Concurrency and Computation: Practice and Experience

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RESEARCH ARTICLE OPEN ACCESS

Predicting the Best Green Growth Performance With Integrated Intuitionistic Fuzzy and Metaheuristic Algorithms

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Received: 18 September 2024 | **Revised:** 12 February 2025 | **Accepted:** 27 March 2025

Keywords: fuzzy inference | green growth | intuitionistic fuzzy | metaheuristic algorithm | performance

ABSTRACT

Although various studies monitor and evaluate green growth performance, no heuristic-based hybrid studies test the reflection of green growth indicators. This study aims to identify the best green growth performance by using intuitionistic fuzzy and metaheuristic algorithms over green growth indicators, contributing to filling the gap in the field and providing inferences about green growth to decision-makers. For this purpose, the green growth levels of 31 selected countries were analyzed based on environmental and resource efficiency indicators, and the best result was predicted. The study was conducted in two phases. In the first phase, countries were ranked according to their green growth performance using intuitionistic fuzzy methods. In the second phase, the best performance value was estimated at different population levels using metaheuristic algorithms. The research results show that the renewable electricity generation variable is the most important criterion. Ireland (1.00), Switzerland (0.98), and Costa Rica (0.95) are the countries with the best green growth performance, respectively. In green growth performance estimation, the ANFIS-TLBO model ($R^2=0.908$; MAE = 0.196; SMAPE = 0.689; MSE = 0.050; RMSE = 0.223; MBE = 0.188) demonstrated the closest estimation accuracy to the real values. In this study, for the first time, a hybrid model combining the intuitionistic fuzzy method and a metaheuristic algorithm was tested and proposed for green growth performance assessment. With this originality, it is expected that the results of this article will make a significant contribution to the literature gap and serve as a guide for policymakers and researchers.

1 | Introduction

The rapid growth of the economy leads to excessive energy and resource consumption, environmental pollution, ecological imbalances, and serious social opportunity inequalities [1]. For societies that are highly dependent on biodiversity and ecosystems, the protection of natural capital is of critical importance in the face of these challenges [2]. Traditional industrial growth

Abbreviations: Act, Actual; AHP, Analytic Hierarchy Process; ANFIS, Adaptive Neuro Fuzzy Inference System; ANP, Analytical Network Process; BRICS, Brazil, Russia, India, China, and South Africa; CRADIS, Compromise Ranking of Alternatives from Distance to Ideal Solution; CO2, Carbon dioxide; CS-ARDL, Cross Sectionally Augmented Auto Regressive Distributed Lag; DEA, Data Envelopment Analysis; DPTM, Dynamic Panel Threshold Model; EU, European Union; FCM, Fuzzy c mean; FFA, Firefly algorithms; GA, Genetic algorithm; GDP, Gross Domestic Product; GGGI, Global Green Growth Institute; IFS, Intuitionistic Fuzzy Set; IFNs, Intuitionistic Fuzzy Numbers; MAE, Mean Absolute Error; MBE, Mean Biased Error; MCDM, Multi-Criteria Decision-Making; MF, Membership Function; MMQR, Method of Moments Quantile Regression; MSE, Mean Square Error; OECD, Organization for Economic Co-operation and Development; PCA, Principal Component Analysis; PLS-SEM, Partial Least Squares—Structural Equation Modeling; Pop, Population; Pred, Prediction; PSO, Particle Swarm Optimization; R^2, R-squared; RMSE, Root Mean Square Error; RSS, Sum of Squares of Residuals; SMAPE, Symmetric Mean Absolute Percentage Error; TLBO, Teaching-Learning-Based Optimization; TFP, Total Factor Productivity; TSS, Total Sum of Squares.

https://doi.org/10.1002/cpe.70089

theories, which focus on generating economic value through physical capital, do not facilitate the preservation and sustainability of natural capital [1]. In classical growth theory, the environment and natural resources are considered depleting assets, and their sustainable impact on economic growth is overlooked [3].

Many countries have begun focusing on new theories and solutions to create a livable society, address environmental issues, and ensure a sustainable economy [4]. Over the last two decades, many international organizations have proposed green growth and the green economy as development pathways to achieve economic, social, and environmental sustainability [5]. Green growth, which has emerged as a solution to climate change and environmental problems at a global level [6], is one of the fundamental drivers of economic sustainability.

Green growth is generally defined as achieving sustainability through the rational use of natural resources while minimizing costly environmental damage, climate change, and biodiversity loss in the pursuit of economic growth and development [7, 8]. It is a development approach that aims to promote economic growth that is both environmentally sustainable and socially inclusive [9]. The concept of green growth, which defines the environment as natural capital and underscores the importance of natural resources [10], seeks to protect natural assets and environmental resources while fostering economic growth and development [7].

Green growth creates a balance between the economy and the environment through the efficient use of resources, green technology research, and the creation of new business opportunities [5]. While increasing production at the macro level, emphasis is placed on the use of environmentally friendly inputs to prevent the depletion of existing environmental and production resources [11].

The green growth strategy is considered an effective way to ensure the sustainable use of natural resources by reducing environmental degradation and minimizing resource waste. Green growth underscores the necessity of meeting the needs of future generations without depleting current resources [12]. The importance, impact, and outcomes of green growth have led to the adoption and promotion of green-focused strategies on international platforms.

Green growth theory, which is closely related to sustainable development in response to the threats and risks posed by rapid industrialization and globalization, is supported by international organizations such as the United Nations and the OECD and is incorporated into policies and practices by decision-makers [12]. International organizations advocate economic growth and the enhancement of natural capital through the rational use of environmental resources in their publications on green growth. They promote preventing waste pollution and facilitating sustainable development by fostering a green economy [13].

Achieving a green and sustainable society at both national and international levels is one of the fundamental goals of states and organizations. Green growth is a global priority strategy aimed at addressing climate change [14]. The effects of green growth at macro and micro levels are actively researched by states, academia, and international organizations [15].

The Global Green Growth Institute (GGGI) introduced the dimensions of green growth within the framework of the Green Growth Index, which was first published in 2019. Efficient and sustainable resource use, natural capital protection, green economic opportunities, and social inclusiveness are the four key dimensions that countries focus on in their green growth performance [16].

This study focuses on efficient and sustainable resource use as a measure of green growth performance. Efficient and sustainable resource use has a strong influence on and a close relationship with the other dimensions of green growth. Ensuring efficient and sustainable resource use at macro and micro levels enables the optimal use of natural capital and the creation of greater economic value with fewer resources, without compromising the well-being of future generations. Consequently, it directly contributes to the preservation of natural capital as well as ecological balance [17]. It should be recognized that without the protection of natural capital, the supply, regulation, and support processes of the ecosystem are at risk.

Natural resources, which are factors of production, play a crucial role in the economic growth of countries. In addition to their fundamental roles in the economy and industry, natural resources are integral to ecosystems that support climate regulation, flood control, natural opportunities, and cultural services. As the population of countries increases, the use of natural resources also rises, leading to various problems [18]. Designing, producing, and using green products within the framework of sustainable and efficient resource use can help mitigate the negative environmental impact of resource consumption [19]. Businesses aim for green growth by integrating cleaner production processes into their strategies and policies while developing green products [18].

In light of the above explanations, it is evident that monitoring and researching green growth through environmental and resource efficiency is both important and necessary. To better understand the level of green growth in a global context and to effectively implement sustainable green growth policies, this study focuses on evaluating green growth through environmental and resource efficiency. The analysis of green growth performance is based on environmental and resource efficiency indicators published by the OECD. In this study, the adaptive neuro-fuzzy inference system (ANFIS) models optimized with intuitionistic fuzzy and metaheuristic algorithms were used to assess green growth performance.

1.1 | Objectives of the Study

In this context, the objectives of the study are as follows:

- Identifying the most appropriate environmental and resource variables for evaluating green growth performance using the Spearman correlation method.
- Determining the importance weights of the selected variables using the Shannon entropy method.

- Measuring the long-term green growth performance of countries across multiple datasets using the proposed intuitionistic fuzzy method.
- Ranking countries based on their green growth performance scores.
- Estimating the optimal green growth performance using metaheuristic algorithms with green growth scores as the output.
- Comparing the estimation results of intuitionistic fuzzy performance scores and metaheuristic algorithms.

The main contribution of this article is the proposal of a comprehensive ranking and estimation model in which the complex and systematically evaluated green growth performance of OECD countries is assessed based on the most appropriate variables. This study introduces a hybrid measurement model based on intuitionistic fuzzy logic and metaheuristics to the green growth literature for the first time. This highlights the originality of the study and its significance in the field. The methods used in the hybrid model can both address the uncertainty inherent in multiple datasets and provide artificial intelligence-based optimization capabilities. With this model, it is possible to achieve the most accurate green growth performance ranking and estimation using OECD data. In this regard, the study differentiates itself from traditional green growth reports and offers unique contributions, methodological advancements, and advantages.

The remaining sections of the study are structured as follows: The literature review section provides a summary of relevant studies that form the foundation of the research. The methodology section explains the method specifications, mathematical notations, and application procedures. The findings and discussion section presents the results obtained from the analysis. Finally, the conclusion section interprets the overall findings of the study.

2 | Literatüre Review

Governments, international organizations, and researchers have made significant efforts to conduct scientific studies that reflect green growth at various levels. Although there is substantial conceptual literature on green growth, no common model, methodology, or estimation approach exists for evaluating green growth performance [20]. The existing green growth literature related to this study has been examined from both national and international perspectives.

At the national level, studies conducted in China stand out. Chen et al. [21] analyzed the impact of economic activity on green growth from a dynamic perspective using Data Envelopment Analysis (DEA) techniques, incorporating production function and total factor productivity (TFP) methods. Cheng and Li [22] measured the TFP of carbon emissions using the Directional Distance Function and the Malmquist Productivity Index model to assess the impact of manufacturing industries in China on green growth. Lin and Benjamin [23] investigated key determinants in measuring dynamic variables of the green growth index specific to China through multi-way distance functions and DEA methods. Yi and Liu [24] examined China's clean energy economy and policies using an analytical approach focused on green professions and firms. Dai et al. [25] explored the economic impact of green growth in China.

Regarding studies in other countries, Qureshi et al. [26] examined the long-term relationship between air pollution, environmental indicators, and health services in Malaysia. Bagheri et al. [27] proposed a multi-factor energy input–output model to aid energy policy development and green growth planning in Canada. Lee and Chou [14] analyzed Taiwan's green growth trend from 2002 to 2011 using 20 OECD indicators and applying Principal Component Analysis (PCA) and the Analytic Hierarchy Process (AHP). Sohag et al. [28] explored the role of cleaner energy, technological innovation, and militarization in green economic growth under different economic conditions in Turkey. Houssini and Geng [29] assessed Morocco's green growth efficiency from 2000 to 2018 using multi-criteria decision-making (MCDM) methods and DEA for a comprehensive efficiency evaluation. Lin and Ullah [30] examined the impact of CO2 emissions in Pakistan, highlighting the significance of green growth and innovation in sustainable development.

At the global level, studies have explored key questions in the green growth literature. Akhmat et al. [31] and Zeb et al. [32] investigated the impact and causality of green growth variables in selected countries at a macro level. Zaman et al. [33] analyzed the energy, environment, health, and wealth dimensions of green growth in BRICS (Brazil, Russia, India, China, and South Africa) countries. Pahle et al. [34] assessed how green growth contributes to socioeconomic goals in specific countries. Wang and Shao [35] estimated comparative national green growth levels for G20 countries using capital, energy, GDP, and CO2 variables. Talebzadehhosseini and Garibay [36] applied the Partial Least Squares-Structural Equation Modeling (PLS-SEM) method to examine green growth performance relationships among selected countries.

Further global studies have examined green growth strategies and performance at the OECD level. Kim et al. [37] compared the green growth strategies of 30 OECD countries using a model consisting of 12 indicators, evaluating each on a scale of 1–10. Shen et al. [38] measured green productivity changes, including carbon dioxide emissions, for 30 OECD countries between 1971 and 2011, decomposing productivity growth into three components: technological progress, technical productivity change, and structural productivity change. Bak et al. [39] assessed OECD countries' green growth development levels using multidimensional correspondence analysis on seven key indicators from 2004 and 2015. Wang et al. [40] examined the effects and mechanisms of environmental policy stringency on green productivity growth in industrial sectors using dynamic panel regression analysis and the slack-based measured directional distance function model. Gavurova et al. [15] analyzed green growth trends in OECD countries over two decades using univariate and multivariate statistical methods based on OECD green growth indicators.

Additional studies have focused on green growth performance in various contexts. He et al. [41] analyzed economic and environmental performance in 61 developing countries, decomposing total factor productivity growth into economic and environmental components. Doskočil [42] proposed a new multi-criteria assessment model for systematically evaluating green growth in European Union countries, incorporating production-based CO2 efficiency, annual surface temperature, average air pollution exposure, and environmental tax variables. Hussain et al. [43] investigated the effects of green technology and environmental factors on green growth in high-GDP countries from 2000 to 2020 using the cross-sectional autoregressive distributed lag estimator to reveal linear and nonlinear GDP effects on green growth. Chen et al. [44] analyzed the impact of green innovation and financial globalization on green growth in BRICS economies using the Cross-Sectionally Augmented Auto-Regressive Distributed Lag (CS-ARDL) model.

Recent studies have integrated broader economic and policy considerations into green growth research. Razzaq et al. [45] investigated the impact of energy transition and environmental governance on green growth in 37 International Energy Agency economies (2010–2020) using the dynamic panel threshold model (DPTM). Khan et al. [46] examined the role of natural resources in economic growth, considering carbon emissions, human capital, and green growth between 1990 and 2020 using the Method of Moments Quantile Regression (MMQR). Shang et al. [47] explored the effects of tourism and energy resources on green economic growth in Asian countries from 2000 to 2021 across different income levels. Kwilinski et al. [48] expanded the theoretical framework of green economic growth by estimating green growth in EU countries (2005–2020) using the Global Malmquist–Luenberger productivity index. Anwar et al. [49] analyzed the effects of economic policy uncertainty, green innovation, and financial development on green growth from 1996 to 2019 using panel quantile regression, measuring green growth through production-based CO2 emissions. Tawiah et al. [50] investigated the environmental impact of corruption on green growth by applying the System Generalized Method of Moments and Two-Stage Least Squares Instrumental Variable analysis to panel data from 123 countries (2000–2017). Additionally, some studies have systematically mapped and analyzed green development research in detail [51–53].

It is evident that researchers employ AHP, DEA, CS-ARDL, MMQR, Luenberger efficiency indicators, and various MCDM approaches in green growth assessment. However, a review of the literature reveals that studies incorporating intuitionistic fuzzy systems and metaheuristic algorithms for green growth performance measurement and evaluation are relatively scarce. In contrast, the combined use of metaheuristic algorithms and fuzzy systems has been explored in various other fields.

For instance, Sihag et al. [54] successfully applied the ANFIS-Firefly Algorithm (FFA) and ANFIS-Particle Swarm Optimization (PSO) models to estimate hydraulic conductivity. Ebtehaj et al. [55] tested the ANFIS-PSO model for estimating the densimetric Froude number, while Ebtehaj et al. [56] proposed the Fuzzy C-Means Adaptive ANFIS hybrid model for the estimation of WLat Telom and Bertam stations. Khoshnava et al. [57] effectively utilized the Analytical Network Process (ANP) and ANFIS methodologies to prioritize green infrastructure criteria, preparing them for Green Economy enactment. Suresh and Dillibabu [58] successfully adapted the ANFIS-based Heuristic MCDM approach to assess software project risks. Adedeji et al. [59] obtained promising results in analyzing short-term wind resource variability using the ANFIS-Genetic Algorithm (GA) and ANFIS-PSO models.

Recently, Teaching-Learning-Based Optimization (TLBO), a population-based metaheuristic algorithm, has gained attention in hybrid studies. Sharma et al. [60] and Dubey et al. [61] employed Gray-TLBO-based MCDM methods for tuning control variables in machine operations. Das et al. [62] effectively applied TLBO-based MCDM methods to solve parametric optimization problems in micro-electric discharge machining processes. Yektamoghadam et al. [63] successfully optimized traffic light control using MCDM methods enhanced with GA and TLBO. Mondal et al. [64] optimized machining processes with the ANFIS-TLBO algorithm, while Kardan and Habibi [65] demonstrated the effectiveness of the TLBO method based on the ANFIS approach in simulating erosion at culvert outlets. Babanouri and Fattahi [66] successfully employed the ANFIS-TLBO model to establish a new rock shear strength criterion. Zheng et al. [67] confirmed the success of the ANFIS-TLBO model in estimating cooling loads.

While no single algorithm is universally optimal for all optimization problems [68], ANFIS-based PSO, GA, and TLBO algorithms have demonstrated promising performance across various optimization challenges, yielding effective results. Metaheuristic methods generally do not require prior knowledge about the search space properties, making them desirable for tackling complex problems characterized by discontinuity and non-differentiability [69]. The use of metaheuristic and evolutionary algorithms offers a suitable approach for solving nonlinear optimization problems [63].

A literature review indicates a notable gap in studies applying intuitionistic fuzzy systems and metaheuristic algorithms to green growth performance measurement and evaluation. Specifically, hybrid models integrating intuitionistic fuzzy logic and metaheuristics have not been extensively utilized in green growth performance assessment at either national or international levels. Recognizing this gap in the literature, this study aims to address it by examining the green growth performance of selected OECD countries using hybrid models that combine Intuitionistic Fuzzy MCDM with ANFIS-PSO, ANFIS-GA, and ANFIS-TLBO algorithms.

3 | Methodology and Implementation

Over the years, researchers have developed numerous MCDM approaches to enhance decision-making accuracy. Various research studies have introduced new algorithms and mathematical tools to achieve more precise solutions [70]. This section provides a brief explanation of the methodologies employed in this study. First, the mathematical notations of the intuitionistic fuzzy method used for measuring green growth performance values are presented. Next, the fuzzy inference system and metaheuristic algorithms applied to estimate the optimal green growth performance are discussed. Finally, the processes of data preparation, hybrid modeling, and implementation are outlined.

3.1 | Intuitionistic Fuzzy Compromise Ranking of Alternatives From Distance to Ideal Solution

There is a need to apply and validate new methods with different variances to determine the most efficient approach for solving complex problems across various fields [68]. In particular, for robust decision-making in multivariate decision processes, accounting for uncertainty is an essential aspect of problem-solving [71]. Considering uncertainty helps protect decision-makers from incorrect or misleading solutions caused by input data errors and subjective preferences in model parameters [72].

To cope with the uncertainty and ambiguity of the constraints and consequences of possible actions [73], Zadeh [74] proposed the Fuzzy Set (FS) theory as a framework. Due to the fuzziness and uncertainty of the evaluation objects, Bellman and Zadeh [75] extended the FS theory to address decision-making problems. The FS approach, which represents the fuzziness inherent in complex systems, was further developed by Atanassov [76], who introduced the concept of Intuitionistic Fuzzy Sets (IFS). IFS accounts for non-membership and hesitation information, which can more accurately define uncertainty, in addition to set membership. In cases handled by researchers using intuitionistic fuzzy numbers (IFNs), uncertainty can be managed more clearly. IFS, which facilitates decision-making processes, is widely used in many fields [77, 78]. In the decision-making process, decision-makers evaluate and rank alternatives according to various criteria and attempt to determine the most appropriate option [79]. To make decision-making more efficient and of higher quality under an intuitionistic fuzzy environment, many methods have been proposed to improve the MCDM process [80–90]. Innovative and different procedures are being employed while developing new methods.

Puška et al. [91] describe the classical Compromise Ranking of Alternatives from Distance to Ideal Solution (CRADIS) method, which leverages the advantages of ARAS, MARCOS, and TOPSIS methods, and is based on the utility function and the distance of certain alternatives from ideal and non-ideal solutions [91]. In the literature, studies utilize classical CRADIS [92] and fuzzy CRADIS [93, 94] methods. However, there are no examples of the new CRADIS method being applied in an intuitionistic fuzzy environment. To address this gap in the literature, this study tests the application of the Intuitionistic Fuzzy CRADIS (IFCRADIS) method on metadata. The application steps and mathematical notations of the IFCRADIS method, which extends the intuitionistic fuzzy set (IFS) operators presented by Xu [95], are presented below.

Step 1. As shown in Equation (1), a decision matrix containing exact data is created, including row-based alternatives (i) and column-based criteria (j).

$$D = (a_{ij})_{mxn} = \begin{array}{c} \\ A_1 \\ A_2 \\ \vdots \\ A_i \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \cdots & C_j \end{array} \\ \begin{pmatrix} a_{11} & a_{12} & \cdots & a_{1j} \\ a_{21} & a_{22} & \cdots & a_{2j} \\ \vdots & \vdots & \ddots & \vdots \\ a_{i1} & a_{i2} & \cdots & a_{ij} \end{pmatrix} \end{array} \tag{1}$$

Step 2. Normalization is performed with the help of Equation (2) to eliminate the differences between the values in the decision matrix [96].

$$n_{ij} = x_{ij} / \sqrt{\sum_{j=1}^{m} x_{ij}^2}\, i = 1, \ldots, m, j = 1, \ldots, n \tag{2}$$

Step 3. The exact data in the normalized decision matrix are respectively converted into intuitive fuzzy values using Equations (3–5) [76, 97]. The decision matrix consisting of intuitive fuzzy data is shown as $D = [s_{jd}]_{nxk}$ and ($d = 1, 2, \ldots, k, j = 1, 2, \ldots, n$). The IFNs s_{jd}, expresses the value of the dth alternative regarding the jth indicator. Each contains $s_{jd} = (\mu_{sjd}, \gamma_{sjd}, \pi_{sjd})$.

$$v_i^{\prime} = 1 - \mu_i \tag{3}$$

$$\pi_i = \frac{v_i'}{\sum_{i=1}^{n} v_i'} \tag{4}$$

$$v_i = 1 - \mu_i - \pi_i \tag{5}$$

Step 4. Determination of the IF ideal solution: The intuitionistic fuzzy negative-ideal solution is $\varsigma- = (0, 1, 0)$ and the intuitionistic fuzzy positive-ideal solution is $\varsigma+ = (1, 0, 0)$. In some studies, positive and negative ideal solutions are calculated with max and min operators. However, there is no significant difference between the results obtained from both methods in ranking studies [98].

Step 5. The fuzzy normalized Euclidean distance formula developed by Szmidt and Kacprzyk [99] is used to calculate distance measurements. D_j^+ in the formula represents the positive distance measure, and D_j^- represents the negative distance measure. The distance measure for each alternative is calculated as shown in Equations (6) and (7) [99].

$$D_j^+ = \sqrt{\left(\mu_{s_j} - \varsigma^+\right)^2 + \left(v_{s_j} - \varsigma^+\right)^2 + \left(\pi_{s_j} - \varsigma^+\right)^2} \tag{6}$$

$$D_j^- = \sqrt{\left(\mu_{s_j} - \varsigma^-\right)^2 + \left(v_{s_j} - \varsigma^-\right)^2 + \left(\pi_{s_j} - \varsigma^-\right)^2} \tag{7}$$

Step 6. Measurement of closeness coefficient and indicator weight values: The closeness coefficient of J indicators is calculated with the help of Equation (7) using IF positive ideal solution D_j^+ and IF negative ideal solution D_j^-. Closeness coefficient values give the weights of each indicator. However, the sum of the weights must be equal to 1.

$$\acute{C}_j = \frac{D_j^-}{D_j^- + D_j^+}, 0 \leq \acute{C}_j \leq 1, j = 1, 2, \ldots, n. \tag{7}$$

Step 7. Normalization is performed using Equation (8) for the benefit-based criterion and Equation (9) for the cost-based criterion. The weighted total decision matrix is obtained by multiplying the normalized decision matrix values with the mathematical notation expression shown in Equation (10).

$$n_{ij} = \frac{x_{ij}}{xjmax} \tag{8}$$

$$n_{ij} = \frac{x_{jmin}}{xij} \tag{9}$$

$$v_{ij} = n_{ij}.w_j \tag{10}$$

Step 8. In the weighted decision matrix, the ideal solution $t_{id} = maxv_{ij}$ with the largest value of v_{ij}, and the non-ideal solution $t_{aid} = minv_{ij}$ with the smallest value of v_{ij} are determined. The deviations of the individual alternatives from the ideal and non-ideal solutions are measured using Equations (11–14) respectively.

$$d^+ = t_{id} - v_{ij} \tag{11}$$

$$d^- = v_{ij} - t_{aid} \tag{12}$$

$$s_i^+ = \sum_{j=1}^{n} d^+ \tag{13}$$

$$s_i^- = \sum_{j=1}^{n} d^- \tag{14}$$

Step 9. Calculate the utility function for each alternative according to the deviations from the optimal alternatives using Equations (15) and (16). Where s_0^+ is the optimal alternative at the closest distance from the ideal solution and, s_0^- is the optimal alternative at the farthest distance from the non-ideal solution. The final ranking is derived from Equation (17) by looking at the average deviation of the alternatives from the degree of utility. The largest value of Q_i indicates the best alternative.

$$K_i^+ = \frac{s_0^+}{s_i^+} \tag{15}$$

$$K_i^- = \frac{s_i^-}{s_0^-} \tag{16}$$

$$Q_i = \frac{K_i^+ + K_i^-}{2} \tag{17}$$

The IFCRADIS method can be considered a simple, practical, functional, and effective approach for the evaluation and prioritization of available alternatives in an intuitionistic fuzzy environment [100].

3.2 | The Adaptive Neuro-Fuzzy Inference System

Artificial intelligence-based hybrid systems aim to achieve better results by combining the advantages of the most popular methods [101]. ANFIS is a hybrid method that combines the superior aspects of artificial neural networks and fuzzy logic [102]. ANFIS, proposed by Jang [103], is a structure and learning procedure that can create a mapping between input and output using membership functions. The ANFIS hybrid learning algorithm works by combining different algorithms to define and optimize the Sugeno system parameters. The training process continues until the optimum error tolerance is reached. The structure of ANFIS changes according to the input variables, membership functions, rule base, and the number of outputs [104]. The layers in the basic structure of ANFIS are shown in Figure 1 [105, 106]. This figure illustrates the basic ANFIS structure consisting of 2 inputs and 1 output, featuring four membership functions and four rules. To explain the role of each layer, consider the fuzzy if-then rule Equations (18) and (19), where x and y are the input variables, Ai and Bi are fuzzy sets, f is the output, and p, q, and r are the design parameters that need to be determined during the training process of the ANFIS algorithm [107].

$$\text{Rule 1 : if } x \text{ is } A_1 \text{ and } y \text{ is } B_1 \text{ then } f = p_1 x + q_1\, y + r_1 \tag{18}$$

$$\text{Rule 2 : if } x \text{ is } A_2 \text{ and } y \text{ is } B_2 \text{ then } f = p_2 x + q_2\, y + r_2 \tag{19}$$

The combination of the advantages of artificial neural networks and fuzzy logic in ANFIS allows for the modeling and estimation of complex functions and time series [108].

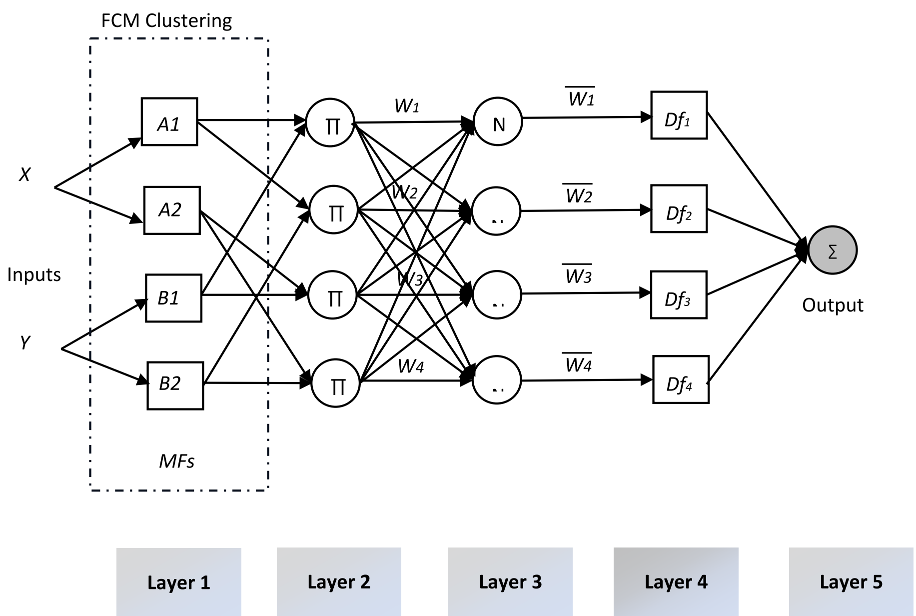

FIGURE 1 | Basic ANFIS structure with two inputs.

3.3 | Particle Swarm Optimization

Particle Swarm Optimization (PSO), an evolutionary computation-based approach, is a population-based global optimization technique proposed by Kennedy and Eberhart [109]. PSO is related to artificial life and swarm theory [110]. It is a stochastic optimization algorithm that models the intelligent collective behavior of certain animals, such as bird flocks or fish schools [111].

Individual particles in the swarm behave unsupervised, and each particle exhibits stochastic behavior due to its perceptions of the environment. Each particle in the swarm tends to move toward a better search area with a speed that dynamically adjusts according to its own and other particles' behavior [112]. Each particle represents a solution with four vectors in high-dimensional space: its current position, the best position found so far, the best position found by its neighbors so far, and its speed, which adjusts its position in the search space according to the best position reached [113]. Many studies present the details and successful results of PSO applications [111, 113–116]. Due to the successful and effective results of applying the ANFIS model optimized with the PSO algorithm in different areas, ANFIS-PSO was used as the first model in this study.

3.4 | Genetic Algorithm

Genetic algorithms (GA), used in problem-solving and modeling evolutionary systems, are computational models of biological evolution. In GA, binary sequences are modified in a computer environment over time through natural selection, similar to the evolution of populations of individuals. Although GAs have a very simple structure, they can provide successful solutions to complex problems [117]. The evolutionary process of chromosomes is simulated using selection, crossover, and mutation operators based on the principle of survival of the fittest. Chromosomes are evaluated according to their suitability for solving a problem [118]. Various studies support that GA algorithms provide successful and valid solutions to estimation and optimization problems [119–122]. In this research, the second model used was the ANFIS-GA model, in which the ANFIS method was optimized with the GA algorithm.

3.5 | Teaching Learning Based Optimization

The Teaching-Learning-Based Optimization (TLBO) algorithm, which simulates the teaching process of teachers with students, was first developed by Rao et al. [123]. TLBO, a population-based method, uses populations to reach a solution. Based on the classical school learning process, the teacher represents the best solution among the population of students' solutions [123]. TLBO executes iterative evolutionary processes similar to those used by standard algorithms. The learning process of TLBO, which performs well with less computational effort for large-scale problems, consists of two basic steps, unlike traditional evolutionary algorithms and swarm intelligence algorithms [124].

The first stage is the Teacher Phase. The best solution in the entire population is considered the teacher of the class; the teacher shares his/her knowledge with students to improve their outcomes (that is grades or scores); the quality of the teacher affects students' results. The second stage is the Learner Phase. In this phase, students learn from other students to improve their results [125].

It has been observed that the TLBO model achieves successful prediction results with higher accuracy compared to existing empirical formulas in ANFIS optimization studies. The TLBO model demonstrates a wider range of applicability by adapting to various conditions [64–66, 105]. In this study, the optimization of the ANFIS model with the TLBO algorithm was chosen as the third model.

3.6 | Methods for Measuring Forecast Accuracy

Six methods were used to analyze the prediction accuracy of the hybrid models employed in the analysis: R-squared (R^2), Root Mean Squared Error (RMSE), Mean Biased Error (MBE), Mean Absolute Error (MAE), Symmetric Mean Absolute Percentage Error (SMAPE), and Mean Squared Error (MSE). The mathematical notations of these measures are briefly explained below [43].

The R^2 method is widely used in regression models to calculate the proportion of variance in the dependent variable that is predictable from the independent variables. The closer the correlation coefficient is to 1, the more accurate the model's predictions are [126]. The mathematical notation for R^2 is expressed in Equation (20), where RSS is the sum of squares of residuals and TSS is the total sum of squares.

$$R^2 = 1 - \frac{RSS}{TSS} \tag{20}$$

RMSE is one of the most popular methods used in time series prediction. It measures the magnitude of error between the predicted and observed values. RMSE is calculated using Equation (21). The closer the value is to 0, the better the result.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} \left(Act_i - Pred_i\right)^2}{N}} \tag{21}$$

MBE is used to estimate the mean deviation in the model. It captures the mean deviation with both positive and negative values. A positive deviation indicates that the data is overestimated, while a negative deviation indicates that the data is underestimated. The method is shown in Equation (22).

$$MBE = \frac{1}{N} \sum_{j=1}^{N} \left(Pred_j - Act_j\right) \tag{22}$$

MAE provides a general measure of model performance by averaging the absolute errors, which is less sensitive to outliers compared to other metrics. MAE is formulated in Equation (23). The best value on the MAE scale is the value closest to 0 [127].

$$MAE = \frac{1}{N} \sum_{j=1}^{N} \left|Pred_j - Act_j\right| \tag{23}$$

TABLE 1 | Evaluation criteria.

Code	Indicator	Measure	References
C1	Energy productivity, GDP per unit of TES	US dollars per tonne of oil equivalent	OECD Green Growth Database
C2	Renewable electricity generation	Percentage of electricity generation	OECD Green Growth Database
C3	Production-based CO_2 productivity, GDP per unit of energy-related CO2 emissions	US dollars per unit of CO_2	OECD Green Growth Database
C4	Demand-based CO_2 productivity, GDP per unit of energy-related CO_2 emissions	US dollars per unit of CO_2	OECD Green Growth Database
C5	Demand-based CO_2 productivity relative to disposable income	US dollars per unit of CO_2	OECD Green Growth Database

The SMAPE measure calculates the percentage of absolute errors relative to the true values. SMAPE, which provides specific information about the magnitude and distribution of errors, is explained by Equation (24). The best value on the SMAPE scale is 0, and the worst value is 2.

$$SMAPE = \frac{100\%}{N} \sum_{j=1}^{N} \frac{\left|Pred_j - Act_j\right|}{\left(\left|Pred_j\right| + \left|Act_j\right|\right)/2} \tag{24}$$

MSE is used to measure the performance of a prediction model by averaging the squares of the differences between the actual and predicted values. The MSE scale is formulated in Equation (25). The best value for MSE is the one closest to 0 [127].

$$MSE = \frac{1}{N} \sum_{j=1}^{N} \left(Pred_j - Act_j\right)^2 \tag{25}$$

3.7 | Data Collection and Preprocessing

The green growth database provided by the OECD includes selected indicators for monitoring green growth. The database aims to support policymaking and inform the public by synthesizing data and indicators from a wide range of areas [128]. It quantifies environmental and resource efficiency to capture the fundamental characteristics of green growth. This allows for an investigation into the greening of economic growth through the efficient use of natural capital.

This study focuses on environmental and resource efficiency, one of the OECD's [128] green growth performance indicators. Spearman correlation analysis was used to determine the most appropriate data set for green growth performance analysis. In this analysis, the relationship level between variables was examined to verify the suitability of the data used in the study and to support the accuracy of the analysis results. Five criteria with significant relationships among the 27 sub-indicators in environmental and resource efficiency were selected as green growth performance indicators (Tables 1 and 2). As shown in Table 2, a high relationship was generally observed between the variables. The strong correlation between variables is important for ensuring the suitability of the data and the accuracy of the analysis results.

The input and output variables used in the analysis were created by averaging the data from 31 European countries from 2013 to 2022 via the OECD Data Explorer. Descriptive statistics of the evaluation criteria for the countries in the sample set are presented in Table 3.

TABLE 2 | Spearman's rho correlations.

	C1	C2	C3	C4	C5
C1	1000	401[a]	685[b]	610[b]	500[b]
C2		1000	599[b]	369[a]	382[a]
C3			1000	804[b]	717[b]
C4				1000	883[b]
C5					1000

[a]Correlation is significant at the 0.05 level (2-tailed).
[b]Correlation is significant at the 0.01 level (2-tailed).

TABLE 3 | Descriptive statistics.

	C1	C2	C3	C4	C5
min	5671.77	3.35	3.02	2.76	2.25
max	2,5975.42	97.95	15.35	6.51	5.79
mean	12702.94	39.09	7.04	4.81	3.85
st	4365.70	24.28	2.93	1.01	0.86
N	31	31	31	31	31

The data were normalized to increase the accuracy of the results and to ensure faster convergence by removing irrelevant or very distant values from the traditional values used in the study. Equation (26) was used in the normalization process of the data.

$$n_j = \frac{X_j - X_{min}}{X_{max} - X_{min}} \tag{26}$$

In the ANFIS models used in the study, all data were randomly divided from the original data set at a rate of 70:30, based on previous successful studies [129, 130]. Seventy percent of the data set (21 data points) was used for training purposes, while the remaining 30% (9 data points) was used for testing model performance.

3.8 | Hybrid Modeling and Implementation

In this study, the green growth performance levels of 31 countries were analyzed based on publicly available OECD data and environmental and resource efficiency indicators, with the goal

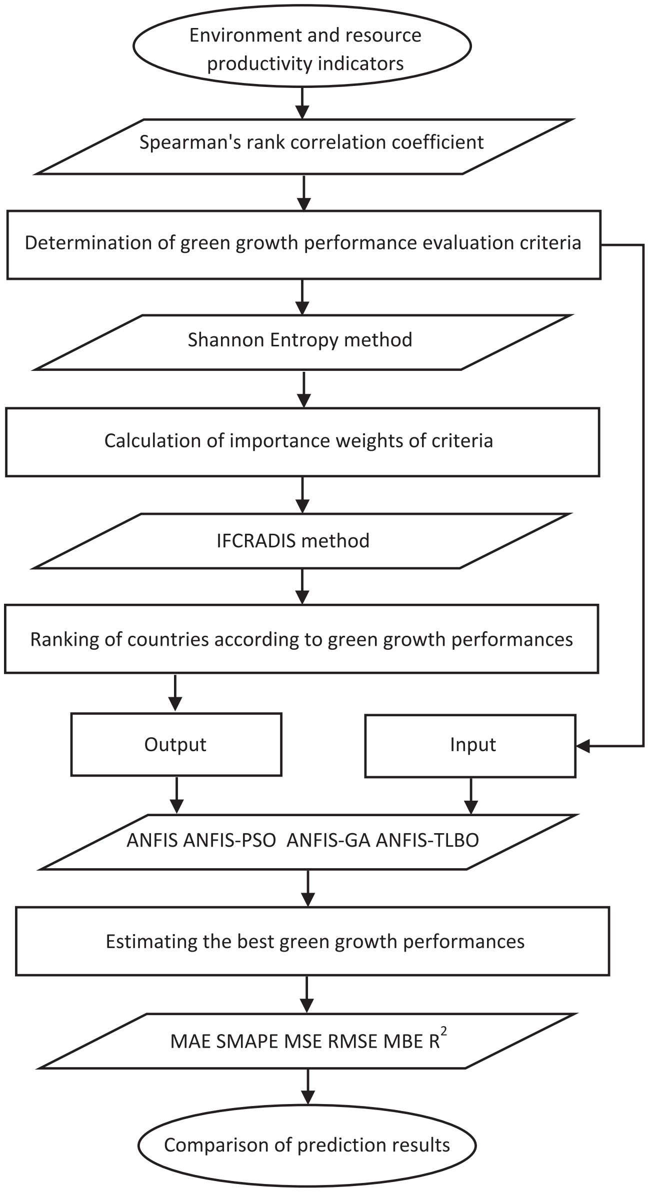

FIGURE 2 | Implementation flowchart.

of estimating the best results. To reveal the green growth performances at the macro level, the research focused on resource utilization and environmental livability issues. The basic flow chart of the methodological approach used in the research is presented in Figure 2.

In this context, the environmental and green growth performance of 31 OECD countries was measured in the first stage of the study based on environmental and resource efficiency variables. Before ranking the countries according to their performances, the importance weights of the evaluation criteria were calculated using the Shannon Entropy method. The entropy method, developed by Shannon [131], uses probability theory to determine uncertain information while calculating the objective weights of the criteria. It eliminates the subjectivity of decision-makers by considering the indicator values contained in the data [131]. In this study, the Shannon Entropy method was preferred to mitigate the effect of subjectivity in determining the importance of the evaluation criteria. The green growth performance ranking of the countries was determined using the IFCRADIS method with weighted evaluation criteria. The Excel program was used for applying both the entropy method and the IFCRADIS method.

In the second stage of the research, the best green growth performance scores obtained using the IFCRADIS method were estimated with hybrid ANFIS models. The models were implemented in the Matlab R2023b environment. To achieve the research objective, 21 data points were divided into training sets, and 9 data points were divided into test sets. The data were normalized and loaded. The architectural structure of the ANFIS model includes 5 input variables and 1 output variable. Four Gaussian membership functions were used for each input variable, and a linear membership function was used for the output. The Takagi–Sugeno fuzzy inference system was run to obtain the results of the ANFIS model. The parameters of the applied ANFIS models are explained in Table 4. During the training step, the ANFIS, ANFIS-PSO, ANFIS-GA, and ANFIS-TLBO optimization parameters presented in Table 4 were adjusted and loaded. In the optimization stage, the error function between the model outputs and the expected values was minimized until the required number of iterations (100 iterations) was reached. Based on the results obtained, the testing phase was initiated. After obtaining the training and test results, the result data were transferred to Microsoft Excel for comparison according to the error scales.

4 | Results and Discussion

To achieve the objectives of this research, the classical ANFIS, ANFIS-PSO, ANFIS-GA, and ANFIS-TLBO models were tested on different population parameters using the data in the sample. PSO, GA, and TLBO optimization algorithms were used to adapt the weights in the ANFIS model, as modified by Ghasemi et al. [105]. In this section, the results of the model proposed for the best green growth performance evaluation and prediction are presented.

4.1 | Green Growth Performance Results

There are significant risk factors that decision-makers face when addressing an MCDM problem. In subjective methods used for criterion weighting, the decisions made by decision-makers can often become inconsistent [132]. In other methods, challenges such as the inability to account for cognitive limitations on rational values, as well as the correlations and internal dependencies between decision criteria, can make the problem quite complex [133]. Even a small change in the inputs can lead to a significant difference in the results, creating a more sensitive situation [134].

To overcome the disadvantages of subjective weighting methods, the importance level weights of the variables used in this study were calculated using the Shannon Entropy method. Unlike subjective weighting methods, the Entropy method derives the importance level weights from the internal values of the indices, providing results that are more aligned with reality [135].

The Shannon Entropy weights for the importance levels of the criteria are presented in Figure 3. Renewable electricity generation

TABLE 4 | Model parameters.

ANFIS parameters		PSO parameters		GA parameters		TLBO parameters	
Type	**Sugeno**	**Type**	**Sugeno**	**Type**	**Sugeno**	**Type**	**Sugeno**
Inputs/outputs	5/1	Inputs/outputs	5/1	Inputs/outputs	5/1	Inputs/outputs	5/1
Input MF type	Gaussian	Input MF type	Gaussian	Input MF type	Gaussian	Input MF type	Gaussian
Output MF type	Linear	Output MF type	Linear	Output MF type	Linear	Output MF type	Linear
Epoch number	100	Population size	20–30–40–50	Population size	20–30–40–50	Population size	20–30–40–50
Error goal	0	Maximum number of iterations	100	Maximum number of iterations	100	Maximum number of iterations	100
Initial step size	0.01	Inertia weight	1	Crossover percentage	0.4		
Step size decrease rate	0.9	Inertia weight damping ratio	0.99	Mutation percentage	0.7		
Step size increase rate	1.1	Personal learning coefficient	1	Mutation rate	0.15		
		Global learning coefficient	2	Selection pressure	8		
				Gamma	0.7		

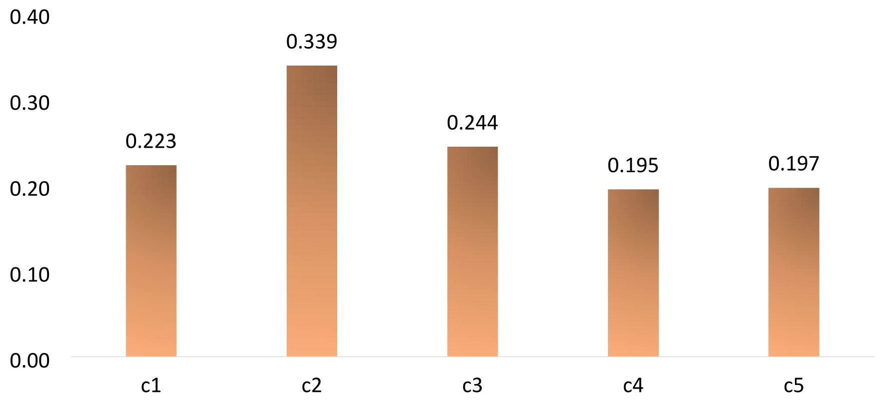

FIGURE 3 | Importance weight of criteria.

(C2) is the variable with the highest significance level (0.339) in the green growth performance evaluation, while demand-based CO2 productivity (C4) has the lowest significance level (0.195) in the performance evaluation.

The IFCRADIS method proposed in the article ranked the selected OECD countries according to their green growth performance. The performance evaluation results are shown in Figure 4. Ireland (1.00), Switzerland (0.98), and Costa Rica (0.95) exhibited the best green growth performance, with the highest environmental and resource use efficiency success. Finland (0.62), Estonia (0.58), and Canada (0.47) are the countries with the worst green growth performance, respectively. Overall, 54% of the countries in the research sample are below the green growth performance average (0.77).

According to Kasztelan's [5] research results, only Denmark achieved the highest green growth level. In contrast, 12 out of the 21 countries analyzed showed the lowest green growth performance. Wang et al. [40] observed the highest growth rates in green productivity in Korea and the Netherlands, respectively, noting that green productivity growth in these countries is mainly due to productivity changes. Kim et al. [37] found that Switzerland, France, and Japan exhibited the highest average green growth levels in their study on the environmental efficiency of production and changes in production models. Doskočil [42], using the multi-criteria model he proposed, evaluated Ireland as the country with the highest level of Green Growth in 2020, while Latvia had the lowest. Acosta et al. [136] evaluated green growth in a general framework, with Denmark, Sweden, and Austria showing the highest success, respectively. Kwilinski et al. [48] reported that Sweden, Belgium, and Germany had the highest average green economic growth values in 2020 in their green economic growth forecast analysis. Although there are studies on similar topics, no research in the literature matches the results of our study due to differences in the sample, method, and variables used.

4.2 | Results of Best Green Growth Performance Predicted

ANFIS, ANFIS-PSO, ANFIS-, GA, and ANFIS-TLBO models were used to estimate the best green growth performance score. Optimization algorithms in hybrid ANFIS models were tested with different population parameters. The evaluation of regression graphs showing the training and test results of optimized ANFIS models is presented below.

4.2.1 | Results of the ANFIS-PSO Model

It is seen in Figures 5 and 6 that the training data results of the ANFIS-PSO model are successful in all different

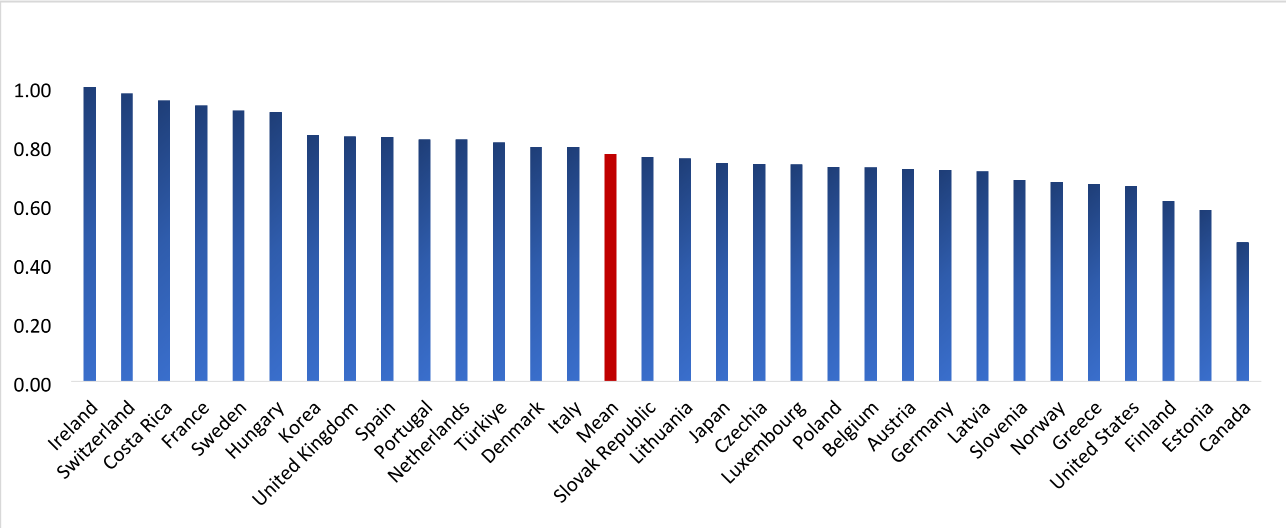

FIGURE 4 | Green growth performances of OECD countries.

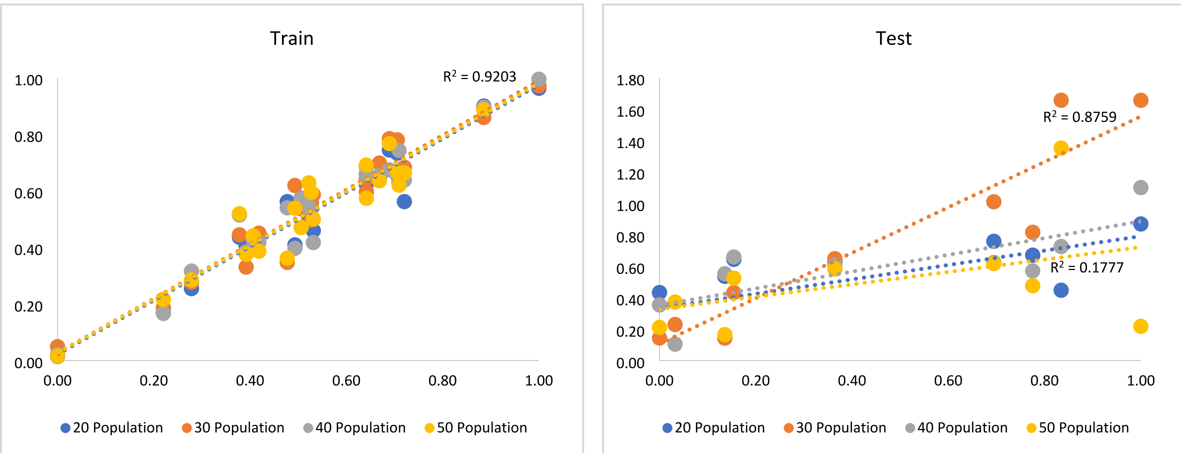

FIGURE 5 | ANFIS-PSO lines.

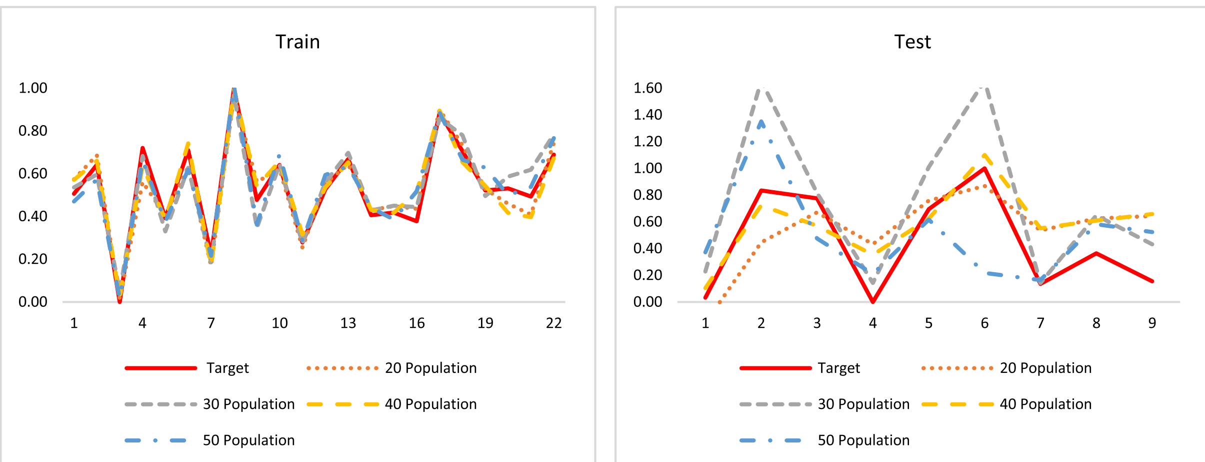

FIGURE 6 | ANFIS-PSO predictions.

population parameters applied. The most successful target values ($R^2 = 0.930$) were obtained in the prediction values in the training data. To understand the accuracy of the prediction values, the test result values of the models should be focused on. In the test results of the ANFIS-PSO model, the highest prediction performance ($R^2 = 0.876$) was measured in 30 population parameters. The lowest performance (0.178) in predicting the target values was determined in 50 population parameters.

When we look at the iteration lines shown in Figure 7, it is understood that the ANFIS-PSO model turns into a horizontal view at the 100 iteration level. It is understood from the figure that the ANFIS-PSO model reaches the optimization result more slowly in all tested population parameters and needs more iterations.

4.2.2 | Results of the ANFIS-GA Model

Figures 8 and 9 show that the ANFIS-GA model produces values ranging from 0.724 to 0.881 depending on the different population parameters applied in the training data results. The ANFIS-GA model achieves the highest prediction performance in the test results with 40 population parameters ($R^2 = 0.675$). The least successful prediction score (0.023) in the test data results was observed at 30 population parameters.

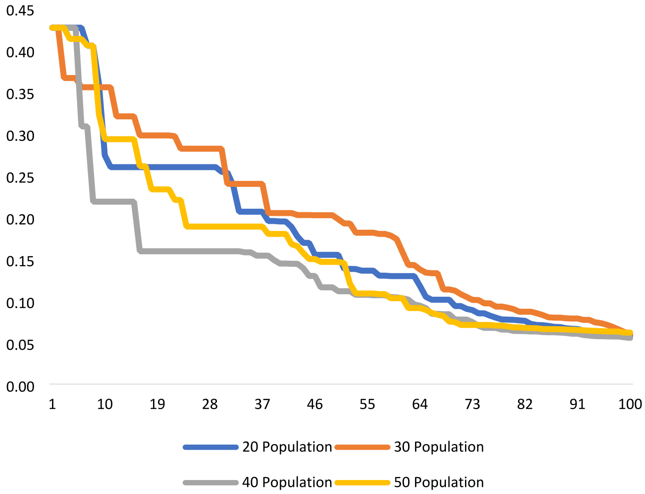

FIGURE 7 | Iteration of the ANFIS-PSO model.

Examining the iteration lines of the ANFIS-GA model shown in Figure 10 reveals that, although there is rapid progress toward the optimization result initially, the progress becomes horizontal toward the 100th iteration. The lines indicate that the ANFIS-GA model shows similar iteration patterns across all tested population parameters, reaches the optimization result slowly, and requires multiple iterations. The wide distribution range in the iteration lines suggests that the ANFIS-PSO model is most affected by changes in population levels.

4.2.3 | Results of the ANFIS-TLBO Model

When examining the results of the training data for the ANFIS-TLBO model, it is evident that a high level of prediction success is achieved. Figures 11 and 12 show the highest prediction score (0.957) achieved with 40 population parameters in the training data results. The best prediction performance of the ANFIS-TLBO model in the test results was found with 20 population parameters ($R^2 = 0.893$). The least successful prediction score (0.449) in the test data results was recorded with 40 population parameters.

The iteration representation of the ANFIS-TLBO model is shown in Figure 13. Examination of this figure reveals that the model progresses rapidly toward optimization and reaches a horizontal appearance. The lines indicate that the ANFIS-TLBO model exhibits similar iteration patterns across all tested population parameters, achieves optimization results quickly, and requires fewer iterations.

4.2.4 | Sensitivity Analysis Results

The R^2 value alone may not be sufficient to demonstrate the success of the results obtained in the study. To ensure the validity and reliability of the research findings, a sensitivity analysis of the prediction accuracy was performed using various error comparison methods. The best green growth performance prediction training

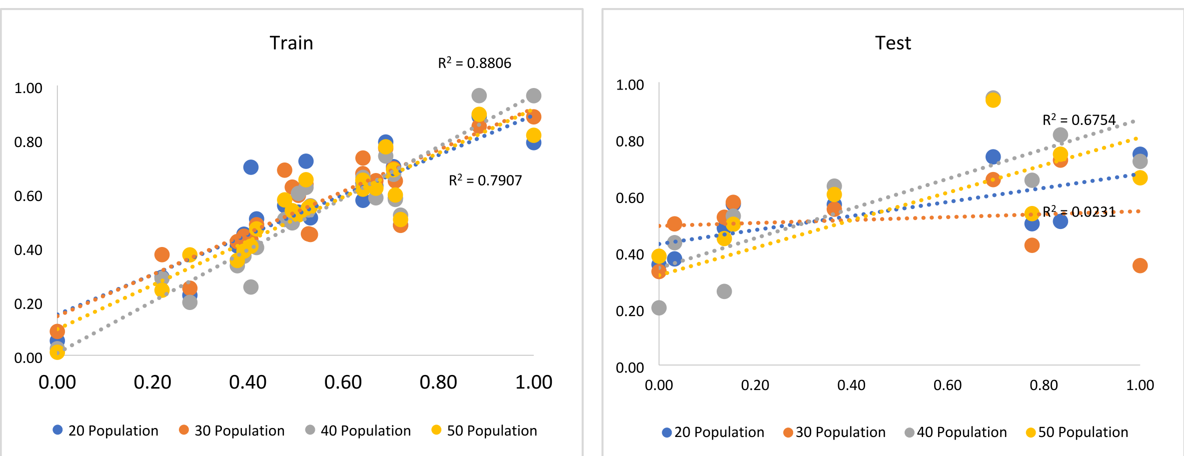

FIGURE 8 | ANFIS-GA lines.

FIGURE 9 | ANFIS-GA predictions.

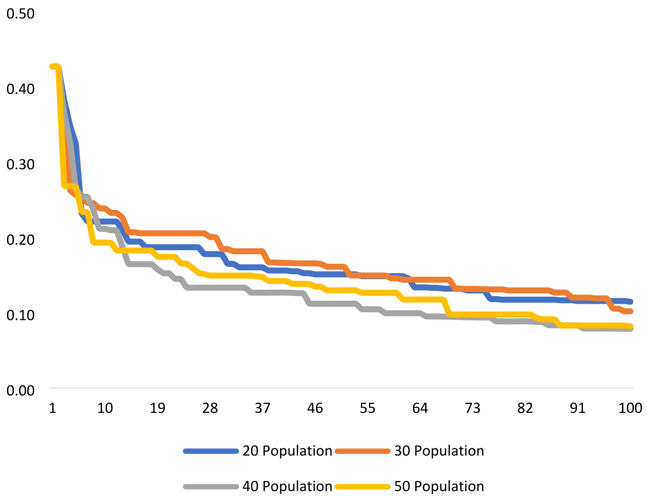

FIGURE 10 | Iteration of the ANFIS-GA model.

and test error comparison results of the models are presented in Table 5. In the error comparison results for the training data, it is evident that the classical ANFIS method exhibits the highest success because it fully captures the real values in the predicted values. However, the results of the test data are crucial to understanding how accurate and successful the proposed models are in predicting the best green growth performance. When examining the error comparison results of the test data:

- The most ideal prediction results in terms of MAE (Mean Absolute Error) values, which indicate the lowest difference between the real values and the predicted values, were measured in the ANFIS-TLBO (20 pop) model (0.196). The worst MAE value was determined in the classical ANFIS model (0.435).
- The most successful result in SMAPE (Symmetric Mean Absolute Percentage Error) values, which show the accuracy of the estimation errors relative to the real values, was found in the ANFIS-TLBO (20 pop) model (0.689). The least successful result was observed in the classical ANFIS model (1.406).
- The MSE (Mean Squared Error) value (0.050) calculated for the ANFIS-TLBO (20 pop) model reflects the most appropriate estimation result. According to MSE values, the worst result in estimation success (0.319) is in the classical ANFIS model.
- The best RMSE (Root Mean Squared Error) value (0.223) was determined for the ANFIS-TLBO (20 pop) model. The worst RMSE estimation error value (0.565) was observed in the classical ANFIS model.
- The highest estimation value (0.304) according to MBE (Mean Bias Error) was determined for the ANFIS-PSO (30 pop) model. The lowest estimation value (−0.297) was measured in the classical ANFIS model. The ANFIS-TLBO (20 pop) model showed an ideal MBE value (0.188).
- The success of the ANFIS-TLBO (20 pop) model in predicting the best green performance, according to the R^2 value (0.893), is also supported by other error comparison methods.

For the best green performance prediction, the ANFIS-TLBO with 20 population parameters is the most powerful model. It is followed by the ANFIS-PSO model. Although the classical ANFIS model showed the highest prediction success in the training data results, it produced the least successful results in the test data error comparison.

5 | Conclusions and Implications

Examining green growth performance has a significant impact on the efficient use of the limited natural resources available to countries. Decision-makers and policymakers may require studies evaluating past environmental and resource use to inform strategic plans for green growth. For decision-makers to take swift and appropriate actions, they need to understand the direction and impact of changes in the current situation. The natural resources and environmental status of countries vary both qualitatively and quantitatively. Considering these differences, examining green growth performance at a macro level provides

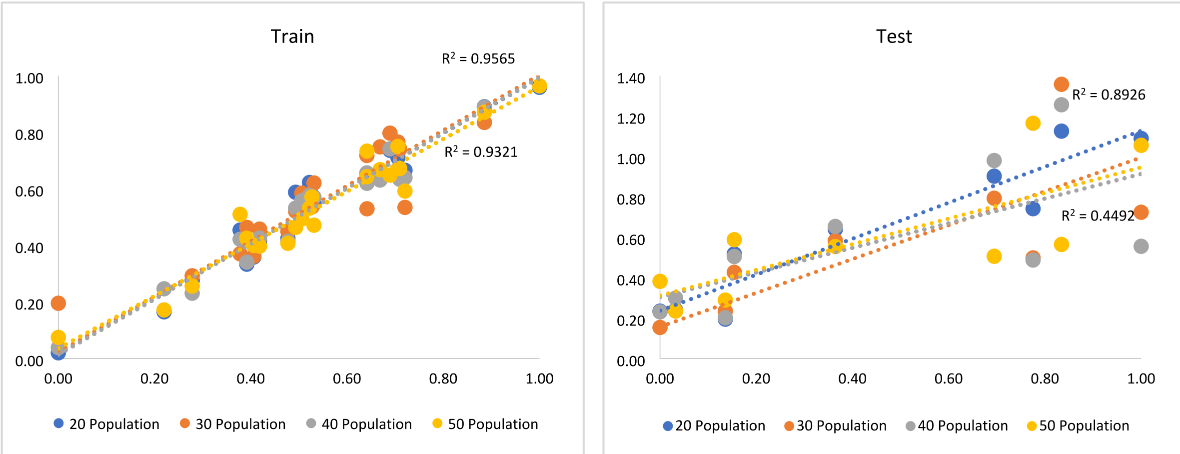

FIGURE 11 | ANFIS-TLBO lines.

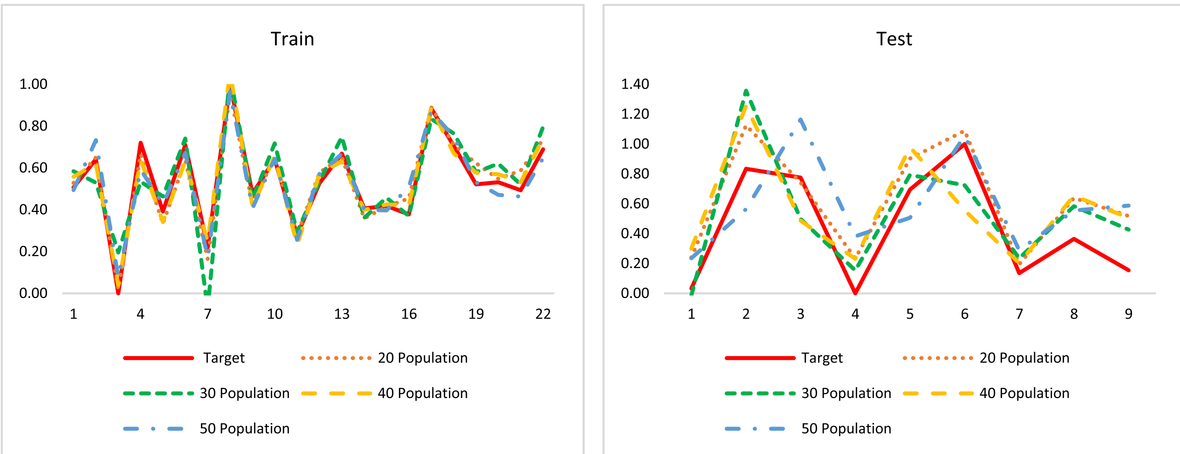

FIGURE 12 | ANFIS-TLBO predictions.

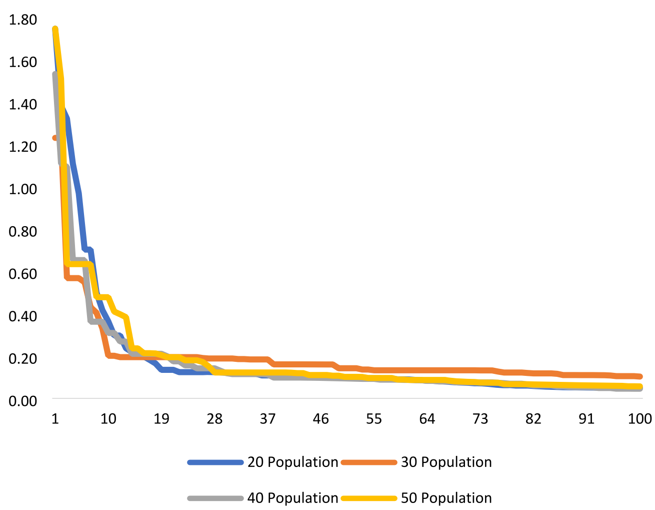

FIGURE 13 | Iteration of the ANFIS-TLBO model.

more accurate interpretations. In this context, analyzing data from countries using intuitionistic fuzzy approaches to eliminate uncertainty will yield both meaningful and more accurate results.

The use of computer-based metaheuristic algorithms in examining macro indicators is advantageous in terms of time and efficiency. With developed hybrid metaheuristic algorithms, multivariate, difficult, and complex problems can be solved quickly and optimally. According to experimental studies with cost and time constraints, hybrid metaheuristic algorithms can be more ergonomic and effective for performance estimation.

This two-stage study focused on the green growth performance of 31 selected OECD countries. In the first stage, the environmental and resource use indicators that best reflect green growth performance were determined. The countries in the sample set were ranked according to their green growth performance using the integrated Shannon Entropy-IFCRADIS model based on the selected variables. In the second stage, classical ANFIS, ANFIS-PSO, ANFIS-GA, and ANFIS-TLBO methods were tested to estimate green growth performance values from different perspectives. Various population parameters were tested to find the highest performance estimate value. Different estimation error comparison methods were employed to compare and evaluate the models. The study offers several recommendations for managers, policymakers, and researchers based on the findings.

A significant relationship was observed at the 0.05 and 0.01 levels between the variables identified in this study for green growth performance measurement, enhancing the validity and

TABLE 5 | Comparison of sensitivity analysis results.

	Training						Testing					
	MAE	**SMAPE**	**MSE**	**RMSE**	**MBE**	R^2	**MAE**	**SMAPE**	**MSE**	**RMSE**	**MBE**	R^2
ANFIS	0.000	0.000	0.000	0.000	0.000	1000	0.435	1406	0.319	0.565	−0.297	0.292
ANFIS PSO (20 Pop)	0.046	0.182	0.003	0.057	−0.004	0.930	0.273	0.880	0.097	0.311	0.092	0.357
ANFIS PSO (30 Pop)	0.049	0.183	0.004	0.060	0.006	0.926	0.304	0.737	0.158	0.398	0.304	0.876
ANFIS PSO (40 Pop)	0.041	0.178	0.003	0.055	0.001	0.935	0.231	0.739	0.076	0.276	0.145	0.585
ANFIS PSO (50 Pop)	0.049	0.181	0.004	0.062	0.001	0.920	0.316	0.864	0.147	0.383	0.058	0.178
ANFIS GA (20 Pop)	0.081	0.235	0.013	0.114	0.011	0.724	0.285	0.851	0.092	0.303	0.094	0.488
ANFIS GA (30 Pop)	0.084	0.242	0.010	0.101	0.022	0.791	0.327	0.915	0.139	0.372	0.071	0.023
ANFIS GA (40 Pop)	0.060	0.215	0.006	0.078	−0.016	0.881	0.227	0.756	0.065	0.255	0.133	0.675
ANFIS GA (50 Pop)	0.057	0.191	0.007	0.082	−0.002	0.860	0.248	0.866	0.073	0.271	0.090	0.505
ANFIS TLBO (20 Pop)	**0.039**	**0.171**	**0.002**	**0.049**	**0.003**	**0.950**	**0.196**	**0.689**	**0.050**	**0.223**	**0.188**	**0.893**
ANFIS TLBO (30 Pop)	0.077	0.276	0.011	0.103	0.012	0.812	0.218	0.811	0.066	0.257	0.085	0.626
ANFIS TLBO (40 Pop)	0.041	0.167	0.002	0.045	0.002	0.957	0.294	0.823	0.097	0.312	0.131	0.449
ANFIS TLBO (50 Pop)	0.044	0.173	0.003	0.057	−0.004	0.932	0.252	0.775	0.077	0.278	0.150	0.586

reliability of the research results. In the study, renewable electricity generation emerged as the most important variable when evaluating green growth performance from environmental and resource efficiency perspectives. Other studies also provide evidence that renewable energy sources are the most suitable solutions for energy security and mitigating global warming [137]. This situation necessitates reducing fossil resources in energy production, promoting renewable electricity investments, and increasing green financing to achieve global green growth targets. International financial institutions should develop a global strategy focused on renewable energy and provide support, particularly to underdeveloped countries. Solutions to climate problems can be found, and ecosystem protection can be ensured through the more conscious and efficient use of environmental and natural resources. Decision-makers, governments, and scientists have important responsibilities to provide theoretical and practical support to energy companies investing in and implementing renewable electricity solutions.

Focusing on the green growth performance of selected OECD countries over the last 10 years, this study shows that Ireland, Switzerland, and Costa Rica have the highest performance values. Ireland has achieved efficiency in environmental and resource use due to increased public investments focused on climate and biodiversity. Ireland's sustainable policy practices regarding the use of energy and natural resources are noteworthy. Switzerland has made significant improvements in environmental performance, particularly in terms of greenhouse gas emissions, by taking serious steps to enhance the performance of its agriculture, energy, and transportation sectors. Switzerland's innovative approaches to environmental and resource use in green growth can serve as an example for other countries. As a financial center, Switzerland plays a crucial role in promoting green finance. Costa Rica, despite an increase in energy use and greenhouse gas emissions in recent years, has been quite successful in reversing deforestation globally and pursuing a growth model based on the sustainable use of environmental resources. Independent OECD Environmental Performance Review reports, which present progress toward environmental policy goals, support the findings of this study for Ireland, Switzerland, and Costa Rica. These findings underscore the critical role of environmental and resource efficiency for managers in promoting green growth and evaluating performance.

The proper adjustment of algorithm-specific variables greatly affects the performance of the algorithms. Incorrectly adjusted algorithm parameters can lead to misleading results. The TLBO method was developed to address the need for an algorithm that does not require specific variables [67]. TLBO, a completely population-dependent technique, has emerged as one of the simplest and most effective techniques for solving single-objective benchmarking and real-life application problems. It has been experimentally shown to perform well in many optimization problems [138].

One of the unique advantages of the TLBO algorithm is that it does not require any special control parameters other than population size and generation number to operate effectively [139]. Based on the results of this research, it is recommended to use optimized and trained ANFIS structures instead of the classical ANFIS method in similar studies. The results of this study will help scientists and decision-makers estimate green growth performance and design and evaluate new policies.

While countries strive for economic development and efficient use of existing resources, they also face climate change and environmental challenges globally. Policymakers and decision-makers often focus on economic values, neglecting the resource and environmental impacts of macro growth indicators. However, the path for countries to achieve sustainable economic structures lies in green growth policies and practices that are based on environmentally sensitive and rational resource use. Monitoring and evaluating green growth performance is crucial at both macro and micro levels. Environmental and resource efficiency indicators can serve as guides in evaluating green growth performance, especially in reports published by international organizations.

The Green Growth Index, published in the GGGI technical report by Acosta et al. [2], provides results that evaluate green growth within a general framework. In this study, an evaluation is made of environmental and resource efficiency associated with green growth. A specific regional approach yields more rational results than a general approach for diagnosis and treatment. In this respect, the study differs from the GGGI green growth reports, offering unique insights and advantages.

5.1 | Policy and Research Implications

When the results of this study are examined from a policy perspective, it is clear that countries need to coordinate with the environmental elements of countries that have demonstrated successful performance, considering each country's unique situation, to address environmental problems. Countries must prioritize the use of renewable electricity while developing foundational sustainable policies. The production and use of renewable energy encourage improved green growth performance. Countries achieving green growth at the macro level can also lay the foundation for social welfare.

To reduce fossil energy consumption across all sectors, increase the use of renewable energy, and ensure sustainable economic development, resource efficiency must be enhanced by changing how resources are utilized. Emphasis should be placed on planning and protecting natural resources, reducing pollution levels, and ensuring the rational use of these resources. Environmental and resource efficiency must be prioritized to boost the dynamism and potential of economic development. Although industrial economic development typically results in resource waste and environmental pollution, this trend can be reversed through well-managed green growth policies. Investments in environmental protection and management can be promoted through appropriate economic development policies. Green growth and resource use efficiency can be encouraged through environmentally friendly investments.

When decision-makers focus on resource efficiency to improve green growth performance, they can enhance their organizational and production processes without requiring significant structural changes. This, in turn, contributes to a cleaner environment and improves national-level green growth performance.

From a research perspective, this study empirically demonstrates how environmental and resource use efficiency impacts a country's overall green growth performance. However, this study has some limitations that may inspire future research. Due to the limited accessibility of data in the use of the proposed model, the study sample consisted of 31 countries. Future studies could increase the number of participating countries and expand the sample set. This study focuses on green growth performance analysis from 2013 to 2022, using environmental and resource efficiency indicators. Future studies could examine the relationship between these factors while considering other dimensions of green growth.

Finally, training the ANFIS method using different optimization algorithms and comparing the results is recommended for future studies. This study is limited to selected OECD countries compared to a global sample. Therefore, future research could expand this study to a global level, increasing the reliability of the results. Due to methodological constraints, only three different algorithms were used to test the predictions. The study could be extended by incorporating additional metaheuristic algorithms. Future studies could further generalize the findings of this study by addressing the data and sample size limitations.

Ethics Statement

The author has nothing to report.

Conflicts of Interest

The author declares no conflicts of interest.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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