,397
lnREN	2,5134	2,6532	4,12	-,92	,95555	0.074	0.000	-,764	,314
lnEFP	1,6784	1,7098	2,85	,67	,36456	0.056	0.000	-,094	,836

The econometric approach was initially established through cross-sectional dependency and homogeneity tests. All econometric analyses for panel data in this study were performed using Stata software.

3.3.1.1. Results of the Cross-Section Dependency Test

The cross-sectional dependency analysis first comprised study of the Breusch and Pagan LM test and the Pesaran CD test. In light of the sample size of 37 countries over a span of 27 years, the results of the Pesaran CD test were incorporated into the cross-sectional dependence test ($N > T$) findings. Below are the statistics for the Breusch-Pagan LM and Pesaran CD tests.

Table 3.4. Results of the Cross Section Dependency Test by Pesaran (2004)

Variables	CD-Test	p-value	Average joint T	Mean ρ	Mean abs (ρ)
lnEF	38,254	0,000	27,00	0,29	0,51
lnGDP	119,79	0,000	27,00	0,89	0,89
lnREC	61,913	0,000	27,00	0,46	0,68
lnKOF	125,407	0,000	27,00	0,94	0,94

The theory of cross-sectional dependence is articulated as follows:

H_0 : *There is no cross – sectional dependence.*

H_1 : *There is cross – sectional dependence.*

Since the p-values derived from the Breusch-Pagan LM test and the Pesaran CD test are below the 0.05 threshold for both dependent and independent variables, H_0 is rejected at the 5% significance level. This indicates the presence of cross-sectional dependence across all countries within the panel.

Any change in one independent variable in a country impacts the others. Consequently, the panel unit root test, which accounts for cross-sectional dependency, will be employed in the study henceforth.

Under the assumption of cross-sectional independence, the cross-sectional dependence test statistic (CD) is expected to follow a standard normal distribution, denoted as $CD \sim N(0,1)$. This indicates that, under the null hypothesis of no cross-sectional dependence, the test statistic is expected to have a mean of zero and a variance of one for all variables considered.

In practical terms, p values associated with the CD statistic provide a measure of evidence against the null hypothesis. Specifically, p-values that are close to zero suggest strong evidence of cross-sectional dependence among the panel groups. In other words, when the p-value is very small, it indicates that the null hypothesis of independence can be rejected, implying that there is significant interdependence between the variables across the cross-sectional units of the panel data. This suggests that the data points are not independent of each other and are related across the different groups or time periods in the analysis.

Conversely, if the p-value is large and thus the assumption of cross-sectional independence holds. Understanding this distinction is crucial for the correct specification of econometric models, as cross-sectional dependence can influence the estimation and inference processes in

panel data analysis. Therefore, proper testing for cross-sectional dependence is a key step in ensuring the reliability and validity of the results (Pesaran, 2004).

3.3.1.2. Panel Unit Root Test

The results of the CIPS test, intended to assess the hypothesis, are displayed in Table 3.5, alongside the critical values from Pesaran (2007) for comparison analysis. Comparing the CIPS results with the tabular numbers in Pesaran (2007) reveals that they fall below the crucial value in the table, resulting in the rejection of the null hypothesis. Upon analyzing the resulting CIPS values, the null hypothesis is rejected for the $\ln EF$, $\ln GDP$, $\ln REC$, and $\ln KOF$ series, concluding that there is no unit root in the pertinent data for all nations in the panel, indicating that the shocks are transient and thus stationary. of all variables are stationary, it is needless to take their first differences.

Table 3.5. CIPS Panel Unit Root Test Results (At Level)

Variables	without trend				with trend			
	CIPS value	Critical value			CIPS value	Critical value		
		10%	5%	1%		10%	5%	1%
$\ln EF$	-2,384	-2,04	-2,11	-2,23	-3,360	-2,54	-2,61	-2,73
$\ln GDP$	-2,193	-2,04	-2,11	-2,23	-2,454	-2,54	-2,61	-2,73
$\ln REC$	-2,255	-2,04	-2,11	-2,23	-2,676	-2,54	-2,61	-2,73
$\ln KOF$	-2,834	-2,04	-2,11	-2,23	-3,390	-2,54	-2,61	-2,73

The hypothesis for the panel unit root test is formulated as follows:

H_0 : All series contain a unit root.

H_1 : At least some series are stationary.

The results derived from the Cross-Sectionally Augmented IPS (CIPS) test provide valuable insights into the stationarity properties of the examined variables. In the case of the ecological footprint (lnEF), the CIPS statistic of -2.384 in the model without a trend component falls below the critical values at the 10%, 5%, and 1% significance levels, while the CIPS value of -3.360 in the trend-inclusive model is also below all critical values, indicating that the ecological footprint series is stationary in both specifications. This suggests that shocks affecting the ecological footprint are transitory and do not have long-term effects. For Gross Domestic Product (lnGDP), the CIPS value of -2.193 in the model without a trend is below the critical values at the 10% and 5% significance levels, but does not meet the 1% threshold. However, in the model with a trend, the CIPS statistic of -2.454 exceeds the critical values at all significance levels, suggesting non-stationarity, and implying that the GDP series is only stationary in the model without a trend. Regarding renewable energy consumption (lnREC), the CIPS statistic of -2.255 in the trendless model and -2.676 in the model with a trend both fall below the critical values at the 10% and 5% significance levels, indicating that the renewable energy consumption series is stationary in both models, with fluctuations likely reverting to a stable long-term path. For the globalization index (lnKOF), the CIPS values of -2.834 in the model without a trend and -3.390 in the trend-inclusive model are both below the critical values at the 10%, 5%, and 1% significance levels, suggesting that the globalization index series is stationary in both models, with external shocks having only short-term effects. Overall, the empirical results demonstrate that all examined variables, except for GDP, exhibit stationarity and do not contain unit roots, implying that fluctuations in the ecological footprint, renewable energy consumption, and globalization index are temporary, while variations in GDP may have long-term effects of not appropriately differenced. These findings have important implications for policy formulation, particularly in areas related to sustainable development and economic stability.

Table 3.6. CIPS Test Results for lnGDP After First Differencing

Variable	CIPS VALUE	Critical Value		
		%10	%5	%1
d_lnGDP	-4.283	-2.54	-2.61	-2.73

To address the non-stationarity of the lnGDP series, the first difference was taken, and the stationarity test was re-conducted. The results indicate that the CIPS value is -4.283, which is lower than the critical values at all significance levels (-2.54, -2.61, and -2.73). Therefore, it can be concluded that stationarity has been achieved for the GDP series.

This finding implies that variations in the data are transitory, meaning that shocks affecting GDP will dissipate over the long term without causing permanent changes in the trend. As a result, any external influences on GDP are expected to have only short-term effects, reinforcing the stability of the dataset over time.

3.3.1.3. F Test

The F-test is employed to determine whether the pooled ordinary least squares (POLS) model or the fixed effects (FE) model is more appropriate for the dataset.

The hypothesis framework for the test is formulated as follows:

$H_0 =$ *The data is suitable for the pooled OLS model.*

$H_1 =$ *The data is more appropriately modeled using the fixed effects model.*

The computed F-test values are presented in the corresponding table. The p-value associated with the F-statistic is 0.000, which is lower than the significance threshold of 0.05.

Consequently, the null hypothesis is rejected, leading to the conclusion that the fixed effects model provides a more suitable representation of the data.

Table 3.7. F Test Statistics

Source	SS	df	MS	Number of obs	=	962
Model	45.3221492	3	15.1073831	F(3, 958)	=	176.51
Residual	81.9940904	958	.085588821	Prob > F	=	0.0000
Total	127.31624	961	.13248308	Adj R-squared	=	0.3540
				Root MSE	=	.29256

lnEFP	Coef.	Std. Err.	t	P > t	[95% Conf. Interval]	
d_lnGDP	.356161	.0973663	3.66	0.000	.1650852	.5472369
lnREN	-.089055	.0099961	-8.91	0.000	-.108671	-.0694383
lnKOFGI	1.63883	.0783449	20.92	0.000	1.485082	1.792577
_cons	-5.24542	.3430892	-15.29	0.000	-5.91871	-4.572127

The F test determines the preference between the pooled model and the fixed effects model (Bekmez and Destek, 2015; Arı and Zeren, 2011). The test hypothesis evaluates the hypothesis that all unit effects are equal to zero (Tatoğlu, 2021).

The study reveals that the probability value (p-value) associated with the F-statistic exceeds the threshold of 0.05. This indicates that the null hypothesis (H_0), which assumes that the unit effects are equal to zero, is rejected. Consequently, the presence of significant unit effects suggests that the fixed effects model is more appropriate for analyzing the data. The detailed results, derived from the application of the fixed effects model, are provided in Table 3.6 for further examination.

The p-value corresponding to the F-statistic is 0.000, which is lower than the significance level of 0.05. Consequently, the null hypothesis, which assumes that unit effects are equal to zero, is rejected. This result indicates that a fixed effect model is more appropriate than the pooled OLS model.

Panel data analysis is typically conducted using two fundamental modeling approaches: the Fixed Effects Model and the Random Effects Model.

Fixed Effects Model (FE): This model assumes that each entity (e.g., a firm or an individual) has its own unique, time-invariant characteristics that influence the dependent variable. These individual-specific effects are treated as fixed and incorporated into the model.

Random Effects Model (RE): In this approach, the individual-specific effects are considered random and uncorrelated with the explanatory variables. The variations among entities are assumed to be stochastic.

To illustrate the application of Fixed Effects (FE) and Random Effects (RE) models in analyzing the relationship between ecological footprint, GDP, renewable energy consumption, and the globalization index, consider the following example.

A researcher aims to examine the factors influencing the ecological footprint across different countries by assessing the impact of GDP, renewable energy consumption, and the globalization index. However, variations in geography, culture, environmental policies, and industrial structures across countries introduce unobservable heterogeneity, making it necessary to determine whether a fixed or random effects model is more appropriate for analysis.

In the Fixed Effects (FE) model, it is assumed that each country possesses unique, time-invariant characteristics that influence the ecological footprint. This model accounts for unobserved heterogeneity by controlling for country-specific factors that do not change over time, thereby focusing solely on variations within each country. For instance, structural factors such as Germany's industrial history, China's environmental policies, or Brazil's geographical features are treated as constant, allowing the analysis to examine how GDP, renewable energy consumption, and globalization influence the ecological footprint within each country over time. In this context, the FE model would address questions such as whether an increase in GDP in Germany leads to changes in the ecological footprint, whether higher renewable energy consumption in China contributes to a reduction in environmental impact, or how fluctuations in the globalization index in Brazil affect its ecological footprint. Rather than comparing countries directly, the FE model emphasizes within-country variations by isolating time-specific effects from cross-sectional differences. A real-world analogy would be monitoring an individual's dietary habits over time while assuming that genetic and environmental factors remain constant, thereby analyzing how dietary changes influence health outcomes.

Conversely, the Random Effects (RE) model assumes that differences across countries are randomly distributed and can be generalized across all observations. Rather than treating country-specific factors as fixed, this model incorporates them into the analysis as part of a broader stochastic process, allowing both within-country and between-country variations to be examined simultaneously. In this framework, differences in environmental policies, industrial structures, and natural resource utilization across countries are considered as part of a random distribution, enabling an assessment of the overall impact of GDP, renewable energy consumption, and globalization on the ecological footprint at a global scale. This approach facilitates answering broader research questions such as whether countries with higher GDP levels generally exhibit greater ecological footprints, whether an overall increase in renewable energy consumption is associated with a decline in environmental impact worldwide, or whether globalization exerts a systematic pressure on environmental sustainability across nations. By incorporating cross-country variations, the RE model provides insights into generalizable trends rather than country-specific relationships.

Both models offer distinct analytical advantages, with the FE model effectively controlling for unobservable country-specific factors, making it suitable for studying within-country dynamics, while the RE model allows for generalizable inferences by incorporating both within- and between-country variations. The selection of the appropriate model depends on the research objective and the underlying assumptions regarding the nature of country-specific heterogeneity.

The F-test only determines whether fixed effects exist; however, rejecting the null hypothesis does not automatically imply that the fixed effects model is the most appropriate. In certain cases, such as when the differences across entities are randomly distributed, the random effects model may still be preferable. Therefore, to determine the most suitable model, the Hausman Test is conducted.

The Hausman test was employed as a statistical procedure to determine the most suitable model specification for analyzing the given dataset. Specifically, this test evaluates whether the fixed effects model or the random effects model is more appropriate by assessing the correlation between the explanatory variables and the unobserved individual-specific effects.

The null hypothesis of the Hausman test posits that the random effects model is the correct specification for the data under consideration. This assumption rests on the premise that the individual-specific effects—unobservable characteristics unique to each cross-sectional unit—are not correlated with the explanatory variables included in the model. In such a scenario, the random effects model provides consistent and efficient parameter estimates because it assumes exogeneity of the individual-specific effects with respect to the regressors.

In contrast, the alternative hypothesis challenges this assumption and asserts that the fixed effects model is more appropriate. This hypothesis is based on the premise that the individual-specific effects are correlated with one or more explanatory variables. Such correlation introduces endogeneity, leading to biased and inconsistent parameter estimates of the random effects model is used. Consequently, the fixed effects model is preferred in this case because it accounts for this correlation by eliminating the time-invariant unobserved heterogeneity through within-group transformation (Wooldridge, 2010; Greene, 2018).

The Hausman test formally evaluates this trade-off between the two models by comparing their parameter estimates. Specifically, the test measures the extent of the difference between the fixed effects and random effects estimators, under the assumption that both estimators should converge if the null hypothesis holds true. A significant test statistic indicates that the difference is too large to attribute to sampling variation alone, leading to a rejection of the null hypothesis and a preference for the fixed effects model (Hausman, 1978). This rigorous testing process ensures the selection of the most appropriate model, thereby enhancing the validity and reliability of econometric analyses.

The Hausman Test is applied in panel data analysis to assess whether the fixed effects or random effects model provides a better fit for the data. The hypotheses tested are as follows:

$H_0 = \text{The random effects model is appropriate.}$

$H_1 = \text{The fixed effects model is appropriate.}$

Table 3.8. Hausman Test Statistics

--Coefficients--				
	(b)	(B)	(b-B)	Sqrt
	fe	re	Difference	S.E.
d_lnGDP	.2006036	.2016493	-.0010457	.0008684
lnREN	-.1442258	-.1444445	.0002187	.0017954
lnKOFGI	.3945062	.4233356	-.0288294	.0105353
Prob>chi2=0.0001				

The results of the Hausman test are interpreted based on the p-value of the test statistic as follows:

of p-value < 0.05, the fixed effects model is deemed more appropriate, indicating that unit-specific effects should not be ignored.

of p-value > 0.05, the random effects model is preferred, suggesting that unit-specific effects are not significantly influential.

In the present analysis, the chi-square statistic obtained from the Hausman test corresponds to a probability value of 0.000. Since this value is lower than the significance level of 0.05, the null hypothesis is rejected. Consequently, it is concluded that the fixed effects model is the more suitable choice.

In this analysis, the Hausman test produced a probability value (p-value) below the threshold of 0.05, signifying statistical significance at the 5% level. As a result, the null hypothesis (H_0), which assumes no correlation between the individual-specific effects and the explanatory variables, is rejected. This outcome supports the alternative hypothesis (H_1), confirming that the fixed effects model is more suitable for this data set.

The rejection of H_0 indicates that the individual-specific effects are not independent of the explanatory variables, meaning that they are correlated. Under such circumstances, the fixed effects model is preferred over the random effects model because it accounts for these correlations, ensuring that the parameter estimates remain unbiased and consistent.

This finding emphasizes the critical importance of selecting the appropriate econometric model when analyzing data. The choice of the fixed effects model in this context enhances the validity and reliability of the results, ensuring that the relationships between the variables are accurately captured and interpreted. Such rigorous methodological decisions are essential for drawing sound conclusions and supporting evidence-based policy or decision-making.

Consequently, in the model where the ecological footprint serves as the dependent variable, both gross domestic product and the KOF globalization index exert a significant positive influence on the ecological footprint at the 10% significance level, whereas renewable energy consumption demonstrates a significant negative impact on the ecological footprint at the 1% significance level. The rise in renewable energy consumption diminishes the ecological footprint, but the growth in gross domestic product and the globalization index exacerbates it.

Table 3.9. Estimation Results of Fixed-Effects Regression

					Number of obs	=	962
					Number of groups	=	37
					F(3,922)	=	102.06
					Prob>F	=	0.0000
lnEFP							
	Coef.	Std. Err.	t	P > t	[95% Conf. Interval]		
d_lnGDP	.2006036	.0352519	5.69	0.000	.1314204	.2697868	
lnREN	-.144226	.0090427	-15.95	0.000	-.161972	-.1264791	
lnKOFGI	.3945062	.0601154	6.56	0.000	.2765274	.512485	
_cons	.3179103	.2525663	1.26	0.208	-.177761	.8135819	
F(36, 922) = 187.02				Prob > F = 0.0000			

Table 3.10. Estimation Results of Random Effects

						Number of obs	=	962
						Number of groups	=	37
						Wald chi2 (3)	=	310.82
						Prob>chi2	=	0.0000
lnEFP								
	Coef.	Std. Err.	t	P > t	[95% Conf. Interval]			
d_lnGDP	.2016493	.0355828	5.67	0.000	.1319084	.2713903		
lnREN	-.144445	.0089521	-16.14	0.000	-.161990	-.1268987		
lnKOFGI	.4233356	.0597764	7.08	0.000	.3061759	.5404952		
_cons	.1928976	.2551134	0.76	0.450	-.307115	.6929107		

An examination of the analysis results presented in Table 3.9. and Table 3.10., corresponding to the fixed effects model and random effects model, respectively, reveals that the estimated coefficients indicate a positive impact of Gross Domestic Product (GDP) and the Globalization Index on the ecological footprint. In contrast, renewable energy consumption exhibits a negative effect on the ecological footprint. These findings suggest that while economic growth and globalization contribute to increased environmental degradation, greater reliance on renewable energy sources mitigates ecological impact.

An examination of the estimation results of the Fixed Effects model presented in Table 2 indicates that the F-test value and its corresponding p-value confirm the overall significance of the model. This suggests that at least one of the independent variables significantly explains variations in the ecological footprint variable.

According to the results of the Hausman test, the Fixed Effects model is deemed appropriate; therefore, the interpretation is based on the Fixed Effects estimation results.

The results of the F-test (Prob > F = 0.0000) indicate that the model is statistically significant as a whole.

A 1% change in a country's GDP leads to an approximately 0.20% increase in the ecological footprint. This suggests that as GDP growth accelerates, the ecological footprint expands correspondingly. A 1% increase in renewable energy consumption reduces the ecological footprint by approximately 0.14%. This finding underscores the positive contribution of renewable energy use to environmental sustainability by mitigating ecological impact. A 1% increase in the globalization index results in an approximately 0.39% increase in the ecological footprint. This implies that globalization exerts a negative influence on environmental sustainability. As globalization intensifies, production and consumption levels rise, potentially leading to an expansion of the ecological footprint. The constant term in the model is not statistically significant, indicating that it does not serve as a standalone factor in explaining variations in the ecological footprint.

These findings highlight the varying impacts of economic growth, globalization, and renewable energy consumption on environmental sustainability. Specifically, the increased utilization of solar, wind, and other clean energy sources mitigates environmental impact. The key takeaway from this analysis is that greater emphasis should be placed on renewable energy to ensure that economic growth and globalization align with sustainability principles. In other words, transitioning to renewable energy sources can facilitate the creation of a more sustainable global environment.

3.3.2. Artificial Neural Networks

3.3.2.1. Development of Artificial Neural Network

The output of a cell in one layer of the ANN is conveyed as input to another layer via weights. Information from the input layer is conveyed to the cells in the hidden layer. The data is processed in the hidden layers and the output layer (Sönmez and Zengin, 2019).

The study focused on using the annual ecological footprint as the dependent variable to analyze its relationship with key influencing factors. Gross domestic product (GDP), renewable energy consumption, and the KOF globalization index were selected as the independent variables to assess their impact on the ecological footprint. These variables were chosen due to their relevance in understanding environmental, economic, and global dynamics.

In constructing the ANN model, the fundamental components of a neural network cell were considered. Each cell consists of several critical elements: inputs, which represent the data fed into the network; weights, which determine the importance of each input; a summation function, which aggregates the weighted inputs; an activation function, which introduces non-linearity and determines whether the neuron "fires"; and outputs, which represent the final processed information passed to the next layer or as the model's prediction.

To build the ANN model, feedforward ANNs were utilized. This type of neural network involves a unidirectional flow of information, where data moves from the input layer through one or more hidden layers to the output layer without looping back. The feedforward structure is widely recognized for its simplicity and effectiveness in modeling complex, non-linear relationships, making it a suitable choice for this study. By employing this approach, the study aimed to capture intricate patterns and dependencies between the variables to provide a more comprehensive understanding of the factors influencing the ecological footprint. Three input parameters were supplied to the ANN for the assessment of ecological footprint. The Levenberg-Marquardt approach was employed to train the ANN, and mean squared errors were considered to assess training efficacy. A trial and error analysis was conducted during model setup to determine the number of hidden layers in the model. Upon identifying the layer count associated with the minimal error as the optimal configuration, the layer count yielding the maximum performance for the model was validated.

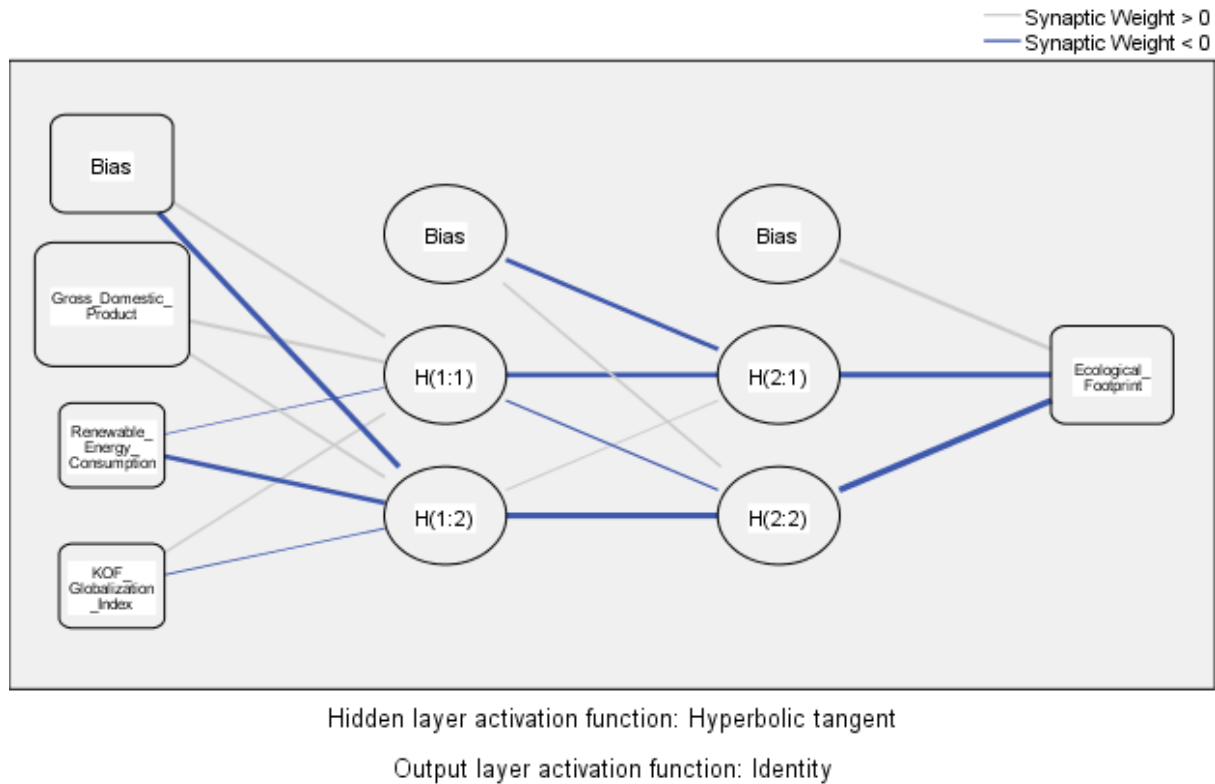


Figure 3.1. General ANN Structure

Figure 3.1 illustrates the construction of a general ANN model pertinent to our research. ANN models were created in the research, and ecological footprint estimates were calculated using data from 1995 to 2021 for each independent variable across all OECD countries. The network is given input information and the corresponding output information, which allows it to learn the relationship between the two, thus training the network. This approach, known as supervised learning, is generally preferred (Haykin, 1998).

3.3.2.1.1. Artificial Neural Network Model for Australia

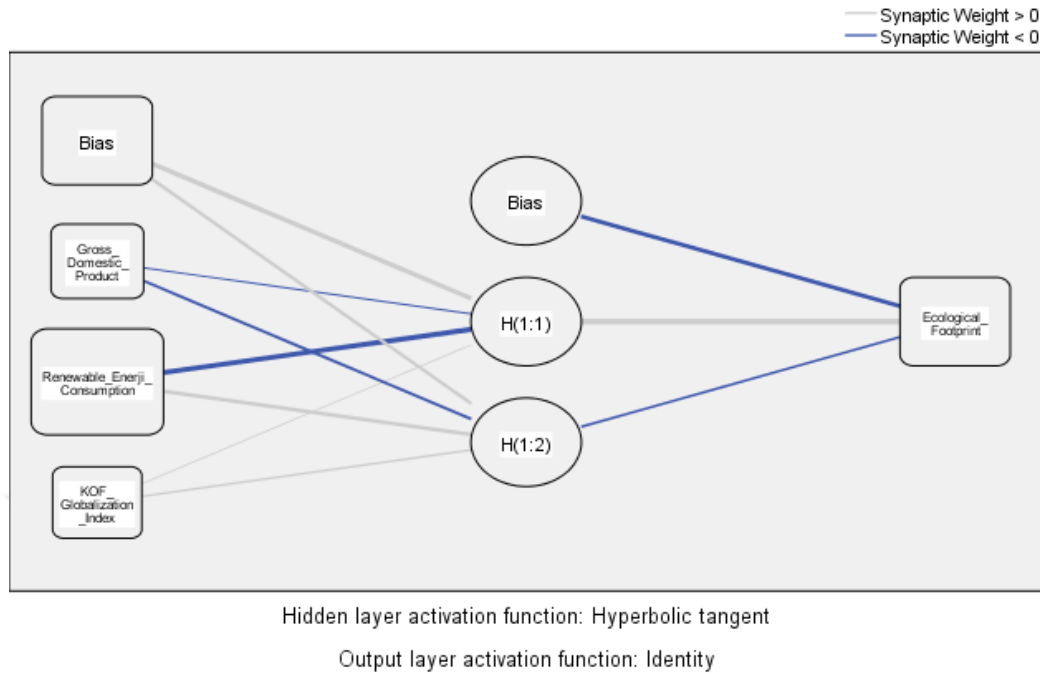


Figure 3.2. ANN Model of Australia

Figure 3.2 illustrates an ANN model designed for Australia, which is a member of the OECD. In the ANN model developed for Australia, three neurons were utilized in the input layer, two neurons in the hidden layer, and one neuron in the output layer. The number of neurons in the hidden layer was determined based on the commonly applied rule of taking the average of the number of input and output neurons. Accordingly, since the model included three input neurons and one output neuron, two neurons were selected for the hidden layer.

Analyses were conducted using SPSS with different numbers of neurons, and it was concluded that the most accurate results were obtained with two neurons. The same methodology was applied to determine the number of neurons for all other OECD countries.

The model employs a feedforward neural network configuration, where each neuron in one layer is fully connected to the neurons in the subsequent layer. The input layer processes the initial features or variables, which are then passed to the hidden layer for transformation and abstraction. The hidden layer, containing two neurons, serves as the computational core of the model, enabling it to capture nonlinear relationships within the data.

In the hidden layer, the tanh (hyperbolic tangent) activation function was employed. This function enables the model to learn complex relationships more effectively, as it can process both positive and negative values. This function is widely applied in neural networks due to its ability to produce outputs in the range of -1 to 1, which helps normalize the data and improve convergence during training. The tanh function also introduces non-linearity, allowing the network to learn complex patterns and interactions among the input variables. In the output layer, the identity activation function was utilized, also referred to as purelin in the literature. This function directly transfers the input value to the output, making it particularly suitable for numerical predictions.

The selection of activation functions was determined automatically by MATLAB, based on the objective of the model.

In summary, MATLAB's application of the tanh activation function in the hidden layer allowed the model to learn in a more flexible and robust manner, while the use of the identity activation function in the output layer enabled accurate and unrestricted numerical predictions.

The output layer, comprising a single neuron, generates the final prediction or output based on the processed information from the hidden layer.

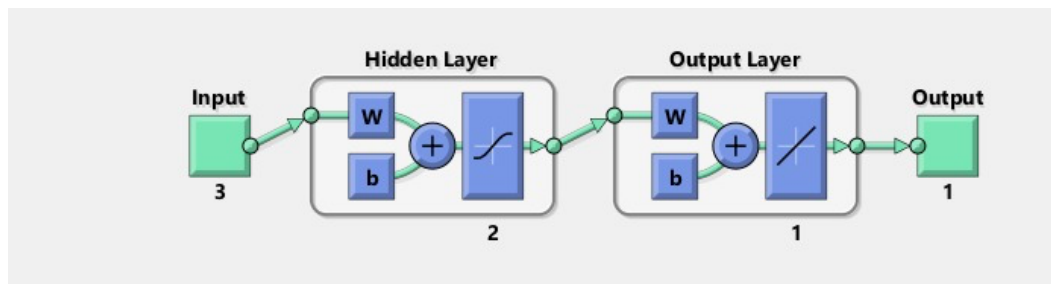


Figure 3.3. MATLAB Implementation of ANN Model for Australia

The input data were analyzed and pre-processed utilizing MATLAB software. Following this step, an ANN model was designed and implemented to address the research objectives. The architecture and structure of the developed ANN model, including the arrangement of input, hidden, and output layers, are illustrated in Figure 3.3. This model was optimized through

systematic parameter tuning to ensure accurate predictions and robust performance in solving the specified problem.

Table 3.11. Summary of the Model for Australia

Model Summary		
Training	Sum of Squares Error	2,205
	Relative Error	,221
	Stopping Rule Used	1 consecutive step(s) with no decrease in error ^a
	Training Time	0:00:00,00
Testing	Sum of Squares Error	,230
	Relative Error	,066

Dependent Variable: Ecological_Footprint

a. Error computations are based on the testing sample.

Table 3.11. presents the values for Training Error and Testing Error, providing insight into the model's learning and generalization performance. The training set is used to train the artificial neural network, where input data and their corresponding outputs allow the model to update its weights and parameters, enabling it to learn patterns and relationships. Once the training process is complete, the test set is used to evaluate the model's performance on previously unseen data, ensuring that it can generalize beyond the training data.

The training error represents the total error accumulated by the model during learning, while the testing error measures how accurately the model performs on new data. In this study, the Sum of Squares Error (SSE) in the training phase is 2.205, whereas the SSE in the test phase is 0.23, indicating that the model performs well on test data. The Relative Error in the training set is 22%, suggesting that the model has learned from the training data to a certain extent, while in the test set, the relative error is approximately 6.6%, demonstrating that the model makes highly accurate predictions on new data.

A Stopping Rule was applied, meaning the training process automatically terminated when no further reduction in error was observed, indicating that the model ceased training once the error

remained unchanged. Additionally, the Training Time is recorded as zero, implying that the model learned very quickly, which may be attributed to a relatively small dataset or a simple network architecture.

Since the dependent variable in this study is the Ecological Footprint, the model is designed to predict individuals' environmental impact. The low test error (6.6%) demonstrates that the model accurately predicts ecological footprint values for new data, indicating that it is both reliable and possesses a strong generalization ability in estimating ecological footprint.

Weight values were established to minimize the inaccuracy. The weight coefficients of the neurons in the model's ANN are presented in Table 3.12.

Table 3.12. Weight Estimates for Australia

		Parameter Estimates		
Predictor		Hidden Layer 1		Predicted Output Layer Ecological_Foot print
Input Layer	(Bias)	H(1:1)	H(1:2)	
	Gross_Domestic_Product	-,184	-,274	
	Renewable_Enerji_Consumption	-1,147	,466	
	KOF_Globalization_Index	,036	,205	
Hidden Layer 1	(Bias)			-,503
	H(1:1)			1,314
	H(1:2)			-,224

The weights assigned to the connections between the independent variables and the hidden layer neurons H(1:1) and H(1:2) represent the influence of these variables on the activation of hidden layer neurons. Positive weights indicate that an increase in the input variable enhances the neuron activation function, whereas negative weights suggest a decrease in neuron activation. The magnitude of the weights determines the strength of their influence, with larger absolute values indicating a stronger effect.

For Gross Domestic Product (GDP), both weights are negative (-0.184, -0.274), meaning that an increase in GDP reduces the activation of hidden layer neurons. In the case of Renewable Energy Consumption, the weights leading to the hidden layer are both positive and negative (-1.147 and 0.466). The negative weight suggests that as renewable energy consumption increases, certain activations in the hidden layer decrease. The GDP weights (-0.184 and -0.274) further confirm that an increase in GDP may lead to a reduction in the activation of hidden layer neurons.

Analyzing the weights from the hidden layer (Hidden Layer 1) to the output layer (Ecological Footprint), the weight from H(1:1) to Ecological Footprint is 1.314, which is both positive and large. This indicates that signals originating from H(1:1) have an increasing effect on ecological footprint, suggesting that the variables linked to H(1:1) contribute to the expansion of the ecological footprint. Conversely, the weight from H(1:2) to Ecological Footprint is -0.224, indicating that signals from H(1:2) exert a reducing effect on the ecological footprint. This suggests that variables associated with H(1:2) tend to lower the ecological footprint. For instance, since GDP has a weight of -0.274 on H(1:2), an increase in GDP sends a negative signal to H(1:2). Given that H(1:2) is negatively linked to the ecological footprint, GDP growth could ultimately lead to an increase in the ecological footprint.

Overall, the model provides insights into how factors such as economic growth and Renewable energy consumption influence the ecological footprint, demonstrating their interconnected impact on environmental sustainability.

The importance table of the independent variables is given in Table 3.10 to see how important each of the independent variables is in predicting the dependent variable.

Table 3.13. Significance of Independent Variables for Australia

Independent Variable Importance		
	Importance	Normalized Importance
Gross_Domestic_Product	,090	10,1%
Renewable_Enerji_Consumption	,890	100,0%
KOF_Globalization_Index	,020	2,3%

The effects of independent variables on the dependent variable within the model are analyzed, as presented in the Table 3.13., which facilitates an understanding of the extent to which each variable contributes to the predictive power of the model. The table includes two key metrics: Importance, which represents the raw effect of each variable on the model, and Normalized Importance, which transforms raw values into a percentage format by setting the variable with the highest importance as 100% and scaling other variables accordingly, using the formula,

$$\text{Normalized Importance} = \left(\frac{\text{Importance}}{\text{Maximum Importance Value}} \right) \times 100$$

Variables with a normalized importance below 10% are considered to have a low impact on the model, those between 10% and 50% exhibit a moderate effect, while those above 50% are deemed highly influential.

The results indicate that renewable energy consumption, with a normalized importance of 100%, is the most significant factor, emphasizing its crucial role in ensuring environmental sustainability. Gross Domestic Product (GDP), with a normalized importance of 10.1%, exhibits a moderate effect, suggesting that while economic growth remains relevant, its direct influence on environmental outcomes is relatively limited. The Globalization Index, with a normalized importance of 2.3%, has a minimal effect within the model.

These findings highlight that mitigating environmental impacts requires prioritizing the expansion of renewable energy usage. Moreover, economic growth must be balanced with environmental sustainability, ensuring that development objectives do not compromise ecological integrity. This analysis underscores the necessity of structuring environmental policies to promote greater investments in renewable energy sources, reinforcing their central role in sustainable development strategies.

To evaluate the performance and goodness of fit of the model, two common statistical measures were computed: R^2 and Mean Squared Error. R^2 is a key indicator of the model's explanatory power, with values ranging from 0 to 1. An R^2 value closer to 1 indicates that a higher proportion of the variance in the dependent variable is explained by the model, suggesting a good fit. Conversely, a value closer to 0 implies that the model does not explain much of the variance, indicating a poor fit.

The Mean Squared Error (MSE), on the other hand, is a measure of the average squared differences between the observed actual outcomes and the values predicted by the model (Ali, Ahmed and Abbod, 2024). The MSE provides an indication of the model's accuracy, with lower values signifying better performance. It is calculated by taking the average of the squared residuals. A lower MSE implies that the model's predictions are closer to the actual data, suggesting more accurate results.

Together, R^2 and MSE offer complementary insights into the model's performance, with R^2 reflecting the proportion of variance explained, and MSE measuring the overall prediction error. These metrics are essential for assessing the model's reliability and guiding improvements or adjustments to the model for better predictive accuracy (Jebli, Belouadha, Kabbaj and Tilioua, 2021; Şahan, 2021).

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - x_i)^2}{\sum_{i=1}^n (x_i - \bar{x}_i)^2} \quad (3.4.)$$

$$MSE = \frac{\sum_{i=1}^n (y_i - x_i)^2}{n} \quad (3.5.)$$

In the aforementioned equations, $\hat{y}_i$ represents the estimated value, y_i denotes the actual value, $\bar{y}$ signifies the mean of the actual values, and n indicates the number of data points (Somuncu and Oral, 2024).

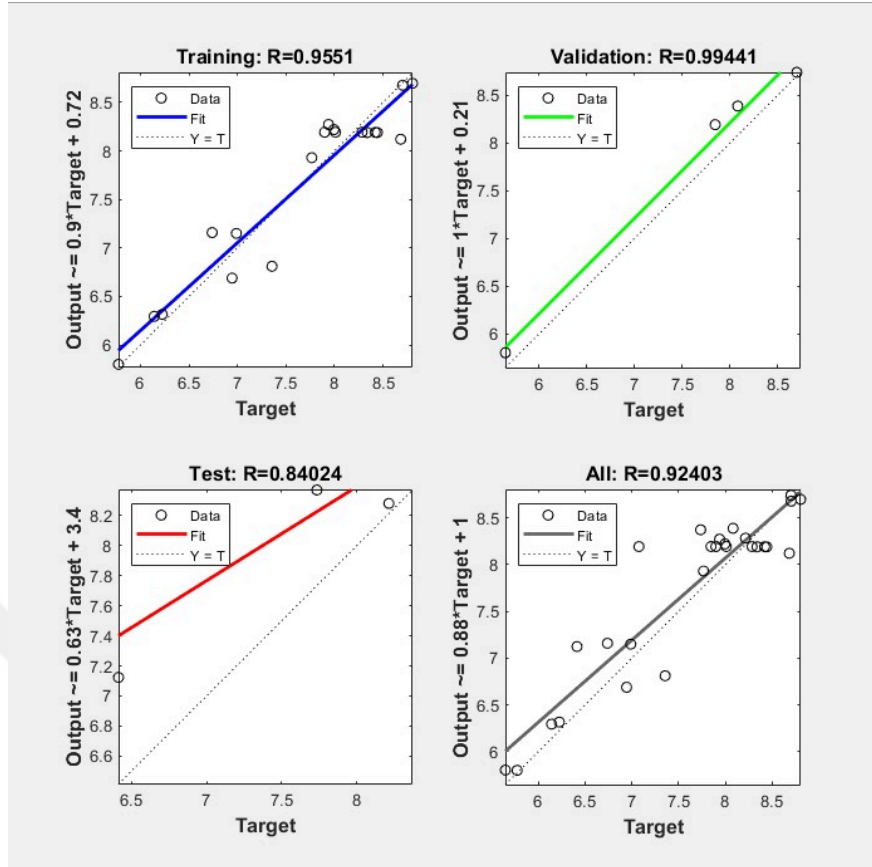


Figure 3.4. Regression Distribution of ANNs for Australia

Figure 3.4 illustrates the performance of an artificial neural network model across training, validation, and test datasets, as well as for the entire dataset. Each graph represents the relationship between the predicted output and the actual target values, demonstrating a direct (positive) correlation. As the target values increase, the predicted values also increase. A negative slope, by contrast, would indicate that predictions decrease as the target values rise.

The correlation coefficient (R) measures the strength and direction of the relationship between the predicted and actual values, ranging from -1 to +1, where +1 denotes a perfect positive correlation, 0 indicates no correlation, and -1 represents a perfect negative correlation. The positive and near-unity R values observed in this analysis indicate that the model exhibits a high degree of predictive accuracy.

The variation in the number of data points across the training, validation, and test graphs is a consequence of the dataset partitioning strategy. The dataset is divided such that 70% is

allocated to training, 15% to validation, and 15% to testing. Consequently, the training dataset contains the largest number of data points, while the validation and test datasets contain fewer observations. This distribution is a standard practice in machine learning applications.

The apparent absence of data points for target values of zero is attributable to the characteristics of the dataset. When the target value is zero, the model still produces a nonzero output, such as 0.72 in the training graph. However, as the dataset does not contain any observations where the target value is precisely zero, the graph does not commence at this point. Instead, it begins at the minimum observed target value, which is 6. This pattern is consistent across the validation, test, and overall dataset graphs.

An analysis of the training dataset reveals an R value of 0.95, indicating a strong positive correlation between the predicted and actual values. This suggests that the model effectively captures the underlying patterns in the training data. The regression equation exhibits a slope of 0.90, which is close to 1, signifying a strong linear relationship. The intercept is 0.72, reflecting a minor deviation in the model's predictions. The blue line represents the fitted regression model, while the dashed line ($Y = T$) denotes the ideal case where predictions perfectly align with actual values.

For the validation dataset, the R value is 0.99, indicating an exceptionally strong correlation. The regression equation features a slope of 1, suggesting that the predicted and actual values align almost perfectly. The intercept is 0.21, implying a minimal deviation in the model's predictions. The green line represents the fitted regression for the validation dataset.

The test dataset exhibits an R value of 0.84, indicating a strong but relatively weaker correlation compared to the training and validation datasets. This reduction in performance may suggest potential overfitting. The regression equation has a slope of 0.63, indicating that the model captures only 63% of the variance in the target values. The intercept of 3.4 suggests a larger deviation in predictions compared to the training and validation datasets. The red line represents the fitted regression for the test dataset.

An evaluation of the overall dataset reveals an R value of 0.92, indicating strong predictive performance across all data. The regression equation features a slope of 0.88, suggesting that the model accurately predicts 88% of the variance in target values. The intercept of 1 reflects a

minor deviation in the predictions. The black line represents the fitted regression for the entire dataset.

In conclusion, the model demonstrates a high level of accuracy in predicting environmental variables. The strong correlation coefficients observed in the training and validation datasets confirm the model’s ability to learn from the data, while the test dataset results indicate its generalizability. The training phase evaluates the model’s capacity to fit the data, the validation phase assesses the risk of overfitting using a separate subset, and the test phase measures predictive performance on previously unseen data. The combined evaluation across all datasets provides a comprehensive assessment of the model’s overall predictive capability and reliability.

3.3.2.1.2. Artificial Neural Network Model for Austria

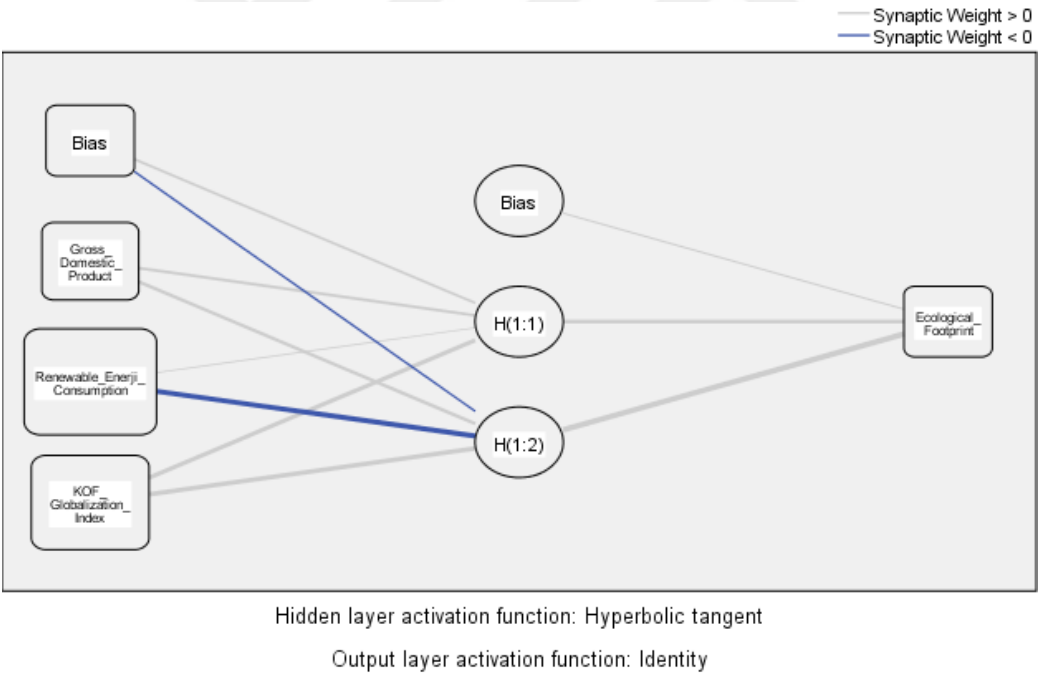


Figure 3.5. ANN Model of Austria

Figure 3.5 illustrates an ANN model designed for Austria, which is a member of the OECD. The network architecture consists of a single hidden layer and is structured with three neurons in the input layer, two neurons in the hidden layer, and one neuron in the output layer. The

model employs a feedforward neural network configuration, where each neuron in one layer is fully connected to the neurons in the subsequent layer. A hyperbolic tangent (tanh) activation function is utilized in the hidden layer.

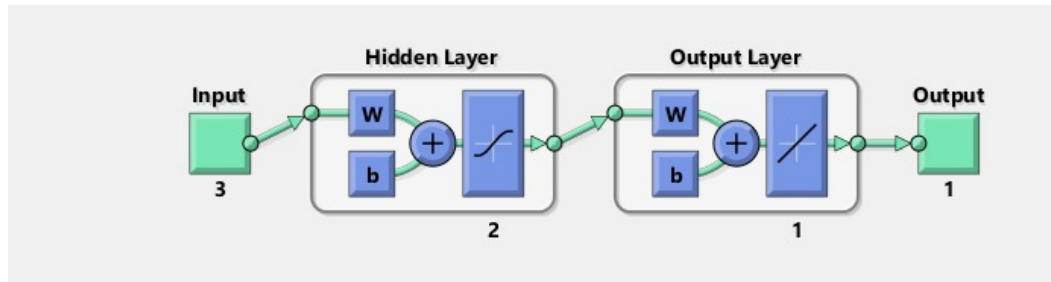


Figure 3.6. MATLAB Implementation of ANN Model for Austria

The input data were analyzed and pre-processed utilizing MATLAB software. Following this step, an ANN model was designed and implemented to address the research objectives. The architecture and structure of the developed ANN model, including the arrangement of input, hidden, and output layers, are illustrated in Figure 3.6.

Table 3.11. Summary of the Model for Austria

Model Summary		
Training	Sum of Squares Error	4,720
	Relative Error	,429
	Stopping Rule Used	1 consecutive step(s) with no decrease in error ^a
	Training Time	0:00:00,00
Testing	Sum of Squares Error	1,078
	Relative Error	,283

Dependent Variable: Ecological_Footprint

a. Error computations are based on the testing sample.

Table 3.11 presents the outcomes of the training and test sets for the model, together with the values of the cumulative squared errors. The proportion of erroneous predictions in the test data is 0.283, indicating an accuracy of 71.7% in the test. The objective is to employ the activation function according to the significance levels of the inputs. Weight values are established to minimize mistake. The weight coefficients of the neurons in the model's ANN are presented in Table 3.12.

Table 3.12. Weight Estimates for Austria

Parameter Estimates				
		Predicted		
		Hidden Layer 1		Output Layer
Predictor		H(1:1)	H(1:2)	Ecological Footprint
Input Layer	(Bias)	-,104	-,039	
	Gross Domestic Product	-,441	-,501	
	Renewable Energy Consumption	1,353	,099	
	KOF Globalization Index	-,891	,227	
Hidden Layer 1	(Bias)			,058
	H(1:1)			-1,587
	H(1:2)			-,201

The network is trained by changing the weights of the connections between neurons in each layer. The importance table of the independent variables is given in Table 3.13 to see how important each of the independent variables is in predicting the dependent variable.

Table 3.13. Significance of Independent Variables for Austria

Independent Variable Importance		
	Importance	Normalized Importance
Gross Domestic Product	,30	62,7%
Renewable Energy Consumption	,48	100,0%
KOF Globalization Index	,22	47,3%

According to the data obtained, it was concluded that renewable energy consumption in Austria has an importance of 48% in estimating the ecological footprint. The values were normalized to 48% and the rest of the 100 variables were found the second is KOF Globalization Index, which has an importance of approximately 62.7%.

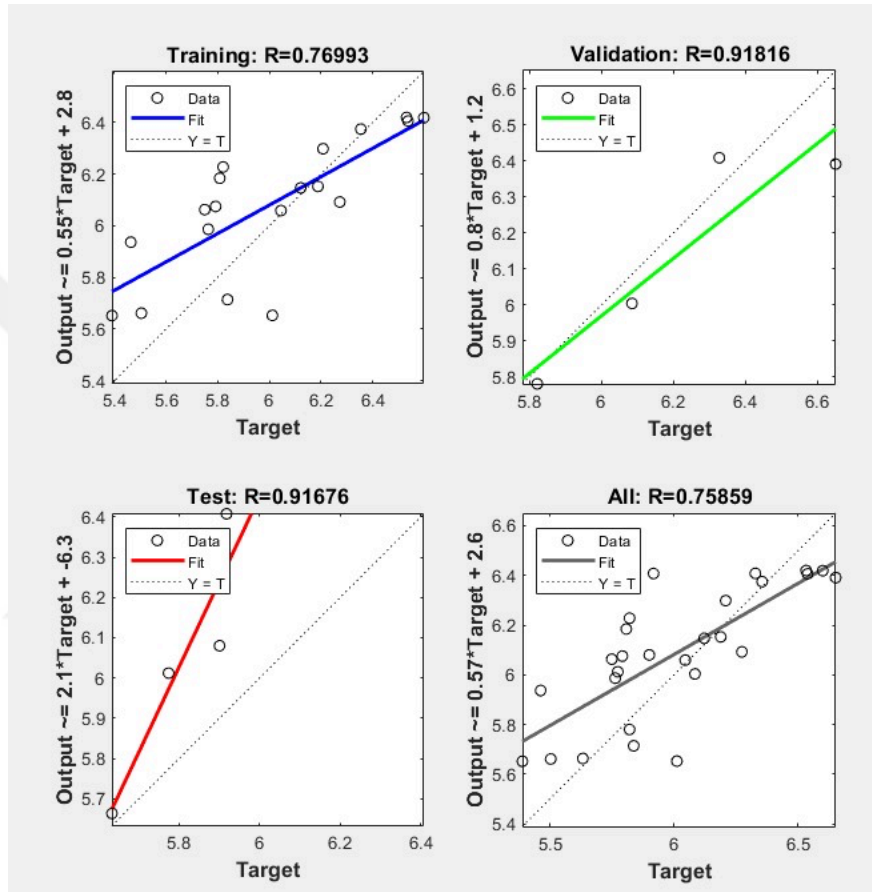


Figure 3.7. Regression Distribution of ANNs for Austria

As a result of the applied model, Figure 3.7. shows the correlation between all the values of the derived model after training, validation, testing and prediction. Training data showed a success rate of $R^2 = 0.76993$, validation data showed a success rate of $R^2 = 0.91816$ and testing data showed a success rate of $R^2 = 0.91676$. The performance metric of the network for the entire dataset is $R^2 = 0.75859$. This rate shows that the network is quite successful. Upon examination of the findings, the effectiveness of the developed model is obvious. The results show that there is a robust relationship between the actual values and the predicted values across all the datasets.

3.3.2.1.3. Artificial Neural Network Model for Belgium

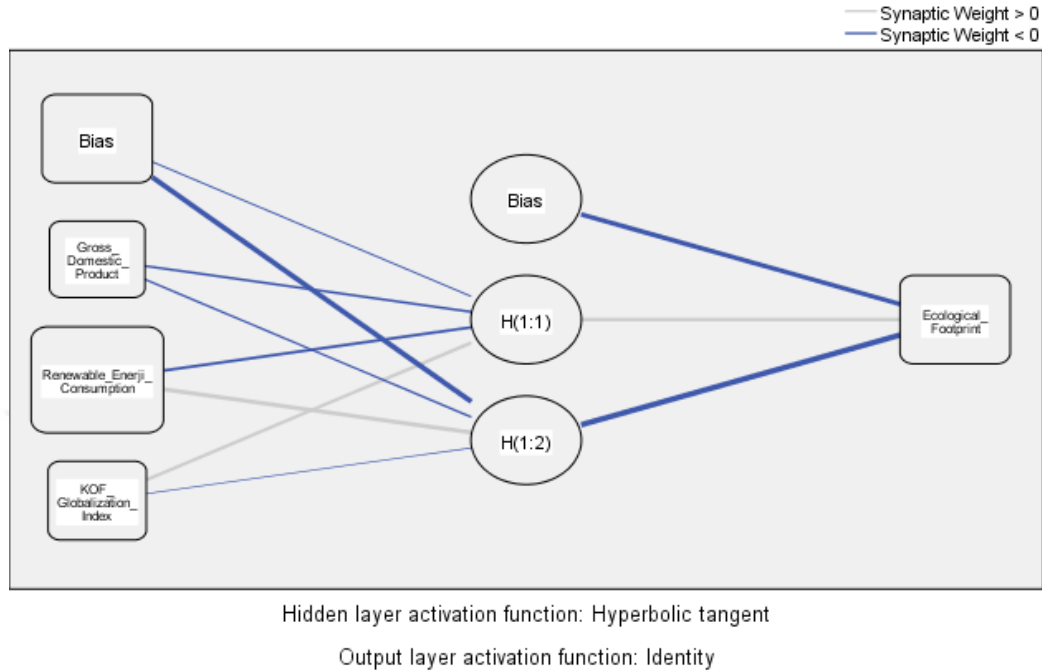


Figure 3.8. ANN Model of Belgium

Figure 3.8 illustrates an ANN model designed for Belgium, which is a member of the OECD. The network architecture consists of a single hidden layer and is structured with three neurons in the input layer, two neurons in the hidden layer, and one neuron in the output layer. The model employs a feedforward neural network configuration, where each neuron in one layer is fully connected to the neurons in the subsequent layer. A hyperbolic tangent (tanh) activation function is utilized in the hidden layer.

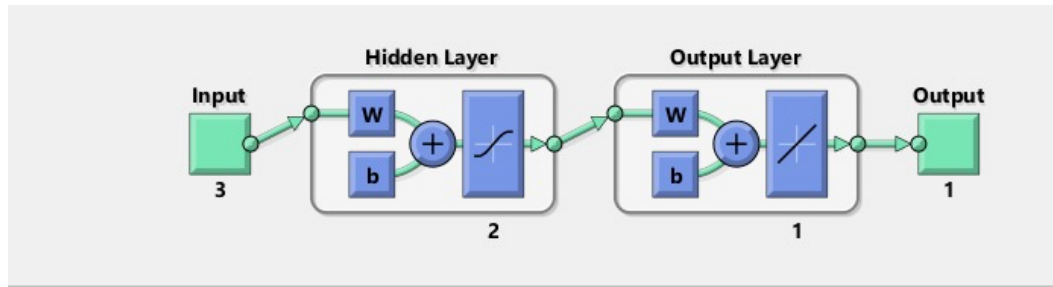


Figure 3.9. MATLAB Implementation of ANN Model for Belgium

The input data were analyzed and pre-processed utilizing MATLAB software. Following this step, an ANN model was designed and implemented to address the research objectives. The architecture and structure of the developed ANN model, including the arrangement of input, hidden, and output layers, are illustrated in Figure 3.9.

Table 3.14. Summary of the Model for Belgium

Model Summary		
Training	Sum of Squares Error	,981
	Relative Error	,098
	Stopping Rule Used	1 consecutive step(s) with no decrease in error ^a
	Training Time	0:00:00,00
Testing	Sum of Squares Error	,247
	Relative Error	,127

Dependent Variable: Ecological_Footprint

a. Error computations are based on the testing sample.

Table 3.14. presents the outcomes of the training and test sets for the model, together with the values of the cumulative squared errors. The test data exhibits a 0.127 proportion of erroneous predictions, indicating an accuracy of 87.3% in the assessment. The objective is to employ the activation function according to the relevance levels of the inputs. Weight values were

established to minimize the inaccuracy. The weight coefficients of the neurons in the model's ANN are presented in Table 3.15.

Table 3.15. Weight Estimates for Belgium

Predictor		Parameter Estimates		
		Hidden Layer 1		Predicted
		H(1:1)	H(1:2)	Output Layer Ecological Foot print
Input Layer	(Bias)	-,157	-1,290	
	Gross_Domestic_Product	-,442	-,228	
	Renewable_Enerji_Consumption	-,504	1,008	
	KOF_Globalization_Index	,554	-,012	
Hidden Layer 1	(Bias)			-1,033
	H(1:1)			,875
	H(1:2)			-1,634

The network is trained by changing the weights of the connections between neurons in each layer. The importance table of the independent variables is given in Table 3.16 to see how important each of the independent variables is in predicting the dependent variable.

Table 3.16. Significance of Independent Variables for Belgium

Independent Variable Importance		
	Importance	Normalized Importance
Gross_Domestic_Product	,116	16,1%
Renewable_Enerji_Consumption	,721	100,0%
KOF_Globalization_Index	,163	22,6%

According to the data obtained, it was concluded that renewable energy consumption in Belgium has an importance of 72.1% in estimating the ecological footprint. The values were normalized to 72.1% and the rest of the 100 variables were found to have no very high weight. The second is KOF Globalization Index, which has an importance of approximately 22.6%.

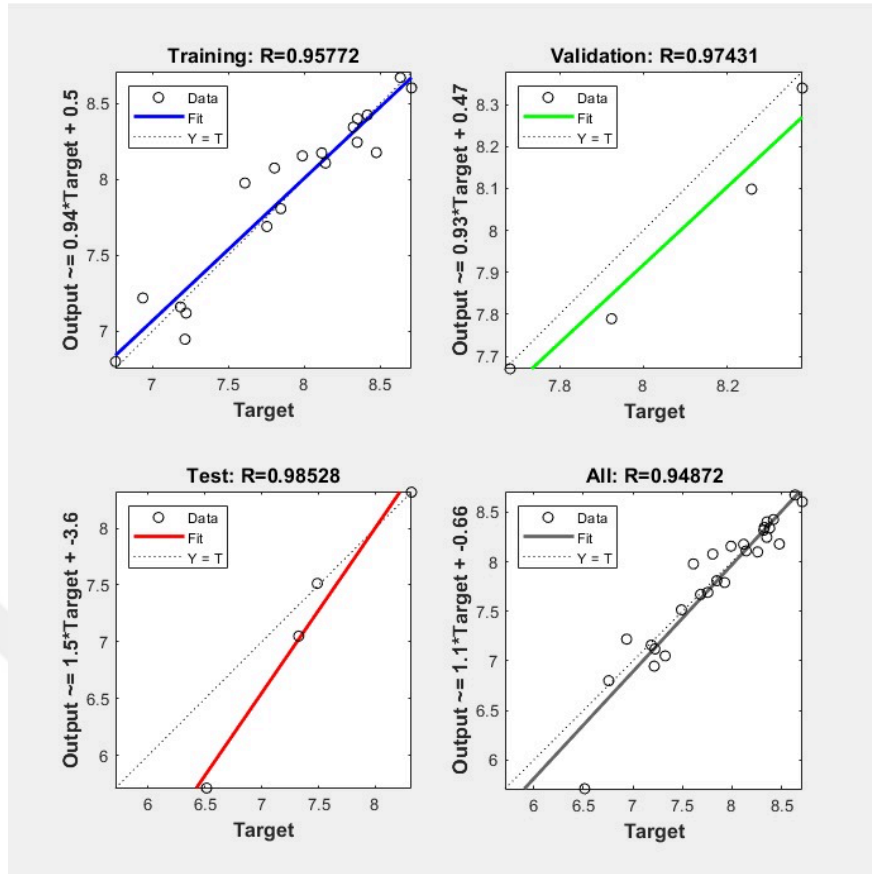


Figure 3.10. Regression Distribution of ANNs for Belgium

As a result of the applied model, Figure 3.10. shows the correlation between all the values of the derived model after training, validation, testing and prediction. Training data showed a success rate of $R^2 = 0.95772$, validation data showed a success rate of $R^2 = 0.97431$ and testing data showed a success rate of $R^2 = 0.98528$. The performance metric of the network for the entire dataset is $R^2 = 0.94872$. This rate shows that the network is quite successful. Upon examination of the findings, the effectiveness of the developed model is obvious. The results show that there is a robust relationship between the actual values and the predicted values across all the datasets.

3.3.2.1.4. Artificial Neural Network Model for Canada

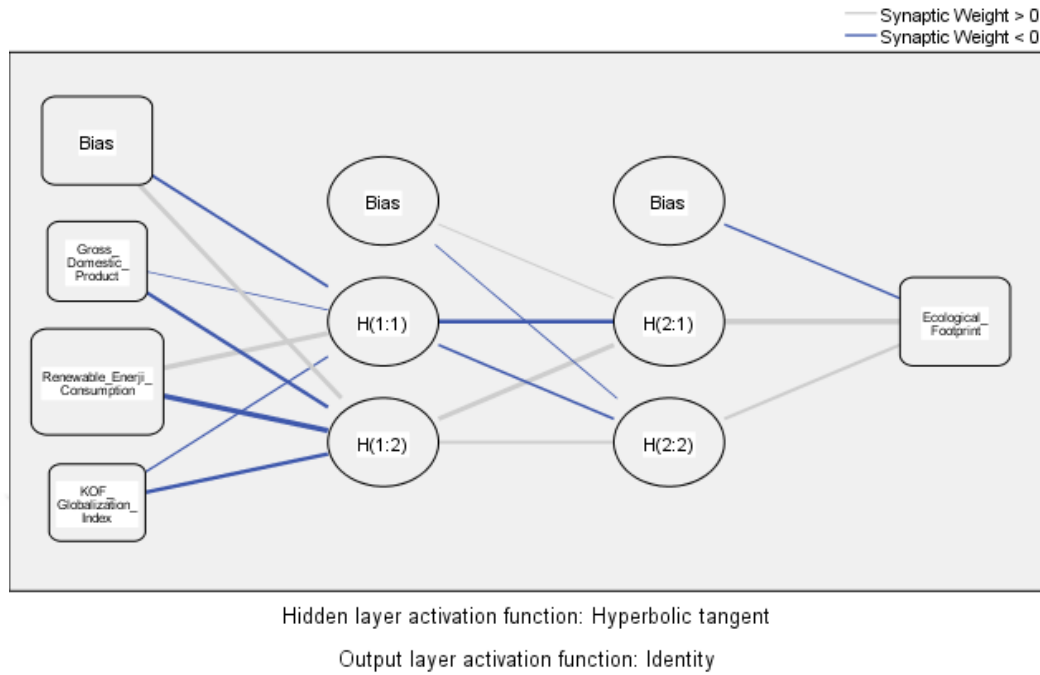


Figure 3.11. ANN Model of Canada

Figure 3.11 illustrates a two-hidden-layer ANN model designed for Canada, an OECD member country. The network architecture comprises three neurons in the input layer, two neurons in the hidden layer, and a single neuron in the output layer. This model adopts a two-layer neural structure with two neurons in the hidden layer. The hyperbolic tangent function is employed as the activation function within the hidden layer, facilitating non-linear transformations and enabling the network to capture complex patterns and relationships within the data.

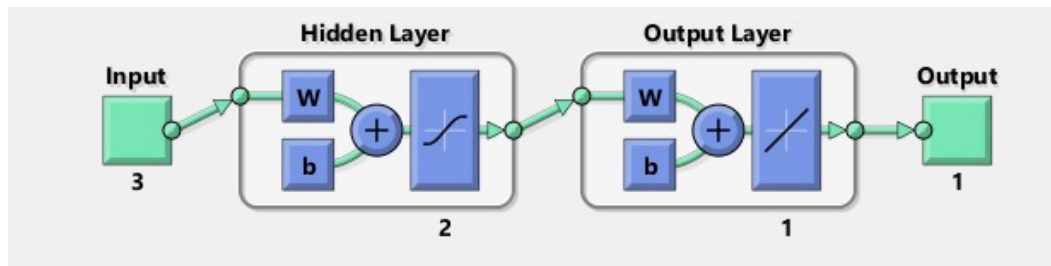


Figure 3.12. MATLAB Implementation of ANN Model for Canada

The input data were analyzed and pre-processed utilizing MATLAB software. Following this step, an ANN model was designed and implemented to address the research objectives. The architecture and structure of the developed ANN model, including the arrangement of input, hidden, and output layers, are illustrated in Figure 3.12.

Table 3.17. Summary of the Model for Canada

Model Summary		
Training	Sum of Squares Error	4,515
	Relative Error	,475
	Stopping Rule Used	1 consecutive step(s) with no decrease in error ^a
	Training Time	0:00:00,02
Testing	Sum of Squares Error	2,042
	Relative Error	,455

Dependent Variable: Ecological Footprint

a. Error computations are based on the testing sample.

Table 3.17. presents the outcomes of the training and test sets for the model, together with the values of the cumulative squared errors. The test data exhibits a 0.455 proportion of erroneous predictions, indicating an accuracy of 54.5% in the assessment. Weight values were established to minimize the inaccuracy. The weight coefficients of the neurons in the model's ANN are presented in Table 3.18.

Table 3.18. Weight Estimates for Canada

Parameter Estimates					
Predictor		Hidden Layer 1		Predicted Hidden Layer 2	Output Layer Ecological Footprint
		H(1:1)	H(1:2)	H(2:1)	H(2:2)
Input Layer	(Bias)	-,534	,708		
	Gross_Domestic_Product	-,058	-,588		
	Renewable_Enerji_Consumption	,805	-,827		
	KOF_Globalization_Index	-,311	-,596		
Hidden Layer 1	(Bias)			,201	-,087
	H(1:1)			-,676	-,370
	H(1:2)			,708	,547
Hidden Layer 2	(Bias)				-,345
	H(2:1)				,954
	H(2:2)				,555

The network is trained by changing the weights of the connections between neurons in each layer. The importance table of the independent variables is given in Table 3.19 to see how important each of the independent variables is in predicting the dependent variable.

Table 3.19. Significance of Independent Variables for Canada

Independent Variable Importance		
	Importance	Normalized Importance
Gross_Domestic_Product	,179	25,7%
Renewable_Enerji_Consumption	,695	100,0%
KOF_Globalization_Index	,126	18,1%

According to the data obtained, it was concluded that renewable energy consumption in Belgium has an importance of 69.5% in estimating the ecological footprint. The values were normalized to 69.5% and the rest of the 100 variables were found to have no very high weight. The second is Gross Domestic Product, which has an importance of approximately 25.7%.

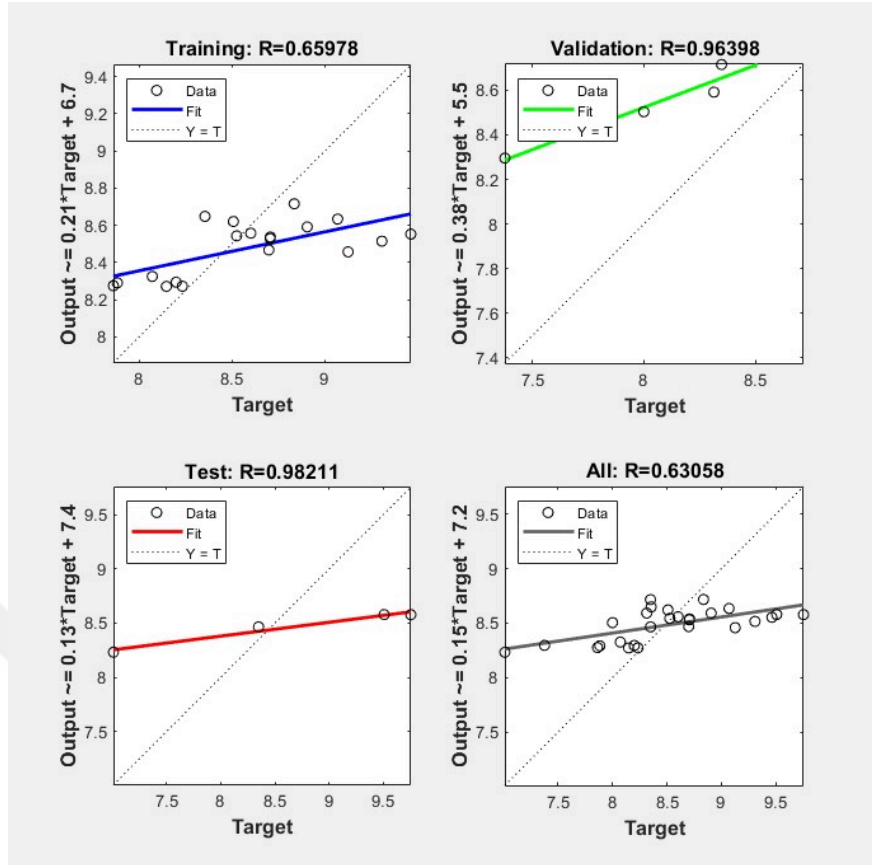


Figure 3.13. Regression Distribution of ANNs for Canada

As a result of the applied model, Figure 3.13. shows the correlation between all the values of the derived model after training, validation, testing and prediction. Training data showed a success rate of $R^2 = 0.65978$, validation data showed a success rate of $R^2 = 0.96398$ and testing data showed a success rate of $R^2 = 0.98211$. The performance metric of the network for the entire dataset is $R^2 = 0.63058$.

3.3.2.1.5. Artificial Neural Network Model for Switzerland

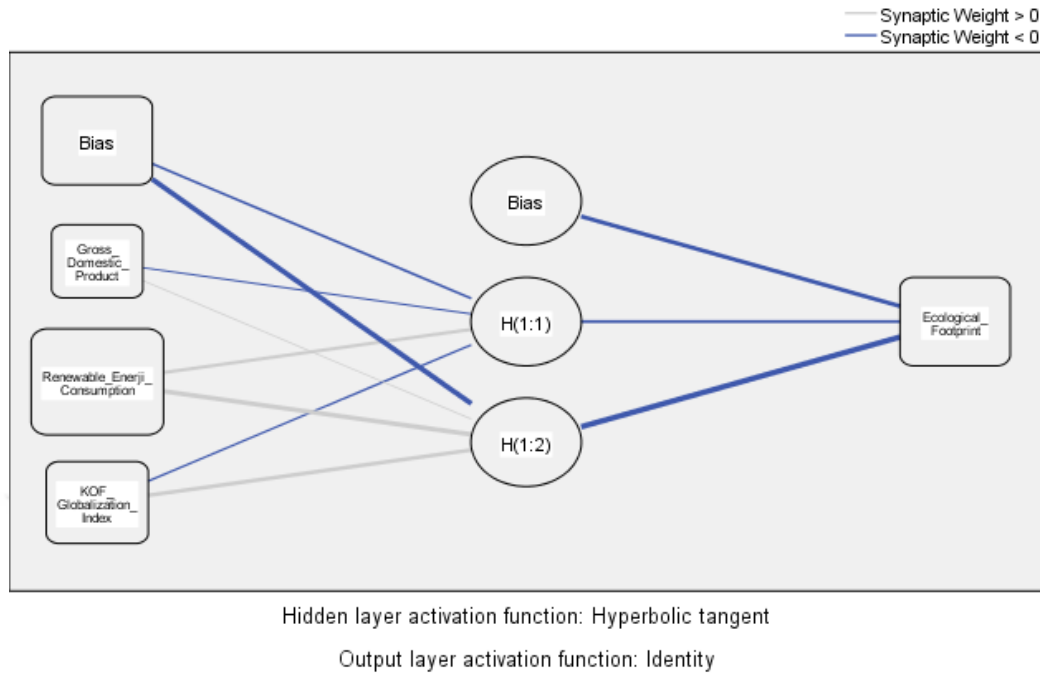


Figure 3.14. ANN Model of Switzerland

Figure 3.14 illustrates an ANN model designed for Austria, which is a member of the OECD. The network architecture consists of a single hidden layer and is structured with three neurons in the input layer, two neurons in the hidden layer, and one neuron in the output layer. The model employs a feedforward neural network configuration, where each neuron in one layer is fully connected to the neurons in the subsequent layer. A hyperbolic tangent (tanh) activation function is utilized in the hidden layer.

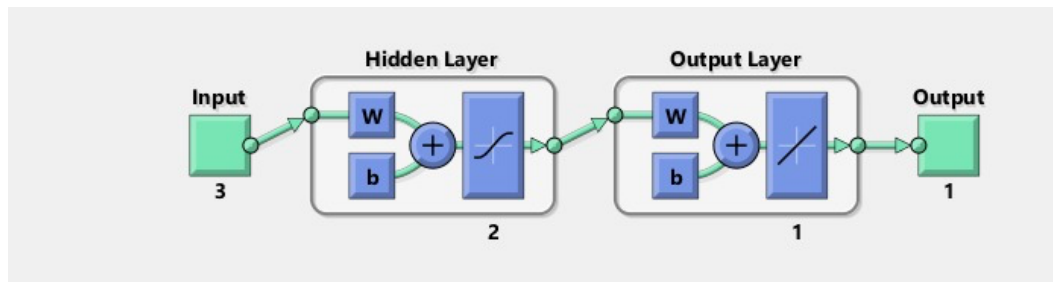


Figure 3.15. MATLAB Implementation of ANN Model for Switzerland

The input data were analyzed and pre-processed utilizing MATLAB software. Following this step, an ANN model was designed and implemented to address the research objectives. The architecture and structure of the developed ANN model, including the arrangement of input, hidden, and output layers, are illustrated in Figure 3.15.

Table 3.20. Summary of the Model for Switzerland

Model Summary		
Training	Sum of Squares Error	,672
	Relative Error	,071
	Stopping Rule Used	1 consecutive step(s) with no decrease in error ^a
	Training Time	0:00:00,00
Testing	Sum of Squares Error	,084
	Relative Error	,015

Dependent Variable: Ecological Footprint

a. Error computations are based on the testing sample.

Table 3.20. presents the outcomes of the training and test sets for the model, together with the values of the cumulative squared errors. The test data exhibits a 0.015 proportion of erroneous predictions, indicating an accuracy of 98.5% in the assessment. The objective is to employ the activation function according to the relevance levels of the inputs. Weight values were established to minimize the inaccuracy. The weight coefficients of the neurons in the model's ANN are presented in Table 3.21.

Table 3.21. Weight Estimates for Switzerland

Predictor		Hidden Layer 1		Predicted
		H(1:1)	H(1:2)	Output Layer Ecological_Foot print
Input Layer	(Bias)	-,334	-,959	
	Gross_Domestic_Product	-,171	,046	
	Renewable_Enerji_Consumption	,566	,837	
	KOF_Globalization_Index	-,292	,593	
Hidden Layer 1	(Bias)			-,639
	H(1:1)			-,488
	H(1:2)			-1,261

The network is trained by changing the weights of the connections between neurons in each layer. The importance table of the independent variables is given in Table 3.22 to see how important each of the independent variables is in predicting the dependent variable.

Table 3.22. Significance of Independent Variables for Switzerland

Independent Variable Importance		
	Importance	Normalized Importance
Gross_Domestic_Product	,050	7,0%
Renewable_Enerji_Consumption	,723	100,0%
KOF_Globalization_Index	,227	31,3%

According to the data obtained, it was concluded that renewable energy consumption in Switzerland has an importance of 72.3% in estimating the ecological footprint. The values were normalized to 72.3% and the rest of the 100 variables were found to have no very high weight. The second is KOF Globalization Index, which has an importance of approximately 31.3%.

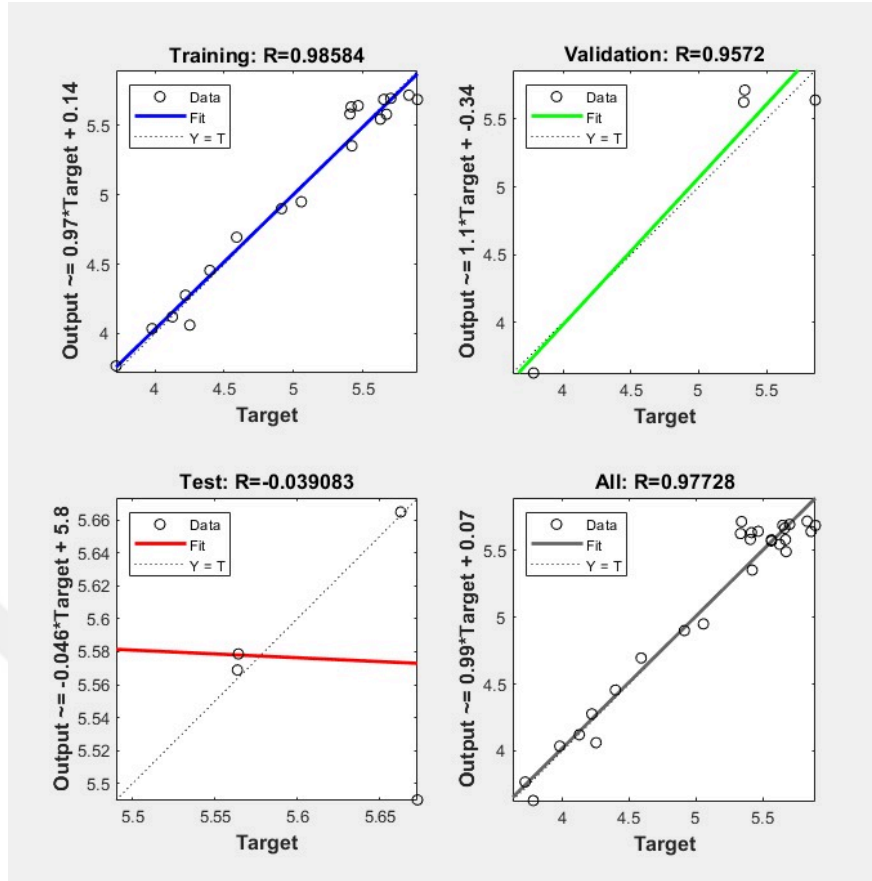


Figure 3.16. Regression Distribution of ANNs for Switzerland

As a result of the applied model, Figure 3.16. shows the correlation between all the values of the derived model after training, validation, testing and prediction. Training data showed a success rate of $R^2 = 0.98584$, validation data showed a success rate of $R^2 = 0.9572$. The performance metric of the network for the entire dataset is $R^2 = 0.97728$. This rate shows that the network is quite successful. Upon examination of the findings, the effectiveness of the developed model is obvious. The results show that there is a robust relationship between the actual values and the predicted values across all the datasets.

3.3.2.1.6. Artificial Neural Network Model for Chile

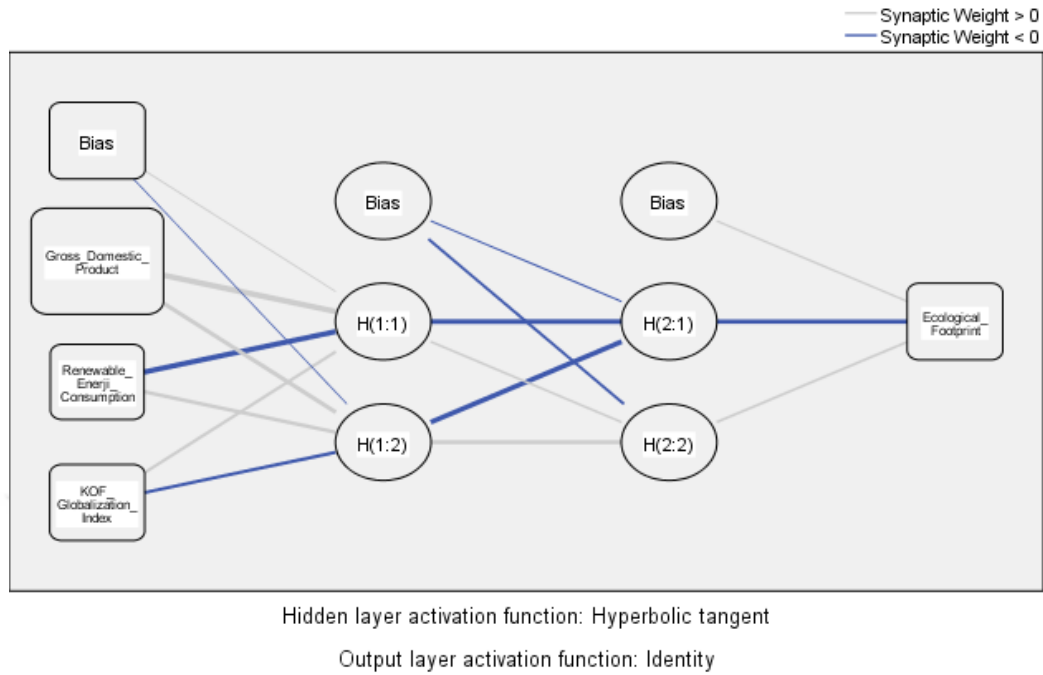


Figure 3.17. ANN Model of Chile

Figure 3.17 illustrates a two-hidden-layer ANN model designed for Chile, an OECD member country. The network architecture comprises three neurons in the input layer, two neurons in the hidden layer, and a single neuron in the output layer. This model adopts a two-layer neural structure with two neurons in the hidden layer. The hyperbolic tangent function is employed as the activation function within the hidden layer, facilitating non-linear transformations and enabling the network to capture complex patterns and relationships within the data.

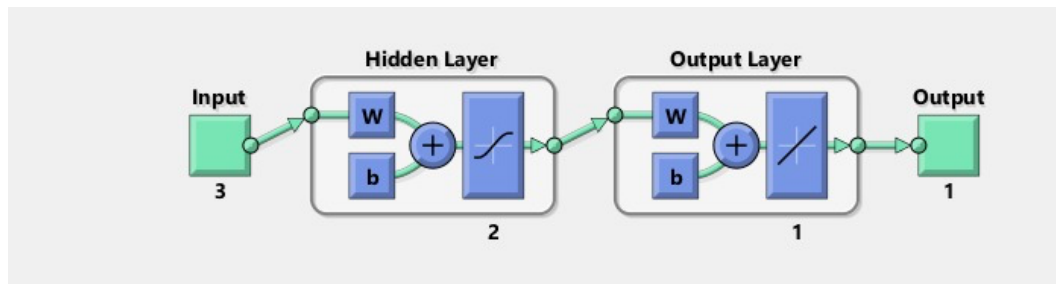


Figure 3.18. MATLAB Implementation of ANN Model for Chile

The input data were analyzed and pre-processed utilizing MATLAB software. Following this step, an ANN model was designed and implemented to address the research objectives. The architecture and structure of the developed ANN model, including the arrangement of input, hidden, and output layers, are illustrated in Figure 3.18.

Table 3.23. Summary of the Model for Chile

Model Summary		
Training	Sum of Squares Error	3,153
	Relative Error	,332
	Stopping Rule Used	1 consecutive step(s) with no decrease in error ^a
	Training Time	0:00:00,00
Testing	Sum of Squares Error	1,396
	Relative Error	,316
Dependent Variable: Ecological_Footprint		
a. Error computations are based on the testing sample.		

Table 3.23. presents the outcomes of the training and test sets for the model, together with the values of the cumulative squared errors. The test data exhibits a 0.316 proportion of erroneous predictions, indicating an accuracy of 68.4% in the assessment. The objective is to employ the activation function according to the relevance levels of the inputs. Weight values were established to minimize the inaccuracy. The weight coefficients of the neurons in the model's ANN are presented in Table 3.24.

Table 3.24. Weight Estimates for Chile

Parameter Estimates					
Predictor		Hidden Layer 1		Predicted Hidden Layer 2	Output Layer Ecological Footprint
		H(1:1)	H(1:2)	H(2:1)	H(2:2)
Input Layer	(Bias)	,096	-,076		
	Gross_Domestic_Product	2,298	,908		
	Renewable_Enerji_Consumption	-1,980	,755		
	KOF_Globalization_Index	,607	-,699		
Hidden Layer 1	(Bias)			-,118	-,568
	H(1:1)			-1,211	,488
	H(1:2)			-1,627	,861
Hidden Layer 2	(Bias)				,270
	H(2:1)				-1,169
	H(2:2)				,488

The network is trained by changing the weights of the connections between neurons in each layer. The importance table of the independent variables is given in Table 3.25 to see how important each of the independent variables is in predicting the dependent variable.

Table 3.25. Significance of Independent Variables for Chile

Independent Variable Importance		
	Importance	Normalized Importance
Gross_Domestic_Product	,509	100,0%
Renewable_Enerji_Consumption	,242	47,5%
KOF_Globalization_Index	,250	49,0%

According to the data obtained, it was concluded that gross domestic product in Chile has an importance of 50.9% in estimating the ecological footprint. The values were normalized to 50.9% and the rest of the 100 variables were found to have no very high weight. The second one is KOF Globalization Index, which has an importance of approximately 49.0%.

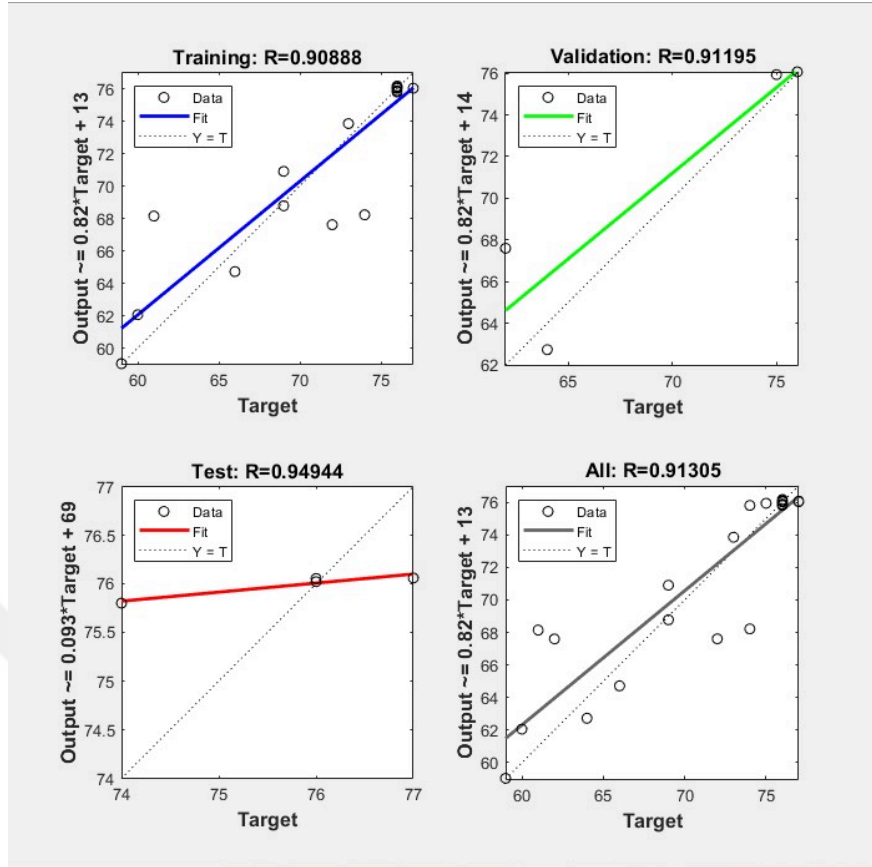


Figure 3.19. Regression Distribution of ANNs for Chile

As a result of the applied model, Figure 3.19. shows the correlation between all the values of the derived model after training, validation, testing and prediction. Training data showed a success rate of $R^2 = 0.90888$, validation data showed a success rate of $R^2 = 0.91195$ and testing data showed a success rate of $R^2 = 0.94944$. The performance metric of the network for the entire dataset is $R^2 = 0.91305$. This rate shows that the network is quite successful. Upon examination of the findings, the effectiveness of the developed model is obvious. The results show that there is a robust relationship between the actual values and the predicted values across all the datasets.

3.3.2.1.7. Artificial Neural Network Model for Colombia

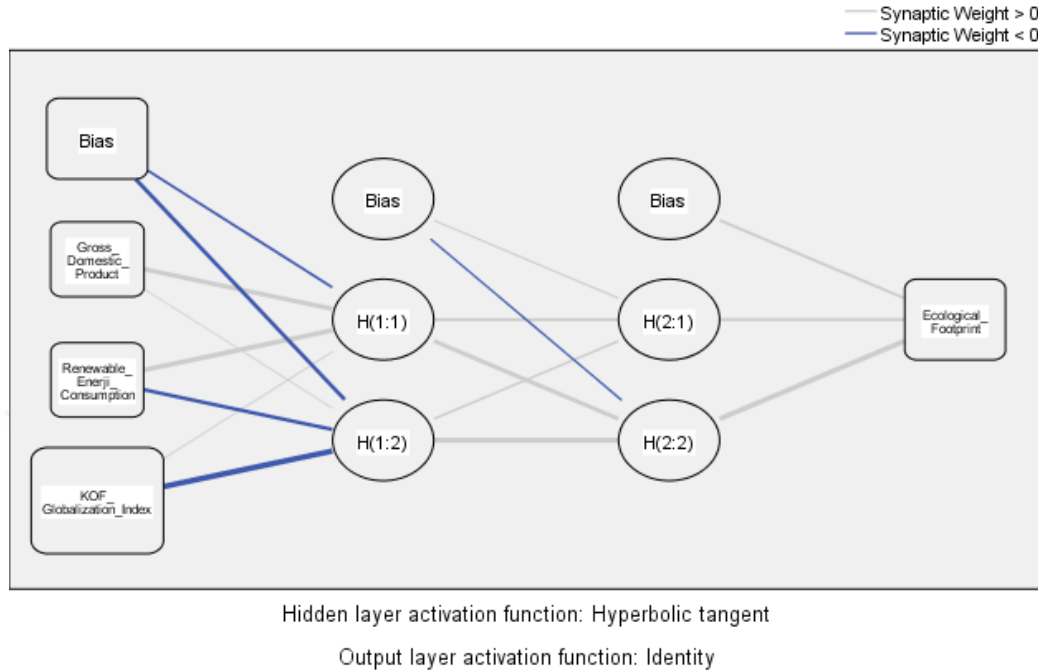


Figure 3.20. ANN Model of Colombia

Figure 3.20 illustrates a two-hidden-layer ANN model designed for Colombia, an OECD member country. The network architecture comprises three neurons in the input layer, two neurons in the hidden layer, and a single neuron in the output layer. This model adopts a two-layer neural structure with two neurons in the hidden layer. The hyperbolic tangent function is employed as the activation function within the hidden layer, facilitating non-linear transformations and enabling the network to capture complex patterns and relationships within the data.

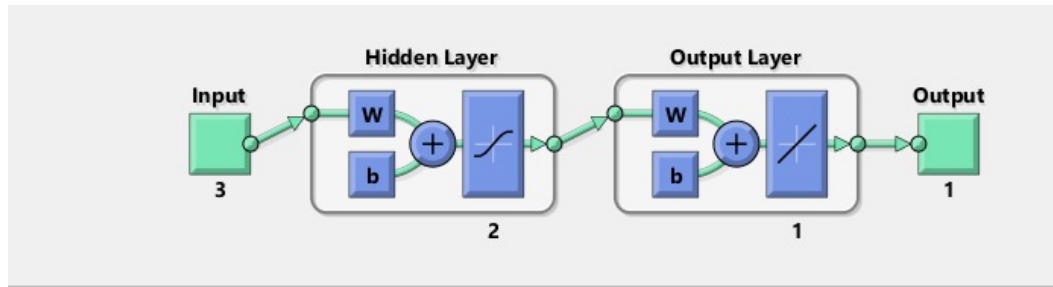


Figure 3.21. MATLAB Implementation of ANN Model for Colombia

The input data were analyzed and pre-processed utilizing MATLAB software. Following this step, an ANN model was designed and implemented to address the research objectives. The architecture and structure of the developed ANN model, including the arrangement of input, hidden, and output layers, are illustrated in Figure 3.21.

Table 3.26. Summary of the Model for Colombia

Model Summary		
Training	Sum of Squares Error	2,670
	Relative Error	,314
	Stopping Rule Used	1 consecutive step(s) with no decrease in error ^a
	Training Time	0:00:00,00
Testing	Sum of Squares Error	2,352
	Relative Error	,581

Dependent Variable: Ecological Footprint

a. Error computations are based on the testing sample.

Table 3.26. presents the outcomes of the training and test sets for the model, together with the values of the cumulative squared errors. The test data exhibits a 0.581 proportion of erroneous predictions, indicating an accuracy of 41.9% in the assessment. The objective is to employ the activation function according to the relevance levels of the inputs. Weight values were established to minimize the inaccuracy. The weight coefficients of the neurons in the model's ANN are presented in Table 3.27.

Table 3.27. Weight Estimates for Colombia

Parameter Estimates					
Predictor		Hidden Layer 1		Predicted Hidden Layer 2	
		H(1:1)	H(1:2)	H(2:1)	H(2:2)
Input Layer	(Bias)	-,543	-,929		
	Gross_Domestic_Product	1,085	,002		
	Renewable_Enerji_Consumption	1,369	-,616		
	KOF_Globalization_Index	,094	-1,987		
Hidden Layer 1	(Bias)			,101	-,313
	H(1:1)			,593	1,021
	H(1:2)			,364	1,737
Hidden Layer 2	(Bias)				,562
	H(2:1)				,606
	H(2:2)				1,439

The network is trained by changing the weights of the connections between neurons in each layer. The importance table of the independent variables is given in Table 3.28 to see how important each of the independent variables is in predicting the dependent variable.

Table 3.28. Significance of Independent Variables for Colombia

Independent Variable Importance		
	Importance	Normalized Importance
Gross_Domestic_Product	,218	38,2%
Renewable_Enerji_Consumption	,213	37,4%
KOF_Globalization_Index	,569	100,0%

According to the data obtained, it was concluded that KOF Globalization Index in Colombia has an importance of 56.9% in estimating the ecological footprint. The values were normalized to 56.9% and the rest of the 100 variables were found to have very close values. The second is the gross domestic product index, which has an importance of approximately 38.2%. Then, renewable energy consumption affects the ecological footprint by 37.4%.

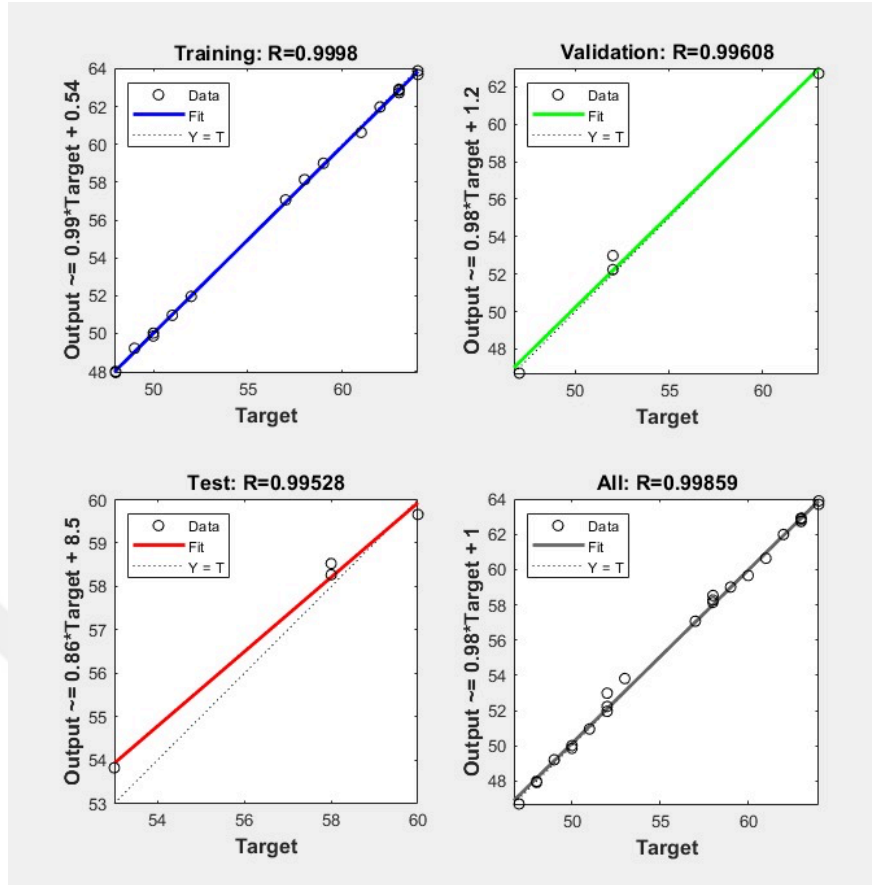


Figure 3.22. Regression Distribution of ANNs for Colombia

As a result of the applied model, Figure 3.22. shows the correlation between all the values of the derived model after training, validation, testing and prediction. Training data showed a success rate of $R^2 = 0.9998$, validation data showed a success rate of $R^2 = 0.99608$ and testing data showed a success rate of $R^2 = 0.99528$. The performance metric of the network for the entire dataset is $R^2 = 0.99859$. This rate shows that the network is quite successful. Upon examination of the findings, the effectiveness of the developed model is obvious. The results show that there is a robust relationship between the actual values and the predicted values across all the datasets.

3.3.2.1.8. Artificial Neural Network Model for Costa Rica

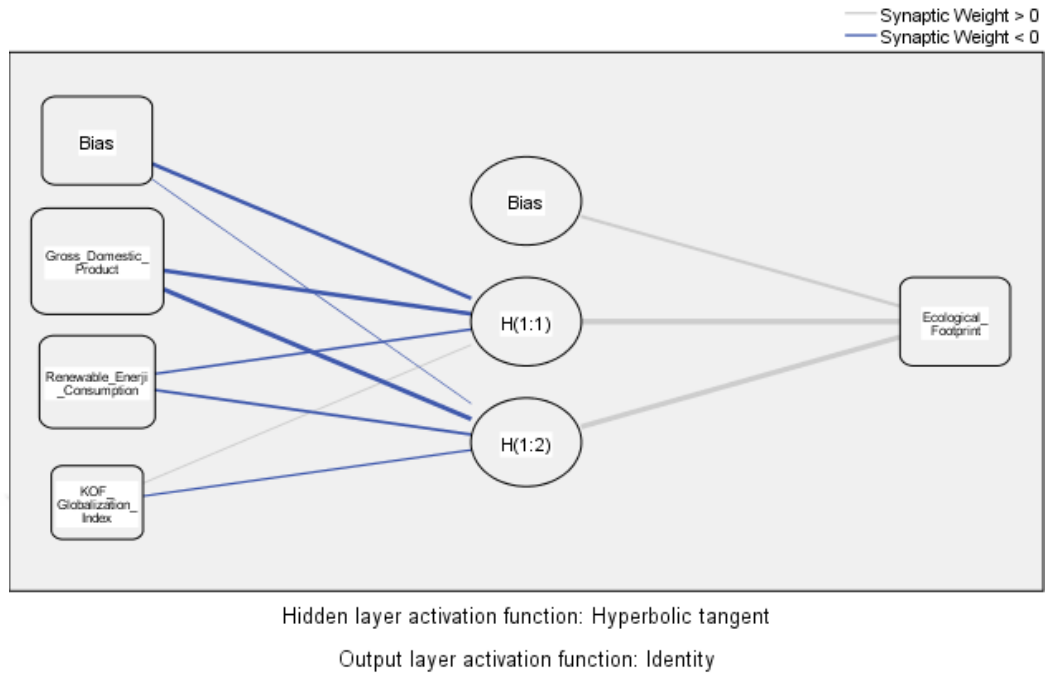


Figure 3.23. ANN Model of Costa Rica

Figure 3.23 illustrates an ANN model designed for Costa Rica, which is a member of the OECD. The network architecture consists of a single hidden layer and is structured with three neurons in the input layer, two neurons in the hidden layer, and one neuron in the output layer. The model employs a feedforward neural network configuration, where each neuron in one layer is fully connected to the neurons in the subsequent layer. A hyperbolic tangent (tanh) activation function is utilized in the hidden layer.

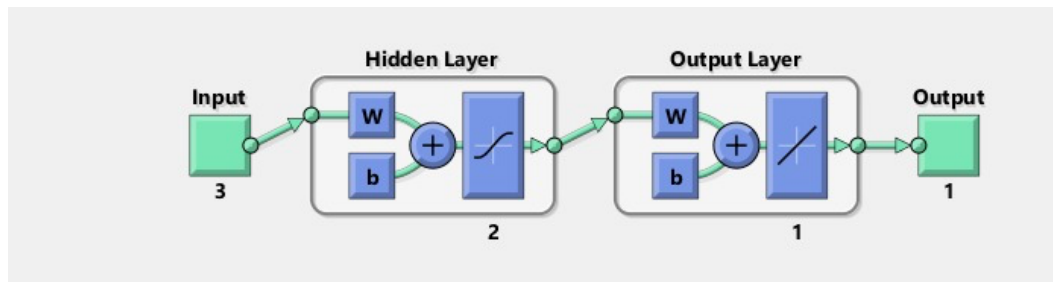


Figure 3.24. MATLAB Implementation of ANN Model for Costa Rica

The input data were analyzed and pre-processed utilizing MATLAB software. Following this step, an ANN model was designed and implemented to address the research objectives. The architecture and structure of the developed ANN model, including the arrangement of input, hidden, and output layers, are illustrated in Figure 3.24.

Table 3.29. Summary of the Model for Costa Rica

Model Summary		
Training	Sum of Squares Error	5,057
	Relative Error	,562
	Stopping Rule Used	1 consecutive step(s) with no decrease in error ^a
	Training Time	0:00:00,00
Testing	Sum of Squares Error	1,081
	Relative Error	,369
Dependent Variable: Ecological Footprint		
a. Error computations are based on the testing sample.		

Table 3.29. presents the outcomes of the training and test sets for the model, together with the values of the cumulative squared errors. The test data exhibits a 0.369 proportion of erroneous predictions, indicating an accuracy of 63.1% in the assessment. The objective is to employ the activation function according to the relevance levels of the inputs. Weight values were established to minimize the inaccuracy. The weight coefficients of the neurons in the model's ANN are presented in Table 3.30.

Table 3.30. Weight Estimates for Costa Rica

Predictor		Hidden Layer 1		Predicted
		H(1:1)	H(1:2)	Output Layer
				Ecological_Footprint
Input Layer	(Bias)	-,352	-,054	
	Gross_Domestic_Product	-,421	-,568	
	Renewable_Enerji_Consumption	-,225	-,249	
	KOF_Globalization_Index	,173	-,187	
Hidden Layer 1	(Bias)			,256
	H(1:1)			,758
	H(1:2)			,682

The network is trained by changing the weights of the connections between neurons in each layer. The importance table of the independent variables is given in Table 3.31 to see how important each of the independent variables is in predicting the dependent variable.

Table 3.31. Significance of Independent Variables for Costa Rica

Independent Variable Importance		
	Importance	Normalized Importance
Gross_Domestic_Product	,590	100,0%
Renewable_Enerji_Consumption	,365	61,8%
KOF_Globalization_Index	,045	7,7%

According to the data obtained, it was concluded that gross domestic product in Costa Rica has an importance of 59% in estimating the ecological footprint. The values were normalized to 59% and the rest of the 100 variables were found to have no very high weight. The second is Renewable Energy consumption, which has an importance of approximately 61.8%.

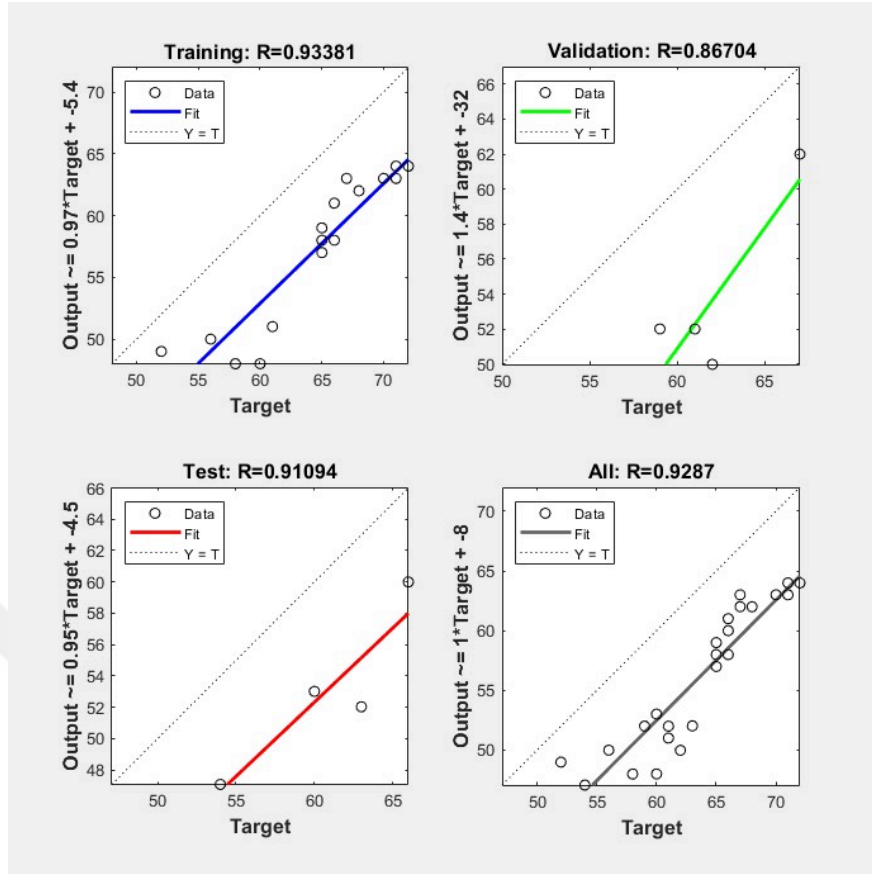


Figure 3.25. Regression Distribution of ANNs for Costa Rica

As a result of the applied model, Figure 3.25. shows the correlation between all the values of the derived model after training, validation, testing and prediction. Training data showed a success rate of $R^2 = 0.93381$, validation data showed a success rate of $R^2 = 0.86704$ and testing data showed a success rate of $R^2 = 0.91094$. The performance metric of the network for the entire dataset is $R^2 = 0.9287$. This rate shows that the network is quite successful. Upon examination of the findings, the effectiveness of the developed model is obvious. The results show that there is a robust relationship between the actual values and the predicted values across all the datasets.

3.3.2.1.9. Artificial Neural Network Model for Czech Republic

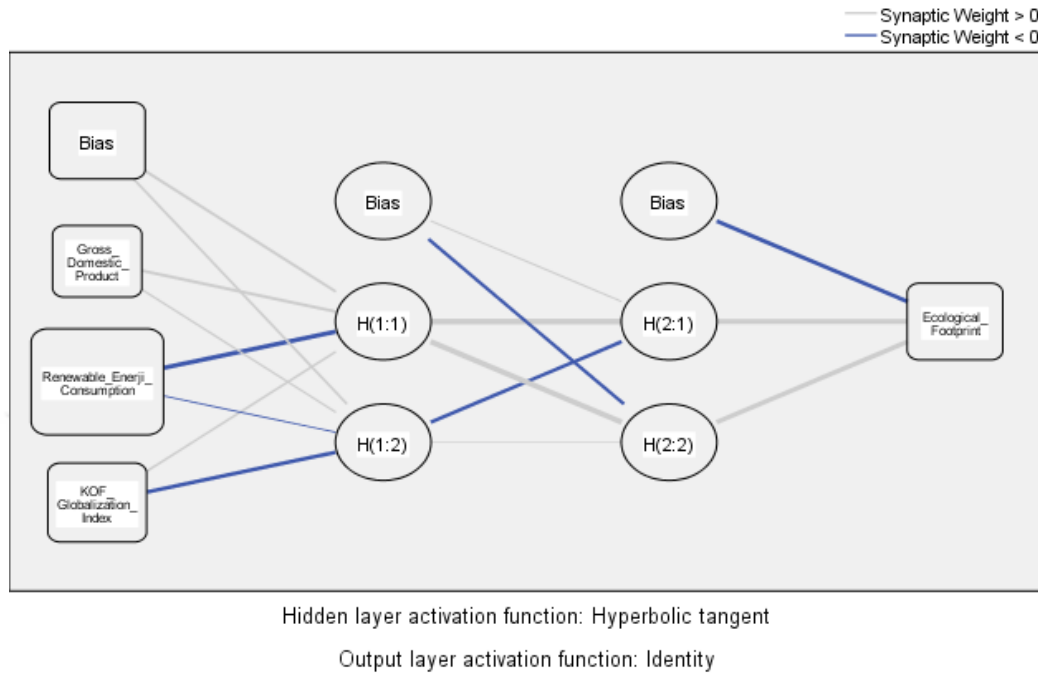


Figure 3.26. ANN Model of Czech Republic

Figure 3.26 illustrates a two-hidden-layer ANN model designed for Czech Republic, an OECD member country. The network architecture comprises three neurons in the input layer, two neurons in the hidden layer, and a single neuron in the output layer. This model adopts a two-layer neural structure with two neurons in the hidden layer. The hyperbolic tangent function is employed as the activation function within the hidden layer, facilitating non-linear transformations and enabling the network to capture complex patterns and relationships within the data.

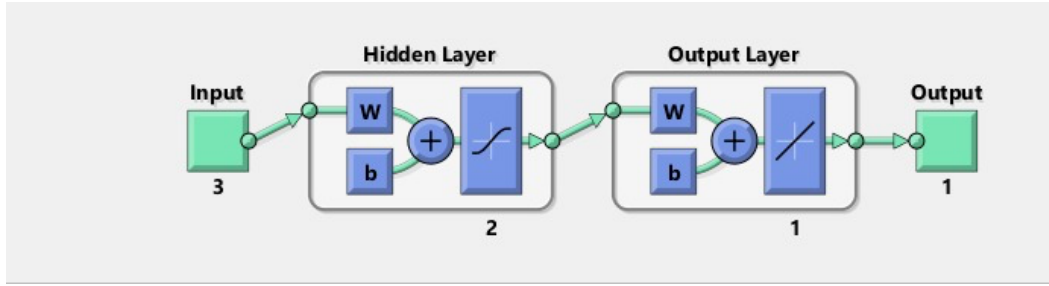


Figure 3.27. MATLAB Implementation of ANN Model for Czech Republic

The input data were analyzed and pre-processed utilizing MATLAB software. Following this step, an ANN model was designed and implemented to address the research objectives. The architecture and structure of the developed ANN model, including the arrangement of input, hidden, and output layers, are illustrated in Figure 3.27.

Table 3.32. Summary of the Model for Czech Republic

Model Summary		
Training	Sum of Squares Error	3,555
	Relative Error	,418
	Stopping Rule Used	1 consecutive step(s) with no decrease in error ^a
	Training Time	0:00:00,00
Testing	Sum of Squares Error	,899
	Relative Error	,429

Dependent Variable: Ecological_Footprint

a. Error computations are based on the testing sample.

Table 3.32. presents the outcomes of the training and test sets for the model, together with the values of the cumulative squared errors. The test data exhibits a 0.429 proportion of erroneous predictions, indicating an accuracy of 57.1% in the assessment. The objective is to employ the activation function according to the relevance levels of the inputs. Weight values were

established to minimize the inaccuracy. The weight coefficients of the neurons in the model's ANN are presented in Table 3.33.

Table 3.33. Weight Estimates for Czech Republic

Parameter Estimates					
Predictor		Hidden Layer 1		Predicted Hidden Layer 2	
		H(1:1)	H(1:2)	H(2:1)	H(2:2)
Input Layer	(Bias)	,245	,220		
	Gross_Domestic_Product	,265	,206		
	Renewable_Enerji_Consump tion	-,667	-,126		
	KOF_Globalization_Index	,207	-,509		
Hidden Layer 1	(Bias)			,194	-,386
	H(1:1)			1,754	1,563
	H(1:2)			-,436	,028
Hidden Layer 2	(Bias)				-,519
	H(2:1)				1,261
	H(2:2)				,683

The network is trained by changing the weights of the connections between neurons in each layer. The importance table of the independent variables is given in Table 3.34 to see how important each of the independent variables is in predicting the dependent variable.

Table 3.34. Significance of Independent Variables for Czech Republic

Independent Variable Importance		
	Importance	Normalized Importance
Gross_Domestic_Product	,211	41,2%
Renewable_Enerji_Consumption	,512	100,0%
KOF_Globalization_Index	,277	54,0%

According to the obtained data, it was concluded that renewable energy consumption in the Czech Republic has an importance of 0.512 in estimating the ecological footprint. The values were normalized to 51.2%, and it was determined that the KOF Globalization Index provided 54% importance and the gross domestic product 41.2% importance in estimating the ecological footprint.

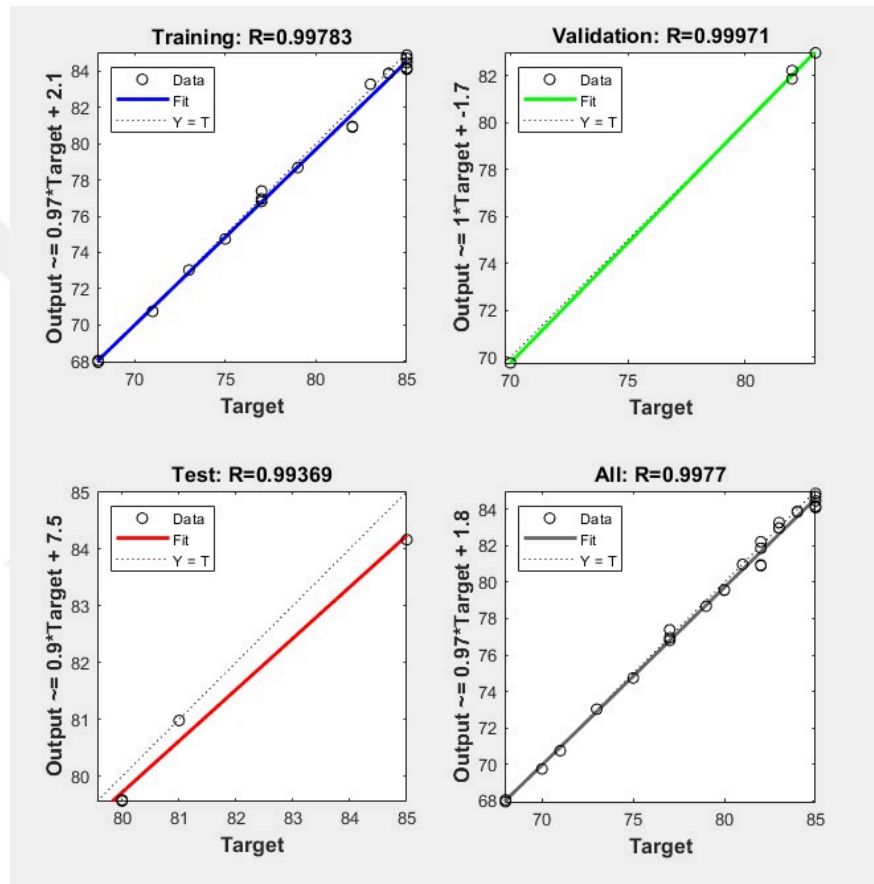


Figure 3.28. Regression Distribution of ANNs for Czech Republic

As a result of the applied model, Figure 3.28. shows the correlation between all the values of the derived model after training, validation, testing and prediction. Training data showed a success rate of $R^2 = 0.99783$, validation data showed a success rate of $R^2 = 0.99971$ and testing data showed a success rate of $R^2 = 0.99369$. The performance metric of the network for the entire dataset is $R^2 = 0.9977$. This rate shows that the network is quite successful. Upon examination of the findings, the effectiveness of the developed model is obvious. The results

show that there is a robust relationship between the actual values and the predicted values across all the datasets.

3.3.2.1.10. Artificial Neural Network Model for Germany

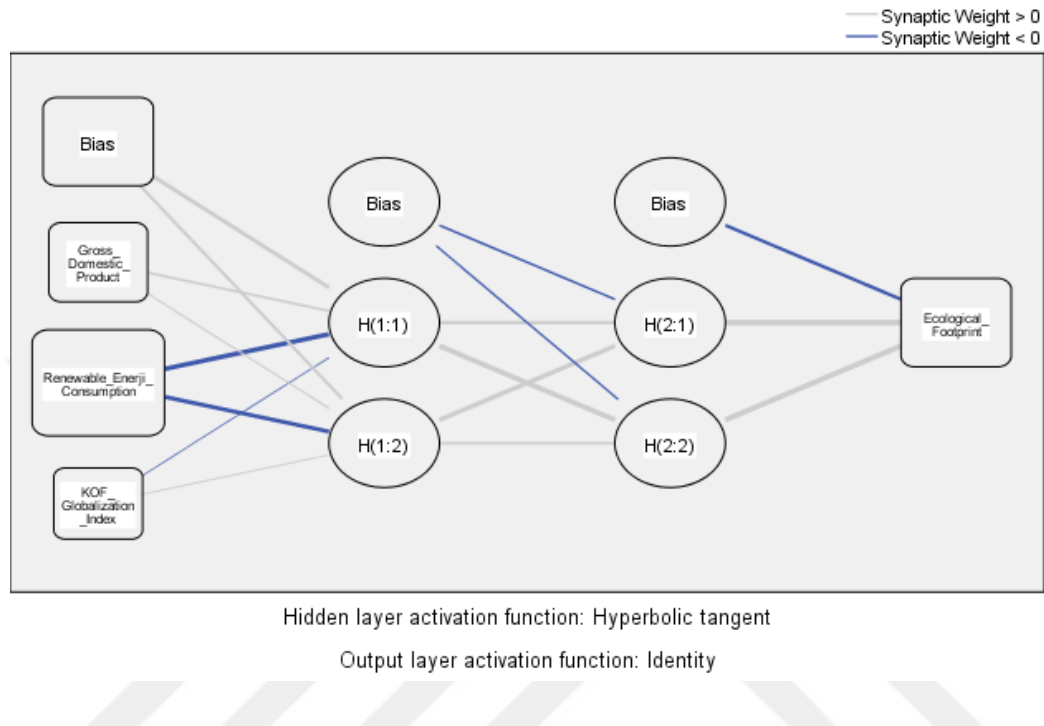


Figure 3.29. ANN Model of Germany

Figure 3.29 illustrates a two-hidden-layer ANN model designed for Germany, an OECD member country. The network architecture comprises three neurons in the input layer, two neurons in the hidden layer, and a single neuron in the output layer. This model adopts a two-layer neural structure with two neurons in the hidden layer. The hyperbolic tangent function is employed as the activation function within the hidden layer, facilitating non-linear transformations and enabling the network to capture complex patterns and relationships within the data.

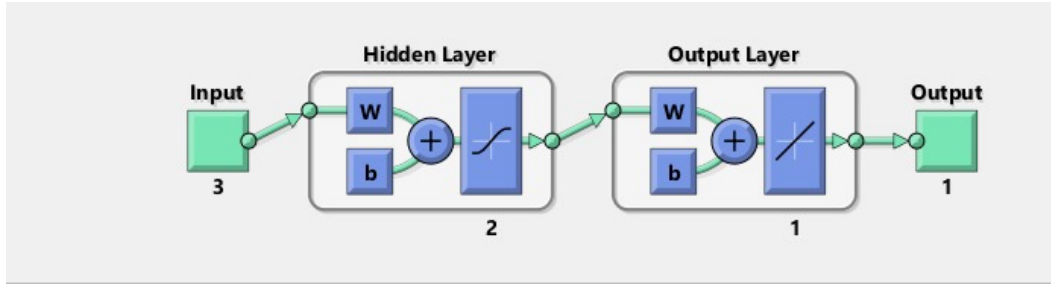


Figure 3.30. MATLAB Implementation of ANN Model for Germany

The input data were analyzed and pre-processed utilizing MATLAB software. Following this step, an ANN model was designed and implemented to address the research objectives. The architecture and structure of the developed ANN model, including the arrangement of input, hidden, and output layers, are illustrated in Figure 3.30.

Table 3.35. Summary of the Model for Germany

Model Summary		
Training	Sum of Squares Error	1,951
	Relative Error	,195
	Stopping Rule Used	1 consecutive step(s) with no decrease in error ^a
	Training Time	0:00:00,00
Testing	Sum of Squares Error	,413
	Relative Error	,140

Dependent Variable: Ecological_Footprint

a. Error computations are based on the testing sample.

Table 3.35. presents the outcomes of the training and test sets for the model, together with the values of the cumulative squared errors. The test data exhibits a 0.14 proportion of erroneous predictions, indicating an accuracy of 86% in the assessment. The objective is to employ the activation function according to the relevance levels of the inputs. Weight values were

established to minimize the inaccuracy. The weight coefficients of the neurons in the model's ANN are presented in Table 3.35.

Table 3.36. Weight Estimates for Germany

Parameter Estimates					
Predictor		Hidden Layer 1		Predicted Hidden Layer 2	Output Layer Ecological Foot print
		H(1:1)	H(1:2)	H(2:1)	H(2:2)
Input Layer	(Bias)	,540	,334		
	Gross_Domestic_Product	,259	,081		
	Renewable_Enerji_Consump tion	-,851	-,562		
	KOF_Globalization_Index	-,016	,029		
Hidden Layer 1	(Bias)			-,159	-,143
	H(1:1)			,517	,896
	H(1:2)			,750	,305
Hidden Layer 2	(Bias)				-,410
	H(2:1)				1,141
	H(2:2)				,967

The network is trained by changing the weights of the connections between neurons in each layer. The importance table of the independent variables is given in Table 3.37 to see how important each of the independent variables is in predicting the dependent variable.

Table 3.37. Significance of Independent Variables for Germany

Independent Variable Importance		
	Importance	Normalized Importance
Gross_Domestic_Product	,190	23,7%
Renewable_Enerji_Consumption	,802	100,0%
KOF_Globalization_Index	,007	0,9%

According to the data obtained, it was concluded that renewable energy consumption in Germany has an importance of 80.2% in estimating the ecological footprint. The values were normalized to 80.2% and the rest of the 100 variables were found to have no very high weight. The second is gross domestic product, which has an importance of approximately 23.7%.

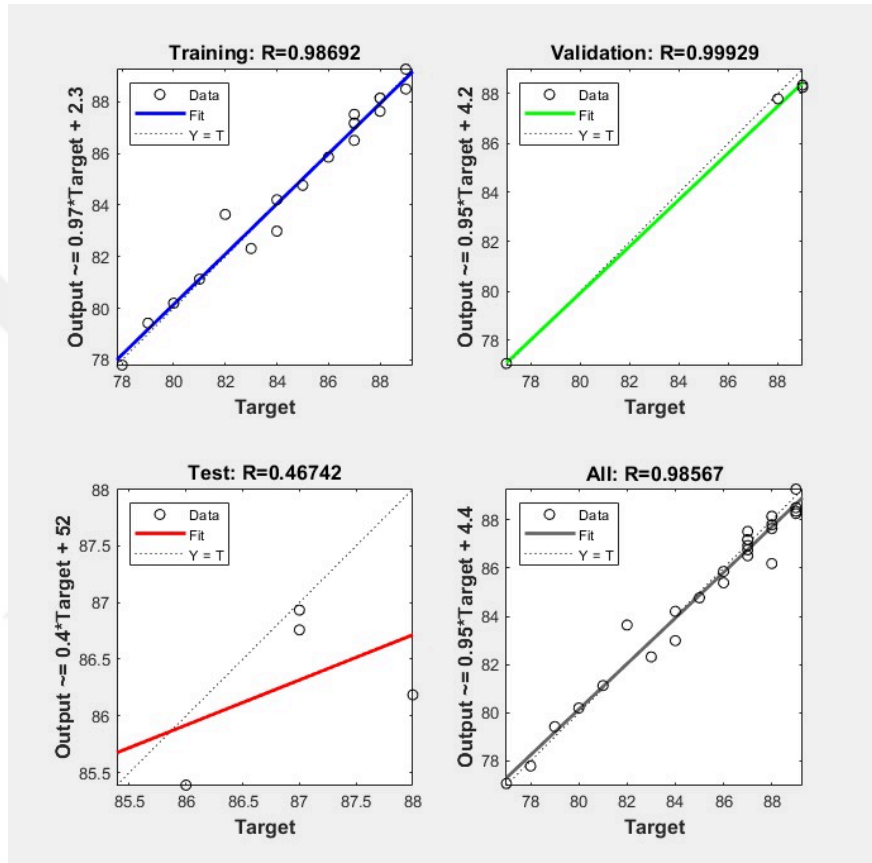


Figure 3.31. Regression Distribution of ANNs for Germany

As a result of the applied model, Figure 3.31. shows the correlation between all the values of the derived model after training, validation, testing and prediction. Training data showed a success rate of $R^2 = 0.98692$, validation data showed a success rate of $R^2 = 0.99929$ and testing data showed a success rate of $R^2 = 0.46742$. The performance metric of the network for the entire dataset is $R^2 = 0.98567$. This rate shows that the network is quite successful. Upon examination of the findings, the effectiveness of the developed model is obvious. The results

show that there is a robust relationship between the actual values and the predicted values across all the datasets.

3.3.2.1.11. Artificial Neural Network Model for Denmark

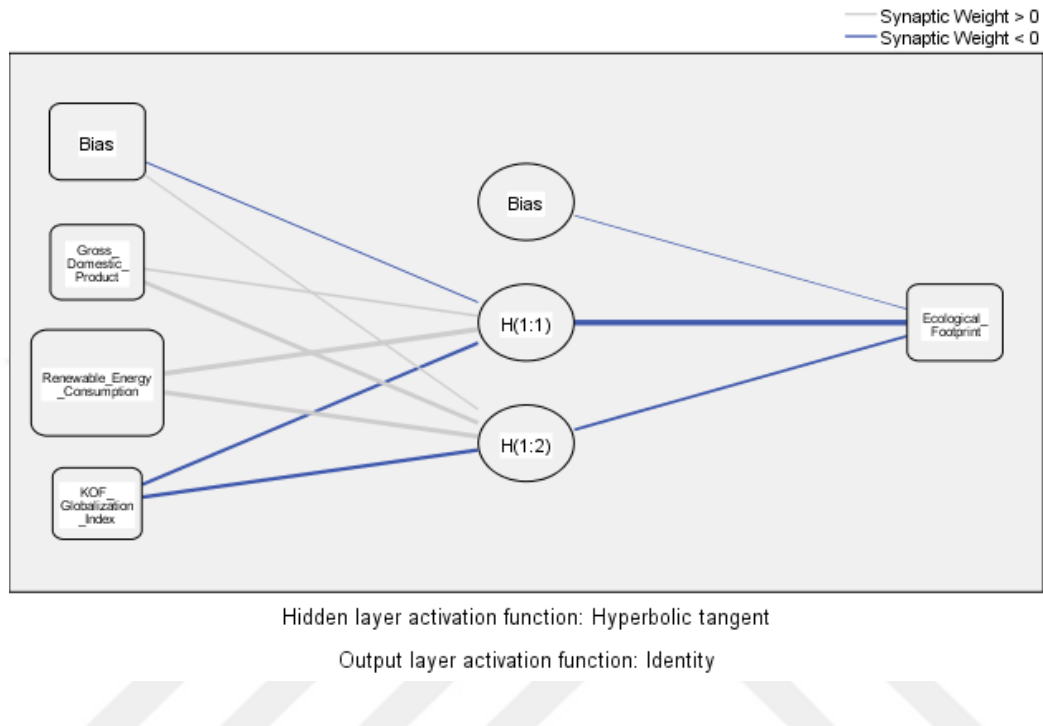


Figure 3.32. ANN Model of Denmark

Figure 3.32 illustrates an ANN model designed for Denmark, which is a member of the OECD. The network architecture consists of a single hidden layer and is structured with three neurons in the input layer, two neurons in the hidden layer, and one neuron in the output layer. The model employs a feedforward neural network configuration, where each neuron in one layer is fully connected to the neurons in the subsequent layer. A hyperbolic tangent (tanh) activation function is utilized in the hidden layer.

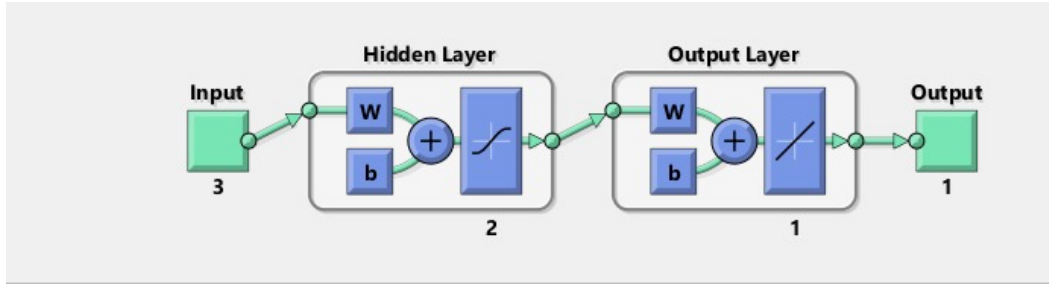


Figure 3.33. MATLAB Implementation of ANN Model for Denmark

The input data were analyzed and pre-processed utilizing MATLAB software. Following this step, an ANN model was designed and implemented to address the research objectives. The architecture and structure of the developed ANN model, including the arrangement of input, hidden, and output layers, are illustrated in Figure 3.33.

Table 3.38. Summary of the Model for Denmark

Model Summary		
Training	Sum of Squares Error	,829
	Relative Error	,083
	Stopping Rule Used	1 consecutive step(s) with no decrease in error ^a
	Training Time	0:00:00,00
Testing	Sum of Squares Error	,240
	Relative Error	,049

Dependent Variable: Ecological Footprint

a. Error computations are based on the testing sample.

Table 3.38. presents the outcomes of the training and test sets for the model, together with the values of the cumulative squared errors. The test data exhibits a 0.049 proportion of erroneous predictions, indicating an accuracy of 95.1% in the assessment. The objective is to employ the activation function according to the relevance levels of the inputs. Weight values were

established to minimize the inaccuracy. The weight coefficients of the neurons in the model's ANN are presented in Table 3.39.

Table 3.39. Weight Estimates for Denmark

Predictor		Predicted		
		Hidden Layer 1		Output Layer
		H(1:1)	H(1:2)	Ecological_Footprint
Input Layer	(Bias)	-,048	,080	
	Gross_Domestic_Product	,314	,470	
	Renewable_Energy_Consumption	,802	,511	
	KOF_Globalization_Index	-,396	-,399	
Hidden Layer 1	(Bias)			-,022
	H(1:1)			-1,256
	H(1:2)			-,376

The network is trained by changing the weights of the connections between neurons in each layer. The importance table of the independent variables is given in Table 3.40 to see how important each of the independent variables is in predicting the dependent variable.

Table 3.40. Significance of Independent Variables for Denmark

Independent Variable Importance		
	Importance	Normalized Importance
Gross_Domestic_Product	,251	47,2%
Renewable_Energy_Consumption	,531	100,0%
KOF_Globalization_Index	,218	41,1%

According to the obtained data, it was concluded that Denmark renewable energy consumption has an importance of 0.531 in estimating the ecological footprint. The values were normalized to 53.1% and the rest of the variables were found to have very close weights. While the gross domestic product index has an importance of 47.2%, the KOF globalization index has an importance of 41.1%.

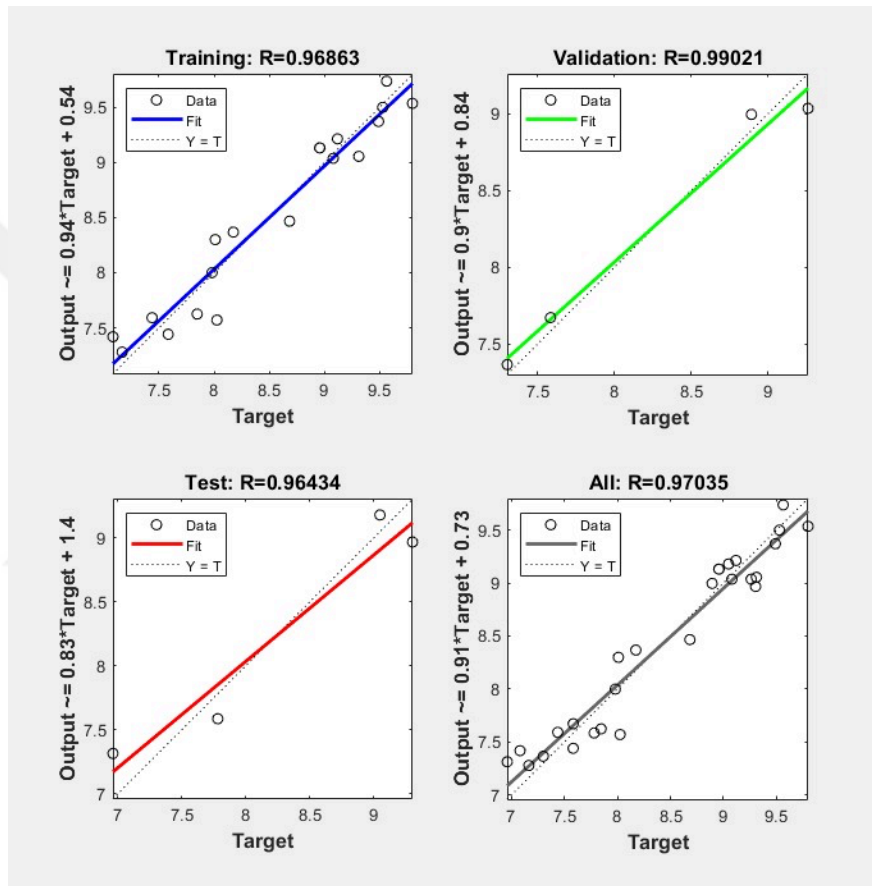


Figure 3.34. Regression Distribution of ANNs for Denmark

As a result of the applied model, Figure 3.34. shows the correlation between all the values of the derived model after training, validation, testing and prediction. Training data showed a success rate of $R^2 = 0.96863$, validation data showed a success rate of $R^2 = 0.99021$ and testing data showed a success rate of $R^2 = 0.96434$. The performance metric of the network for the entire dataset is $R^2 = 0.97035$. This rate shows that the network is quite successful. Upon examination of the findings, the effectiveness of the developed model is obvious. The results

show that there is a robust relationship between the actual values and the predicted values across all the datasets.

3.3.2.1.12. Artificial Neural Network Model for Spain

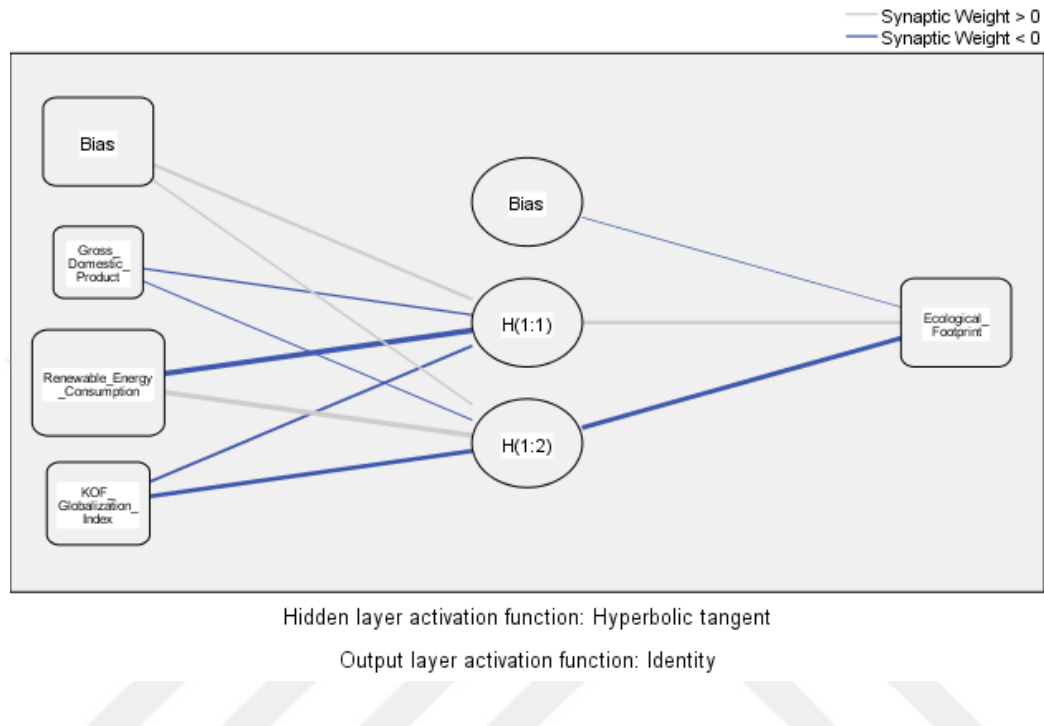


Figure 3.35. ANN Model of Spain

Figure 3.35 illustrates an ANN model designed for Spain, which is a member of the OECD. The network architecture consists of a single hidden layer and is structured with three neurons in the input layer, two neurons in the hidden layer, and one neuron in the output layer. The model employs a feedforward neural network configuration, where each neuron in one layer is fully connected to the neurons in the subsequent layer. A hyperbolic tangent (tanh) activation function is utilized in the hidden layer.

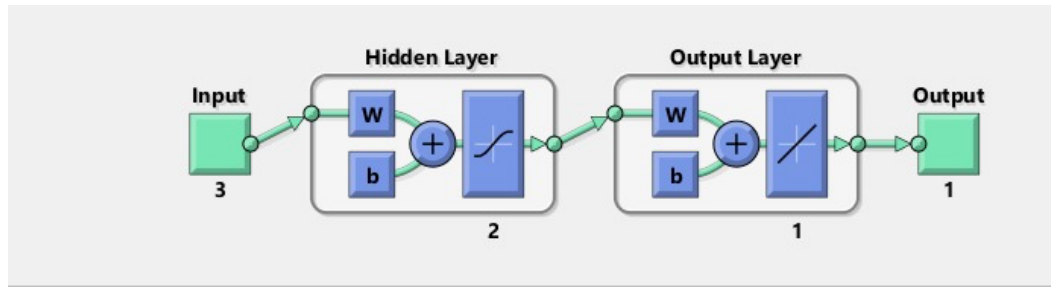


Figure 3.36. MATLAB Implementation of ANN Model for Spain

The input data were analyzed and pre-processed utilizing MATLAB software. Following this step, an ANN model was designed and implemented to address the research objectives. The architecture and structure of the developed ANN model, including the arrangement of input, hidden, and output layers, are illustrated in Figure 3.36.

Table 3.41. Summary of the Model for Spain

Model Summary		
Training	Sum of Squares Error	,935
	Relative Error	,110
	Stopping Rule Used	1 consecutive step(s) with no decrease in error ^a
	Training Time	0:00:00,00
Testing	Sum of Squares Error	,098
	Relative Error	,015

Dependent Variable: Ecological Footprint

a. Error computations are based on the testing sample.

Table 3.41. presents the outcomes of the training and test sets for the model, together with the values of the cumulative squared errors. The test data exhibits a 0.015 proportion of erroneous predictions, indicating an accuracy of 98.5% in the assessment. The objective is to employ the activation function according to the relevance levels of the inputs. Weight values were established to minimize the inaccuracy. The weight coefficients of the neurons in the model's ANN are presented in Table 3.42.

Table 3.42. Weight Estimates for Spain

Predictor		Hidden Layer 1		Predicted
		H(1:1)	H(1:2)	Output Layer Ecological_Footprint
Input Layer	(Bias)	,410	,190	
	Gross_Domestic_Product	-,128	-,083	
	Renewable_Energy_Consumption	-1,397	1,006	
	KOF_Globalization_Index	-,282	-,822	
Hidden Layer 1	(Bias)			-,076
	H(1:1)			,755
	H(1:2)			-,895

The network is trained by changing the weights of the connections between neurons in each layer. The importance table of the independent variables is given in Table 3.42 to see how important each of the independent variables is in predicting the dependent variable.

Table 3.43. Significance of Independent Variables for Spain

Independent Variable Importance		
	Importance	Normalized Importance
Gross_Domestic_Product	,023	3,1%
Renewable_Energy_Consumption	,732	100,0%
KOF_Globalization_Index	,245	33,5%

According to the obtained data, it was concluded that Spain's renewable energy consumption has an importance of 0.732 in estimating the ecological footprint. The values were normalized to 73.2% and the rest of the variables were found to have no very high weight. The second is the KOF globalization index, which has an importance of approximately 33.5%.

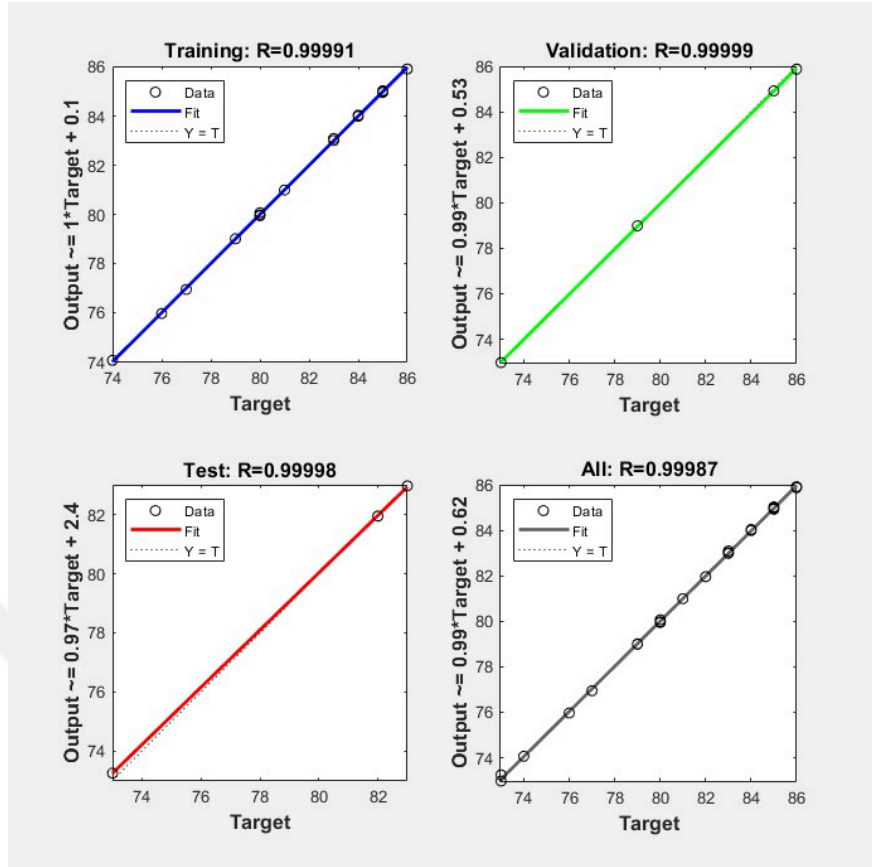


Figure 3.37. Regression Distribution of ANNs for Spain

As a result of the applied model, Figure 3.37. shows the correlation between all the values of the derived model after training, validation, testing and prediction. Training data showed a success rate of $R^2 = 0.99991$, validation data showed a success rate of $R^2 = 0.99999$ and testing data showed a success rate of $R^2 = 0.99998$. The performance metric of the network for the entire dataset is $R^2 = 0.99987$. This rate shows that the network is quite successful. Upon examination of the findings, the effectiveness of the developed model is obvious. The results show that there is a robust relationship between the actual values and the predicted values across all the datasets.

3.3.2.1.13. Artificial Neural Network Model for Estonia

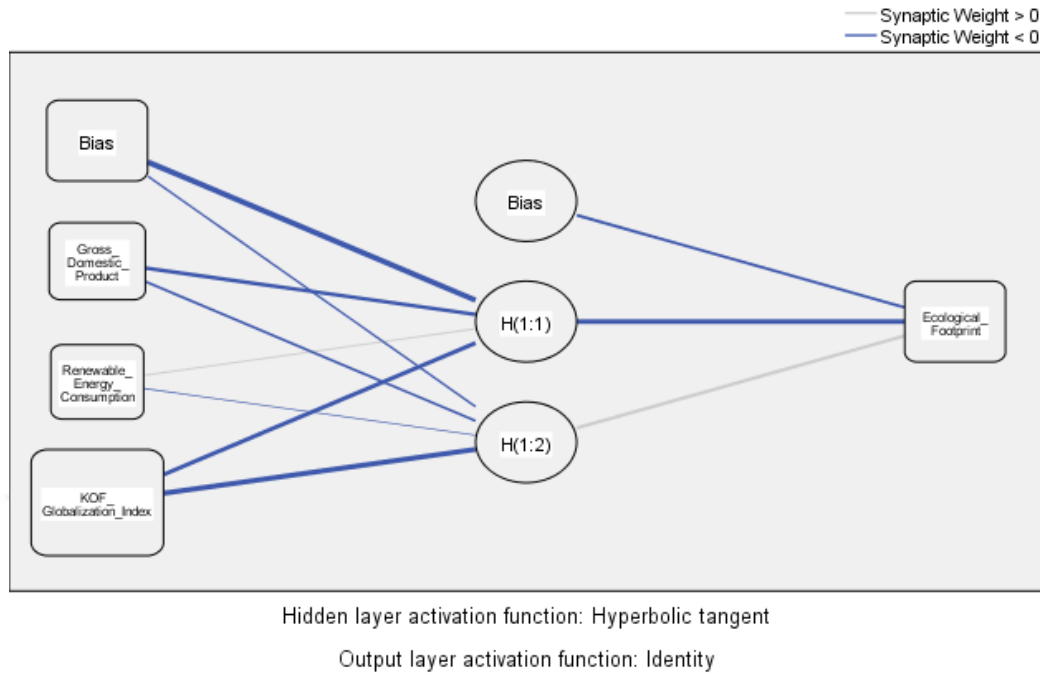


Figure 3.38. ANN Model of Estonia

Figure 3.38 illustrates an ANN model designed for Estonia, which is a member of the OECD. The network architecture consists of a single hidden layer and is structured with three neurons in the input layer, two neurons in the hidden layer, and one neuron in the output layer. The model employs a feedforward neural network configuration, where each neuron in one layer is fully connected to the neurons in the subsequent layer. A hyperbolic tangent (tanh) activation function is utilized in the hidden layer.

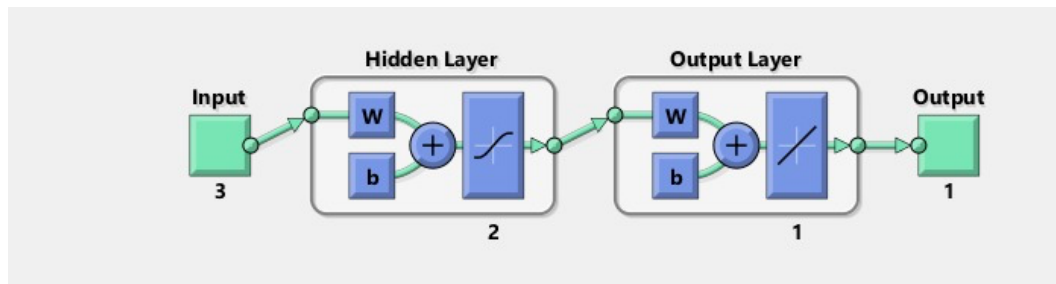


Figure 3.39. MATLAB Implementation of ANN Model for Estonia

The input data were analyzed and pre-processed utilizing MATLAB software. Following this step, an ANN model was designed and implemented to address the research objectives. The architecture and structure of the developed ANN model, including the arrangement of input, hidden, and output layers, are illustrated in Figure 3.39.

Table 3.44. Summary of the Model for Estonia

Model Summary		
Training	Sum of Squares Error	4,889
	Relative Error	,444
	Stopping Rule Used	1 consecutive step(s) with no decrease in error ^a
	Training Time	0:00:00,02
Testing	Sum of Squares Error	,306
	Relative Error	,314
Dependent Variable: Ecological_Footprint		
a. Error computations are based on the testing sample.		

Table 3.44. presents the outcomes of the training and test sets for the model, together with the values of the cumulative squared errors. The test data exhibits a 0.314 proportion of erroneous predictions, indicating an accuracy of 68.6% in the assessment. The objective is to employ the activation function according to the relevance levels of the inputs. Weight values were established to minimize the inaccuracy. The weight coefficients of the neurons in the model's ANN are presented in Table 3.45.

Table 3.45. Weight Estimates for Estonia

Predictor		Hidden Layer 1		Predicted
		H(1:1)	H(1:2)	Output Layer Ecological_Footprint
Input Layer	(Bias)	-2,187	-,811	
	Gross_Domestic_Product	-1,048	-,868	
	Renewable_Energy_Consumption	,605	-,341	
	KOF_Globalization_Index	-1,831	-1,919	
Hidden Layer 1	(Bias)			-,883
	H(1:1)			-1,915
	H(1:2)			1,014

The network is trained by changing the weights of the connections between neurons in each layer. The importance table of the independent variables is given in Table 3.46 to see how important each of the independent variables is in predicting the dependent variable.

Table 3.46. Significance of Independent Variables for Estonia

Independent Variable Importance		
	Importance	Normalized Importance
Gross_Domestic_Product	,236	42,5%
Renewable_Energy_Consumption	,207	37,3%
KOF_Globalization_Index	,556	100,0%

According to the obtained data, it was concluded that the Estonia KOF globalization index has an importance of 0.556 in estimating the ecological footprint. The values were normalized to 55.6% and the rest of the variables were found to have very close weights. Gross domestic product has an importance of 42.5% and renewable energy consumption has an importance of 37.3%.

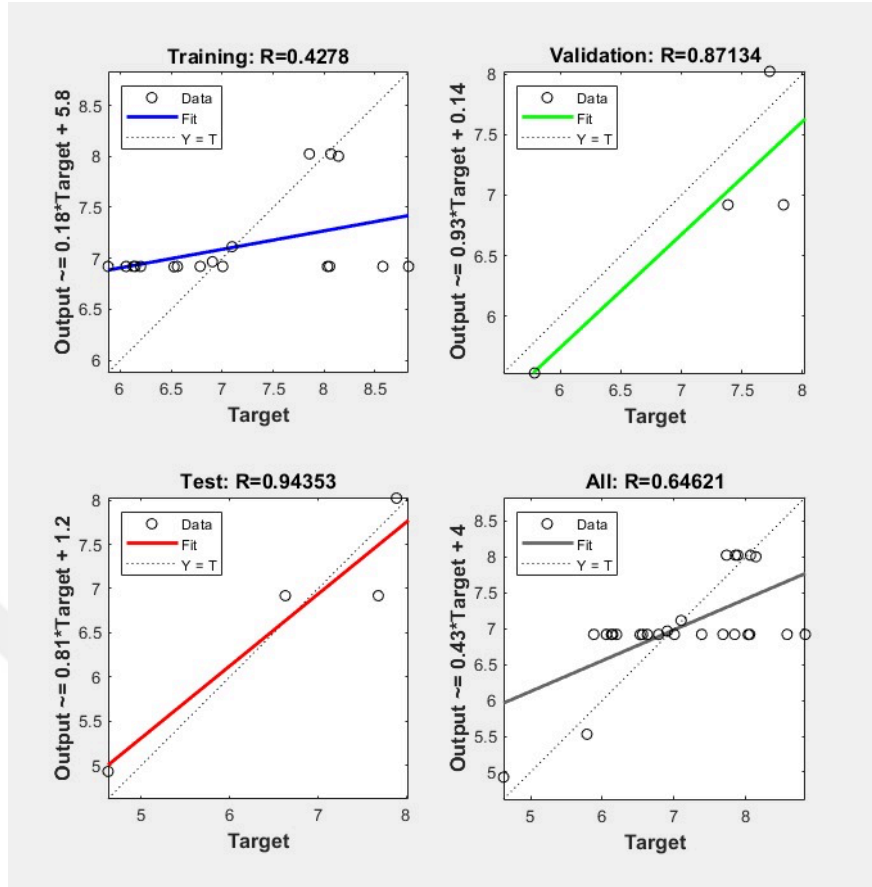


Figure 3.40. Regression Distribution of ANNs for Estonia

As a result of the applied model, Figure 3.40. shows the correlation between all the values of the derived model after training, validation, testing and prediction. Training data showed a success rate of $R^2 = 0.4278$, validation data showed a success rate of $R^2 = 0.87134$ and testing data showed a success rate of $R^2 = 0.94353$. The performance metric of the network for the entire dataset is $R^2 = 0.64621$. The results show that there is a robust relationship between the actual values and the predicted values across all the datasets.

3.3.2.1.14. Artificial Neural Network Model for Finland

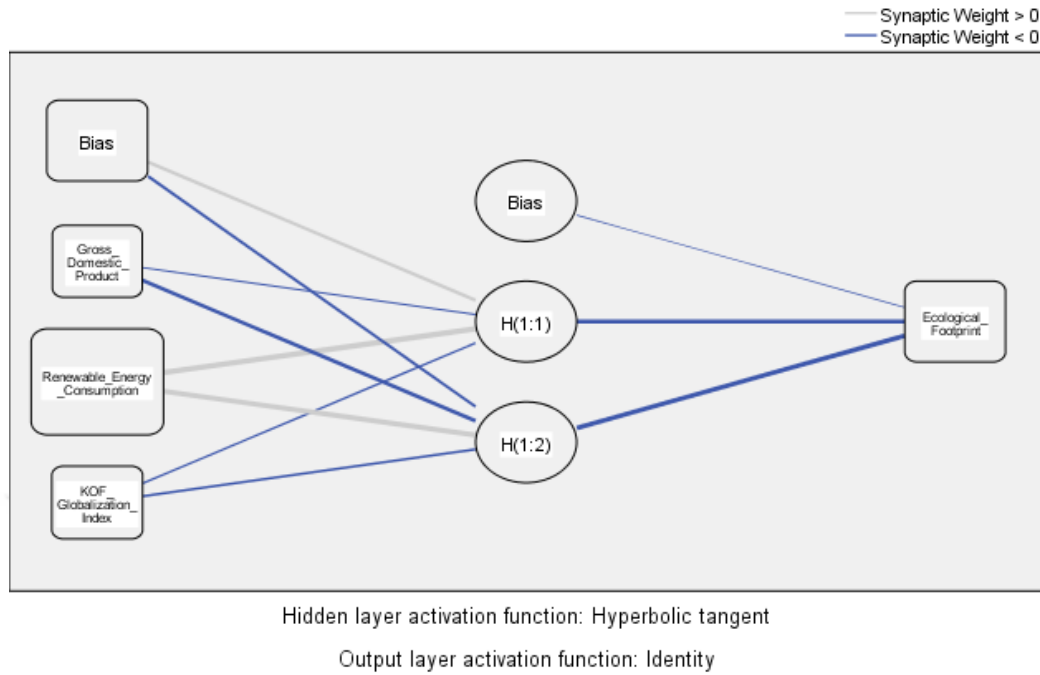


Figure 3.41. ANN Model of Finland

Figure 3.41 illustrates an ANN model designed for Finland, which is a member of the OECD. The network architecture consists of a single hidden layer and is structured with three neurons in the input layer, two neurons in the hidden layer, and one neuron in the output layer. The model employs a feedforward neural network configuration, where each neuron in one layer is fully connected to the neurons in the subsequent layer. A hyperbolic tangent (tanh) activation function is utilized in the hidden layer.

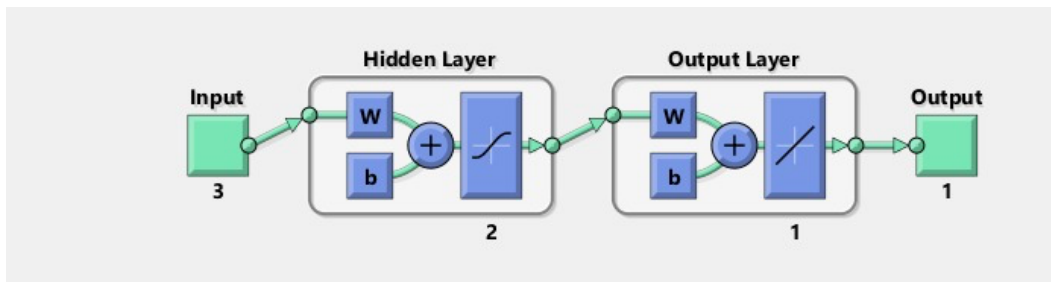


Figure 3.42. MATLAB Implementation of ANN Model for Finland

The input data were analyzed and pre-processed utilizing MATLAB software. Following this step, an ANN model was designed and implemented to address the research objectives. The architecture and structure of the developed ANN model, including the arrangement of input, hidden, and output layers, are illustrated in Figure 3.42.

Table 3.47. Summary of the Model for Finland

Model Summary		
Training	Sum of Squares Error	2,686
	Relative Error	,269
	Stopping Rule Used	1 consecutive step(s) with no decrease in error ^a
	Training Time	0:00:00,00
Testing	Sum of Squares Error	2,037
	Relative Error	,358
Dependent Variable: Ecological Footprint		
a. Error computations are based on the testing sample.		

Table 3.47. presents the outcomes of the training and test sets for the model, together with the values of the cumulative squared errors. The test data exhibits a 0.358 proportion of erroneous predictions, indicating an accuracy of 64.2% in the assessment. The objective is to employ the activation function according to the relevance levels of the inputs. Weight values were established to minimize the inaccuracy. The weight coefficients of the neurons in the model's ANN are presented in Table 3.48.

Table 3.48. Weight Estimates for Finland

Predictor		Hidden Layer 1		Predicted
		H(1:1)	H(1:2)	Output Layer Ecological_Footprint
Input Layer	(Bias)	,487	-,364	
	Gross_Domestic_Product	-,103	-,565	
	Renewable_Energy_Consumption	1,165	1,049	
	KOF_Globalization_Index	-,160	-,348	
Hidden Layer 1	(Bias)			-,088
	H(1:1)			-,914
	H(1:2)			-1,014

The network is trained by changing the weights of the connections between neurons in each layer. The importance table of the independent variables is given in Table 3.49 to see how important each of the independent variables is in predicting the dependent variable.

Table 3.49. Significance of Independent Variables for Finland

Independent Variable Importance		
	Importance	Normalized Importance
Gross_Domestic_Product	,195	32,4%
Renewable_Energy_Consumption	,601	100,0%
KOF_Globalization_Index	,204	33,9%

According to the obtained data, it was concluded that the Finland renewable energy consumption index has an importance of 0.601 in estimating the ecological footprint. The values were normalized to 60.1% and the rest of the variables were found to have very close weights. The KOF globalization index has an importance of 33.9%, while the gross domestic product index has an importance of 32.4%.

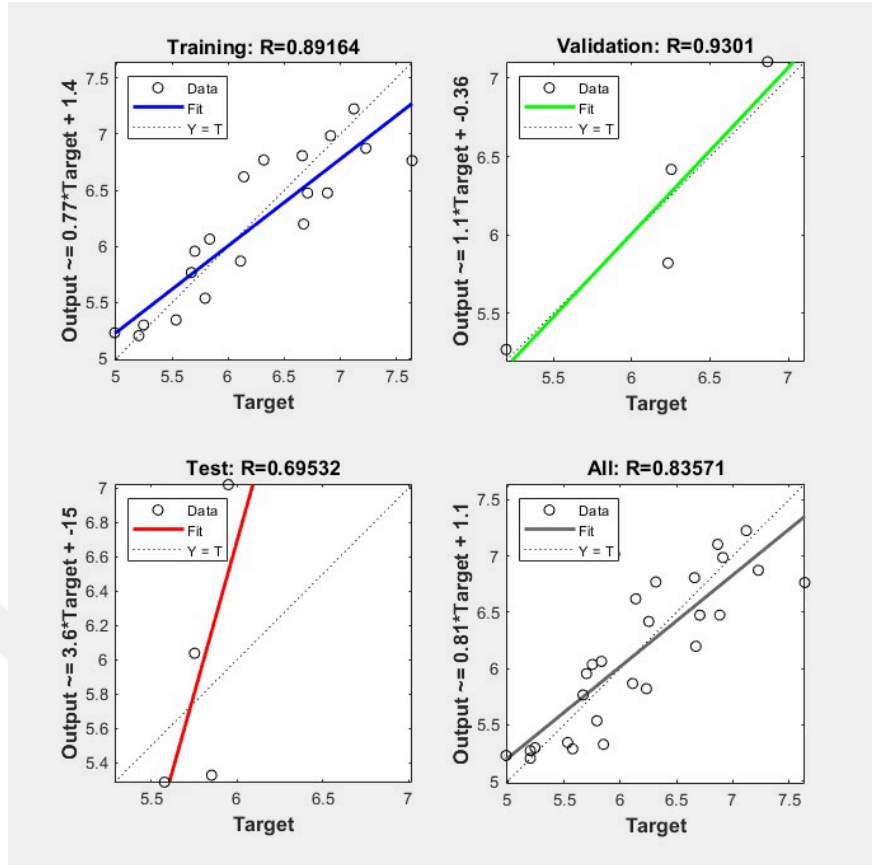


Figure 3.43. Regression Distribution of ANNs for Finland

As a result of the applied model, Figure 3.43. shows the correlation between all the values of the derived model after training, validation, testing and prediction. Training data showed a success rate of $R^2 = 0.89164$, validation data showed a success rate of $R^2 = 0.9301$ and testing data showed a success rate of $R^2 = 0.69532$. The performance metric of the network for the entire dataset is $R^2 = 0.83571$. The results show that there is a robust relationship between the actual values and the predicted values across all the datasets.

3.3.2.1.15. Artificial Neural Network Model for France

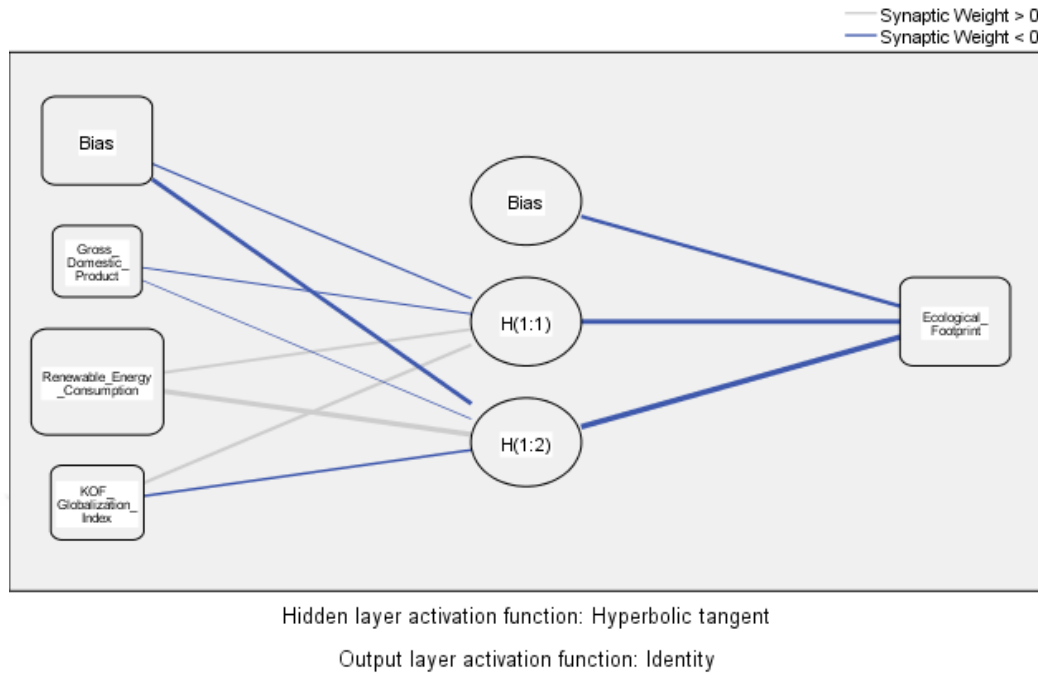


Figure 3.44. ANN Model of France

Figure 3.44 illustrates an ANN model designed for France, which is a member of the OECD. The network architecture consists of a single hidden layer and is structured with three neurons in the input layer, two neurons in the hidden layer, and one neuron in the output layer. The model employs a feedforward neural network configuration, where each neuron in one layer is fully connected to the neurons in the subsequent layer. A hyperbolic tangent (tanh) activation function is utilized in the hidden layer.

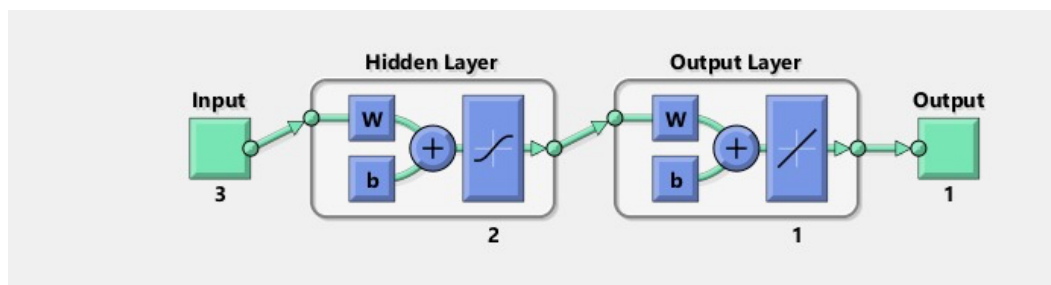


Figure 3.45. MATLAB Implementation of ANN Model for France

The input data were analyzed and pre-processed utilizing MATLAB software. Following this step, an ANN model was designed and implemented to address the research objectives. The architecture and structure of the developed ANN model, including the arrangement of input, hidden, and output layers, are illustrated in Figure 3.45.

Table 3.50. Summary of the Model for France

Model Summary		
Training	Sum of Squares Error	,767
	Relative Error	,081
	Stopping Rule Used	1 consecutive step(s) with no decrease in error ^a
	Training Time	0:00:00,00
Testing	Sum of Squares Error	,327
	Relative Error	,133
Dependent Variable: Ecological Footprint		
a. Error computations are based on the testing sample.		

Table 3.50. presents the outcomes of the training and test sets for the model, together with the values of the cumulative squared errors. The test data exhibits a 0.133 proportion of erroneous predictions, indicating an accuracy of 86.7% in the assessment. The objective is to employ the activation function according to the relevance levels of the inputs. Weight values were established to minimize the inaccuracy. The weight coefficients of the neurons in the model's ANN are presented in Table 3.51.

Table 3.51. Weight Estimates for France

Predictor		Parameter Estimates		
		Hidden Layer 1		Predicted
		H(1:1)	H(1:2)	Output Layer Ecological Footprint
Input Layer	(Bias)	-,042	-,554	
	Gross_Domestic_Product	-,038	-,008	
	Renewable_Energy_Consumption	,431	,903	
	KOF_Globalization_Index	,436	-,239	
Hidden Layer 1	(Bias)			-,453
	H(1:1)			-,682
	H(1:2)			-1,085

The network is trained by changing the weights of the connections between neurons in each layer. The importance table of the independent variables is given in Table 3.52 to see how important each of the independent variables is in predicting the dependent variable.

Table 3.52. Significance of Independent Variables for France

Independent Variable Importance		
	Importance	Normalized Importance
Gross_Domestic_Product	,021	2,3%
Renewable_Energy_Consumption	,883	100,0%
KOF_Globalization_Index	,096	10,9%

According to the obtained data, it was concluded that France's renewable energy consumption has an importance of 88.3% in estimating the ecological footprint. The values were normalized to 88.3% and the rest of the 100 variables were found to have no very high weight. The second is the KOF globalization index, which has an importance of approximately 10.9%.

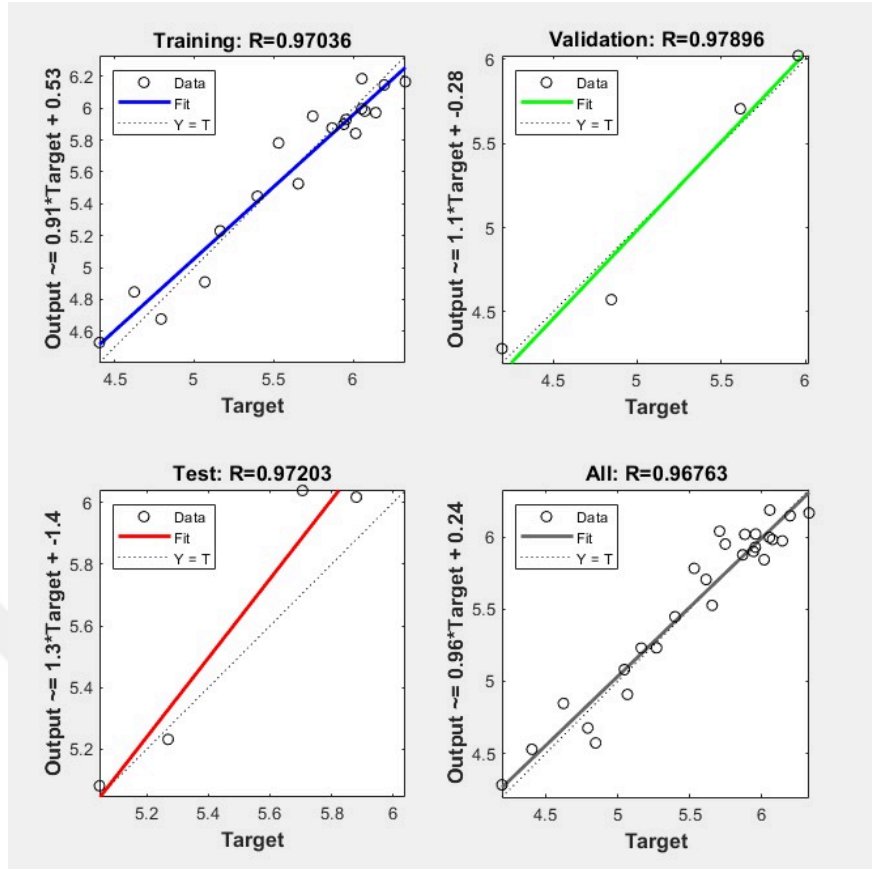


Figure 3.46. Regression Distribution of ANN's for France

As a result of the applied model, Figure 3.46. shows the correlation between all the values of the derived model after training, validation, testing and prediction. Training data showed a success rate of $R^2 = 0.97036$, validation data showed a success rate of $R^2 = 0.97896$ and testing data showed a success rate of $R^2 = 0.97203$. The performance metric of the network for the entire dataset is $R^2 = 0.96763$. This rate shows that the network is quite successful. Upon examination of the findings, the effectiveness of the developed model is obvious. The results show that there is a robust relationship between the actual values and the predicted values across all the datasets.

3.3.2.1.16. Artificial Neural Network Model for United Kingdom

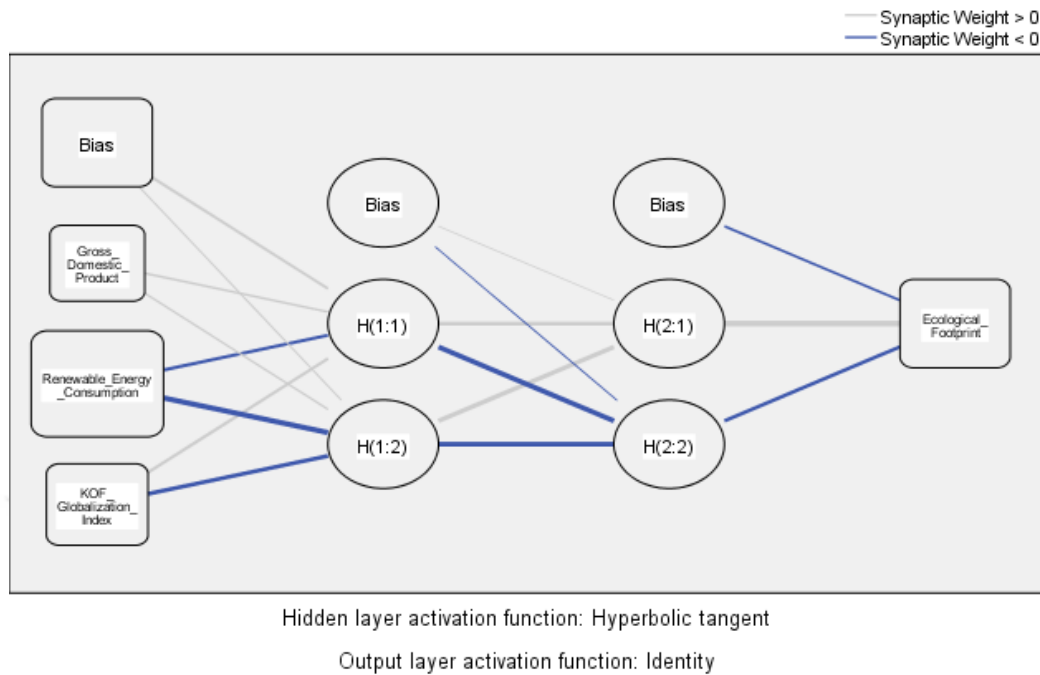


Figure 3.47. ANN Model of United Kingdom

Figure 3.47 illustrates a two-hidden-layer ANN model designed for United Kingdom, an OECD member country. The network architecture comprises three neurons in the input layer, two neurons in the hidden layer, and a single neuron in the output layer. This model adopts a two-layer neural structure with two neurons in the hidden layer. The hyperbolic tangent function is employed as the activation function within the hidden layer, facilitating non-linear transformations and enabling the network to capture complex patterns and relationships within the data.

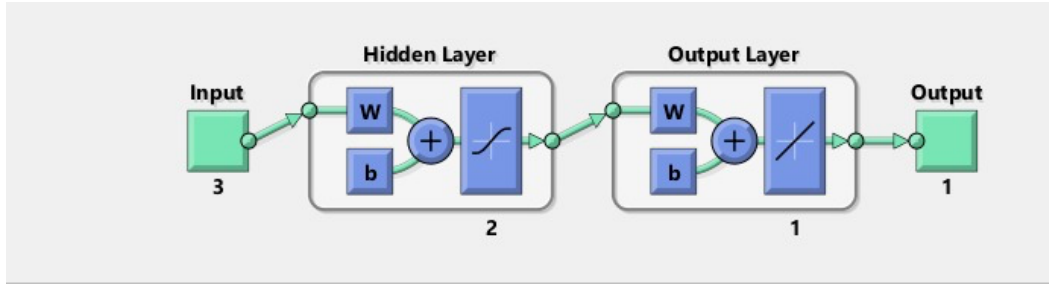


Figure 3.48. MATLAB Implementation of ANN Model for United Kingdom

The input data were analyzed and pre-processed utilizing MATLAB software. Following this step, an ANN model was designed and implemented to address the research objectives. The architecture and structure of the developed ANN model, including the arrangement of input, hidden, and output layers, are illustrated in Figure 3.48.

Table 3.53. Summary of the Model for United Kingdom

Model Summary		
Training	Sum of Squares Error	,440
	Relative Error	,049
	Stopping Rule Used	1 consecutive step(s) with no decrease in error ^a
	Training Time	0:00:00,00
Testing	Sum of Squares Error	,189
	Relative Error	,059

Dependent Variable: Ecological Footprint

a. Error computations are based on the testing sample.

Table 3.53. presents the outcomes of the training and test sets for the model, together with the values of the cumulative squared errors. The test data exhibits a 0.059 proportion of erroneous predictions, indicating an accuracy of 94.1% in the assessment. The objective is to employ the activation function according to the relevance levels of the inputs. Weight values were

established to minimize the inaccuracy. The weight coefficients of the neurons in the model's ANN are presented in Table 3.54.

Table 3.54. Weight Estimates for United Kingdom

Parameter Estimates					
Predictor		Hidden Layer 1		Predicted Hidden Layer 2	Output Layer Ecological_Foot print
		H(1:1)	H(1:2)	H(2:1)	H(2:2)
Input Layer	(Bias)	,229	,037		
	Gross_Domestic_Product	,129	,072		
	Renewable_Energy_Consumption	-,468	-,948		
	KOF_Globalization_Index	,414	-,808		
Hidden Layer 1	(Bias)			,016	-,028
	H(1:1)			,496	-,878
	H(1:2)			,863	-,868
Hidden Layer 2	(Bias)				-,169
	H(2:1)				1,125
	H(2:2)				-,491

The network is trained by changing the weights of the connections between neurons in each layer. The importance table of the independent variables is given in Table 3.54 to see how important each of the independent variables is in predicting the dependent variable.

Table 3.55. Significance of Independent Variables for United Kingdom

Independent Variable Importance		
	Importance	Normalized Importance
Gross_Domestic_Product	,101	14,6%
Renewable_Energy_Consumption	,692	100,0%
KOF_Globalization_Index	,208	30,0%

According to the obtained data, it was concluded that the renewable energy consumption of the United Kingdom has an importance of 69.2% in estimating the ecological footprint. The values are normalized to 69.2% and the second most important variable among the remaining 100 variables is the KOF globalization index, which has an importance of approximately 30%.

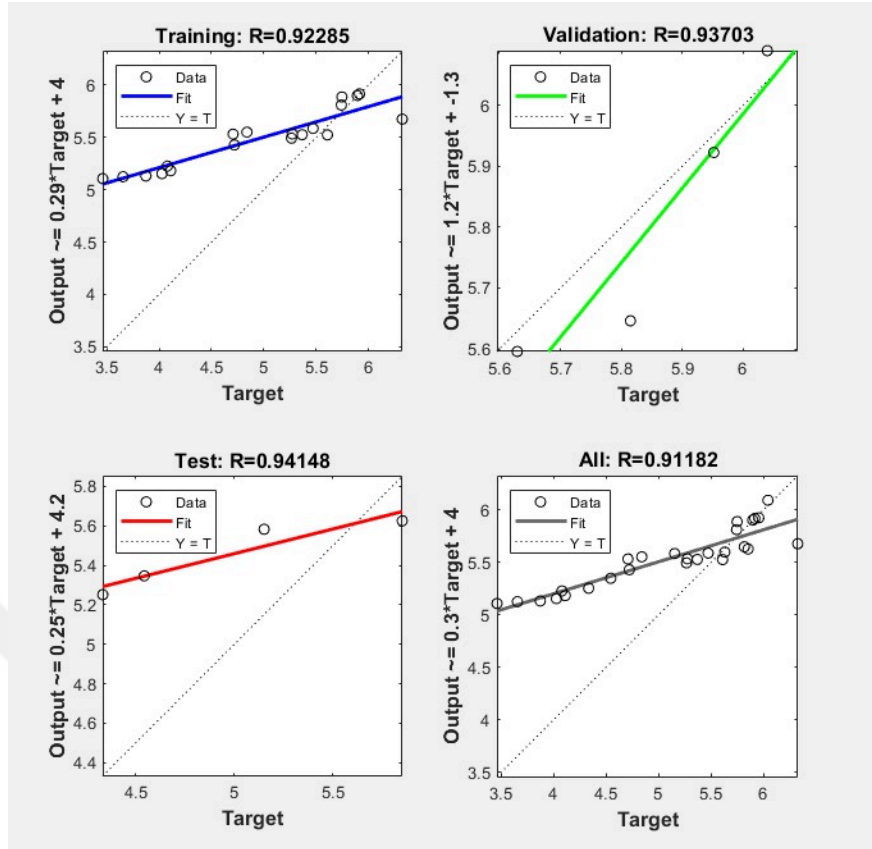


Figure 3.49. Regression Distribution of ANN's for United Kingdom

As a result of the applied model, Figure 3.49. shows the correlation between all the values of the derived model after training, validation, testing and prediction. Training data showed a success rate of $R^2 = 0.92285$, validation data showed a success rate of $R^2 = 0.93703$ and testing data showed a success rate of $R^2 = 0.94148$. The performance metric of the network for the entire dataset is $R^2 = 0.91182$. This rate shows that the network is quite successful. Upon examination of the findings, the effectiveness of the developed model is obvious. The results show that there is a robust relationship between the actual values and the predicted values across all the datasets.

3.3.2.1.17. Artificial Neural Network Model for Greece

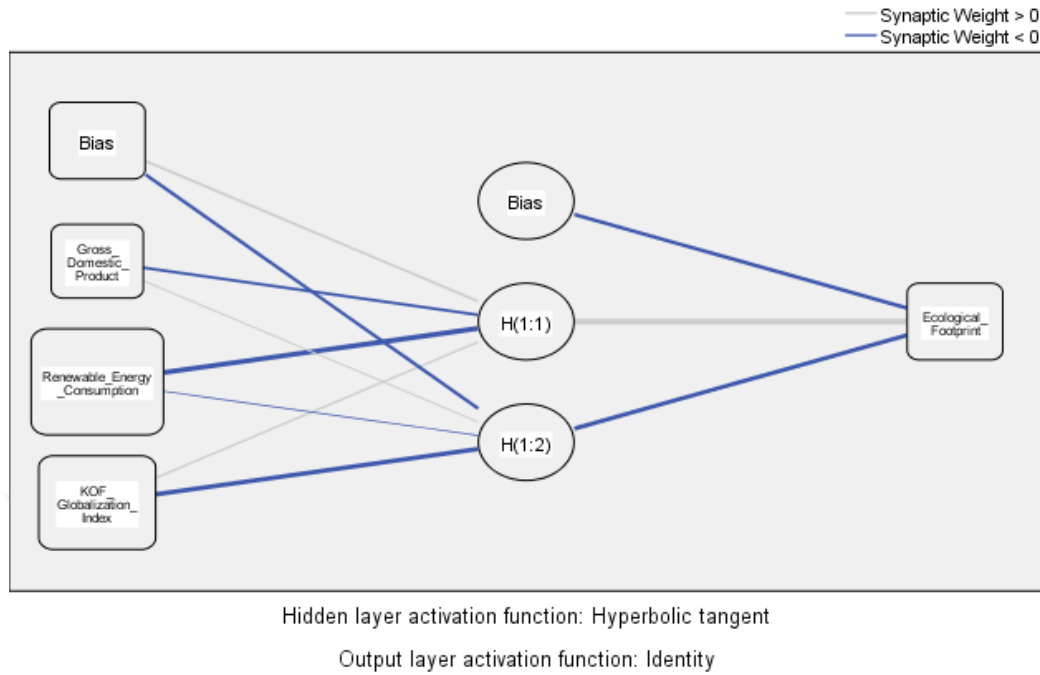


Figure 3.50. ANN Model of Greece

Figure 3.50 illustrates an ANN model designed for Greece, which is a member of the OECD. The network architecture consists of a single hidden layer and is structured with three neurons in the input layer, two neurons in the hidden layer, and one neuron in the output layer. The model employs a feedforward neural network configuration, where each neuron in one layer is fully connected to the neurons in the subsequent layer. A hyperbolic tangent (tanh) activation function is utilized in the hidden layer.

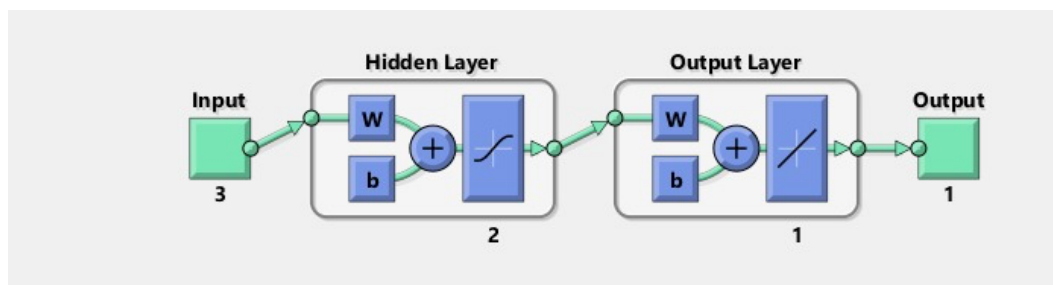


Figure 3.51. MATLAB Implementation of ANN Model for Greece

The input data were analyzed and pre-processed utilizing MATLAB software. Following this step, an ANN model was designed and implemented to address the research objectives. The architecture and structure of the developed ANN model, including the arrangement of input, hidden, and output layers, are illustrated in Figure 3.51.

Table 3.56. Summary of the Model for Greece

Model Summary		
Training	Sum of Squares Error	,539
	Relative Error	,060
	Stopping Rule Used	1 consecutive step(s) with no decrease in error ^a
	Training Time	0:00:00,00
Testing	Sum of Squares Error	,306
	Relative Error	,164

Dependent Variable: Ecological Footprint

a. Error computations are based on the testing sample.

Table 3.56. presents the outcomes of the training and test sets for the model, together with the values of the cumulative squared errors. The test data exhibits a 0.164 proportion of erroneous predictions, indicating an accuracy of 83.6% in the assessment. The objective is to employ the activation function according to the relevance levels of the inputs. Weight values were established to minimize the inaccuracy. The weight coefficients of the neurons in the model's ANN are presented in Table 3.57.

Table 3.57. Weight Estimates for Greece

Predictor		Hidden Layer 1		Predicted
		H(1:1)	H(1:2)	Output Layer Ecological_Footprint
Input Layer	(Bias)	,482	-,693	
	Gross_Domestic_Product	-,531	,284	
	Renewable_Energy_Consumption	-1,556	-,128	
	KOF_Globalization_Index	,353	-1,381	
Hidden Layer 1	(Bias)			-,799
	H(1:1)			1,722
	H(1:2)			-,952

The network is trained by changing the weights of the connections between neurons in each layer. The importance table of the independent variables is given in Table 3.58 to see how important each of the independent variables is in predicting the dependent variable.

Table 3.58. Significance of Independent Variables for Greece

Independent Variable Importance		
	Importance	Normalized Importance
Gross Domestic Product	,202	45,2%
Renewable_Energy_Consumption	,446	100,0%
KOF_Globalization_Index	,352	79,0%

According to the obtained data, it was concluded that renewable energy consumption in Greece has an importance of 44.6% in the ecological footprint estimation. The values are normalized to 44.6% and the second most important variable among the remaining 100 variables is the KOF globalization index, which has an importance of approximately 79%.

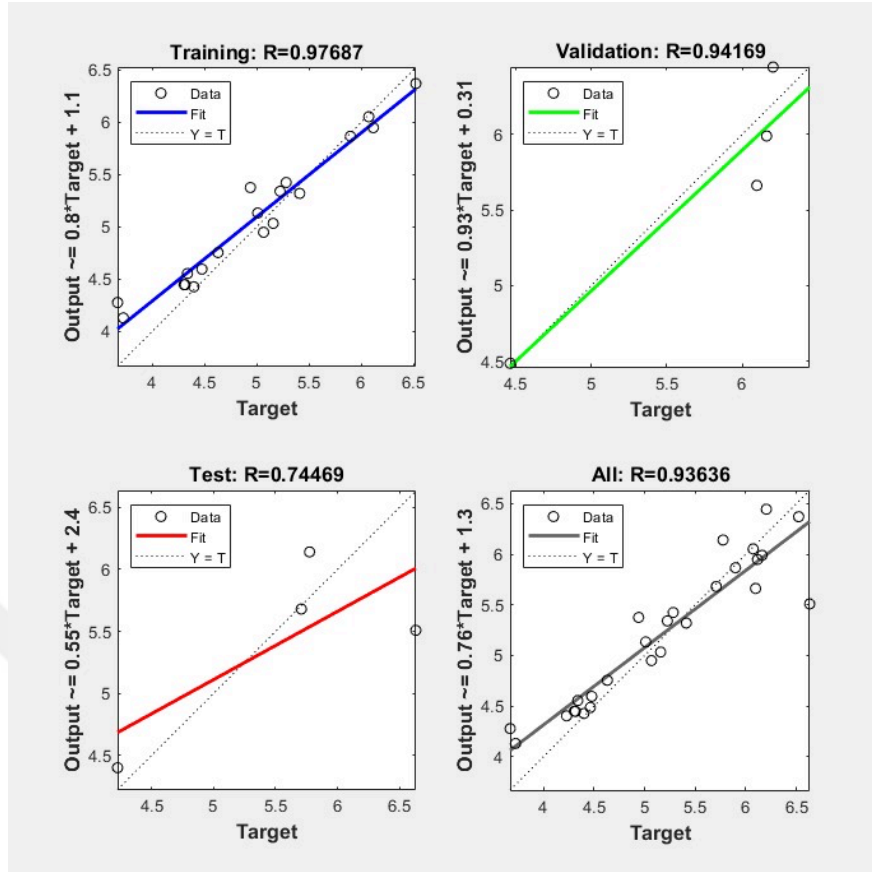


Figure 3.52. Regression Distribution of ANN's for Greece

As a result of the applied model, Figure 3.52. shows the correlation between all the values of the derived model after training, validation, testing and prediction. Training data showed a success rate of $R^2 = 0.97687$, validation data showed a success rate of $R^2 = 0.94169$ and testing data showed a success rate of $R^2 = 0.74469$. The performance metric of the network for the entire dataset is $R^2 = 0.93636$. This rate shows that the network is quite successful. Upon examination of the findings, the effectiveness of the developed model is obvious. The results show that there is a robust relationship between the actual values and the predicted values across all the datasets.

3.3.2.1.18. Artificial Neural Network Model for Hungary

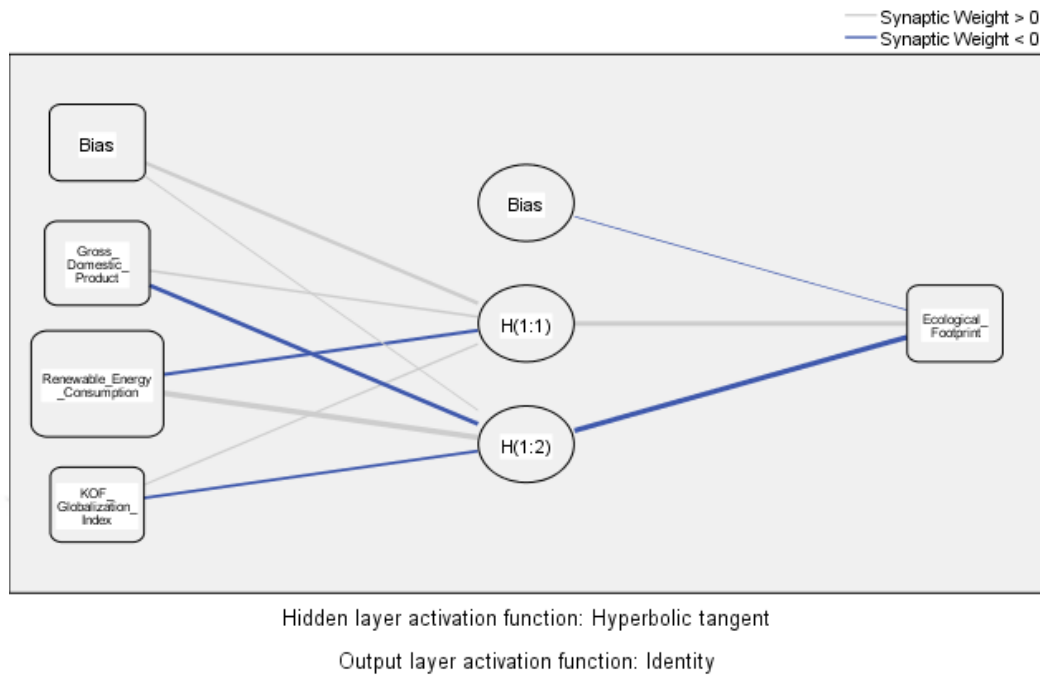


Figure 3.53. ANN Model of Hungary

Figure 3.53 illustrates an ANN model designed for Hungary, which is a member of the OECD. The network architecture consists of a single hidden layer and is structured with three neurons in the input layer, two neurons in the hidden layer, and one neuron in the output layer. The model employs a feedforward neural network configuration, where each neuron in one layer is fully connected to the neurons in the subsequent layer. A hyperbolic tangent (tanh) activation function is utilized in the hidden layer.

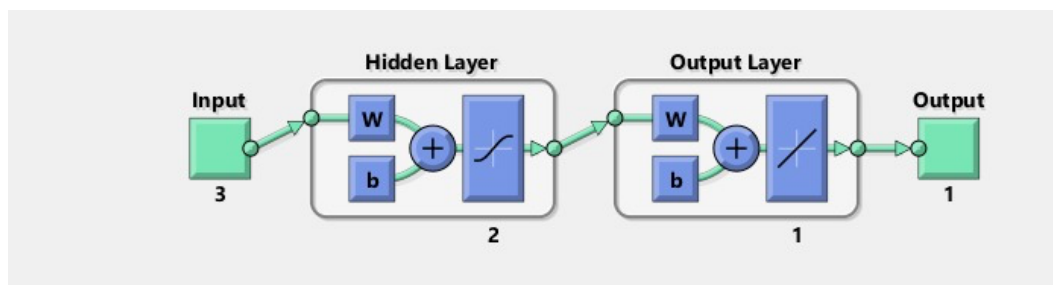


Figure 3.54. MATLAB Implementation of ANN Model for Hungary

The input data were analyzed and pre-processed utilizing MATLAB software. Following this step, an ANN model was designed and implemented to address the research objectives. The architecture and structure of the developed ANN model, including the arrangement of input, hidden, and output layers, are illustrated in Figure 3.54.

Table 3.59. Summary of the Model for Hungary

Model Summary		
Training	Sum of Squares Error	7,114
	Relative Error	,711
	Stopping Rule Used	1 consecutive step(s) with no decrease in error ^a
	Training Time	0:00:00,00
Testing	Sum of Squares Error	,757
	Relative Error	,400

Dependent Variable: Ecological_Footprint

a. Error computations are based on the testing sample.

Table 3.59. presents the outcomes of the training and test sets for the model, together with the values of the cumulative squared errors. The test data exhibits a 0.40 proportion of erroneous predictions, indicating an accuracy of 60% in the assessment. The objective is to employ the activation function according to the relevance levels of the inputs. Weight values were established to minimize the inaccuracy. The weight coefficients of the neurons in the model's ANN are presented in Table 3.60.

Table 3.60. Weight Estimates for Hungary

Predictor		Parameter Estimates		
		Hidden Layer 1		Predicted
		H(1:1)	H(1:2)	Output Layer Ecological_Footprint
Input Layer	(Bias)	,455	,071	
	Gross_Domestic_Product	,224	-,540	
	Renewable_Energy_Consumption	-,404	1,173	
	KOF_Globalization_Index	,222	-,318	
Hidden Layer 1	(Bias)			-,035
	H(1:1)			,590
	H(1:2)			-,810

The network is trained by changing the weights of the connections between neurons in each layer. The importance table of the independent variables is given in Table 3.60 to see how important each of the independent variables is in predicting the dependent variable.

Table 3.61. Significance of Independent Variables for Hungary

Independent Variable Importance		
	Importance	Normalized Importance
Gross_Domestic_Product	,298	62,7%
Renewable_Energy_Consumption	,476	100,0%
KOF_Globalization_Index	,225	47,3%

According to the obtained data, it was concluded that renewable energy consumption in Greece has an importance of 47.6% in the ecological footprint estimation. The values are normalized to 47.6% and the second most important variable among the remaining 100 variables is the gross domestic product index, which has an importance of 62.7%.

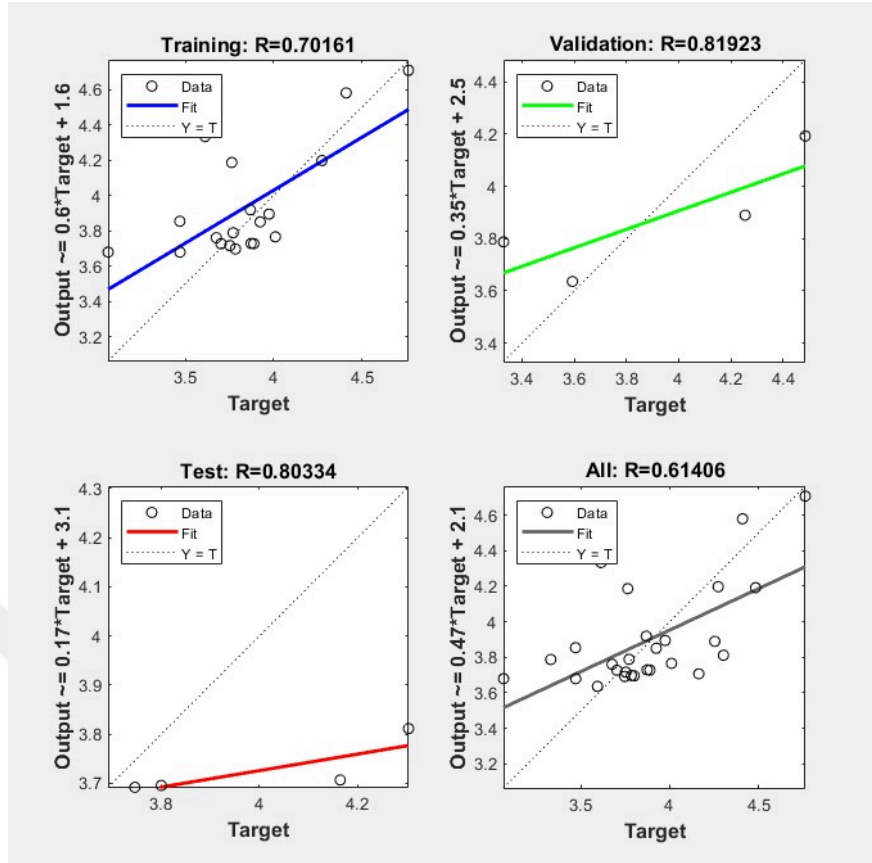


Figure 3.55. Regression Distribution of ANN's for Hungary

As a result of the applied model, Figure 3.55. shows the correlation between all the values of the derived model after training, validation, testing and prediction. Training data showed a success rate of $R^2 = 0.70161$, validation data showed a success rate of $R^2 = 0.81923$ and testing data showed a success rate of $R^2 = 0.80334$. The performance metric of the network for the entire dataset is $R^2 = 0.61406$. This rate shows that the network is quite successful. Upon examination of the findings, the effectiveness of the developed model is obvious. The results show that there is a robust relationship between the actual values and the predicted values across all the datasets.

3.3.2.1.19. Artificial Neural Network Model for Ireland

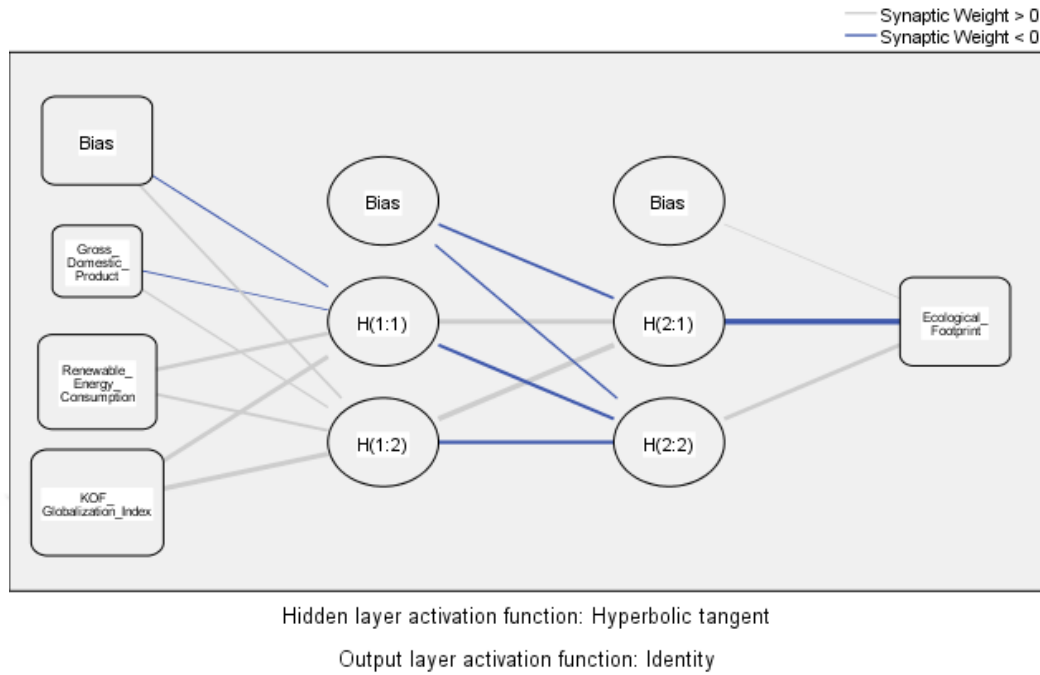


Figure 3.56. ANN Model of Ireland

Figure 3.56 illustrates a two-hidden-layer ANN model designed for Ireland, an OECD member country. The network architecture comprises three neurons in the input layer, two neurons in the hidden layer, and a single neuron in the output layer. This model adopts a two-layer neural structure with two neurons in the hidden layer. The hyperbolic tangent function is employed as the activation function within the hidden layer, facilitating non-linear transformations and enabling the network to capture complex patterns and relationships within the data.

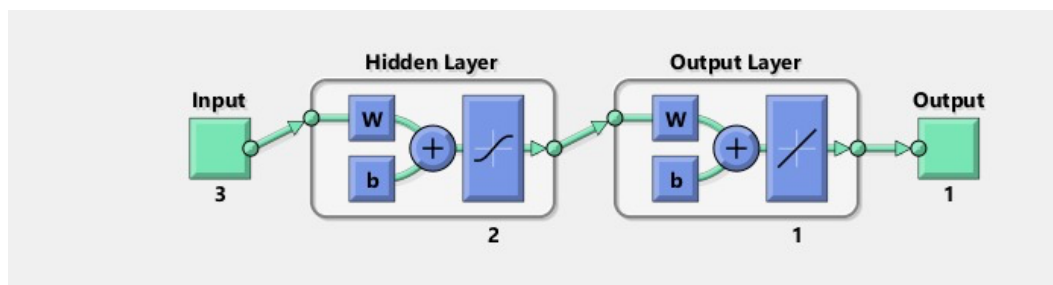


Figure 3.57. MATLAB Implementation of ANN Model for Ireland

The input data were analyzed and pre-processed utilizing MATLAB software. Following this step, an ANN model was designed and implemented to address the research objectives. The architecture and structure of the developed ANN model, including the arrangement of input, hidden, and output layers, are illustrated in Figure 3.57.

Table 3.62. Summary of the Model for Ireland

Model Summary		
Training	Sum of Squares Error	1,060
	Relative Error	,112
	Stopping Rule Used	1 consecutive step(s) with no decrease in error ^a
	Training Time	0:00:00,00
Testing	Sum of Squares Error	,390
	Relative Error	,121
Dependent Variable: Ecological_Footprint		
a. Error computations are based on the testing sample.		

Table 3.62. presents the outcomes of the training and test sets for the model, together with the values of the cumulative squared errors. The test data exhibits a 0.121 proportion of erroneous predictions, indicating an accuracy of 87.9% in the assessment. The objective is to employ the activation function according to the relevance levels of the inputs. Weight values were established to minimize the inaccuracy. The weight coefficients of the neurons in the model's ANN are presented in Table 3.63.

Table 3.63. Weight Estimates for Ireland

Parameter Estimates					
Predictor		Hidden Layer 1		Predicted Hidden Layer 2	
		H(1:1)	H(1:2)	H(2:1)	H(2:2)
Input Layer	(Bias)	-,086	,355		
	Gross_Domestic_Product	-,067	,100		
	Renewable_Energy_Consumption	,524	,442		
	KOF_Globalization_Index	,644	,683		
Hidden Layer 1	(Bias)			-,418	-,344
	H(1:1)			,677	-,500
	H(1:2)			,789	-,521
Hidden Layer 2	(Bias)				,039
	H(2:1)				-,815
	H(2:2)				,644

The network is trained by changing the weights of the connections between neurons in each layer. The importance table of the independent variables is given in Table 3.64 to see how important each of the independent variables is in predicting the dependent variable.

Table 3.64. Significance of Independent Variables for Ireland

Independent Variable Importance		
	Importance	Normalized Importance
Gross Domestic Product	,016	2,7%
Renewable Energy Consumption	,399	68,0%
KOF Globalization Index	,586	100,0%

According to the obtained data, it was concluded that the KOF globalization index has an importance of 58.6% in the estimation of the ecological footprint in Ireland. The values are normalized to 58.6% and the second most important variable among the remaining 100 variables is the renewable energy consumption index, which has an importance of 68%.

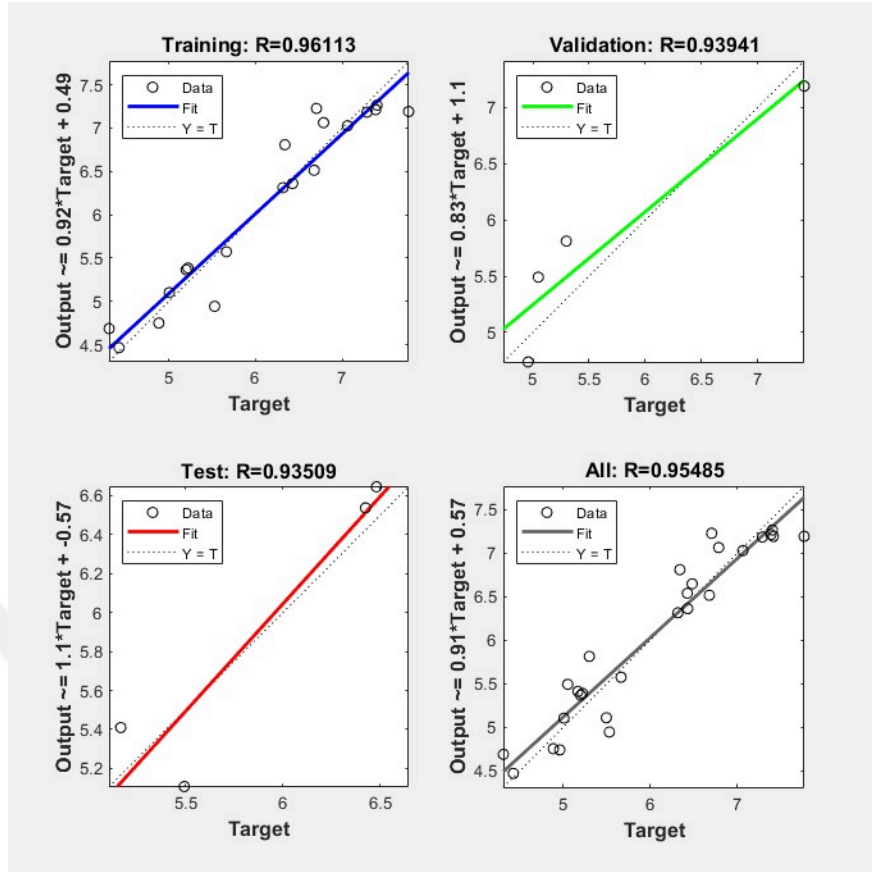


Figure 3.58. Regression Distribution of ANN's for Ireland

As a result of the applied model, Figure 3.58. shows the correlation between all the values of the derived model after training, validation, testing and prediction. Training data showed a success rate of $R^2 = 0.96113$, validation data showed a success rate of $R^2 = 0.93941$ and testing data showed a success rate of $R^2 = 0.93509$. The performance metric of the network for the entire dataset is $R^2 = 0.95485$. This rate shows that the network is quite successful. Upon examination of the findings, the effectiveness of the developed model is obvious. The results show that there is a robust relationship between the actual values and the predicted values across all the datasets.

3.3.2.1.20. Artificial Neural Network Model for Israel

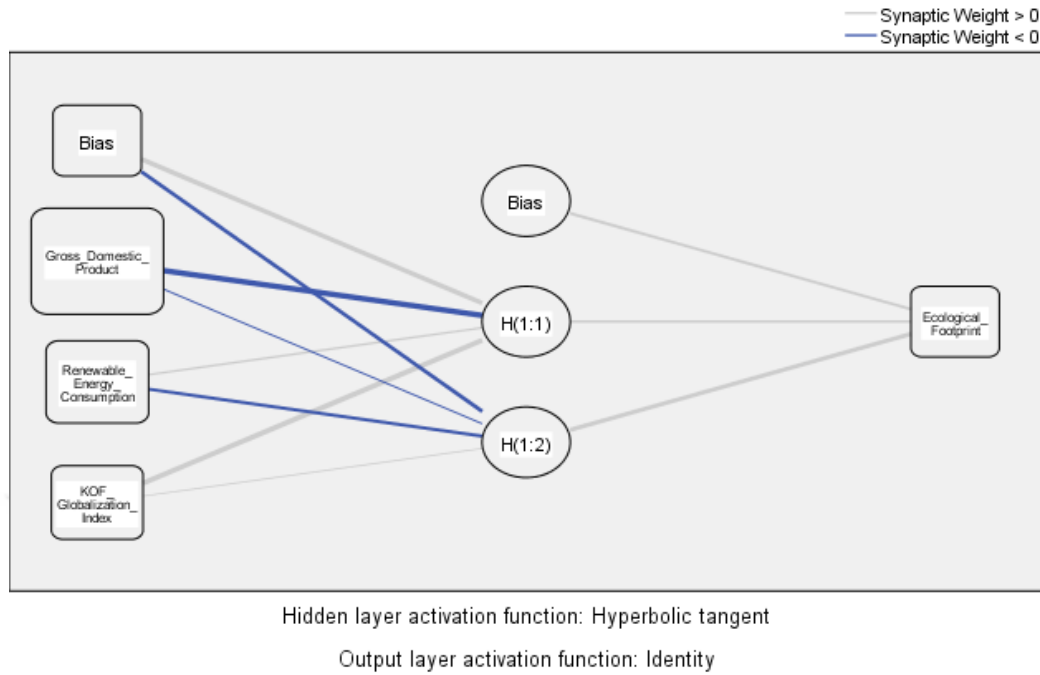


Figure 3.59. ANN Model of Israel

Figure 3.59 illustrates an ANN model designed for Israel, which is a member of the OECD. The network architecture consists of a single hidden layer and is structured with three neurons in the input layer, two neurons in the hidden layer, and one neuron in the output layer. The model employs a feedforward neural network configuration, where each neuron in one layer is fully connected to the neurons in the subsequent layer. A hyperbolic tangent (tanh) activation function is utilized in the hidden layer.

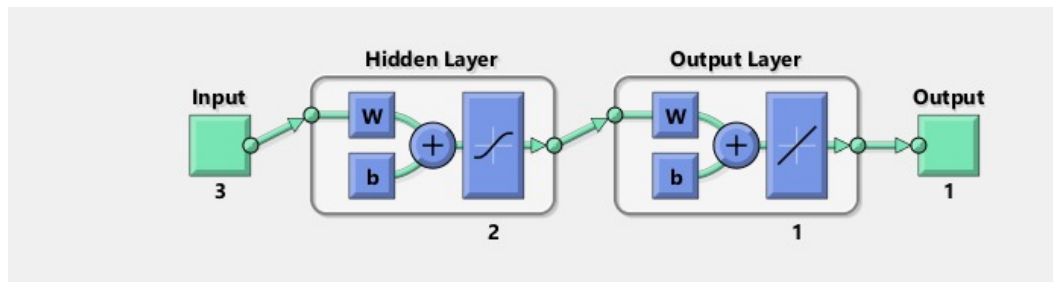


Figure 3.60. MATLAB Implementation of ANN Model for Israel

The input data were analyzed and pre-processed utilizing MATLAB software. Following this step, an ANN model was designed and implemented to address the research objectives. The architecture and structure of the developed ANN model, including the arrangement of input, hidden, and output layers, are illustrated in Figure 3.60.

Table 3.65. Summary of the Model for Israel

Model Summary		
Training	Sum of Squares Error	2,462
	Relative Error	,274
	Stopping Rule Used	1 consecutive step(s) with no decrease in error ^a
	Training Time	0:00:00,00
Testing	Sum of Squares Error	,732
	Relative Error	,166

Dependent Variable: Ecological Footprint

a. Error computations are based on the testing sample.

Table 3.65. presents the outcomes of the training and test sets for the model, together with the values of the cumulative squared errors. The test data exhibits a 0.166 proportion of erroneous predictions, indicating an accuracy of 83.4% in the assessment. The objective is to employ the activation function according to the relevance levels of the inputs. Weight values were established to minimize the inaccuracy. The weight coefficients of the neurons in the model's ANN are presented in Table 3.66.

Table 3.66. Weight Estimates for Israel

Predictor		Parameter Estimates		
		Hidden Layer 1		Predicted
		H(1:1)	H(1:2)	Output Layer Ecological_Footprint
Input Layer	(Bias)	2,028	-1,940	
	Gross_Domestic_Product	-3,691	-,793	
	Renewable_Energy_Consumption	,821	-1,302	
	KOF_Globalization_Index	2,378	,673	
Hidden Layer 1	(Bias)			1,218
	H(1:1)			1,121
	H(1:2)			2,012

The network is trained by changing the weights of the connections between neurons in each layer. The importance table of the independent variables is given in Table 3.67 to see how important each of the independent variables is in predicting the dependent variable.

Table 3.67. Significance of Independent Variables for Israel

Independent Variable Importance		
	Importance	Normalized Importance
Gross Domestic Product	,454	100,0%
Renewable_Energy_Consumption	,301	66,2%
KOF Globalization Index	,245	53,9%

According to the obtained data, it was concluded that the gross domestic product in Israel has an importance of 45.4% in the ecological footprint estimate. The values are normalized to 45.4% and the second most important variable among the remaining 100 variables is the renewable energy consumption index, which has an importance of 66.2%.

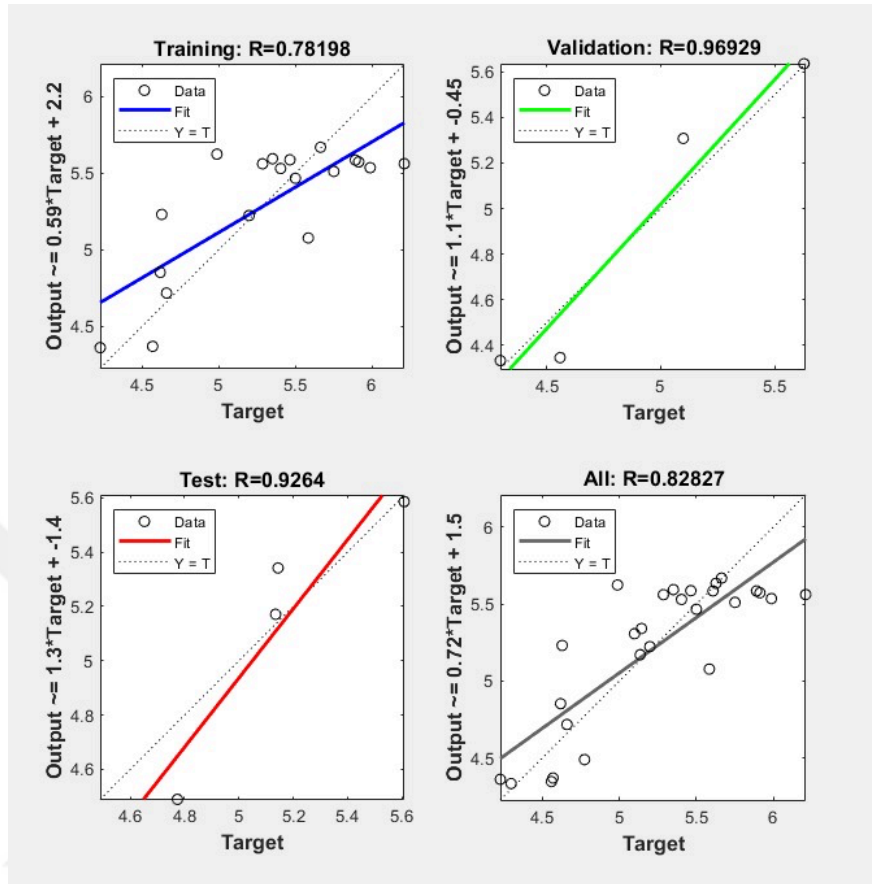


Figure 3.61. Regression Distribution of ANN's for Israel

As a result of the applied model, Figure 3.61. shows the correlation between all the values of the derived model after training, validation, testing and prediction. Training data showed a success rate of $R^2 = 0.78198$, validation data showed a success rate of $R^2 = 0.96929$ and testing data showed a success rate of $R^2 = 0.9264$. The performance metric of the network for the entire dataset is $R^2 = 0.82827$. This rate shows that the network is quite successful. Upon examination of the findings, the effectiveness of the developed model is obvious. The results show that there is a robust relationship between the actual values and the predicted values across all the datasets.

3.3.2.1.21. Artificial Neural Network Model for Italy

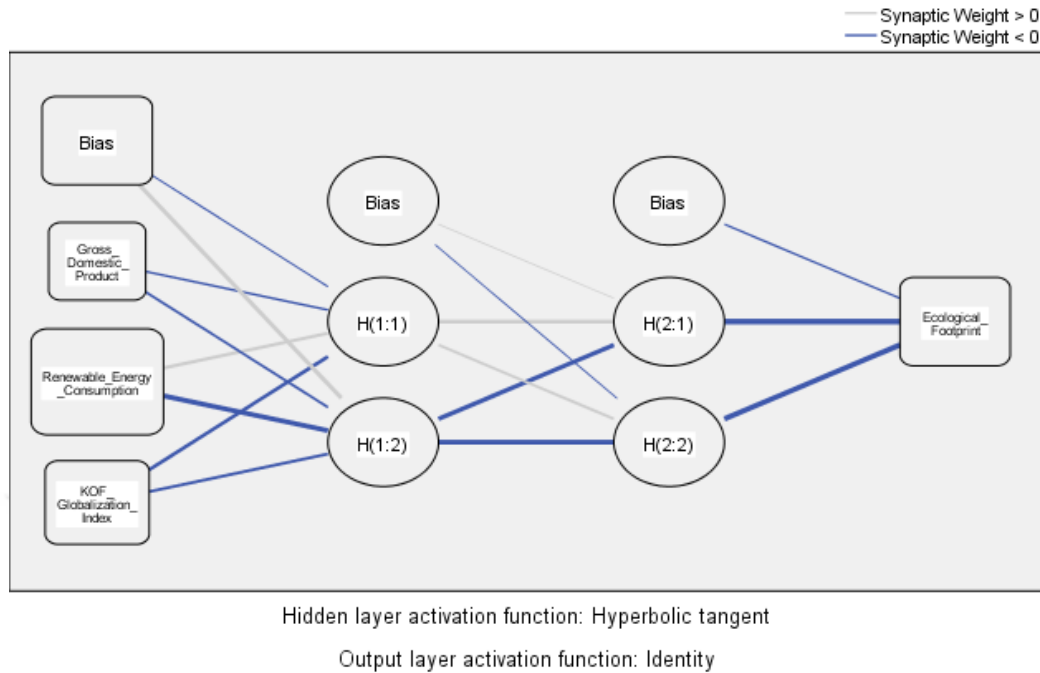


Figure 3.62. ANN Model of Italy

Figure 3.62 illustrates a two-hidden-layer ANN model designed for Italy, an OECD member country. The network architecture comprises three neurons in the input layer, two neurons in the hidden layer, and a single neuron in the output layer. This model adopts a two-layer neural structure with two neurons in the hidden layer. The hyperbolic tangent function is employed as the activation function within the hidden layer, facilitating non-linear transformations and enabling the network to capture complex patterns and relationships within the data.

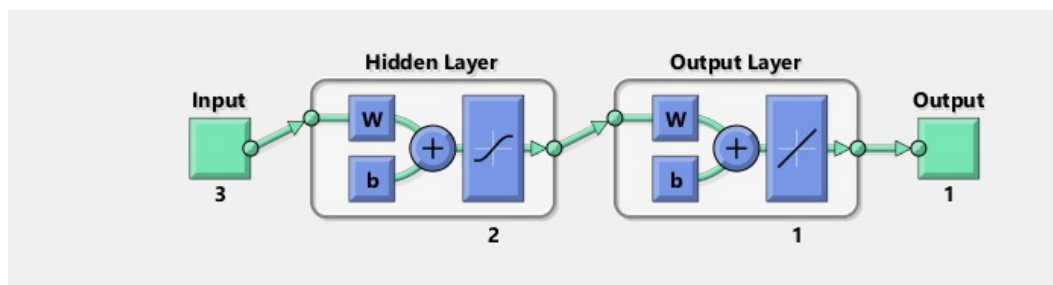


Figure 3.63. MATLAB Implementation of ANN Model for Italy

The input data were analyzed and pre-processed utilizing MATLAB software. Following this step, an ANN model was designed and implemented to address the research objectives. The architecture and structure of the developed ANN model, including the arrangement of input, hidden, and output layers, are illustrated in Figure 3.63.

Table 3.68. Summary of the Model for Italy

Model Summary		
Training	Sum of Squares Error	,189
	Relative Error	,021
	Stopping Rule Used	1 consecutive step(s) with no decrease in error ^a
	Training Time	0:00:00,00
Testing	Sum of Squares Error	,129
	Relative Error	,033

Dependent Variable: Ecological Footprint

a. Error computations are based on the testing sample.

Table 3.68. presents the outcomes of the training and test sets for the model, together with the values of the cumulative squared errors. The test data exhibits a 0.033 proportion of erroneous predictions, indicating an accuracy of 96.7% in the assessment. The objective is to employ the activation function according to the relevance levels of the inputs. Weight values were established to minimize the inaccuracy. The weight coefficients of the neurons in the model's ANN are presented in Table 3.69.

Table 3.69. Weight Estimates for Italy

Parameter Estimates					
Predictor		Hidden Layer 1		Predicted Hidden Layer 2	
		H(1:1)	H(1:2)	H(2:1)	H(2:2)
Input Layer	(Bias)	-,236	,749		
	Gross_Domestic_Product	-,440	-,457		
	Renewable_Energy_Consumption	,573	-1,000		
	KOF_Globalization_Index	-,631	-,552		
Hidden Layer 1	(Bias)			,119	-,162
	H(1:1)			,658	,536
	H(1:2)			-,770	-,869
Hidden Layer 2	(Bias)				-,377
	H(2:1)				-1,065
	H(2:2)				-1,051

The network is trained by changing the weights of the connections between neurons in each layer. The importance table of the independent variables is given in Table 3.69 to see how important each of the independent variables is in predicting the dependent variable.

Table 3.70. Significance of Independent Variables for Italy

Independent Variable Importance		
	Importance	Normalized Importance
Gross Domestic Product	,127	19,7%
Renewable Energy Consumption	,642	100,0%
KOF Globalization Index	,232	36,1%

According to the obtained data, it was concluded that renewable energy consumption in Italy has an importance of 64.2% in the ecological footprint estimation. The values are normalized to 64.2% and the second most important variable among the remaining 100 variables is the KOF globalization index, which has an importance of 36.1%.

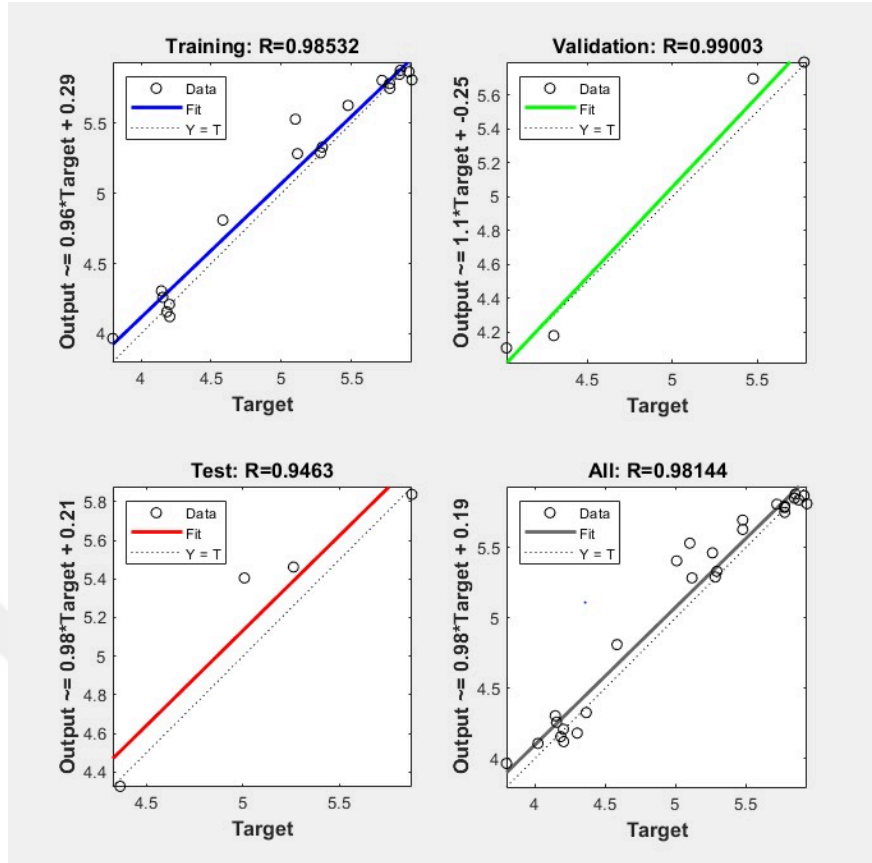


Figure 3.64. Regression Distribution of ANN's for Italy

As a result of the applied model, Figure 3.64. shows the correlation between all the values of the derived model after training, validation, testing and prediction. Training data showed a success rate of $R^2 = 0.98532$, validation data showed a success rate of $R^2 = 0.99003$ and testing data showed a success rate of $R^2 = 0.9463$. The performance metric of the network for the entire dataset is $R^2 = 0.98144$. This rate shows that the network is quite successful. Upon examination of the findings, the effectiveness of the developed model is obvious. The results show that there is a robust relationship between the actual values and the predicted values across all the datasets.

3.3.2.1.22. Artificial Neural Network Model for Japan

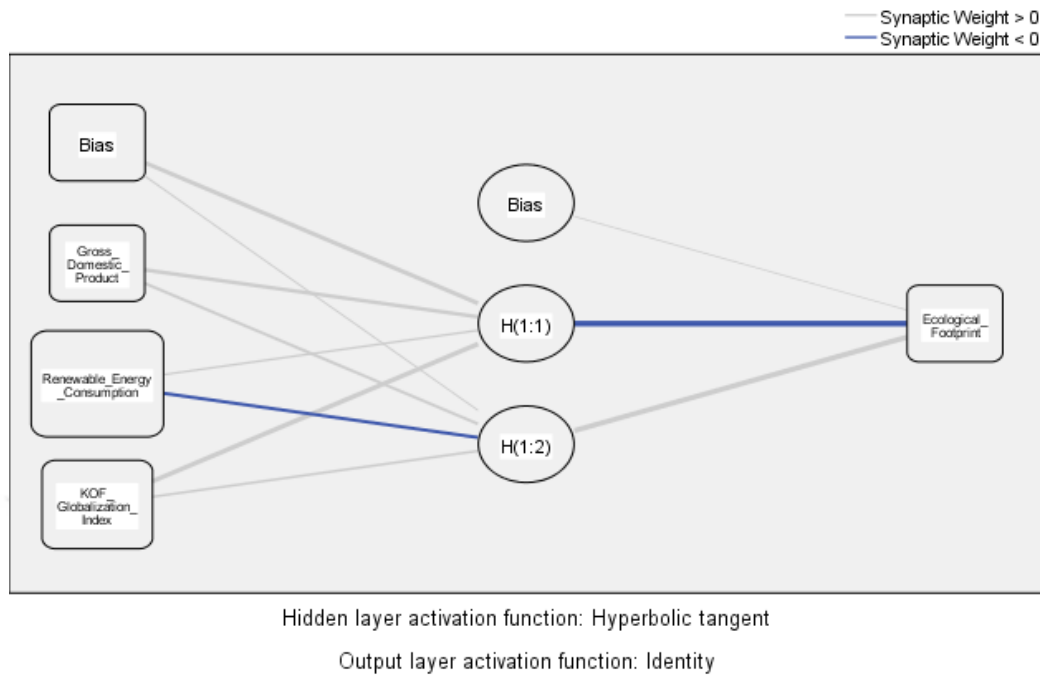


Figure 3.65. ANN Model of Japan

Figure 3.65 illustrates an ANN model designed for Japan, which is a member of the OECD. The network architecture consists of a single hidden layer and is structured with three neurons in the input layer, two neurons in the hidden layer, and one neuron in the output layer. The model employs a feedforward neural network configuration, where each neuron in one layer is fully connected to the neurons in the subsequent layer. A hyperbolic tangent (tanh) activation function is utilized in the hidden layer.

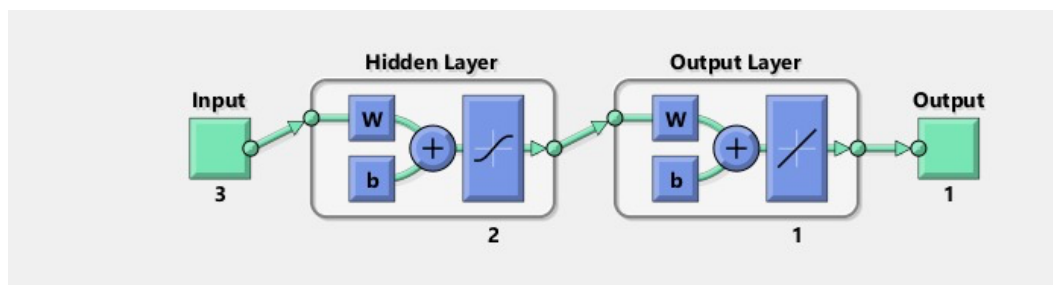


Figure 3.66. MATLAB Implementation of ANN Model for Japan

The input data were analyzed and pre-processed utilizing MATLAB software. Following this step, an ANN model was designed and implemented to address the research objectives. The architecture and structure of the developed ANN model, including the arrangement of input, hidden, and output layers, are illustrated in Figure 3.66.

Table 3.71. Summary of the Model for Japan

Model Summary		
Training	Sum of Squares Error	,648
	Relative Error	,076
	Stopping Rule Used	1 consecutive step(s) with no decrease in error ^a
	Training Time	0:00:00,02
Testing	Sum of Squares Error	,205
	Relative Error	,099

Dependent Variable: Ecological_Footprint

a. Error computations are based on the testing sample.

Table 3.71. presents the outcomes of the training and test sets for the model, together with the values of the cumulative squared errors. The test data exhibits a 0.099 proportion of erroneous predictions, indicating an accuracy of 90.1% in the assessment. The objective is to employ the activation function according to the relevance levels of the inputs. Weight values were established to minimize the inaccuracy. The weight coefficients of the neurons in the model's ANN are presented in Table 3.72.

Table 3.72. Weight Estimates for Japan

Predictor		Parameter Estimates		
		Hidden Layer 1		Predicted
		H(1:1)	H(1:2)	Output Layer Ecological Footprint
Input Layer	(Bias)	,822	,352	
	Gross_Domestic_Product	,622	,510	
	Renewable_Energy_Consumption	,379	-,598	
	KOF_Globalization_Index	1,106	,487	
Hidden Layer 1	(Bias)			,059
	H(1:1)			-1,269
	H(1:2)			1,143

The network is trained by changing the weights of the connections between neurons in each layer. The importance table of the independent variables is given in Table 3.73 to see how important each of the independent variables is in predicting the dependent variable.

Table 3.73. Significance of Independent Variables for Japan

Independent Variable Importance		
	Importance	Normalized Importance
Gross_Domestic_Product	,224	49,2%
Renewable_Energy_Consumption	,456	100,0%
KOF_Globalization_Index	,320	70,2%

According to the obtained data, it was concluded that renewable energy consumption in Japan has an importance of 45.6% in the ecological footprint estimation. The values are normalized to 45.6% and the second most important variable among the remaining 100 variables is the KOF globalization index, which has an importance of 70.2%.

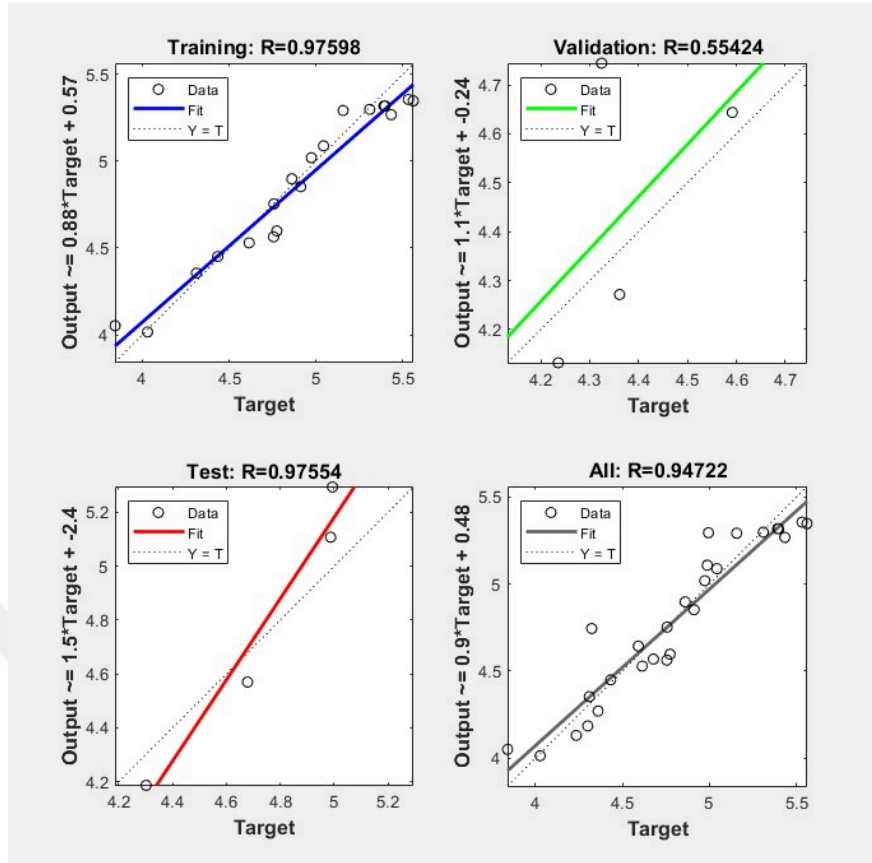


Figure 3.67. Regression Distribution of ANN's for Japan

As a result of the applied model, Figure 3.67. shows the correlation between all the values of the derived model after training, validation, testing and prediction. Training data showed a success rate of $R^2 = 0.97598$, validation data showed a success rate of $R^2 = 0.55424$ and testing data showed a success rate of $R^2 = 0.97554$. The performance metric of the network for the entire dataset is $R^2 = 0.94722$. This rate shows that the network is quite successful. Upon examination of the findings, the effectiveness of the developed model is obvious. The results show that there is a robust relationship between the actual values and the predicted values across all the datasets.

3.3.2.1.23. Artificial Neural Network Model for Korea, Rep

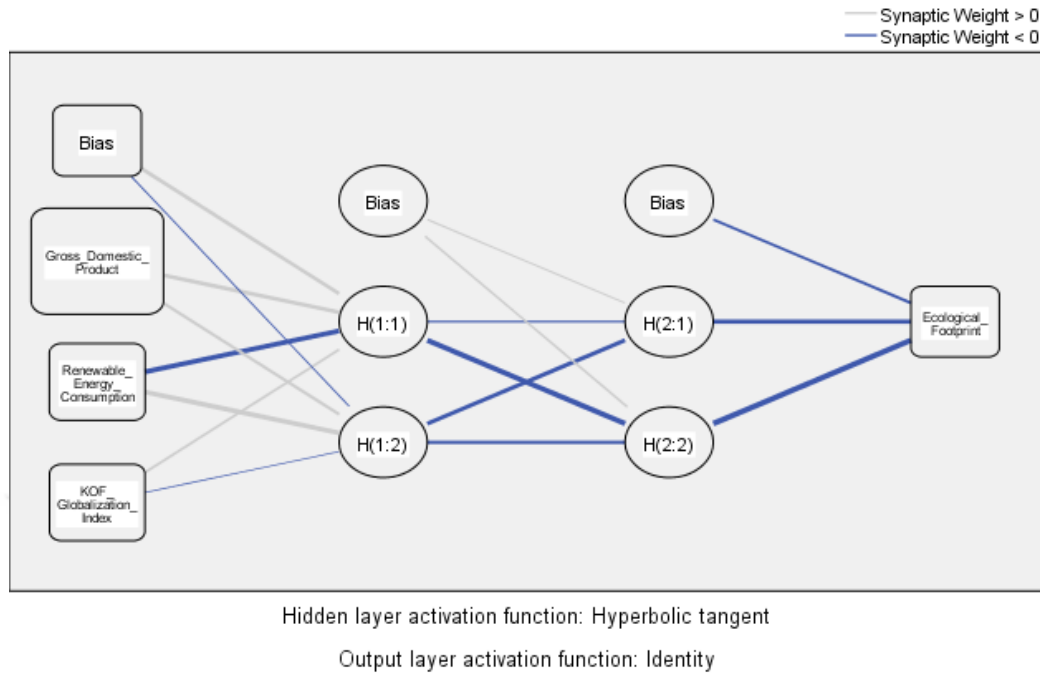


Figure 3.68. ANN Model of Korea, Rep

Figure 3.68 illustrates a two-hidden-layer ANN model designed for Korea, Rep, an OECD member country. The network architecture comprises three neurons in the input layer, two neurons in the hidden layer, and a single neuron in the output layer. This model adopts a two-layer neural structure with two neurons in the hidden layer. The hyperbolic tangent function is employed as the activation function within the hidden layer, facilitating non-linear transformations and enabling the network to capture complex patterns and relationships within the data.

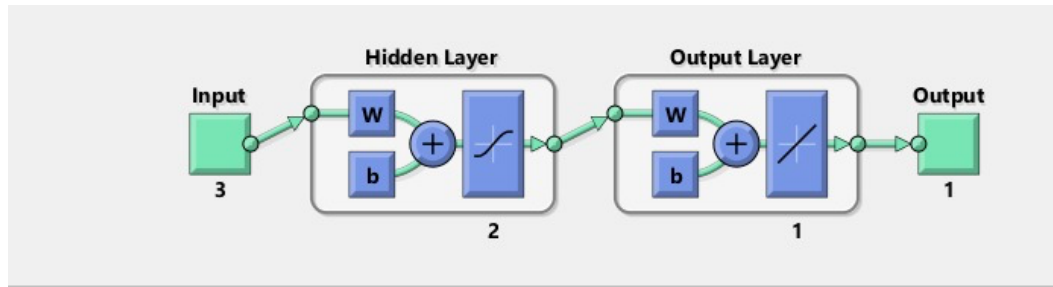


Figure 3.69. MATLAB Implementation of ANN Model for Korea, Rep

The input data were analyzed and pre-processed utilizing MATLAB software. Following this step, an ANN model was designed and implemented to address the research objectives. The architecture and structure of the developed ANN model, including the arrangement of input, hidden, and output layers, are illustrated in Figure 3.69.

Table 3.74. Summary of the Model for Korea, Rep

Model Summary		
Training	Sum of Squares Error	1,220
	Relative Error	,143
	Stopping Rule Used	1 consecutive step(s) with no decrease in error ^a
	Training Time	0:00:00,00
Testing	Sum of Squares Error	2,632
	Relative Error	,211

Dependent Variable: Ecological_Footprint

a. Error computations are based on the testing sample.

Table 3.74. presents the outcomes of the training and test sets for the model, together with the values of the cumulative squared errors. The test data exhibits a 0.211 proportion of erroneous predictions, indicating an accuracy of 78.9% in the assessment. The objective is to employ the activation function according to the relevance levels of the inputs. Weight values were established to minimize the inaccuracy. The weight coefficients of the neurons in the model's ANN are presented in Table 3.74.

Table 3.75. Weight Estimates for Korea, Rep

Parameter Estimates						
Predictor		Hidden Layer 1		Predicted Hidden Layer 2		Output Layer
		H(1:1)	H(1:2)	H(2:1)	H(2:2)	Ecological Foot print
Input Layer	(Bias)	,531	-,216			
	Gross_Domestic_Product	,617	,390			
	Renewable_Energy_Consumption	-,956	,762			
	KOF_Globalization_Index	,334	-,113			
Hidden Layer 1	(Bias)			,224	,266	
	H(1:1)			-,233	-1,332	
	H(1:2)			-,674	-,401	
Hidden Layer 2	(Bias)					-,365
	H(2:1)					-,685
	H(2:2)					-2,051

The network is trained by changing the weights of the connections between neurons in each layer. The importance table of the independent variables is given in Table 3.76 to see how important each of the independent variables is in predicting the dependent variable.

Table 3.76. Significance of Independent Variables for Korea, Rep

Independent Variable Importance		
	Importance	Normalized Importance
Gross Domestic Product	,462	100,0%
Renewable Energy Consumption	,270	58,5%
KOF Globalization Index	,269	58,2%

According to the obtained data, it was concluded that Korea, Rep. has an importance of 46.2% in estimating the gross domestic product ecological footprint. The values are normalized to 46.2%, the second most important variable among the rest of the 100 variables is the renewable energy consumption index with 58.5%, followed by the KOF globalization index with 58.2% importance.

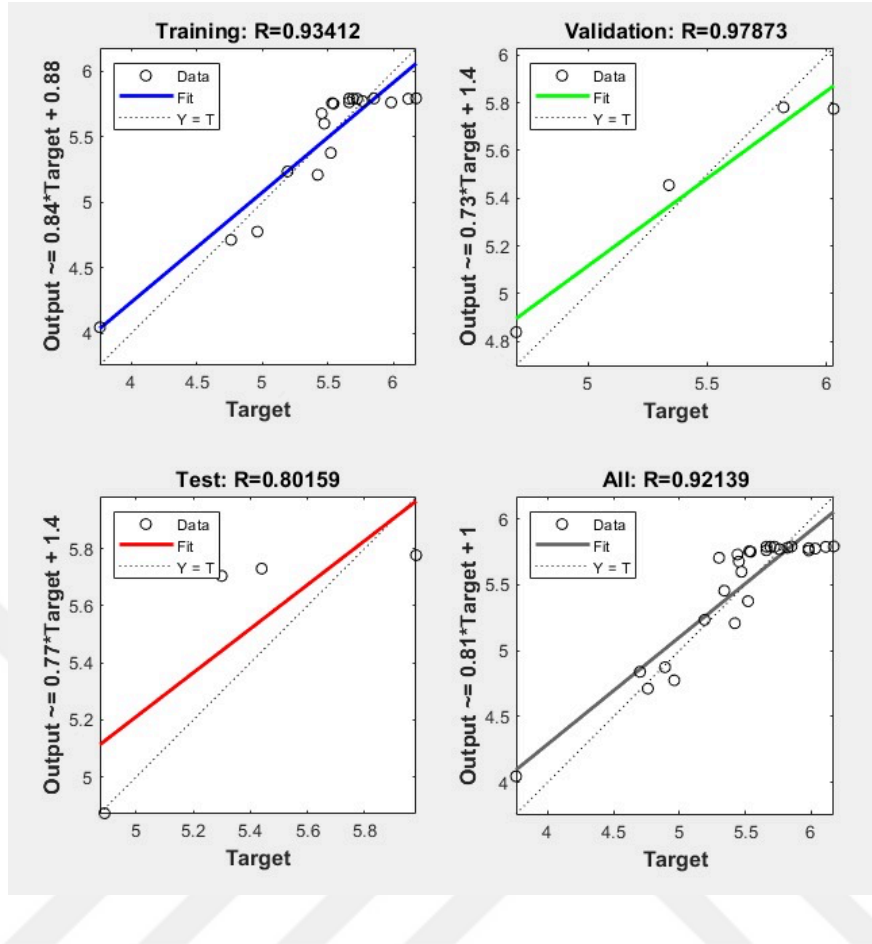


Figure 3.70. Regression Distribution of ANN's for Korea, Rep

As a result of the applied model, Figure 3.70. shows the correlation between all the values of the derived model after training, validation, testing and prediction. Training data showed a success rate of $R^2 = 0.93412$, validation data showed a success rate of $R^2 = 0.97873$ and testing data showed a success rate of $R^2 = 0.80159$. The performance metric of the network for the entire dataset is $R^2 = 0.92139$. This rate shows that the network is quite successful. Upon examination of the findings, the effectiveness of the developed model is obvious. The results show that there is a robust relationship between the actual values and the predicted values across all the datasets.

3.3.2.1.24. Artificial Neural Network Model for Lithuania

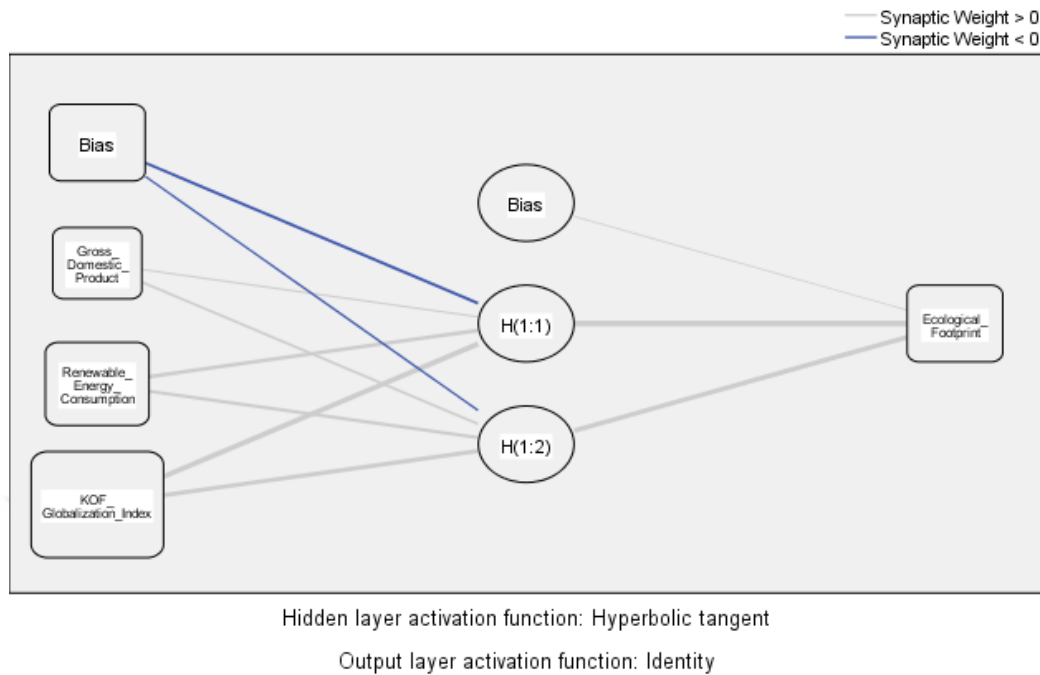


Figure 3.71. ANN Model of Lithuania

Figure 3.71 illustrates an ANN model designed for Lithuania, which is a member of the OECD. The network architecture consists of a single hidden layer and is structured with three neurons in the input layer, two neurons in the hidden layer, and one neuron in the output layer. The model employs a feedforward neural network configuration, where each neuron in one layer is fully connected to the neurons in the subsequent layer. A hyperbolic tangent (tanh) activation function is utilized in the hidden layer.

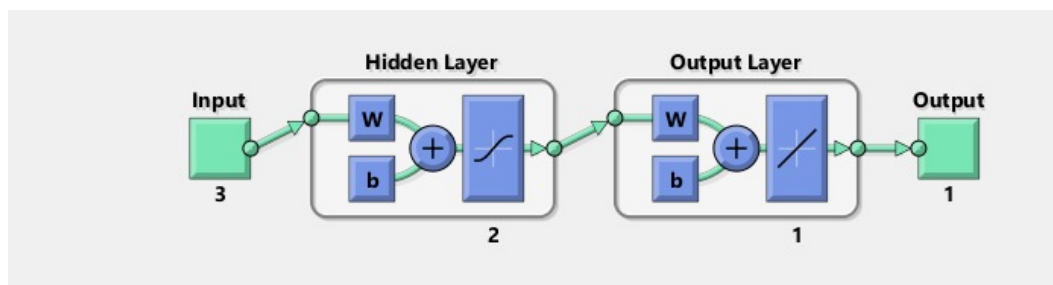


Figure 3.72. MATLAB Implementation of ANN Model for Lithuania

The input data were analyzed and pre-processed utilizing MATLAB software. Following this step, an ANN model was designed and implemented to address the research objectives. The architecture and structure of the developed ANN model, including the arrangement of input, hidden, and output layers, are illustrated in Figure 3.72.

Table 3.77. Summary of the Model for Lithuania

Model Summary		
Training	Sum of Squares Error	,729
	Relative Error	,081
	Stopping Rule Used	1 consecutive step(s) with no decrease in error ^a
	Training Time	0:00:00,00
Testing	Sum of Squares Error	,376
	Relative Error	,174

Dependent Variable: Ecological_Footprint

a. Error computations are based on the testing sample.

Table 3.77. presents the outcomes of the training and test sets for the model, together with the values of the cumulative squared errors. The test data exhibits a 0.174 proportion of erroneous predictions, indicating an accuracy of 82.6% in the assessment. The objective is to employ the activation function according to the relevance levels of the inputs. Weight values were established to minimize the inaccuracy. The weight coefficients of the neurons in the model's ANN are presented in Table 3.77.

Table 3.78. Weight Estimates for Lithuania

Predictor		Parameter Estimates		
		Hidden Layer 1		Predicted
		H(1:1)	H(1:2)	Output Layer Ecological_Foot print
Input Layer	(Bias)	-,236	-,216	
	Gross_Domestic_Product	,209	,232	
	Renewable_Energy_Consumption	,407	,238	
	KOF_Globalization_Index	,640	,438	
Hidden Layer 1	(Bias)			,080
	H(1:1)			,903
	H(1:2)			,468

The network is trained by changing the weights of the connections between neurons in each layer. The importance table of the independent variables is given in Table 3.79 to see how important each of the independent variables is in predicting the dependent variable.

Table 3.79. Significance of Independent Variables for Lithuania

Independent Variable Importance		
	Importance	Normalized Importance
Gross_Domestic_Product	,203	40,9%
Renewable_Energy_Consumption	,302	61,0%
KOF_Globalization_Index	,495	100,0%

According to the obtained data, it was concluded that KOF globalization index has an importance of 49.5% in estimating the ecological footprint in Lithuania. The values are normalized to 49.5% and the second most important variable among the remaining 100 variables is the renewable energy consumption index with 61%.

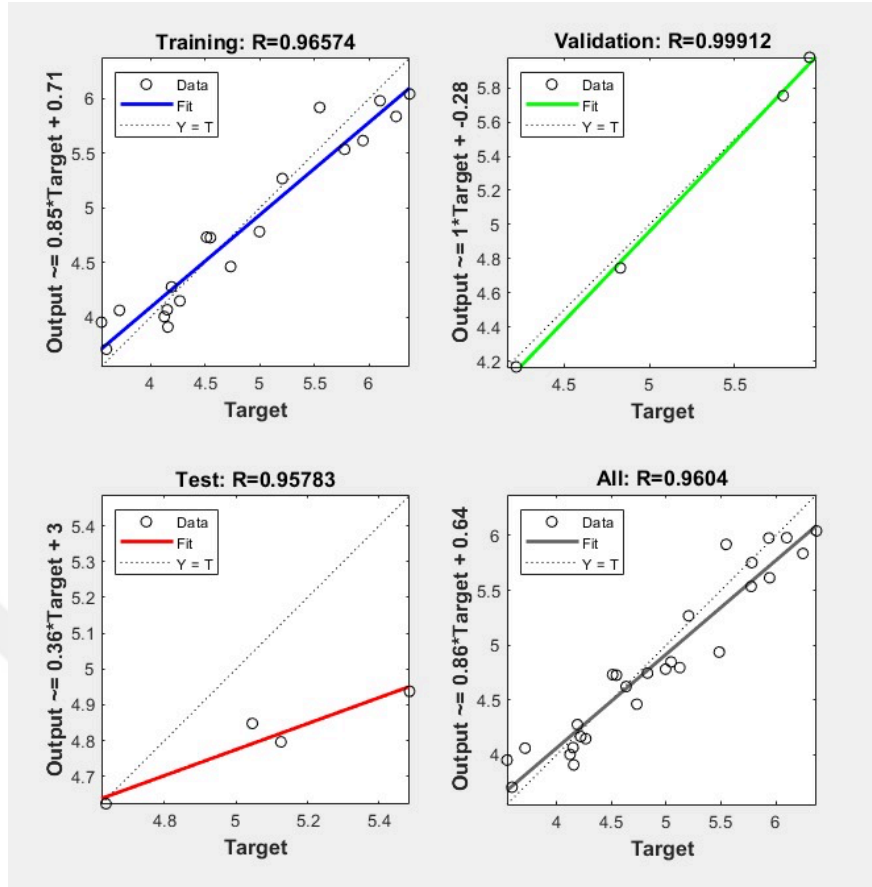


Figure 3.73. Regression Distribution of ANN's for Lithuania

As a result of the applied model, Figure 3.73. shows the correlation between all the values of the derived model after training, validation, testing and prediction. Training data showed a success rate of $R^2 = 0.96574$, validation data showed a success rate of $R^2 = 0.99912$ and testing data showed a success rate of $R^2 = 0.95783$. The performance metric of the network for the entire dataset is $R^2 = 0.9604$. This rate shows that the network is quite successful. Upon examination of the findings, the effectiveness of the developed model is obvious. The results show that there is a robust relationship between the actual values and the predicted values across all the datasets.

3.3.2.1.25. Artificial Neural Network Model for Luxembourg

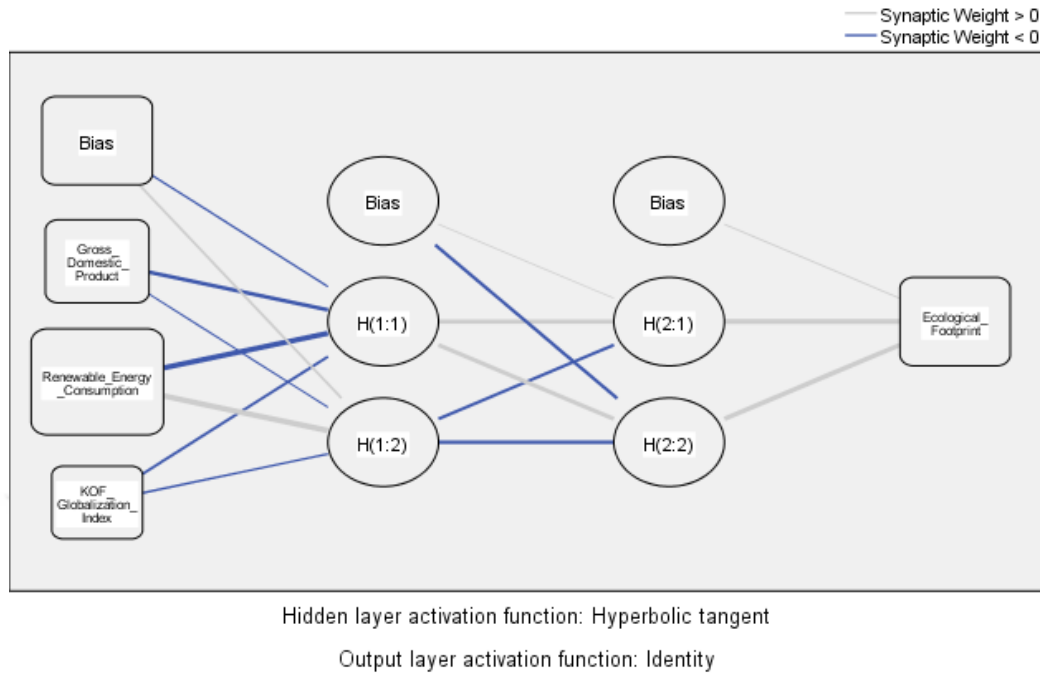


Figure 3.74. ANN Model of Luxembourg

Figure 3.74 illustrates a two-hidden-layer ANN model designed for Luxembourg, an OECD member country. The network architecture comprises three neurons in the input layer, two neurons in the hidden layer, and a single neuron in the output layer. This model adopts a two-layer neural structure with two neurons in the hidden layer. The hyperbolic tangent function is employed as the activation function within the hidden layer, facilitating non-linear transformations and enabling the network to capture complex patterns and relationships within the data.

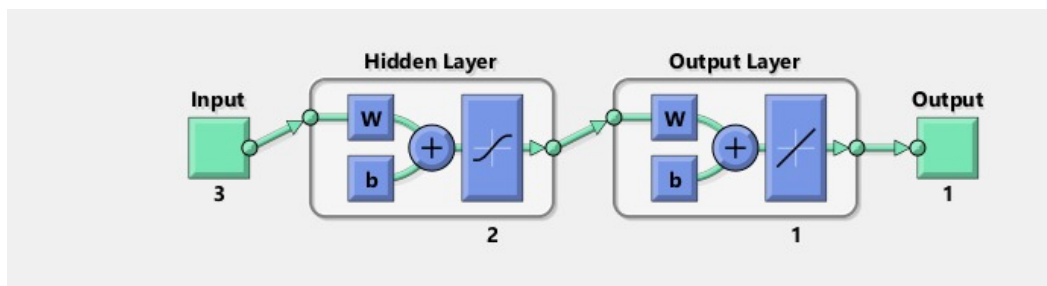


Figure 3.75. MATLAB Implementation of ANN Model for Luxembourg

The input data were analyzed and pre-processed utilizing MATLAB software. Following this step, an ANN model was designed and implemented to address the research objectives. The architecture and structure of the developed ANN model, including the arrangement of input, hidden, and output layers, are illustrated in Figure 3.75.

Table 3.80. Summary of the Model for Luxembourg

Model Summary		
Training	Sum of Squares Error	4,759
	Relative Error	,414
	Stopping Rule Used	1 consecutive step(s) with no decrease in error ^a
	Training Time	0:00:00,00
Testing	Sum of Squares Error	1,112
	Relative Error	,361

Dependent Variable: Ecological Footprint

a. Error computations are based on the testing sample.

Table 3.80. presents the outcomes of the training and test sets for the model, together with the values of the cumulative squared errors. The test data exhibits a 0.361 proportion of erroneous predictions, indicating an accuracy of 63.9% in the assessment. The objective is to employ the activation function according to the relevance levels of the inputs. Weight values were established to minimize the inaccuracy. The weight coefficients of the neurons in the model's ANN are presented in Table 3.81.

Table 3.81. Weight Estimates for Luxembourg

Parameter Estimates					
Predictor		Hidden Layer 1		Predicted Hidden Layer 2	
		H(1:1)	H(1:2)	H(2:1)	H(2:2)
Input Layer	(Bias)	-,092	,140		
	Gross_Domestic_Product	-,515	-,073		
	Renewable_Energy_Consumption	-1,107	1,167		
	KOF_Globalization_Index	-,156	-,118		
Hidden Layer 1	(Bias)			,011	-,335
	H(1:1)			,692	,607
	H(1:2)			-,243	-,395
Hidden Layer 2	(Bias)				,015
	H(2:1)				,824
	H(2:2)				,741

The network is trained by changing the weights of the connections between neurons in each layer. The importance table of the independent variables is given in Table 3.82 to see how important each of the independent variables is in predicting the dependent variable.

Table 3.82. Significance of Independent Variables for Luxembourg

Independent Variable Importance		
	Importance	Normalized Importance
Gross_Domestic_Product	,248	35,0%
Renewable_Energy_Consumption	,709	100,0%
KOF_Globalization_Index	,042	5,9%

According to the obtained data, it was concluded that the renewable energy consumption index in Luxembourg has 70.9% importance in estimating the ecological footprint. The values are normalized to 70.9% and the second most important variable among the remaining 100 variables is the gross domestic product index with 35%.

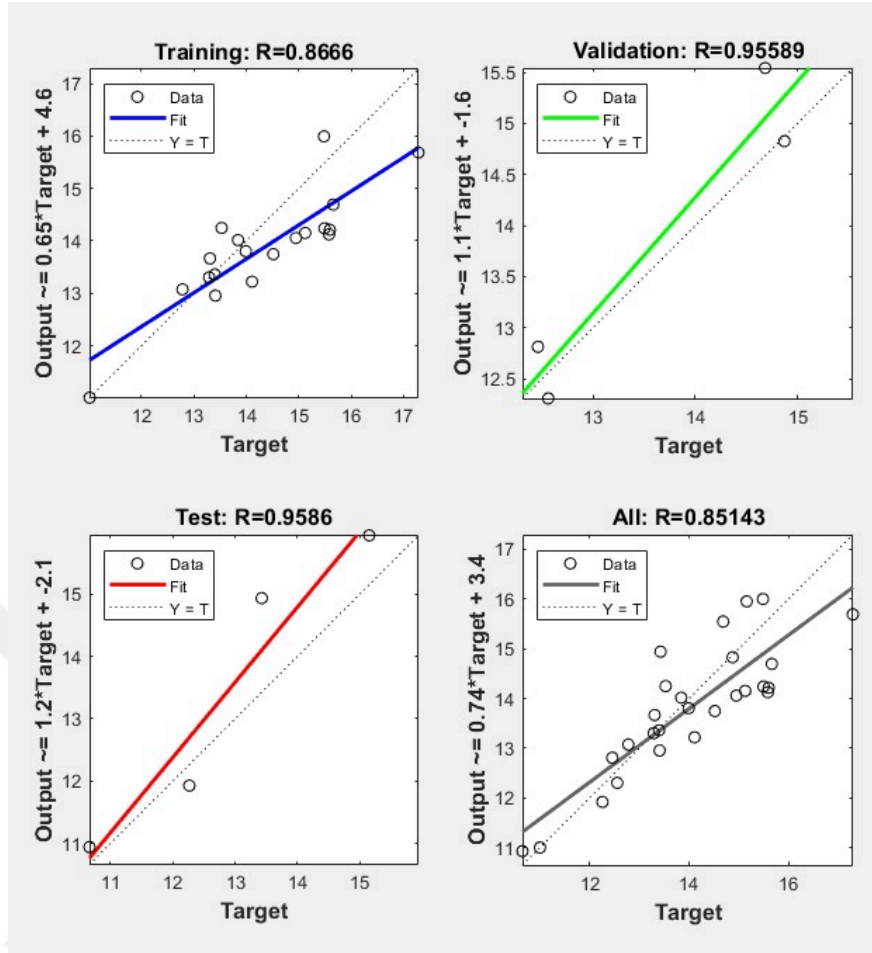


Figure 3.76. Regression Distribution of ANN's for Luxembourg

As a result of the applied model, Figure 3.76. shows the correlation between all the values of the derived model after training, validation, testing and prediction. Training data showed a success rate of $R^2 = 0.8666$, validation data showed a success rate of $R^2 = 0.95589$ and testing data showed a success rate of $R^2 = 0.9586$. The performance metric of the network for the entire dataset is $R^2 = 0.85143$. Upon examination of the findings, the effectiveness of the developed model is obvious. The results show that there is a robust relationship between the actual values and the predicted values across all the datasets.

3.3.2.1.26. Artificial Neural Network Model for Latvia

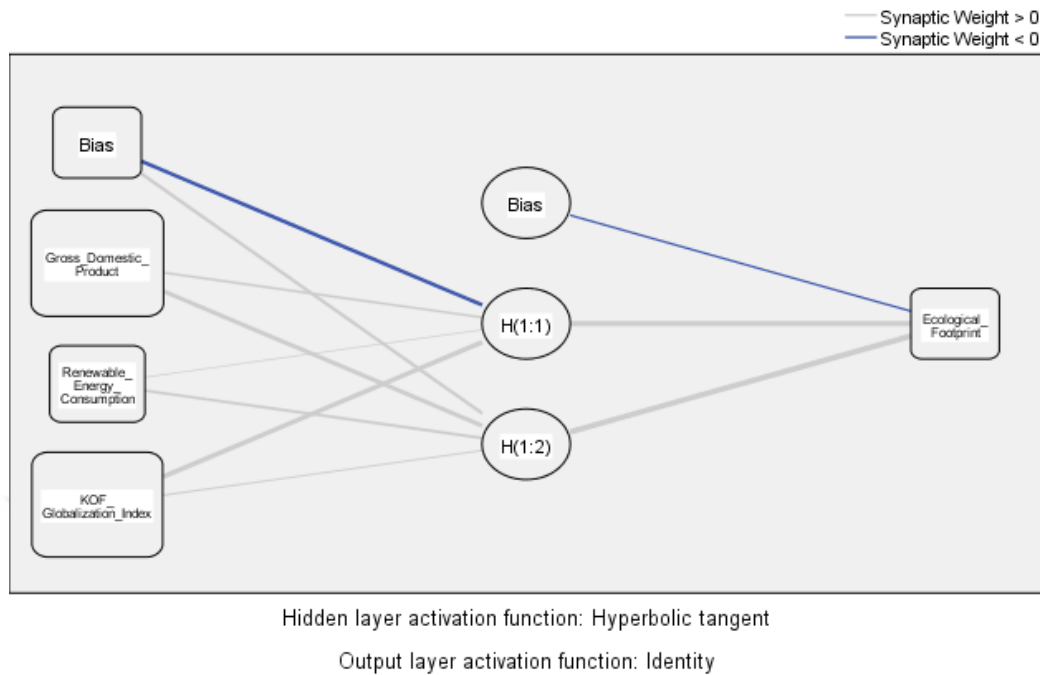


Figure 3.77. ANN Model of Latvia

Figure 3.77 illustrates an ANN model designed for Latvia, which is a member of the OECD. The network architecture consists of a single hidden layer and is structured with three neurons in the input layer, two neurons in the hidden layer, and one neuron in the output layer. The model employs a feedforward neural network configuration, where each neuron in one layer is fully connected to the neurons in the subsequent layer. A hyperbolic tangent (tanh) activation function is utilized in the hidden layer.

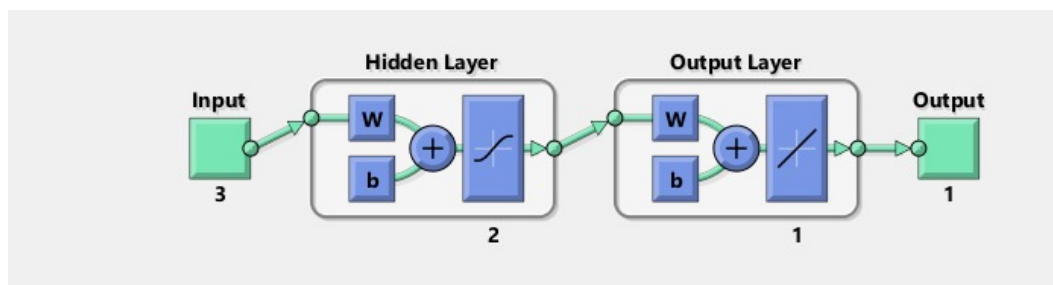


Figure 3.78. MATLAB Implementation of ANN Model for Latvia

The input data were analyzed and pre-processed utilizing MATLAB software. Following this step, an ANN model was designed and implemented to address the research objectives. The architecture and structure of the developed ANN model, including the arrangement of input, hidden, and output layers, are illustrated in Figure 3.78.

Table 3.83. Summary of the Model for Latvia

Model Summary		
Training	Sum of Squares Error	2,357
	Relative Error	,277
	Stopping Rule Used	1 consecutive step(s) with no decrease in error ^a
	Training Time	0:00:00,02
Testing	Sum of Squares Error	,789
	Relative Error	,143

Dependent Variable: Ecological_Footprint

a. Error computations are based on the testing sample.

Table 3.82. presents the outcomes of the training and test sets for the model, together with the values of the cumulative squared errors. The test data exhibits a 0.143 proportion of erroneous predictions, indicating an accuracy of 85.7% in the assessment. The objective is to employ the activation function according to the relevance levels of the inputs. Weight values were established to minimize the inaccuracy. The weight coefficients of the neurons in the model's ANN are presented in Table 3.84.

Table 3.84. Weight Estimates for Latvia

Predictor		Hidden Layer 1		Predicted
		H(1:1)	H(1:2)	Output Layer Ecological_Foot print
Input Layer	(Bias)	-,303	,286	
	Gross_Domestic_Product	,140	,406	
	Renewable_Energy_Consumption	,070	,223	
	KOF_Globalization_Index	,524	,115	
Hidden Layer 1	(Bias)			-,140
	H(1:1)			,673
	H(1:2)			,958

The network is trained by changing the weights of the connections between neurons in each layer. The importance table of the independent variables is given in Table 3.85 to see how important each of the independent variables is in predicting the dependent variable.

Table 3.85. Significance of Independent Variables for Latvia

Independent Variable Importance		
	Importance	Normalized Importance
Gross_Domestic_Product	,391	100,0%
Renewable_Energy_Consumption	,226	57,8%
KOF_Globalization_Index	,383	98,1%

According to the obtained data, it was concluded that the gross domestic product index in Latvia has 39.1% importance in estimating the ecological footprint. The second most important variable among the remaining 100 variables whose values were normalized is the KOF globalization index with 98.1%.

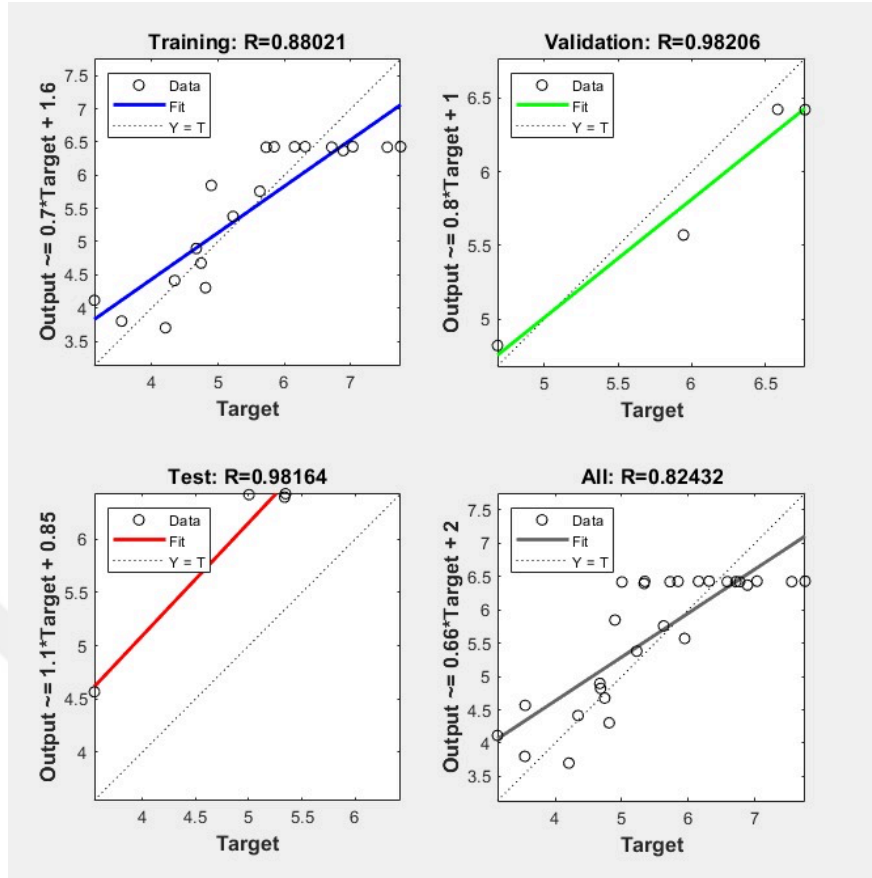


Figure 3.79. Regression Distribution of ANN's for Latvia

As a result of the applied model, Figure 3.79. shows the correlation between all the values of the derived model after training, validation, testing and prediction. Training data showed a success rate of $R^2 = 0.88021$, validation data showed a success rate of $R^2 = 0.98206$ and testing data showed a success rate of $R^2 = 0.98164$. The performance metric of the network for the entire dataset is $R^2 = 0.82432$. The results show that there is a robust relationship between the actual values and the predicted values across all the datasets.

3.3.2.1.27. Artificial Neural Network Model for Mexico

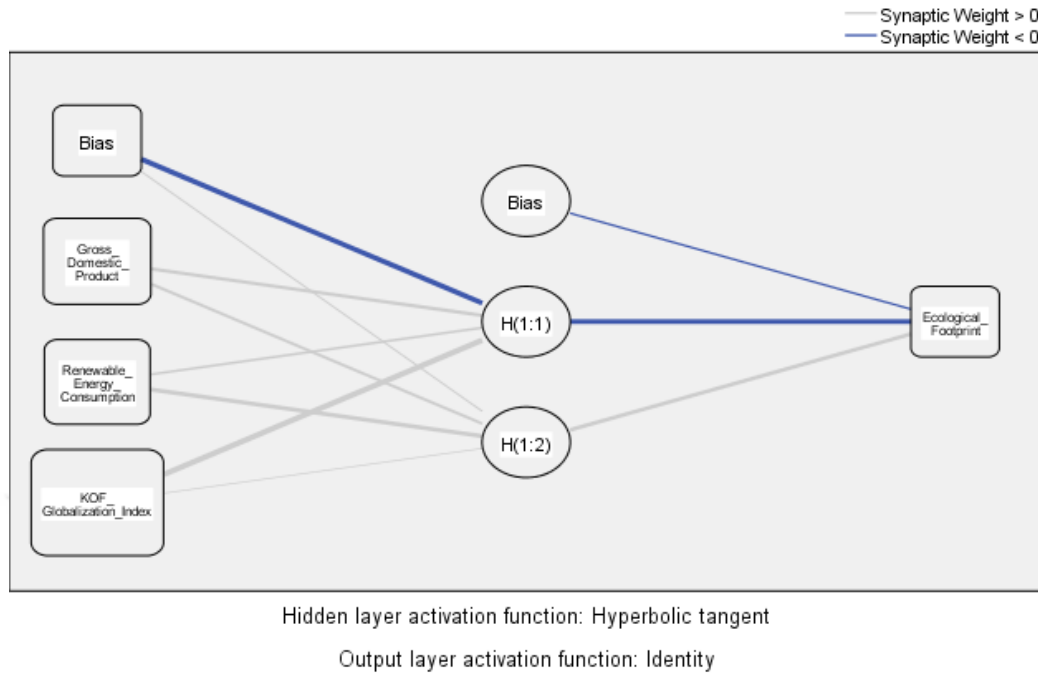


Figure 3.80. ANN Model of Mexico

Figure 3.80 illustrates an ANN model designed for Mexico, which is a member of the OECD. The network architecture consists of a single hidden layer and is structured with three neurons in the input layer, two neurons in the hidden layer, and one neuron in the output layer. The model employs a feedforward neural network configuration, where each neuron in one layer is fully connected to the neurons in the subsequent layer. A hyperbolic tangent (tanh) activation function is utilized in the hidden layer.

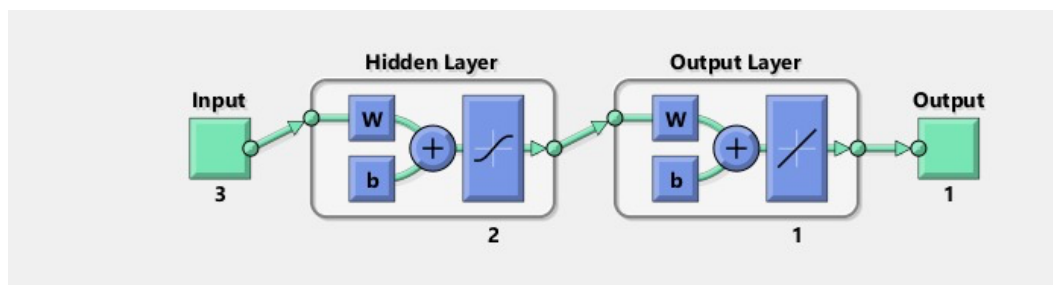


Figure 3.81. MATLAB Implementation of ANN Model for Mexico

The input data were analyzed and pre-processed utilizing MATLAB software. Following this step, an ANN model was designed and implemented to address the research objectives. The architecture and structure of the developed ANN model, including the arrangement of input, hidden, and output layers, are illustrated in Figure 3.81.

Table 3.86. Summary of the Model for Mexico

Model Summary		
Training	Sum of Squares Error	3,732
	Relative Error	,393
	Stopping Rule Used	1 consecutive step(s) with no decrease in error ^a
	Training Time	0:00:00,02
Testing	Sum of Squares Error	,641
	Relative Error	,187

Dependent Variable: Ecological Footprint

a. Error computations are based on the testing sample.

Table 3.85. presents the outcomes of the training and test sets for the model, together with the values of the cumulative squared errors. The test data exhibits a 0.187 proportion of erroneous predictions, indicating an accuracy of 81.3% in the assessment. The objective is to employ the activation function according to the relevance levels of the inputs. Weight values were established to minimize the inaccuracy. The weight coefficients of the neurons in the model's ANN are presented in Table 3.86.

Table 3.87. Weight Estimates for Mexico

Predictor		Parameter Estimates		
		Hidden Layer 1		Predicted
		H(1:1)	H(1:2)	Output Layer Ecological_Foot print
Input Layer	(Bias)	-1,416	,704	
	Gross_Domestic_Product	1,178	1,114	
	Renewable_Energy_Consumption	1,093	1,364	
	KOF_Globalization_Index	2,165	,582	
Hidden Layer 1	(Bias)			-,960
	H(1:1)			-1,386
	H(1:2)			1,270

The network is trained by changing the weights of the connections between neurons in each layer. The importance table of the independent variables is given in Table 3.88 to see how important each of the independent variables is in predicting the dependent variable.

Table 3.88. Significance of Independent Variables for Mexico

Independent Variable Importance		
	Importance	Normalized Importance
Gross Domestic Product	,297	71,7%
Renewable Energy Consumption	,289	69,7%
KOF Globalization Index	,414	100,0%

According to the data obtained, it was concluded that the KOF globalization index has 41.4% importance in estimating the ecological footprint in Mexico. The second most important variable among the remaining 100 variables whose values were normalized is the gross domestic product index with 71.7%.

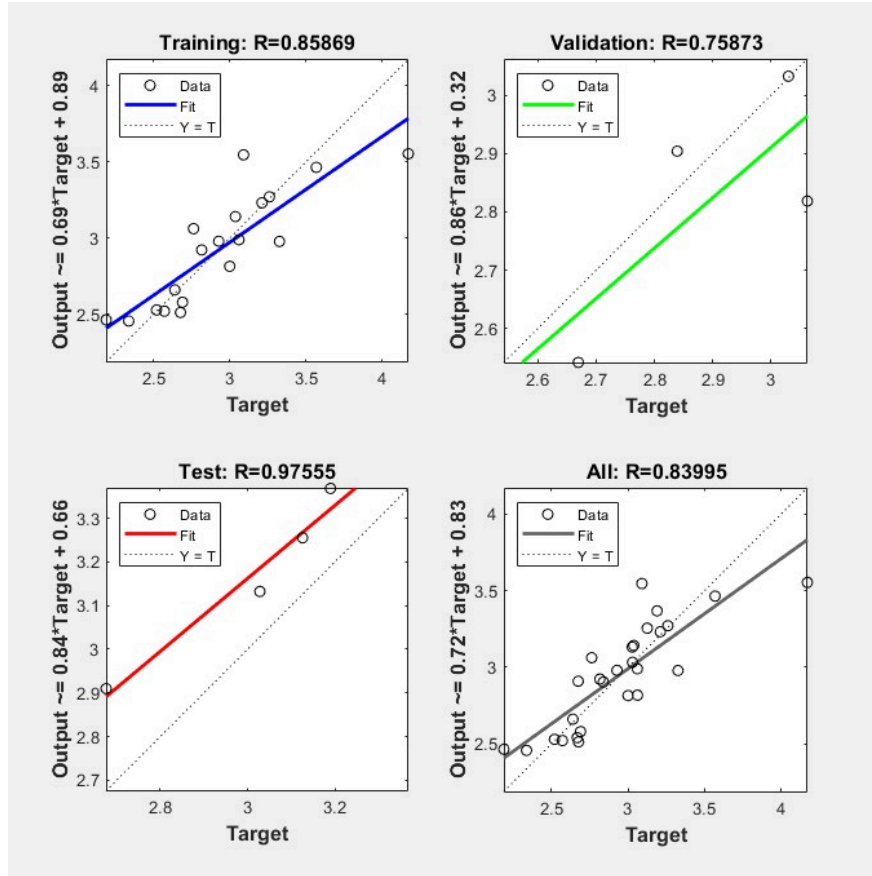


Figure 3.82. Regression Distribution of ANN's for Mexico

As a result of the applied model, Figure 3.82. shows the correlation between all the values of the derived model after training, validation, testing and prediction. Training data showed a success rate of $R^2 = 0.85869$, validation data showed a success rate of $R^2 = 0.75873$ and testing data showed a success rate of $R^2 = 0.97555$. The performance metric of the network for the entire dataset is $R^2 = 0.83995$. The results show that there is a robust relationship between the actual values and the predicted values across all the datasets.

3.3.2.1.28. Artificial Neural Network Model for Netherlands

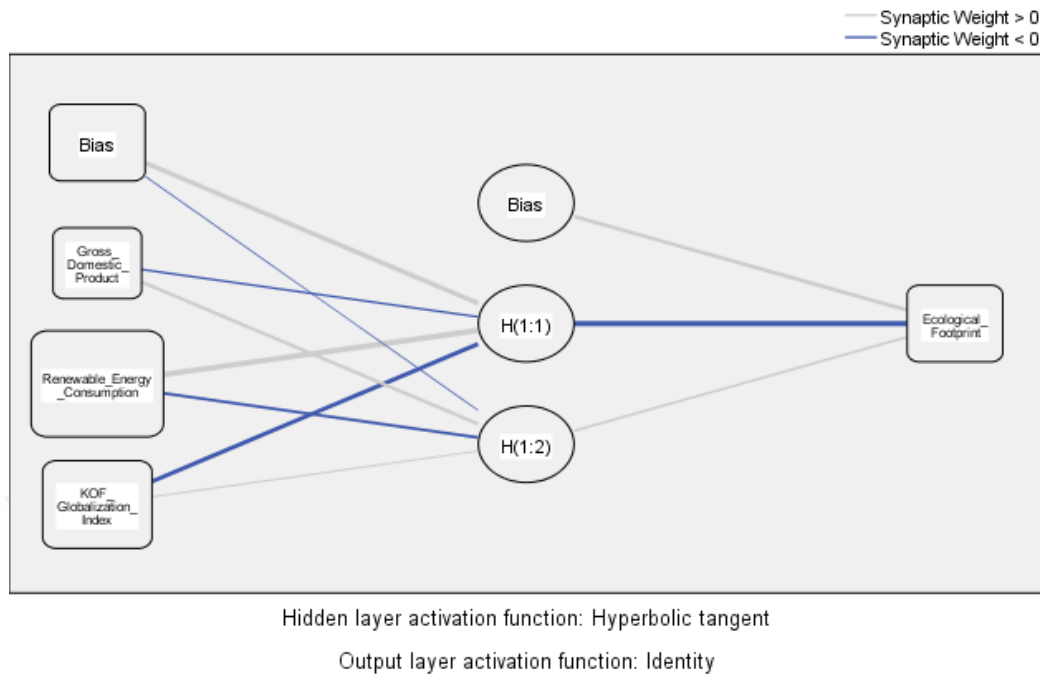


Figure 3.83. ANN Model of Netherlands

Figure 3.83 illustrates an ANN model designed for Netherlands, which is a member of the OECD. The network architecture consists of a single hidden layer and is structured with three neurons in the input layer, two neurons in the hidden layer, and one neuron in the output layer. The model employs a feedforward neural network configuration, where each neuron in one layer is fully connected to the neurons in the subsequent layer. A hyperbolic tangent (tanh) activation function is utilized in the hidden layer.

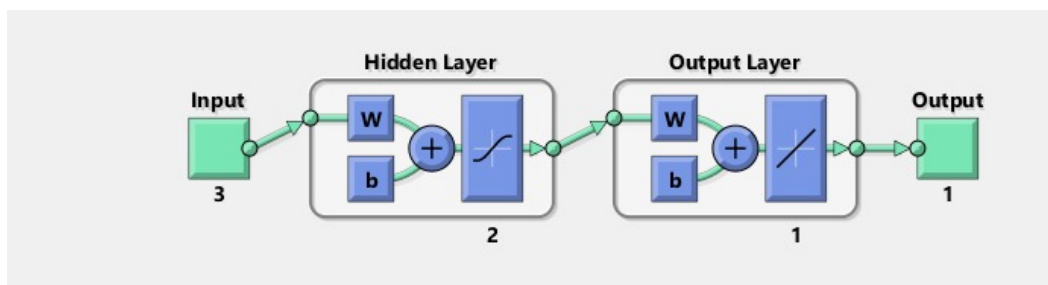


Figure 3.84. MATLAB Implementation of ANN Model for Netherlands

The input data were analyzed and pre-processed utilizing MATLAB software. Following this step, an ANN model was designed and implemented to address the research objectives. The architecture and structure of the developed ANN model, including the arrangement of input, hidden, and output layers, are illustrated in Figure 3.84.

Table 3.89. Summary of the Model for Netherlands

Model Summary		
Training	Sum of Squares Error	3,235
	Relative Error	,359
	Stopping Rule Used	1 consecutive step(s) with no decrease in error ^a
	Training Time	0:00:00,00
Testing	Sum of Squares Error	2,444
	Relative Error	,422

Dependent Variable: Ecological_Footprint

a. Error computations are based on the testing sample.

Table 3.89. presents the outcomes of the training and test sets for the model, together with the values of the cumulative squared errors. The test data exhibits a 0.422 proportion of erroneous predictions, indicating an accuracy of 57.8% in the assessment. The objective is to employ the activation function according to the relevance levels of the inputs. Weight values were established to minimize the inaccuracy. The weight coefficients of the neurons in the model's ANN are presented in Table 3.90.

Table 3.90. Weight Estimates for Netherlands

Predictor		Hidden Layer 1		Predicted
		H(1:1)	H(1:2)	Output Layer
				Ecological_Footprint
Input Layer	(Bias)	1,012	-,084	
	Gross_Domestic_Product	-,267	,670	
	Renewable_Energy_Consumption	2,268	-,632	
	KOF_Globalization_Index	-,972	,130	
Hidden Layer 1	(Bias)			,965
	H(1:1)			-2,003
	H(1:2)			,371

The network is trained by changing the weights of the connections between neurons in each layer. The importance table of the independent variables is given in Table 3.91 to see how important each of the independent variables is in predicting the dependent variable.

Table 3.91. Significance of Independent Variables for Netherlands

Independent Variable Importance		
	Importance	Normalized Importance
Gross_Domestic_Product	,193	40,4%
Renewable_Energy_Consumption	,479	100,0%
KOF_Globalization_Index	,328	68,5%

According to the obtained data, it was concluded that the renewable energy consumption index in the Netherlands has 47.9% importance in estimating the ecological footprint. The second most important variable among the remaining 100 variables whose values were normalized is the KOF globalization index with 68.5%.

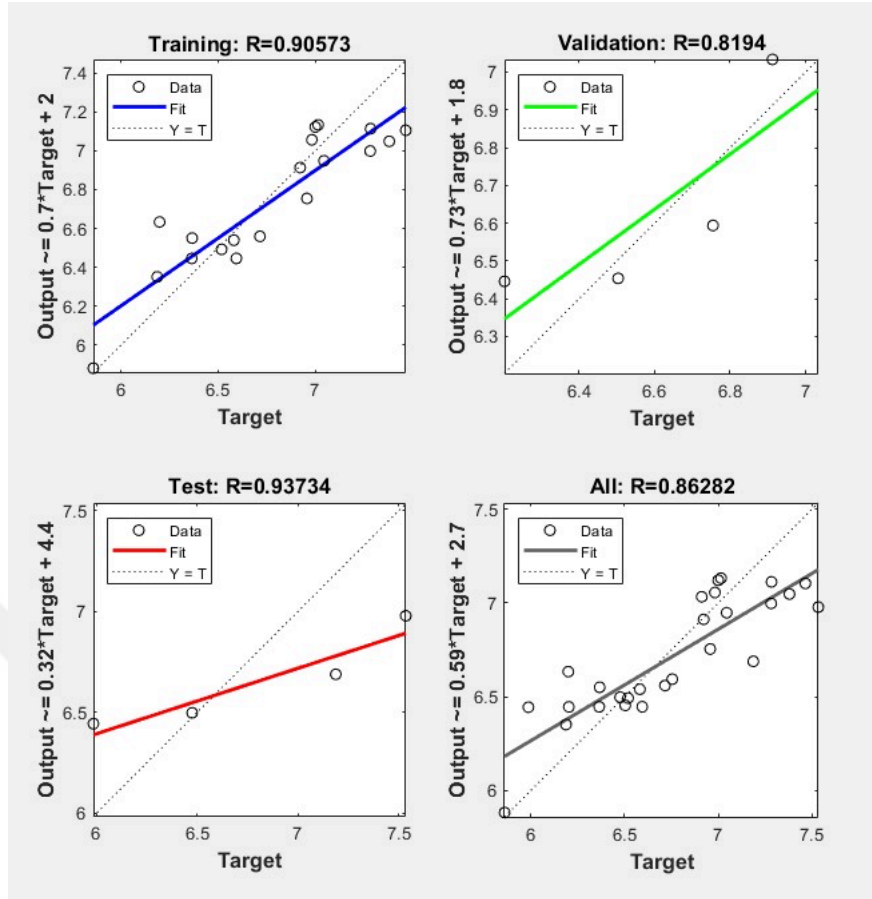


Figure 3.85. Regression Distribution of ANN's for Netherlands

As a result of the applied model, Figure 3.85. shows the correlation between all the values of the derived model after training, validation, testing and prediction. Training data showed a success rate of $R^2 = 0.90573$, validation data showed a success rate of $R^2 = 0.8194$ and testing data showed a success rate of $R^2 = 0.93734$. The performance metric of the network for the entire dataset is $R^2 = 0.86282$. The results show that there is a robust relationship between the actual values and the predicted values across all the datasets.

3.3.2.1.29. Artificial Neural Network Model for Norway

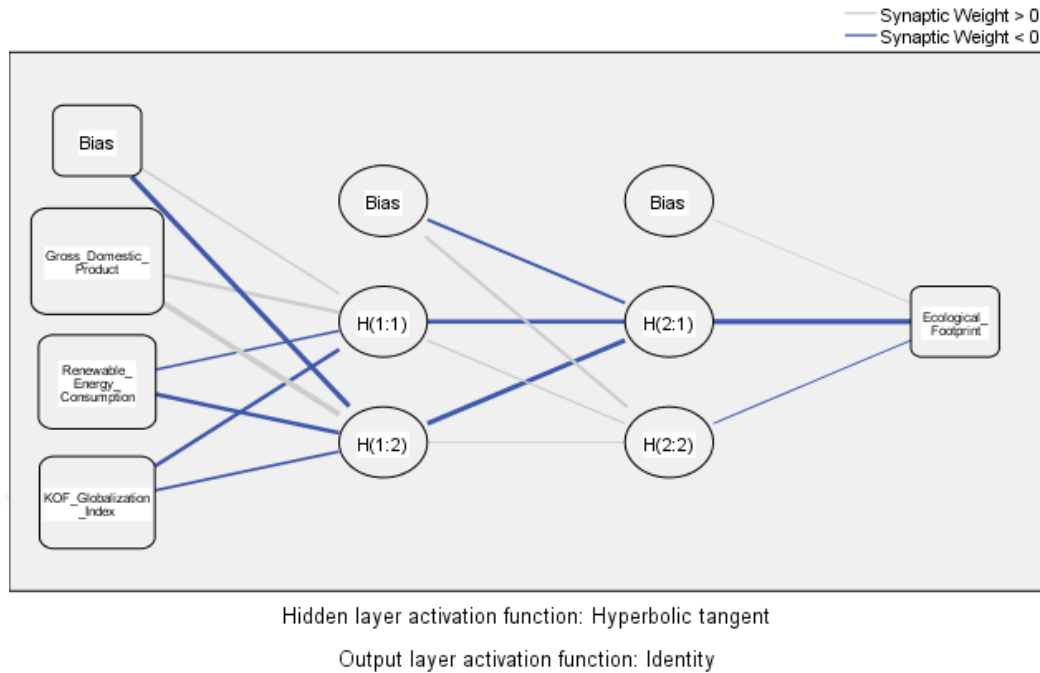


Figure 3.86. ANN Model of Norway

Figure 3.86 illustrates a two-hidden-layer ANN model designed for Norway, an OECD member country. The network architecture comprises three neurons in the input layer, two neurons in the hidden layer, and a single neuron in the output layer. This model adopts a two-layer neural structure with two neurons in the hidden layer. The hyperbolic tangent function is employed as the activation function within the hidden layer, facilitating non-linear transformations and enabling the network to capture complex patterns and relationships within the data.

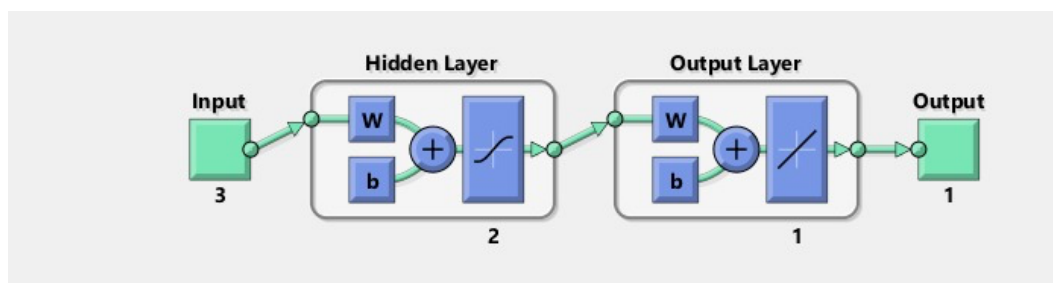


Figure 3.87. MATLAB Implementation of ANN Model for Norway

The input data were analyzed and pre-processed utilizing MATLAB software. Following this step, an ANN model was designed and implemented to address the research objectives. The architecture and structure of the developed ANN model, including the arrangement of input, hidden, and output layers, are illustrated in Figure 3.87.

Table 3.92. Summary of the Model for Norway

Model Summary		
Training	Sum of Squares Error	5,568
	Relative Error	,586
	Stopping Rule Used	1 consecutive step(s) with no decrease in error ^a
	Training Time	0:00:00,02
Testing	Sum of Squares Error	1,739
	Relative Error	,672
Dependent Variable: Ecological Footprint		
a. Error computations are based on the testing sample.		

Table 3.92. presents the outcomes of the training and test sets for the model, together with the values of the cumulative squared errors. The test data exhibits a 0.672 proportion of erroneous predictions, indicating an accuracy of 32.8% in the assessment. The objective is to employ the activation function according to the relevance levels of the inputs. Weight values were established to minimize the inaccuracy. The weight coefficients of the neurons in the model's ANN are presented in Table 3.93.

Table 3.93. Weight Estimates for Norway

Parameter Estimates						
Predictor		Hidden Layer 1		Predicted Hidden Layer 2		Output Layer
		H(1:1)	H(1:2)	H(2:1)	H(2:2)	Ecological Footprint
Input Layer	(Bias)	,235	-,805			
	Gross_Domestic_Product	,444	1,129			
	Renewable_Energy_Consumption	-,291	-,661			
	KOF_Globalization_Index	-,650	-,336			
Hidden Layer 1	(Bias)			-,391	,422	
	H(1:1)			-,721	,080	
	H(1:2)			-,727	,047	
Hidden Layer 2	(Bias)					,006
	H(2:1)					-,947
	H(2:2)					-,074

The network is trained by changing the weights of the connections between neurons in each layer. The importance table of the independent variables is given in Table 3.94 to see how important each of the independent variables is in predicting the dependent variable.

Table 3.94. Significance of Independent Variables for Norway

Independent Variable Importance		
	Importance	Normalized Importance
Gross_Domestic_Product	,380	100,0%
Renewable_Energy_Consumption	,315	82,9%
KOF_Globalization_Index	,306	80,5%

According to the obtained data, it was concluded that the gross domestic product index in Norway has 38% importance in estimating the ecological footprint. The second most important variable among the remaining 100 variables whose values were normalized is the renewable energy consumption index with 82.9%.

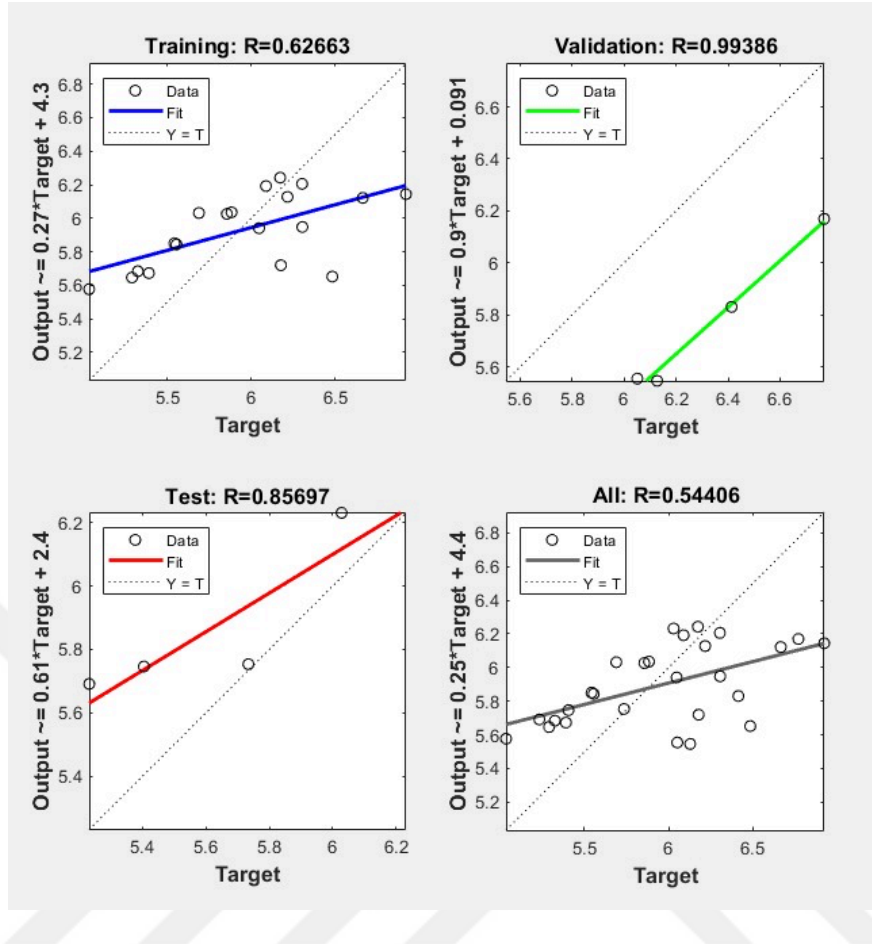


Figure 3.88. Regression Distribution of ANN's for Norway

As a result of the applied model, Figure 3.88. shows the correlation between all the values of the derived model after training, validation, testing and prediction. Training data showed a success rate of $R^2 = 0.62663$, validation data showed a success rate of $R^2 = 0.99386$ and testing data showed a success rate of $R^2 = 0.85697$. The performance metric of the network for the entire dataset is $R^2 = 0.54406$. This rate is not enough to say that the network is successful. Upon examination of the findings, the results show that there is no very strong relationship between the actual values and the predicted values in all data sets.

3.3.2.1.30. Artificial Neural Network Model for New Zealand

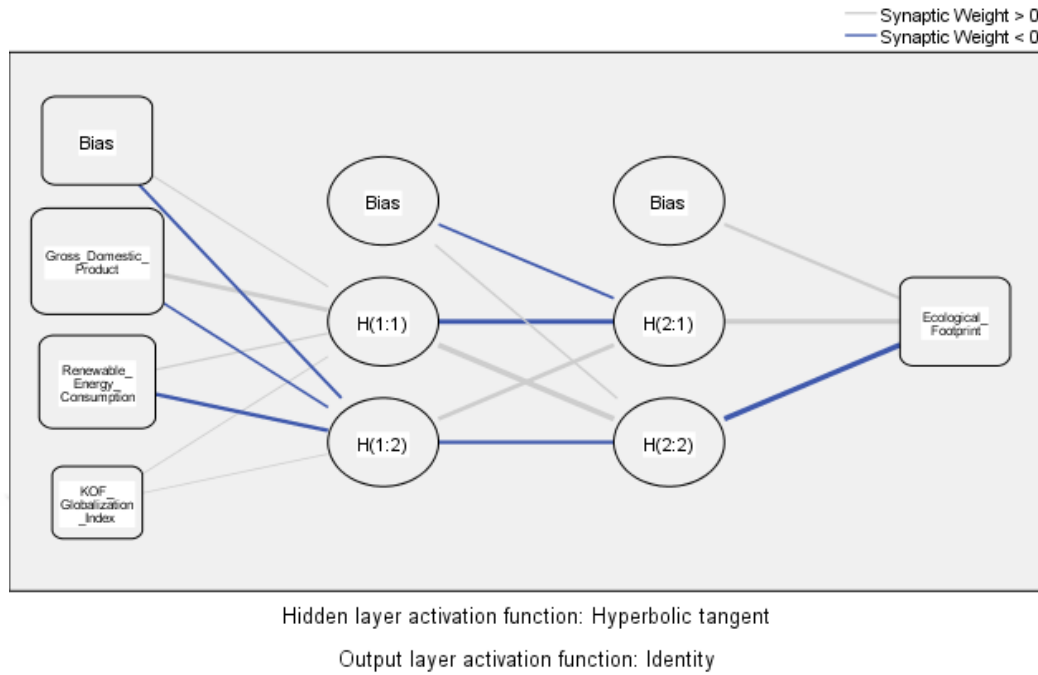


Figure 3.89. ANN Model of New Zealand

Figure 3.89 illustrates a two-hidden-layer ANN model designed for New Zealand, an OECD member country. The network architecture comprises three neurons in the input layer, two neurons in the hidden layer, and a single neuron in the output layer. This model adopts a two-layer neural structure with two neurons in the hidden layer. The hyperbolic tangent function is employed as the activation function within the hidden layer, facilitating non-linear transformations and enabling the network to capture complex patterns and relationships within the data.

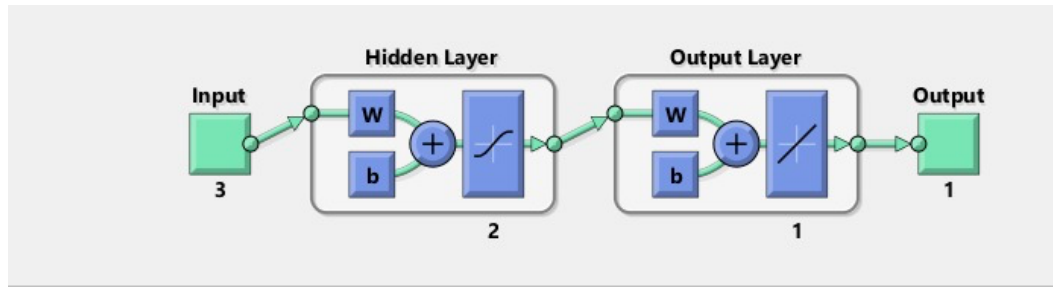


Figure 3.90. MATLAB Implementation of ANN Model for New Zealand

The input data were analyzed and pre-processed utilizing MATLAB software. Following this step, an ANN model was designed and implemented to address the research objectives. The architecture and structure of the developed ANN model, including the arrangement of input, hidden, and output layers, are illustrated in Figure 3.90.

Table 3.95. Summary of the Model for New Zealand

Model Summary		
Training	Sum of Squares Error	,333
	Relative Error	,060
	Stopping Rule Used	1 consecutive step(s) with no decrease in error ^a
	Training Time	0:00:00,00
Testing	Sum of Squares Error	1,787
	Relative Error	,273

Dependent Variable: Ecological_Footprint

a. Error computations are based on the testing sample.

Table 3.95. presents the outcomes of the training and test sets for the model, together with the values of the cumulative squared errors. The test data exhibits a 0.273 proportion of erroneous predictions, indicating an accuracy of 72.7% in the assessment. The objective is to employ the activation function according to the relevance levels of the inputs. Weight values were established to minimize the inaccuracy. The weight coefficients of the neurons in the model's ANN are presented in Table 3.95.

Table 3.96. Weight Estimates for New Zealand

Parameter Estimates					
		Hidden Layer 1		Predicted Hidden Layer 2	Output Layer Ecological_Footprint
Predictor		H(1:1)	H(1:2)	H(2:1)	H(2:2)
Input Layer	(Bias)	,171	-,314		
	Gross_Domestic_Product	,686	-,257		
	Renewable_Energy_Consumption	,193	-,424		
	KOF_Globalization_Index	,057	,024		
Hidden Layer 1	(Bias)			-,263	,213
	H(1:1)			-,741	,954
	H(1:2)			,505	-,409
Hidden Layer 2	(Bias)				,378
	H(2:1)				,875
	H(2:2)				-,893

The network is trained by changing the weights of the connections between neurons in each layer. The importance table of the independent variables is given in Table 3.97 to see how important each of the independent variables is in predicting the dependent variable.

Table 3.97. Significance of Independent Variables for New Zealand

Independent Variable Importance		
	Importance	Normalized Importance
Gross_Domestic_Product	,596	100,0%
Renewable_Energy_Consumption	,378	63,5%
KOF_Globalization_Index	,026	4,4%

According to the data obtained, it was concluded that the gross domestic product index in New Zealand has 59.6% importance in estimating the ecological footprint. The second most important variable among the remaining 100 variables whose values were normalized is the renewable energy consumption index with 63.5%.

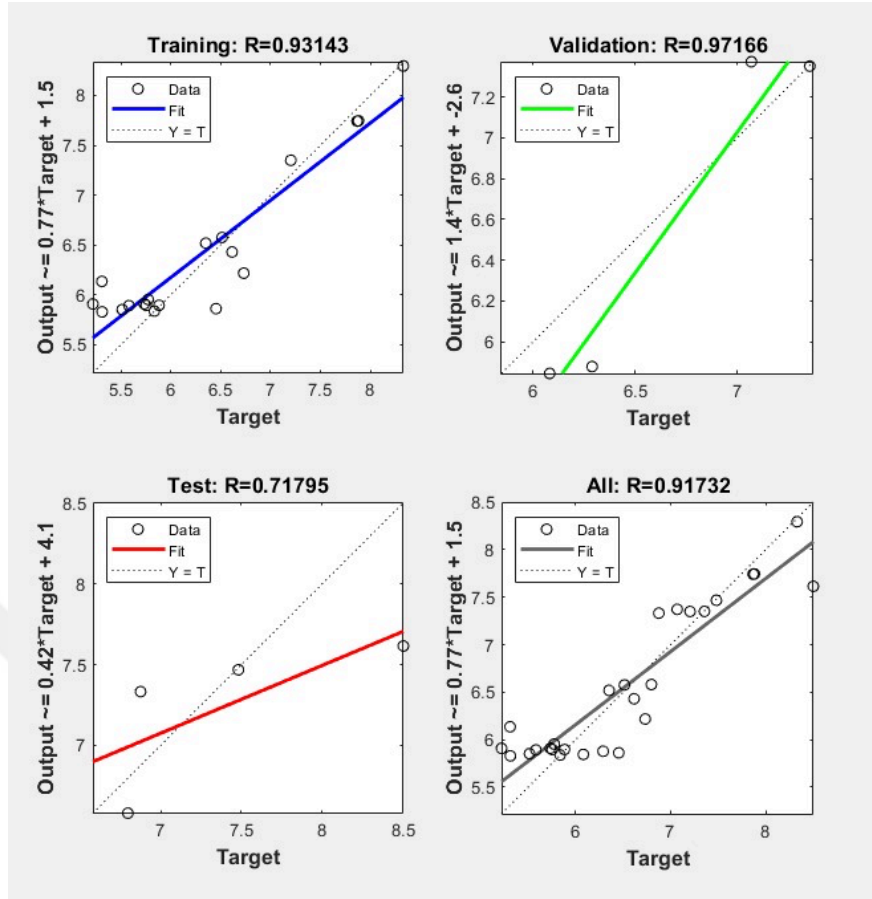


Figure 3.91. Regression Distribution of ANN's for New Zealand

As a result of the applied model, Figure 3.91. shows the correlation between all the values of the derived model after training, validation, testing and prediction. Training data showed a success rate of $R^2 = 0.93143$, validation data showed a success rate of $R^2 = 0.97166$ and testing data showed a success rate of $R^2 = 0.71795$. The performance metric of the network for the entire dataset is $R^2 = 0.91732$.

3.3.2.1.31. Artificial Neural Network Model for Poland

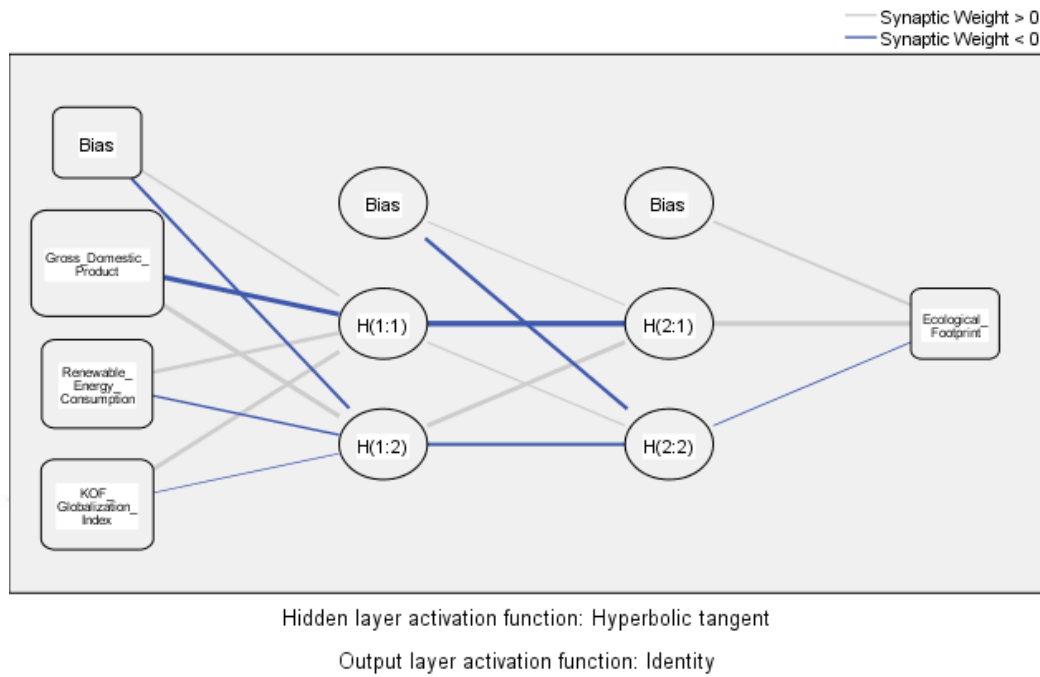


Figure 3.92. ANN Model of Poland

Figure 3.92 illustrates a two-hidden-layer ANN model designed for Poland, an OECD member country. The network architecture comprises three neurons in the input layer, two neurons in the hidden layer, and a single neuron in the output layer. This model adopts a two-layer neural structure with two neurons in the hidden layer. The hyperbolic tangent function is employed as the activation function within the hidden layer, facilitating non-linear transformations and enabling the network to capture complex patterns and relationships within the data.

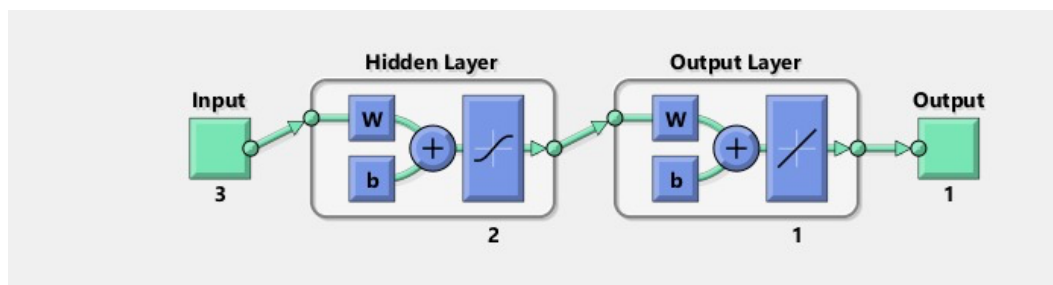


Figure 3.93. MATLAB Implementation of ANN Model for Poland

The input data were analyzed and pre-processed utilizing MATLAB software. Following this step, an ANN model was designed and implemented to address the research objectives. The architecture and structure of the developed ANN model, including the arrangement of input, hidden, and output layers, are illustrated in Figure 3.93.

Table 3.98. Summary of the Model for Poland

Model Summary		
Training	Sum of Squares Error	3,630
	Relative Error	,346
	Stopping Rule Used	1 consecutive step(s) with no decrease in error ^a
	Training Time	0:00:00,02
Testing	Sum of Squares Error	,860
	Relative Error	,330

Dependent Variable: Ecological_Footprint

a. Error computations are based on the testing sample.

Table 3.98. presents the outcomes of the training and test sets for the model, together with the values of the cumulative squared errors. The test data exhibits a 0.33 proportion of erroneous predictions, indicating an accuracy of 67% in the assessment. The objective is to employ the activation function according to the relevance levels of the inputs. Weight values were established to minimize the inaccuracy. The weight coefficients of the neurons in the model's ANN are presented in Table 3.99.

Table 3.99. Weight Estimates for Poland

Parameter Estimates					
Predictor		Hidden Layer 1		Predicted Hidden Layer 2	Output Layer Ecological_Foot print
		H(1:1)	H(1:2)	H(2:1)	H(2:2)
Input Layer	(Bias)	,237	-,519		
	Gross_Domestic_Product	-1,229	1,146		
	Renewable_Energy_Consumption	,773	-,184		
	KOF_Globalization_Index	,863	-,120		
Hidden Layer 1	(Bias)			,163	-,639
	H(1:1)			-1,901	,181
	H(1:2)			1,074	-,581
Hidden Layer 2	(Bias)				,411
	H(2:1)				1,603
	H(2:2)				-,154

The network is trained by changing the weights of the connections between neurons in each layer. The importance table of the independent variables is given in Table 3.100 to see how important each of the independent variables is in predicting the dependent variable.

Table 3.100. Significance of Independent Variables for Poland

Independent Variable Importance		
	Importance	Normalized Importance
Gross_Domestic_Product	,396	100,0%
Renewable_Energy_Consumption	,298	75,3%
KOF_Globalization_Index	,306	77,3%

According to the obtained data, it was concluded that the gross domestic product index in Poland has 39.6% importance in estimating the ecological footprint. The second most important variable among the remaining 100 variables whose values were normalized is the renewable energy consumption index with 77.3%.

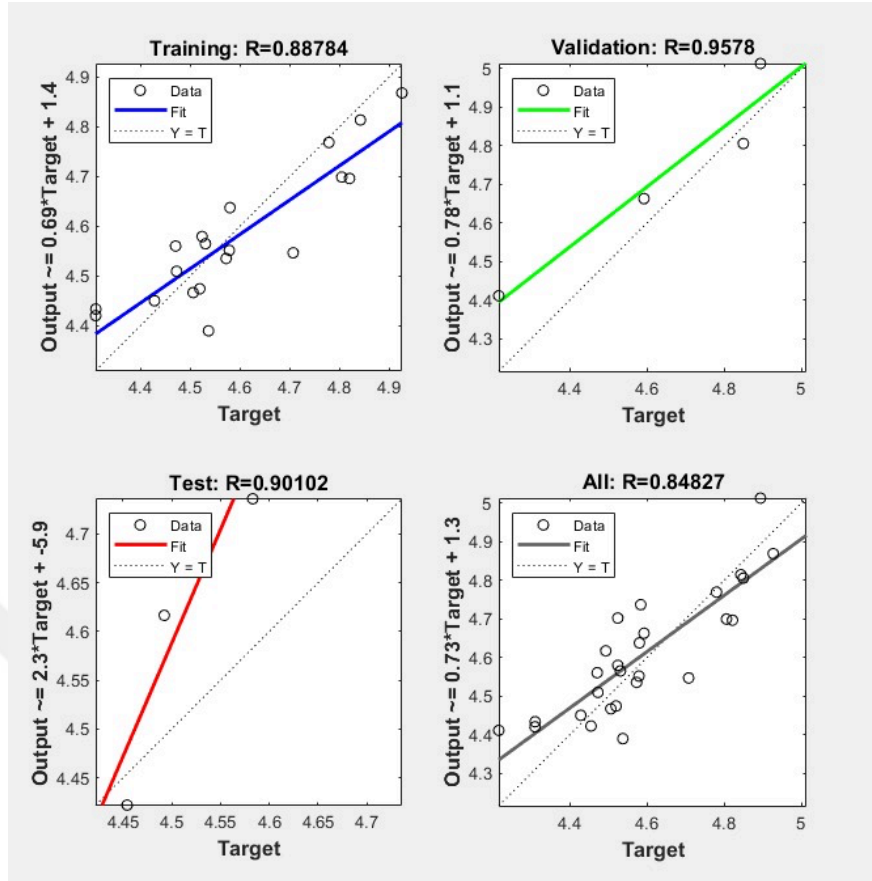


Figure 3.94. Regression Distribution of ANN's for Poland

As a result of the applied model, Figure 3.94. shows the correlation between all the values of the derived model after training, validation, testing and prediction. Training data showed a success rate of $R^2 = 0.88784$, validation data showed a success rate of $R^2 = 0.9578$ and testing data showed a success rate of $R^2 = 0.90102$. The performance metric of the network for the entire dataset is $R^2 = 0.84827$. The results show that there is a relationship between the actual values and the predicted values across all the datasets.

3.3.2.1.32. Artificial Neural Network Model for Portugal

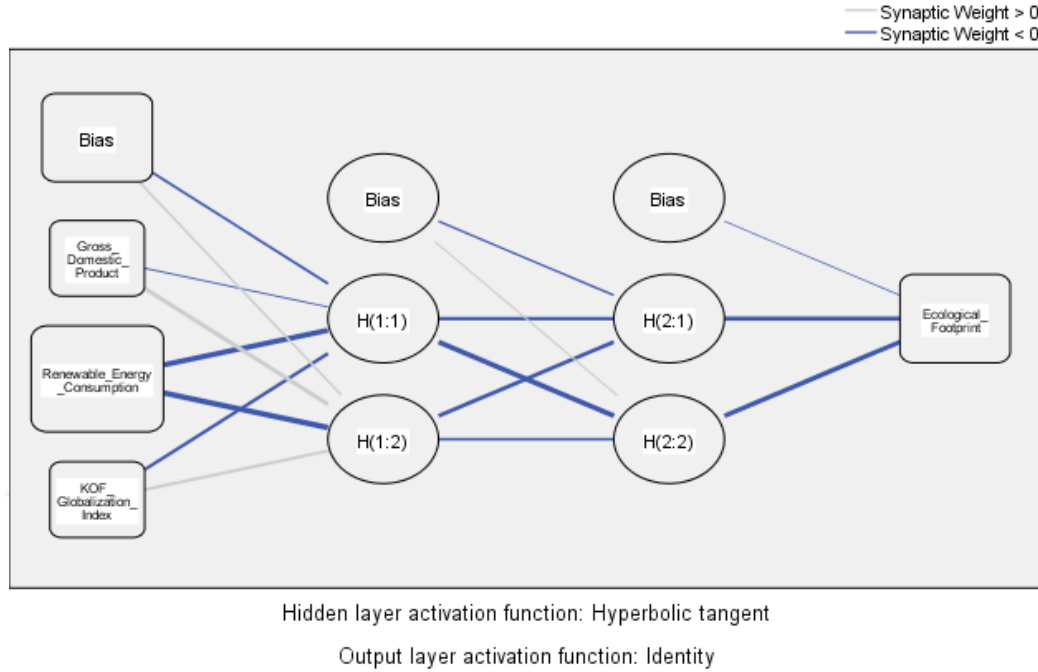


Figure 3.95. ANN Model of Portugal

Figure 3.95 illustrates a two-hidden-layer ANN model designed for Portugal, an OECD member country. The network architecture comprises three neurons in the input layer, two neurons in the hidden layer, and a single neuron in the output layer. This model adopts a two-layer neural structure with two neurons in the hidden layer. The hyperbolic tangent function is employed as the activation function within the hidden layer, facilitating non-linear transformations and enabling the network to capture complex patterns and relationships within the data.

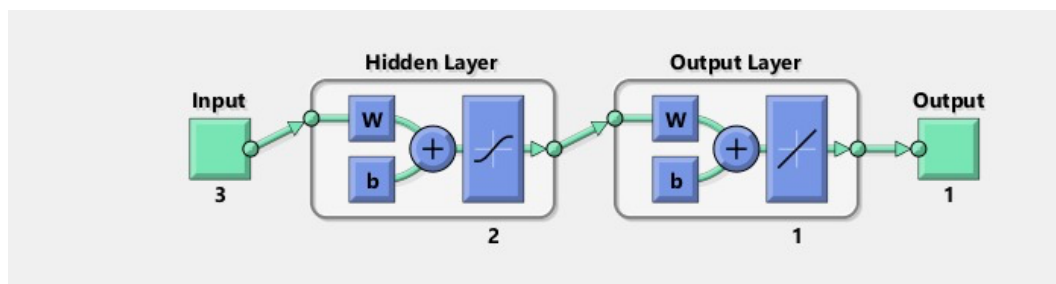


Figure 3.96. MATLAB Implementation of ANN Model for Portugal

The input data were analyzed and pre-processed utilizing MATLAB software. Following this step, an ANN model was designed and implemented to address the research objectives. The architecture and structure of the developed ANN model, including the arrangement of input, hidden, and output layers, are illustrated in Figure 3.96.

Table 3.101. Summary of the Model for Portugal

Model Summary		
Training	Sum of Squares Error	2,124
	Relative Error	,250
	Stopping Rule Used	1 consecutive step(s) with no decrease in error ^a
	Training Time	0:00:00,02
Testing	Sum of Squares Error	,483
	Relative Error	,099
Dependent Variable: Ecological Footprint		
a. Error computations are based on the testing sample.		

Table 3.101. presents the outcomes of the training and test sets for the model, together with the values of the cumulative squared errors. The test data exhibits a 0.099 proportion of erroneous predictions, indicating an accuracy of 90.1% in the assessment. The objective is to employ the activation function according to the relevance levels of the inputs. Weight values were established to minimize the inaccuracy. The weight coefficients of the neurons in the model's ANN are presented in Table 3.101.

Table 3.102. Weight Estimates for Portugal

Parameter Estimates					
Predictor		Hidden Layer 1		Predicted Hidden Layer 2	Output Layer Ecological Footprint
		H(1:1)	H(1:2)	H(2:1)	H(2:2)
Input Layer	(Bias)	-,271	,266		
	Gross_Domestic_Product	-,095	,608		
	Renewable_Energy_Consumption	-1,008	-1,385		
	KOF_Globalization_Index	-,466	,449		
Hidden Layer 1	(Bias)			-,174	,139
	H(1:1)			-,555	-,853
	H(1:2)			-,565	-,448
Hidden Layer 2	(Bias)				-,014
	H(2:1)				-,722
	H(2:2)				-,837

The network is trained by changing the weights of the connections between neurons in each layer. The importance table of the independent variables is given in Table 3.103 to see how important each of the independent variables is in predicting the dependent variable.

Table 3.103. Significance of Independent Variables for Portugal

Independent Variable Importance		
	Importance	Normalized Importance
Gross_Domestic_Product	,110	14,2%
Renewable_Energy_Consumption	,776	100,0%
KOF_Globalization_Index	,114	14,6%

According to the obtained data, it was concluded that the renewable energy consumption index in Portugal has 77.6% importance in estimating the ecological footprint. The second most important variable among the remaining 100 variables whose values were normalized is the KOF globalization index with 14.6% importance.

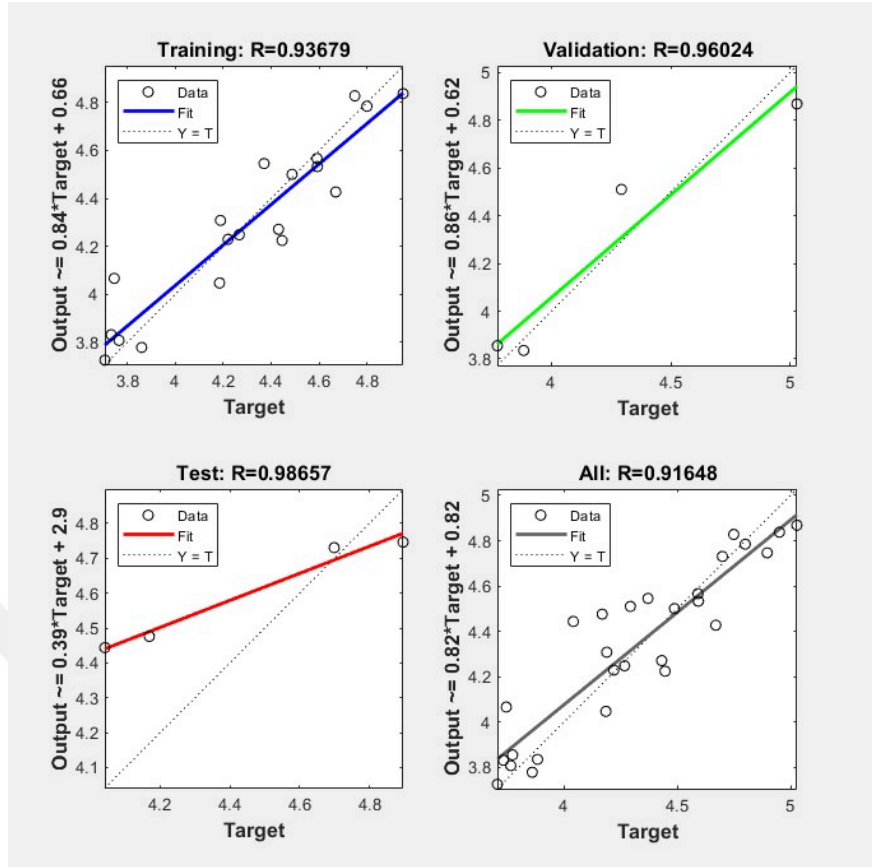


Figure 3.97. Regression Distribution of ANN's for Portugal

As a result of the applied model, Figure 3.97. shows the correlation between all the values of the derived model after training, validation, testing and prediction. Training data showed a success rate of $R^2 = 0.93679$, validation data showed a success rate of $R^2 = 0.96024$ and testing data showed a success rate of $R^2 = 0.98657$. The performance metric of the network for the entire dataset is $R^2 = 0.91648$. This rate shows that the network is quite successful. Upon examination of the findings, the effectiveness of the developed model is obvious. The results show that there is a robust relationship between the actual values and the predicted values across all the datasets.

3.3.2.1.33. Artificial Neural Network Model for Slovak Republic

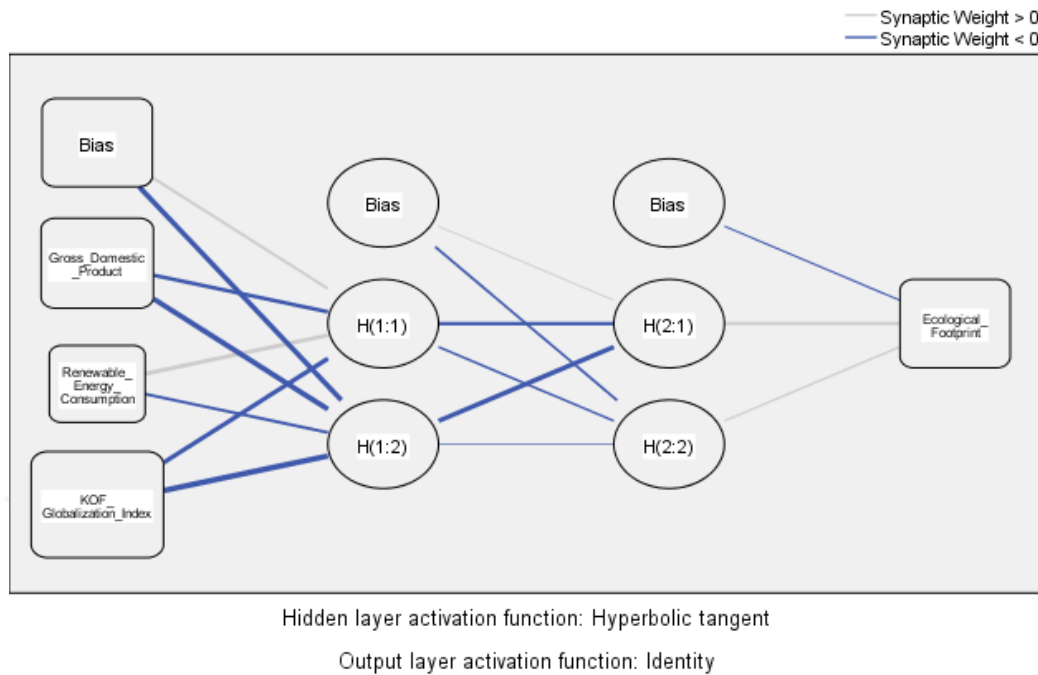


Figure 3.98. ANN Model of Slovak Republic

Figure 3.98 illustrates a two-hidden-layer ANN model designed for Slovak Republic, an OECD member country. The network architecture comprises three neurons in the input layer, two neurons in the hidden layer, and a single neuron in the output layer. This model adopts a two-layer neural structure with two neurons in the hidden layer. The hyperbolic tangent function is employed as the activation function within the hidden layer, facilitating non-linear transformations and enabling the network to capture complex patterns and relationships within the data.

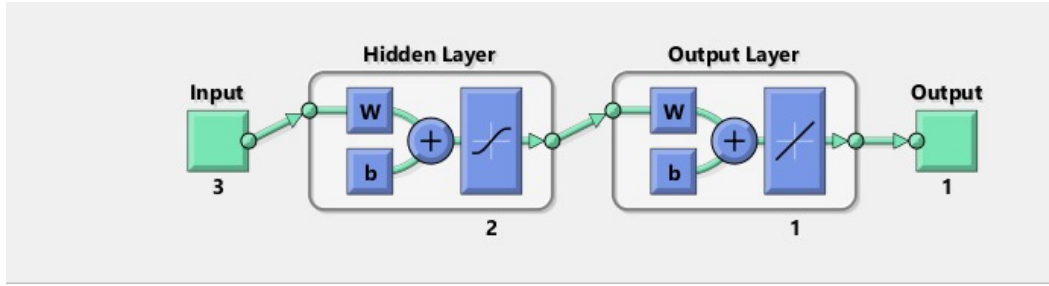


Figure 3.99. MATLAB Implementation of ANN Model for Slovak Republic

The input data were analyzed and pre-processed utilizing MATLAB software. Following this step, an ANN model was designed and implemented to address the research objectives. The architecture and structure of the developed ANN model, including the arrangement of input, hidden, and output layers, are illustrated in Figure 3.6.

Table 3.104. Summary of the Model for Slovak Republic

Model Summary		
Training	Sum of Squares Error	7,107
	Relative Error	,677
	Stopping Rule Used	1 consecutive step(s) with no decrease in error ^a
	Training Time	0:00:00,00
Testing	Sum of Squares Error	,471
	Relative Error	,228

Dependent Variable: Ecological_Footprint

a. Error computations are based on the testing sample.

Table 3.104. presents the outcomes of the training and test sets for the model, together with the values of the cumulative squared errors. The test data exhibits a 0.228 proportion of erroneous predictions, indicating an accuracy of 77.2% in the assessment. The objective is to employ the activation function according to the relevance levels of the inputs. Weight values were established to minimize the inaccuracy. The weight coefficients of the neurons in the model's ANN are presented in Table 3.104.

Table 3.105. Weight Estimates for Slovak Republic

Parameter Estimates						
		Hidden Layer 1		Predicted Hidden Layer 2		Output Layer Ecological_Foot print
		H(1:1)	H(1:2)	H(2:1)	H(2:2)	
Input Layer	(Bias)	,542	-1,448			
	Gross_Domestic_Product	-1,137	-1,456			
	Renewable_Energy_Consumption	1,336	-,588			
	KOF_Globalization_Index	-1,338	-2,141			
Hidden Layer 1	(Bias)			,148	-,471	
	H(1:1)			-,825	-,354	
	H(1:2)			-1,432	-,055	
Hidden Layer 2	(Bias)					-,221
	H(2:1)					,754
	H(2:2)					,271

The network is trained by changing the weights of the connections between neurons in each layer. The importance table of the independent variables is given in Table 3.106 to see how important each of the independent variables is in predicting the dependent variable.

Table 3.106. Significance of Independent Variables for Slovak Republic

Independent Variable Importance		
	Importance	Normalized Importance
Gross_Domestic_Product	,317	54,4%
Renewable_Energy_Consumption	,100	17,2%
KOF_Globalization_Index	,583	100,0%

According to the obtained data, it was concluded that KOF globalization index has 58.3% importance in estimating the ecological footprint in Slovak Republic. The second most important variable among the remaining 100 variables whose values are normalized is the gross domestic product index with 54.4%.

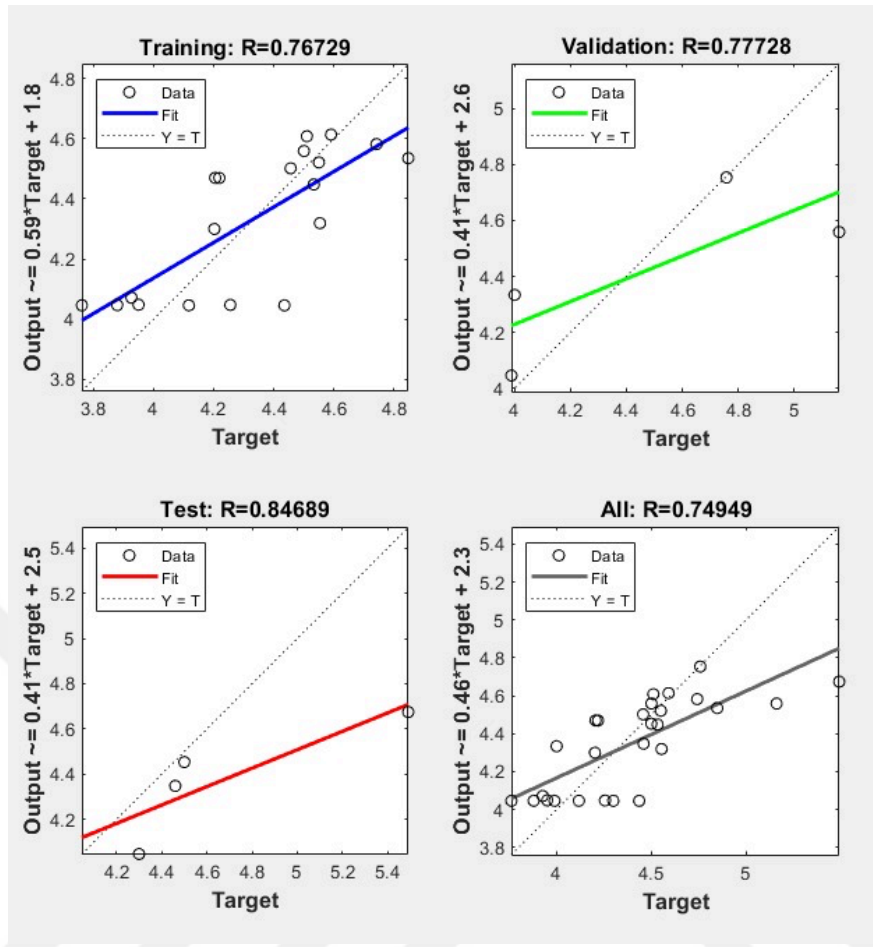


Figure 3.100. Regression Distribution of ANN's for Slovak Republic

As a result of the applied model, Figure 3.100. shows the correlation between all the values of the derived model after training, validation, testing and prediction. Training data showed a success rate of $R^2 = 0.76729$, validation data showed a success rate of $R^2 = 0.77728$ and testing data showed a success rate of $R^2 = 0.84689$. The performance metric of the network for the entire dataset is $R^2 = 0.74949$.

3.3.2.1.34. Artificial Neural Network Model for Slovenia

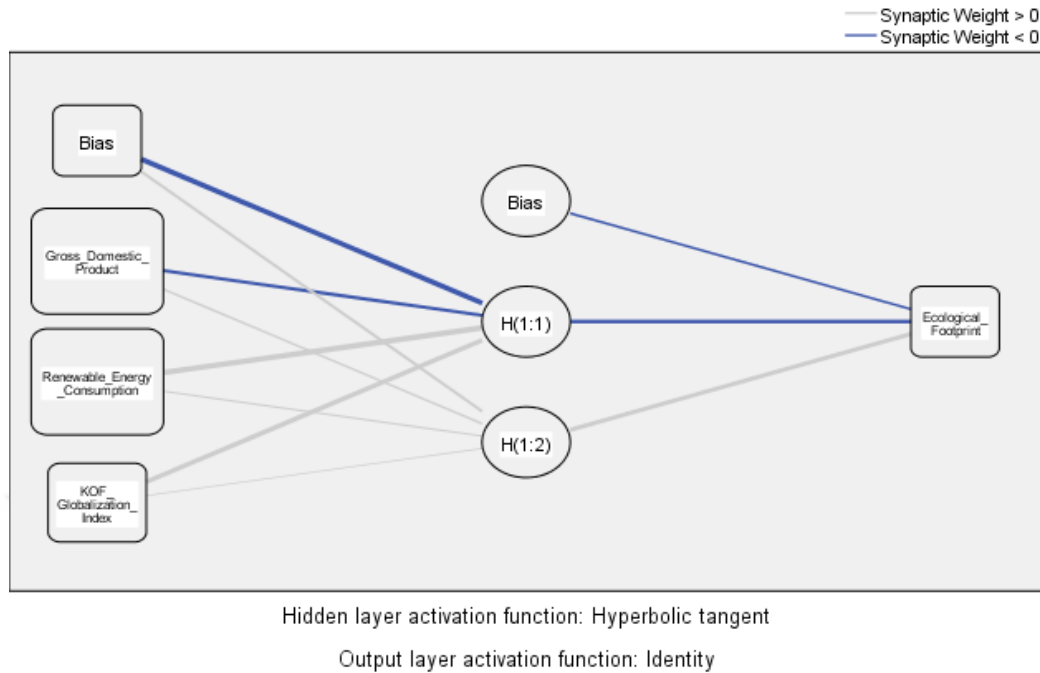


Figure 3.101. ANN Model of Slovenia

Figure 3.101 illustrates an ANN model designed for Slovenia, which is a member of the OECD. The network architecture consists of a single hidden layer and is structured with three neurons in the input layer, two neurons in the hidden layer, and one neuron in the output layer. The model employs a feedforward neural network configuration, where each neuron in one layer is fully connected to the neurons in the subsequent layer. A hyperbolic tangent (tanh) activation function is utilized in the hidden layer.

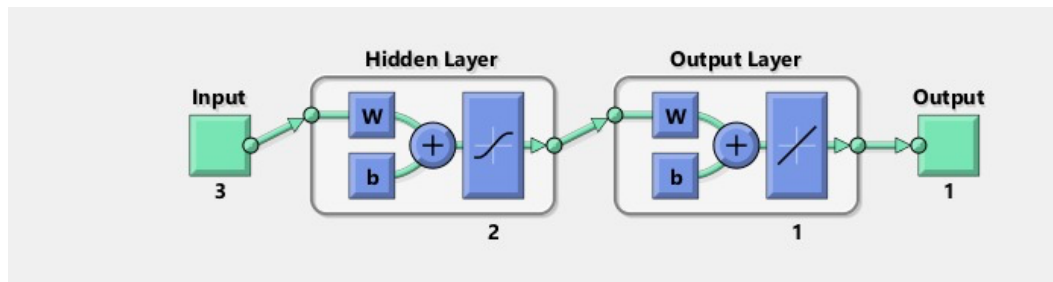


Figure 3.102. MATLAB Implementation of ANN Model for Slovenia

The input data were analyzed and pre-processed utilizing MATLAB software. Following this step, an ANN model was designed and implemented to address the research objectives. The architecture and structure of the developed ANN model, including the arrangement of input, hidden, and output layers, are illustrated in Figure 3.102.

Table 3.107. Summary of the Model for Slovenia

Model Summary		
Training	Sum of Squares Error	3,888
	Relative Error	,432
	Stopping Rule Used	1 consecutive step(s) with no decrease in error ^a
	Training Time	0:00:00,00
Testing	Sum of Squares Error	,748
	Relative Error	,120

Dependent Variable: Ecological Footprint

a. Error computations are based on the testing sample.

Table 3.107. presents the outcomes of the training and test sets for the model, together with the values of the cumulative squared errors. The test data exhibits a 0.12 proportion of erroneous predictions, indicating an accuracy of 88% in the assessment. The objective is to employ the activation function according to the relevance levels of the inputs. Weight values were established to minimize the inaccuracy. The weight coefficients of the neurons in the model's ANN are presented in Table 3.108.

Table 3.108. Weight Estimates for Slovenia

Predictor		Parameter Estimates		
		Hidden Layer 1		Predicted
		H(1:1)	H(1:2)	Output Layer Ecological_Foot print
Input Layer	(Bias)	-1,947	1,174	
	Gross_Domestic_Product	-1,185	,828	
	Renewable_Energy_Consumption	5,160	,378	
	KOF_Globalization_Index	1,802	,002	
Hidden Layer 1	(Bias)			-,970
	H(1:1)			-1,263
	H(1:2)			1,746

The network is trained by changing the weights of the connections between neurons in each layer. The importance table of the independent variables is given in Table 3.109 to see how important each of the independent variables is in predicting the dependent variable.

Table 3.109. Significance of Independent Variables for Slovenia

Independent Variable Importance		
	Importance	Normalized Importance
Gross_Domestic_Product	,382	99,6%
Renewable_Energy_Consumption	,383	100,0%
KOF_Globalization_Index	,235	61,3%

According to the obtained data, it was concluded that the renewable energy consumption index in Slovenia has 38.3% importance in estimating the ecological footprint. The second most important variable among the remaining 100 variables whose values were normalized is the gross domestic product index with 99.6%.

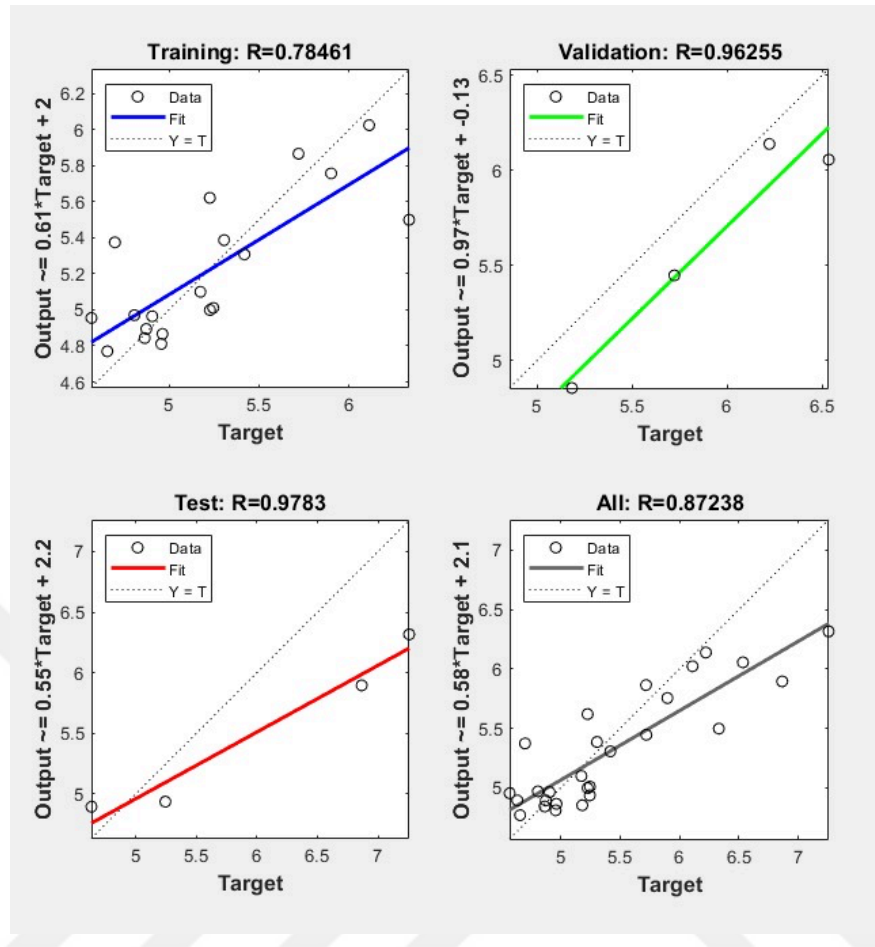


Figure 3.103. Regression Distribution of ANN's for Slovenia

As a result of the applied model, Figure 3.103. shows the correlation between all the values of the derived model after training, validation, testing and prediction. Training data showed a success rate of $R^2 = 0.78461$, validation data showed a success rate of $R^2 = 0.96255$ and testing data showed a success rate of $R^2 = 0.9783$. The performance metric of the network for the entire dataset is $R^2 = 0.87238$. This rate shows that the network is quite successful. Upon examination of the findings, the effectiveness of the developed model is obvious. The results show that there is a relationship between the actual values and the predicted values across all the datasets.

3.3.2.1.35. Artificial Neural Network Model for Sweden

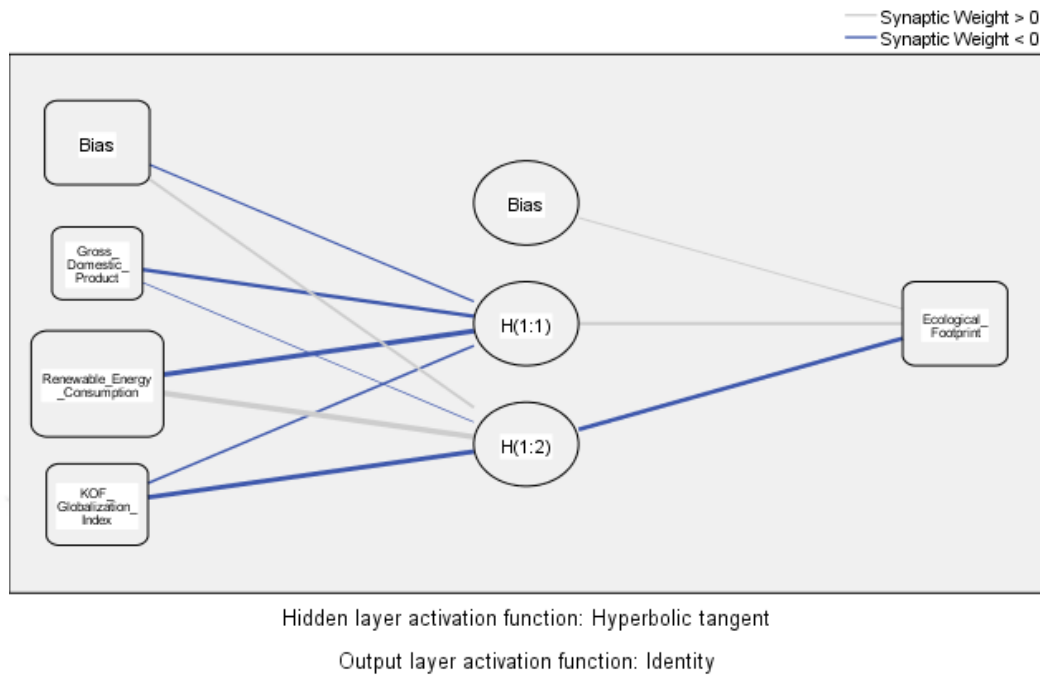


Figure 3.104. ANN Model of Sweden

Figure 3.104 illustrates an ANN model designed for Sweden, which is a member of the OECD. The network architecture consists of a single hidden layer and is structured with three neurons in the input layer, two neurons in the hidden layer, and one neuron in the output layer. The model employs a feedforward neural network configuration, where each neuron in one layer is fully connected to the neurons in the subsequent layer. A hyperbolic tangent (tanh) activation function is utilized in the hidden layer.

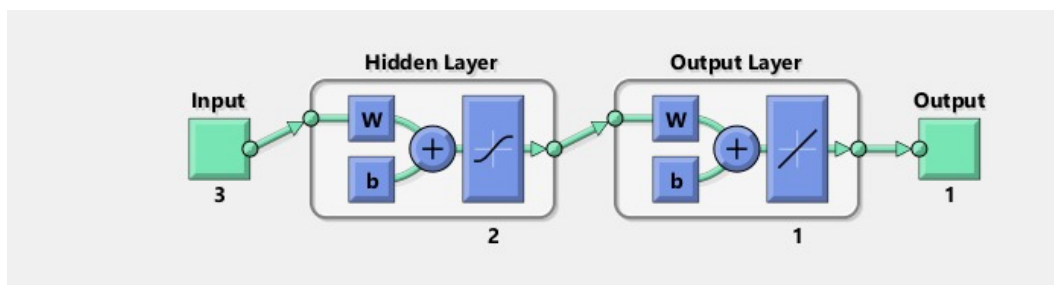


Figure 3.105. MATLAB Implementation of ANN Model for Sweden

The input data were analyzed and pre-processed utilizing MATLAB software. Following this step, an ANN model was designed and implemented to address the research objectives. The architecture and structure of the developed ANN model, including the arrangement of input, hidden, and output layers, are illustrated in Figure 3.105.

Table 3.110. Summary of the Model for Sweden

Model Summary		
Training	Sum of Squares Error	6,659
	Relative Error	,740
	Stopping Rule Used	1 consecutive step(s) with no decrease in error ^a
	Training Time	0:00:00,00
Testing	Sum of Squares Error	,268
	Relative Error	,237

Dependent Variable: Ecological_Footprint

a. Error computations are based on the testing sample.

Table 3.110. presents the outcomes of the training and test sets for the model, together with the values of the cumulative squared errors. The test data exhibits a 0.237 proportion of erroneous predictions, indicating an accuracy of 76.3% in the assessment. The objective is to employ the activation function according to the relevance levels of the inputs. Weight values were established to minimize the inaccuracy. The weight coefficients of the neurons in the model's ANN are presented in Table 3.111.

Table 3.111. Weight Estimates for Sweden

Predictor		Parameter Estimates		
		Hidden Layer 1		Predicted
		H(1:1)	H(1:2)	Output Layer Ecological_Footprint
Input Layer	(Bias)	-,222	,334	
	Gross_Domestic_Product	-,657	-,038	
	Renewable_Energy_Consumption	-,675	,776	
	KOF_Globalization_Index	-,276	-,660	
Hidden Layer 1	(Bias)			,168
	H(1:1)			,369
	H(1:2)			-,659

The network is trained by changing the weights of the connections between neurons in each layer. The importance table of the independent variables is given in Table 3.112 to see how important each of the independent variables is in predicting the dependent variable.

Table 3.112. Significance of Independent Variables for Sweden

Independent Variable Importance		
	Importance	Normalized Importance
Gross_Domestic_Product	,145	24,3%
Renewable_Energy_Consumption	,594	100,0%
KOF_Globalization_Index	,261	44,0%

According to the obtained data, it was concluded that the renewable energy consumption index in Sweden has 59.4% importance in estimating the ecological footprint. The second most important variable among the remaining 100 variables whose values were normalized is the KOF Globalization index with 44%.

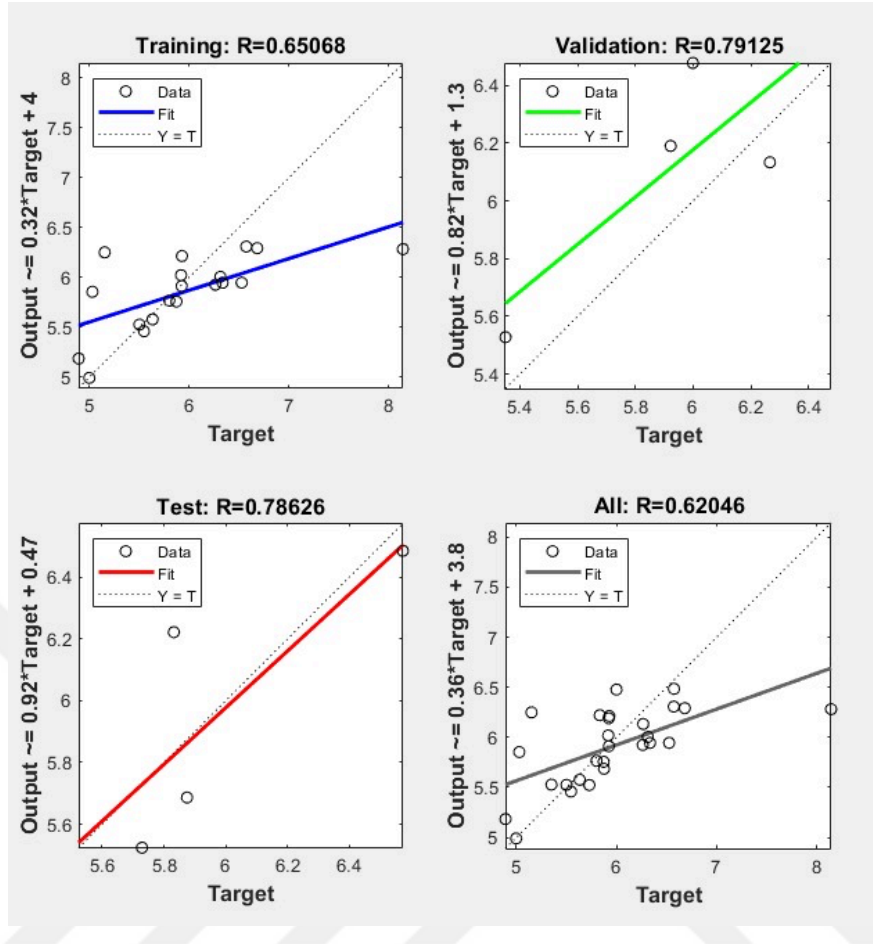


Figure 3.106. Regression Distribution of ANN's for Sweden

As a result of the applied model, Figure 3.106. shows the correlation between all the values of the derived model after training, validation, testing and prediction. Training data showed a success rate of $R^2 = 0.65068$, validation data showed a success rate of $R^2 = 0.79125$ and testing data showed a success rate of $R^2 = 0.78626$. The performance metric of the network for the entire dataset is $R^2 = 0.62046$. The results indicate a weak correlation between the actual values and the anticipated values across all datasets.

3.3.2.1.36. Artificial Neural Network Model for Turkey

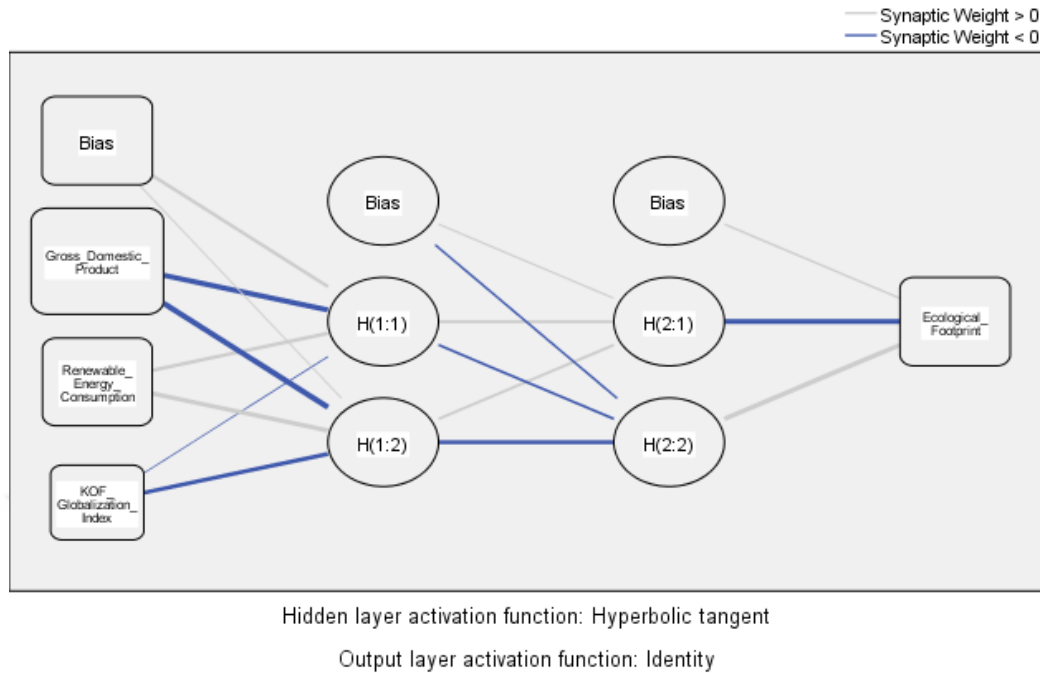


Figure 3.107. ANN Model of Turkey

Figure 3.107 illustrates a two-hidden-layer ANN model designed for Turkey, an OECD member country. The network architecture comprises three neurons in the input layer, two neurons in the hidden layer, and a single neuron in the output layer. This model adopts a two-layer neural structure with two neurons in the hidden layer. The hyperbolic tangent function is employed as the activation function within the hidden layer, facilitating non-linear transformations and enabling the network to capture complex patterns and relationships within the data.

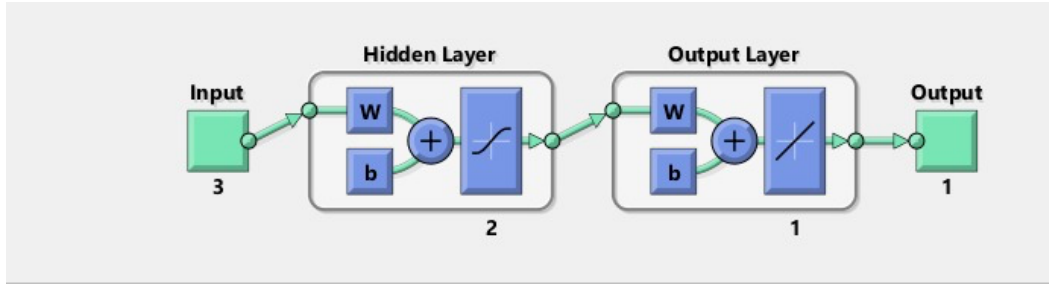


Figure 3.108. MATLAB Implementation of ANN Model for Turkey

The input data were analyzed and pre-processed utilizing MATLAB software. Following this step, an ANN model was designed and implemented to address the research objectives. The architecture and structure of the developed ANN model, including the arrangement of input, hidden, and output layers, are illustrated in Figure 3.108.

Table 3.113. Summary of the Model for Turkey

Model Summary		
Training	Sum of Squares Error	1,080
	Relative Error	,154
	Stopping Rule Used	1 consecutive step(s) with no decrease in error ^a
	Training Time	0:00:00,00
Testing	Sum of Squares Error	,554
	Relative Error	,163

Dependent Variable: Ecological Footprint

a. Error computations are based on the testing sample.

Table 3.113. presents the outcomes of the training and test sets for the model, together with the values of the cumulative squared errors. The test data exhibits a 0.163 proportion of erroneous predictions, indicating an accuracy of 83.7% in the assessment. The objective is to employ the activation function according to the relevance levels of the inputs. Weight values were established to minimize the inaccuracy. The weight coefficients of the neurons in the model's ANN are presented in Table 3.114.

Table 3.114. Weight Estimates for Turkey

Parameter Estimates						
		Hidden Layer 1		Predicted Hidden Layer 2		Output Layer
		H(1:1)	H(1:2)	H(2:1)	H(2:2)	Ecological Foot print
Input Layer	(Bias)	,510	,073			
	Gross_Domestic_Product	-,730	-1,368			
	Renewable_Energy_Consum ption	,554	,661			
	KOF_Globalization_Index	-,001	-,580			
Hidden Layer 1	(Bias)			,290	-,382	
	H(1:1)			,486	-,449	
	H(1:2)			,464	-,566	
Hidden Layer 2	(Bias)					,381
	H(2:1)					-,723
	H(2:2)					,698

The network is trained by changing the weights of the connections between neurons in each layer. The importance table of the independent variables is given in Table 3.115 to see how important each of the independent variables is in predicting the dependent variable.

Table 3.115. Significance of Independent Variables for Turkey

Independent Variable Importance		
	Importance	Normalized Importance
Gross_Domestic_Product	,626	100,0%
Renewable_Energy_Consum ption	,302	48,3%
KOF_Globalization_Index	,071	11,4%

According to the obtained data, it was concluded that the gross domestic product index in Turkey has 62.6% importance in estimating the ecological footprint. The second most important variable among the remaining 100 variables whose values were normalized is the renewable energy consumption index with 48.3%.

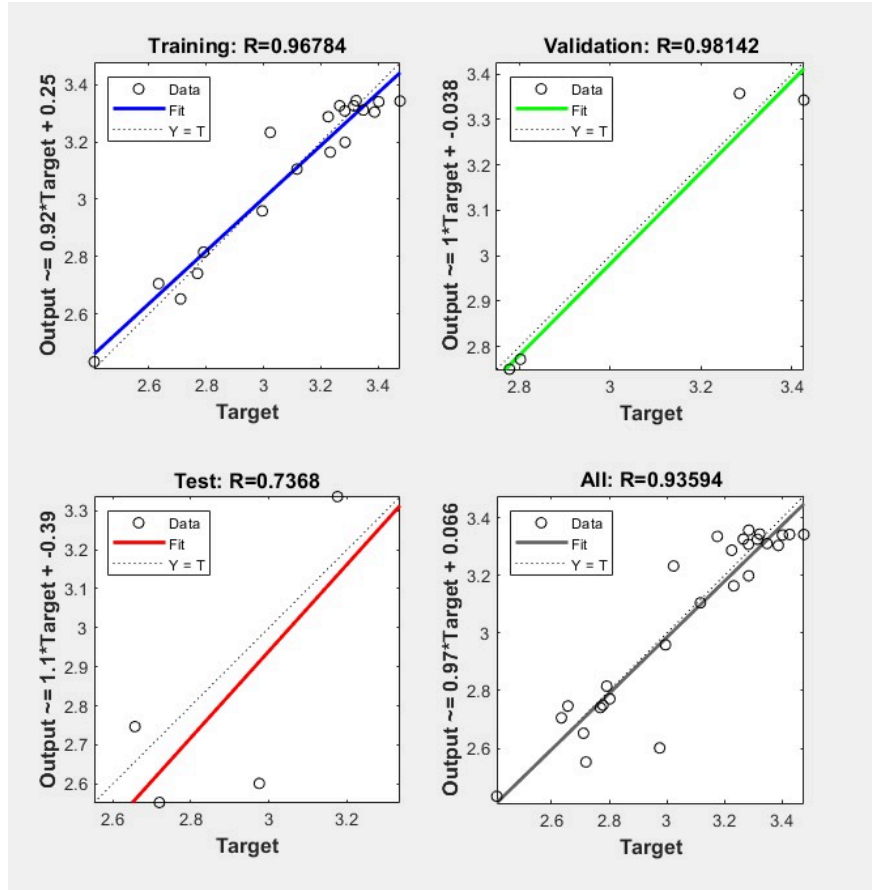


Figure 3.109. Regression Distribution of ANN's for Turkey

As a result of the applied model, Figure 3.10. shows the correlation between all the values of the derived model after training, validation, testing and prediction. Training data showed a success rate of $R^2 = 0.96784$, validation data showed a success rate of $R^2 = 0.98142$ and testing data showed a success rate of $R^2 = 0.7368$. The performance metric of the network for the entire dataset is $R^2 = 0.93594$. This rate shows that the network is quite successful. Upon examination of the findings, the effectiveness of the developed model is obvious. The results show that there is a robust relationship between the actual values and the predicted values across all the datasets.

3.3.2.1.37. Artificial Neural Network Model for United States

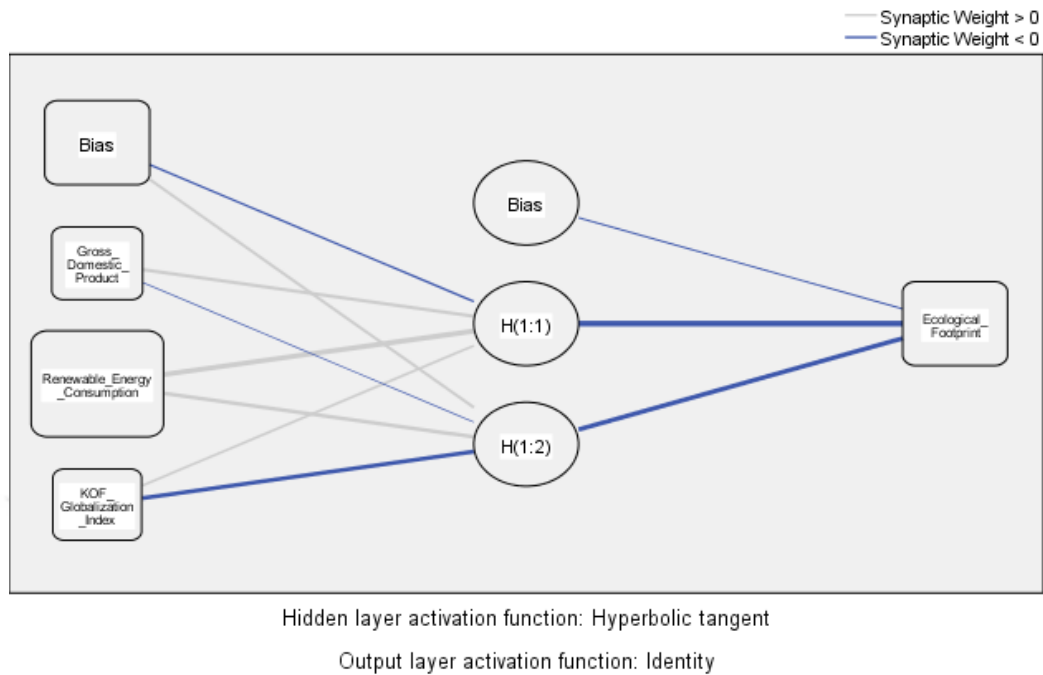


Figure 3.110. ANN Model of United States

Figure 3.110 illustrates an ANN model designed for United States, which is a member of the OECD. The network architecture consists of a single hidden layer and is structured with three neurons in the input layer, two neurons in the hidden layer, and one neuron in the output layer. The model employs a feedforward neural network configuration, where each neuron in one layer is fully connected to the neurons in the subsequent layer. A hyperbolic tangent (tanh) activation function is utilized in the hidden layer.

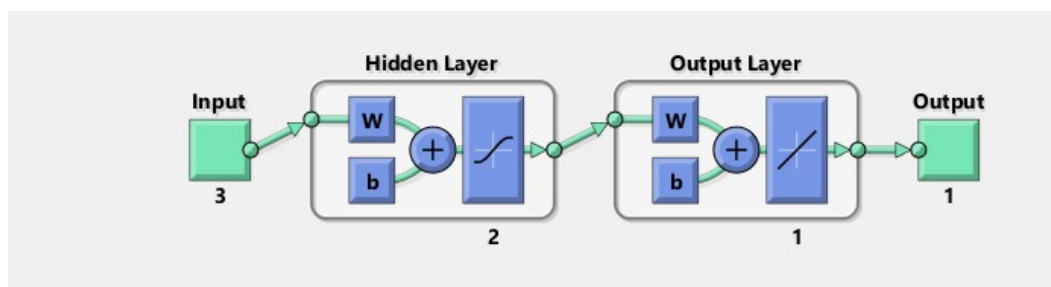


Figure 3.111. MATLAB Implementation of ANN Model for United States

The input data were analyzed and pre-processed utilizing MATLAB software. Following this step, an ANN model was designed and implemented to address the research objectives. The architecture and structure of the developed ANN model, including the arrangement of input, hidden, and output layers, are illustrated in Figure 3.111.

Table 3.116. Summary of the Model for United States

Model Summary		
Training	Sum of Squares Error	,574
	Relative Error	,072
	Stopping Rule Used	1 consecutive step(s) with no decrease in error ^a
	Training Time	0:00:00,00
Testing	Sum of Squares Error	,236
	Relative Error	,048

Dependent Variable: Ecological Footprint

a. Error computations are based on the testing sample.

Table 3.116. presents the outcomes of the training and test sets for the model, together with the values of the cumulative squared errors. The test data exhibits a 0.048 proportion of erroneous predictions, indicating an accuracy of 95.2% in the assessment. The objective is to employ the activation function according to the relevance levels of the inputs. Weight values were established to minimize the inaccuracy. The weight coefficients of the neurons in the model's ANN are presented in Table 3.117.

Table 3.117. Weight Estimates for United States

Predictor		Parameter Estimates		
		Hidden Layer 1		Predicted
		H(1:1)	H(1:2)	Output Layer Ecological_Foot print
Input Layer	(Bias)	-,123	,143	
	Gross_Domestic_Product	,261	-,003	
	Renewable_Energy_Consumption	,849	,498	
	KOF_Globalization_Index	,135	-,646	
Hidden Layer 1	(Bias)			-,056
	H(1:1)			-1,375
	H(1:2)			-,737

The network is trained by changing the weights of the connections between neurons in each layer. The importance table of the independent variables is given in Table 3.118 to see how important each of the independent variables is in predicting the dependent variable.

Table 3.118. Significance of Independent Variables for United States

Independent Variable Importance		
	Importance	Normalized Importance
Gross_Domestic_Product	,168	24,4%
Renewable_Energy_Consumption	,687	100,0%
KOF_Globalization_Index	,145	21,1%

According to the obtained data, it was concluded that the renewable energy consumption index in the United States has 68.7% importance in estimating the ecological footprint. The second most important variable among the remaining 100 variables whose values were normalized is the gross domestic product index with 24.4%.

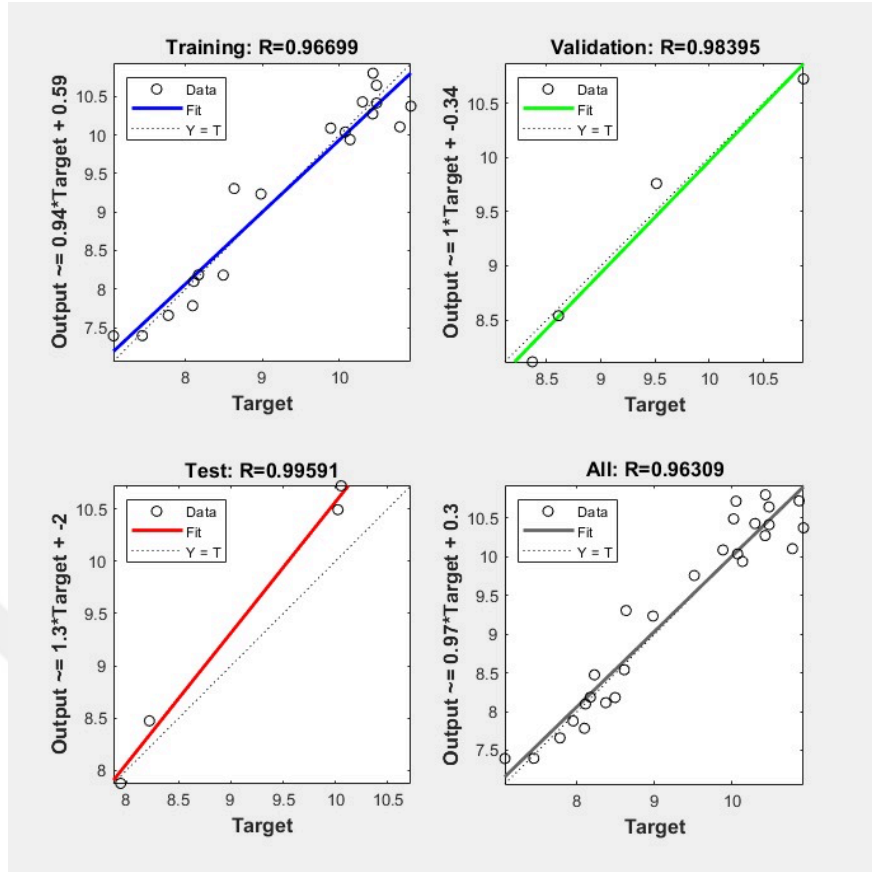


Figure 3.112. Regression Distribution of ANN's for United States

As a result of the applied model, Figure 3.112. shows the correlation between all the values of the derived model after training, validation, testing and prediction. Training data showed a success rate of $R^2 = 0.96699$, validation data showed a success rate of $R^2 = 0.98395$ and testing data showed a success rate of $R^2 = 0.99591$. The performance metric of the network for the entire dataset is $R^2 = 0.96309$. This rate shows that the network is quite successful. Upon examination of the findings, the effectiveness of the developed model is obvious. The results show that there is a robust relationship between the actual values and the predicted values across all the datasets.

4. ANALYSIS AND DISCUSSION

Industrialization, population growth, urbanization, and globalization elevate humanity's environmental demand, resulting in issues such as global warming, climate change, and air pollution (Kılınç, 2021). The primary aspect of these issues is their global emergence rather than their impact being confined to a single place (Bayar, 2008). Ensuring the continuity of life and preserving a safeguarded environment for future generations can be achieved through the optimal utilization of natural resources. The strategy designed to mitigate environmental damage and maybe provide solutions for its eradication, while assessing the capacities of utilized natural areas, is termed the ecological footprint (Dinç, 2016). The Ecological Footprint analyzes the interplay between humans and nature from a novel viewpoint, elucidating the variables that exert strain on natural resources. It quantifies the biologically productive land and aquatic area necessary for the regeneration of resources utilized by individuals, societies, and various activities, as well as for the management of waste generated from consumption (Özsoy and Dinç, 2016). Wackernagel and Rees (1998) pioneered the measurement of the ecological footprint as an indicator of sustainability or sustainable development. The ecological footprint is a measurement method designed to quantify environmental sustainability by calculating the extent of biologically productive land and water utilized globally, reflecting the demand for such resources and illustrating the biologically productive area consumed by individuals (Tosunoğlu, 2014).

Accurate predictions are essential for success, as they enhance the precision of decision-making. This study aimed to identify the factors influencing the ecological footprint of OECD nations, utilizing panel data on gross domestic product, the KOF globalization index, and renewable energy usage from 1995 to 2021. The interrelations among the factors influencing the dependent variable for each OECD nation were analyzed. The independent variables Gross Domestic Product and Globalization Index exhibited a positive influence, whereas renewable energy consumption demonstrated a negative effect. Upon examining the impact of the independent factors on the dependent variable, it is noted that each variable is significant at the 10% level. Upon reviewing the existing research, it is concluded that panel data analyses involving gross domestic product (Akıllı et al., 2008; Ulucak and Erdem, 2017) and the globalization index (Rudolph and Figge, 2017; Sharif et al., 2019; Apaydın, 2020; Kırıkkaleli,

Adebayo, Khan and Ali, 2021) generally exert a positive influence on the ecological footprint, but renewable energy (Pata et al., 2021) use has a negative impact. The results of our investigation corroborate the findings of prior studies.

Following the identification of correlations among variables using panel data analysis, an ANN was developed to estimate the ecological footprint, utilizing the independent variable data as input for the model. The estimation utilizes annual values for several dependent and independent variables across each OECD countries from 1995 to 2021. A feedforward ANN was employed for the model, and the Levenberg-Marquardt method was chosen for its training. Upon examining all acquired R^2 values, it is evident that elevated R^2 values approaching 1 are achieved in ANN-based investigations, indicating that the modeling findings yield statistically significant accuracy.

The thesis employed panel data analysis to investigate the determinants influencing the ecological footprint, then utilizing this data as inputs for an ANN model. The successive implementation of the two techniques will yield a novel contribution to the literature. The objective of the research is to identify the variables influencing the ecological footprint, construct suitable models, generate predictions, and assess the efficacy of ANN in elucidating predictive performance.

The findings indicate that GDP growth and globalization have a positive impact on the ecological footprint, contributing to environmental degradation. Conversely, renewable energy consumption exhibits a negative impact, demonstrating that increasing the use of sustainable energy sources can effectively reduce the ecological footprint.

The results obtained from the analyses further confirm that the artificial neural network models successfully predict the ecological footprint across all OECD countries, thereby providing strong evidence that the artificial neural network approach is an effective method for forecasting ecological footprint trends.

5. CONCLUSION

The factors influencing the ecological footprint were examined by panel data analysis, utilizing data from 37 OECD member nations spanning the years 1995 to 2021. The independent variables believed to influence the ecological footprint were identified as gross domestic product, the KOF globalization index, and renewable energy use. The research indicated that while the independent variables Gross Domestic Product and Globalization Index exerted a favorable influence, renewable energy consumption had a negative effect on ecological footprint. Upon examining the impact of the independent factors on the dependent variables, it is noted that each variable is significant at the 10% level. of the share of gross domestic product, renewable energy consumption, and globalization index each increase by 1 unit, the ecological footprint will increase by 0.043 units, decrease by 0.151 units, and increase by 0.27 units, respectively. This shows that the increase in renewable energy consumption reduces the ecological footprint, while the increase in gross domestic product and the increase in the globalization index increases the ecological footprint.

Annual ecological footprint data for the period between 1995 and 2021 was obtained from the Global Footprint Network. As the data is provided on an annual basis in the database, the study used the available annual data for analysis. The data from the Global Footprint Network was specifically collected according to per capita ecological footprint values, expressed in global hectares (gha). In the case of Iceland, where ecological footprint data was unavailable, the study employed data from 37 OECD member nations to generate estimations. The countries included in the analysis were Australia, Austria, Belgium, Canada, Switzerland, Chile, Colombia, Costa Rica, Czech Republic, Germany, Denmark, Spain, Estonia, Finland, France, the United Kingdom, Greece, Hungary, Ireland, Israel, Italy, Japan, South Korea, Lithuania, Luxembourg, Latvia, Mexico, the Netherlands, Norway, New Zealand, Poland, Portugal, the Slovak Republic, Slovenia, Sweden, Turkey, and the United States. By utilizing data from these 37 countries, the study aimed to investigate the ecological footprints and their trends over time within the context of OECD member nations.

Data on the KOF globalization index for various countries was sourced from the KOF Swiss Economic Institute website. The gross domestic product index, an indicator of economic growth for nations, was sourced from Data World Bank and expressed in per capita current dollars. Data on renewable energy usage was sourced from the World Bank, and the percentage of total final energy consumption was considered.

The study used ecological footprint data as output (dependent) variables, while gross domestic product, KOF globalization index, and renewable energy consumption statistics were regarded as input (independent) factors. The proposed ANN model was developed using MATLAB and SPSS software, and the outcomes were assessed. Upon examination of all generated R^2 values, it was observed that ANN-based studies yielded high R^2 values approaching 1, indicating statistically significant accuracy in the modeling outcomes.

Governments should promote investments in renewable energy sources such as solar, wind, and hydroelectric power to minimize environmental degradation. Policies should focus on green growth by integrating sustainability into economic development strategies. International cooperation should prioritize sustainable production and consumption to mitigate the environmental impact of globalization. Additionally, public education programs and stricter environmental regulations should be implemented at both individual and national levels to reduce the ecological footprint effectively.

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