Next Sustainability 7 (2026) 100241

Contents lists available at ScienceDirect

Next Sustainability

journal homepage: www.sciencedirect.com/journal/next-sustainability

Estimating manufacturing value-added via hybrid ANFIS-GA and PSO optimization: A macro-analysis of European OECD economies

Mustafa Özdemir *, Metin Özkul

Artvin Coruh University, Artvin, Türkiye

ARTICLE INFO

Keywords:
Manufacturing
Value added
Innovation
Entrepreneurship
Environment
ANFIS-GA
ANFIS-PSO

ABSTRACT

In recent years, artificial intelligence-based hybrid methods have gained increasing attention for addressing complex and nonlinear problems in engineering and economic systems. This study proposes an innovative approach to estimate manufacturing value-added at the macro level by integrating innovation, entrepreneurship, and environmental indicators. An Adaptive Neuro-Fuzzy Inference System (ANFIS) model is optimized using Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) to improve estimation accuracy. The proposed hybrid models are tested across different population sizes and benchmarked against the standard ANFIS model. Comparative performance evaluation reveals that the ANFIS-GA model with a population size of 25 outperforms other models, achieving the most consistent and accurate estimation results with R^2= 0.9080, MAE= 0.1455, MSE= 0.0325, RMSE= 0.1801, and PBIAS= 0.7960. The findings demonstrate the robustness and applicability of the ANFIS-GA model for manufacturing value-added prediction, offering valuable insights for policy makers and industrial decision-makers in enhancing production performance and sustainable development strategies.

1. Introduction

The manufacturing industry serves as a fundamental engine for national economic development, transforming resources into high-value-added products and driving productivity growth across related sectors such as banking and logistics [15,52]. Given its pivotal role, accurately estimating manufacturing value-added is essential for effective economic management [14]. Traditionally, value creation has been analyzed through single dimensions; however, modern production dynamics necessitate a multi-dimensional perspective incorporating innovation, environmental sustainability, and entrepreneurship.

Innovation, primarily driven by Research and Development (R&D) expenditures, is widely recognized as a critical determinant of industrial output and total revenue growth [11,73]. Studies consistently demonstrate a strong positive correlation between R&D investment and manufacturing value-added [4,81]. Simultaneously, the environmental impact of industrialization has become a primary global concern. The manufacturing sector's energy demand has led to increased CO2 emissions, creating a dilemma between production growth and environmental sustainability [8,85]. Consequently, integrating environmental indicators into economic models is crucial for achieving sustainable growth goals [91]. Furthermore, entrepreneurship plays a vital role in economic dynamism. Based on Schumpeterian theory, new enterprises act as catalysts for innovation and value creation, directly influencing macro-efficiency [60,83].

Despite the established importance of these factors individually, modeling their complex and non-linear interactions remains a challenge. Traditional econometric approaches often fall short in capturing the stochastic nature of macroeconomic data [38]. To address this, Soft Computing methods, particularly Adaptive Neuro-Fuzzy Inference Systems (ANFIS) optimized with metaheuristic algorithms, offer robust solutions for complex forecasting problems where conventional hardware or methods may fail [24,90].

1.1. Research gap and objectives

Although soft computing methods have been widely applied in engineering optimization, their application in macroeconomic modeling—specifically for estimating manufacturing value-added with a multi-dimensional perspective—remains limited. To the best of the authors' knowledge, no prior study has simultaneously integrated innovation (R&D), entrepreneurship (number of enterprises), and environmental impact (CO_2 emissions) into a single predictive framework using hybrid neuro-fuzzy models. This represents the core novelty

* Corresponding author.
E-mail addresses: mustafaozdemir@artvin.edu.tr (M. Özdemir), metinozkul@artvin.edu.tr (M. Özkul).

https://doi.org/10.1016/j.nxsust.2025.100241
Received 7 November 2025; Received in revised form 9 December 2025; Accepted 17 December 2025
Available online 23 December 2025

of this research.

- Therefore, the primary objective of this study is to bridge this gap by proposing a robust hybrid forecasting model. The main contributions of this paper are threefold:
- New Input Combination: It introduces a holistic approach by combining three distinct indicators (innovation, entrepreneurship, and environment) to estimate manufacturing performance.
- Methodological Application: It applies and compares advanced hybrid algorithms (ANFIS-GA and ANFIS-PSO) specifically for this macroeconomic problem.
- Parameter Sensitivity: It systematically investigates the effect of population size on the estimation accuracy, offering technical insights for future applications.

In line with these objectives, the study seeks to answer the following research questions:

RQ1: Is it possible to accurately estimate manufacturing value-added at the macro level using a multi-dimensional input set?

RQ2: How effective are innovation, R&D, and entrepreneurship indicators when integrated with environmental data for manufacturing value-added estimation?

RQ3: Do ANFIS-based hybrid metaheuristic algorithms (ANFIS-GA and ANFIS-PSO) outperform standard models in this economic context?

RQ4: How does the variation in population size parameters affect the prediction performance and robustness of the proposed models?

The following sections of this article, which seek answers to questions in line with the main purpose of the research, are planned as follows. The literature section includes previous studies that can be associated with the research. Then, methodology, data preparation, modeling, and application are explained. In the last section, findings, discussions, and conclusions are shared.

2. Literature review

The widespread use of computers has accelerated the advancement of optimization theory, particularly the field of meta-heuristics, which has recently received significant attention for solving complex problems involving uncertainty [39]. Algorithms such as Particle Swarm Optimization (PSO) [41], Genetic Algorithm (GA) [29], Differential Evolution (DE) [75], Artificial Bee Colony (ABC) [36], and Teaching-Learning-Based Optimization (TLBO) [61] are widely proposed in the literature for finding optimal solutions within acceptable simulation times.

2.1. Applications of ANFIS and optimization in engineering

Numerous studies have demonstrated the efficacy of Artificial Neural Networks (ANN) and ANFIS in various scientific domains. Takassi et al. [78] compared Fuzzy Simulation results in syngas conversions using the Mamdani algorithm, showing good consistency with experimental data. Similarly, Salehi et al. [65] and Esfandyari et al. [17] applied Multilayer Perceptron (MLP) ANN models to chemical processes, reporting quantitative agreement between model predictions and experimental results. Tanhaei et al. [79] utilized ANFIS to effectively model the nonlinear behavior of magnetic chitosan adsorption. Optimization algorithms have also been integrated into these models; for instance, Shokouhi et al. [74] used a GA-ANN design for gas solubility, and Salooki et al. [66] compared GA-ANN capabilities in gas systems. Further applications include estimating chemical removal percentages [16], water vapor capacity in materials [53], and recovery potential from wastes [5,58], all confirming that ANFIS and ANN methods offer successful and rapid solution potentials compared to traditional experimental approaches. Recent studies further emphasize that integrating AI-driven models into industrial systems significantly enhances operational efficiency and decision-making processes, as highlighted by Fernando et al. [22].

2.2. Innovation, environment, and entrepreneurship in manufacturing

Recent literature emphasizes the critical role of technological innovation, green strategies, and entrepreneurship in enhancing manufacturing performance. Studies by Vuković et al. [84] and Irwanto et al. [31] demonstrate that product/process innovations significantly boost sustainable competitive advantage and productivity. Unanoğlu and Özarı [80] and Vajrapatkul [82] further show that innovation indicators, such as R&D expenditures and patent intensity, explain a substantial share of cross-country differences in manufacturing value-added (MVA). From an environmental perspective, Zahoor et al. [91] identified a significant positive correlation between MVA and CO_2 emissions, while Samargandi [70] linked industrial value-added growth to increased emissions. Febriani [20] argues that green manufacturing is a core pillar of Industry 4.0. Additionally, entrepreneurship acts as a key transmission channel for value creation. Robert [63] and Taan et al. [76] highlight how entrepreneurial orientation drives technological upgrading and performance in manufacturing SMEs. Ongachi et al. [55] underscore the contribution of SMEs to total manufacturing output in emerging economies. Many studies [1,3,35,45,87] support the manufacturing industry as the engine of economic growth.

2.3. Hybrid fuzzy-evolutionary approaches and research gap

To overcome the limitations of classical methods, hybrid models combining ANFIS with meta-heuristic algorithms have gained prominence. Esfandyari et al. [18,19] demonstrated that ANFIS optimized by PSO offers better regulation performance in chemical processes compared to standalone ANFIS. Similarly, Lara-Cerecedo et al. [43] and Zanganeh & Chaji [92] found ANFIS-PSO to be a reliable predictor for electricity generation and sea levels, respectively. In structural engineering, Li et al. [44] showed that ANFIS-GA provides high accuracy for concrete beam shear strength. Comparative studies yield mixed results regarding the "best" algorithm; for instance, Yonar & Yonar [89] and Shafiullah et al. [72] reported superior performance for ANFIS-GA in air pollution and power system stability, whereas Mohammadi Behboud et al. [51] and Ferdosian et al. [21] found ANFIS-PSO to be more accurate in rock property and load estimation. Bharti & Samui [6] concluded that ANFIS-GA is most powerful for slope stability. Furthermore, recent advancements in fuzzy evolutionary hybrids suggest that integrating novel optimization mechanisms can significantly enhance the interpretability and convergence of neuro-fuzzy systems [28].

Despite the extensive use of GA and PSO in various fields [2,10,62], there is a notable gap in the literature regarding the use of hybrid-based learning systems for estimating manufacturing value-added. No prior study has simultaneously integrated innovation, entrepreneurship, and environmental impact into a single predictive framework using these advanced algorithms. To bridge this gap, this study applies the ANFIS method modified by Ghasemi et al. [24] together with GA and PSO algorithms to model manufacturing value-added at the macro level.

3. Methodology and implementation

Although numerous econometric, statistical, and machine learning techniques have been widely utilized to examine the contribution of innovation and entrepreneurship to value creation, these traditional approaches often exhibit limitations in capturing the nonlinear interactions, fuzzy uncertainties, and complex dynamics inherent in macroeconomic systems. Manufacturing value-added is simultaneously influenced by innovation inputs, environmental pressures, and entrepreneurial dynamics, creating a multivariate landscape that interacts in non-linear ways. Consequently, a soft computing-based hybrid framework offers a more robust analytical capability.

In this context, the ANFIS is particularly well-suited for modeling such uncertainty and non-linearity, as it uniquely integrates the interpretability of fuzzy logic rules with the learning capability of artificial neural networks. However, conventional ANFIS training algorithms (typically gradient-based) are prone to getting trapped in local optima, particularly when processing high-dimensional data. To mitigate this limitation and ensure global optimization, evolutionary metaheuristic algorithms—specifically GA and PSO are employed to optimize the ANFIS parameters.

Literature demonstrates that GA and PSO significantly improve convergence speed and predictive accuracy in complex forecasting problems by enhancing the global search capability. Therefore, the hybrid ANFIS-GA and ANFIS-PSO models adopted in this study are not merely a methodological preference but a technical necessity to effectively model the stochastic and non-linear structure of manufacturing value-added.

The remainder of this section details the methodology, data preparation processes, the architecture of the proposed hybrid models, and the implementation steps.

3.1. Adaptive neuro-fuzzy inferences system

ANFIS integrates the learning-based relational structure of ANN with the decision-making mechanism of fuzzy logic [33]. Unlike ANN, ANFIS provides interpretability through fuzzy rules, eliminating the "black box" disadvantage. In this study, a Sugeno-type fuzzy inference system is employed. The network structure consists of five layers, where input-output data pairs are used to determine the parameters of the partitions. The implemented system is functionally equivalent to a first-order Takagi-Sugeno inference system [48,77]. The adaptation of the optimization algorithm within the ANFIS structure is illustrated in Fig. 1.

3.2. Genetic algorithm

GA, an optimization method that models the evolutionary process in nature, was first proposed and developed by Holland [26] (H[27]). GA is a meta-heuristic algorithm based on natural selection [32]. GA is a general random discovery tool for optimization based on the ideas of natural selection and genetics. It uses probabilistic transition rules instead of exact ones, which leads to the capacity to explore large solution spaces [12,88]

To provide high-quality solutions to problems, high-quality solutions can be produced by using mutation, selection, and crossover operators in the evolutionary process in the GA optimization model [44]. In each generation, the deterministic selection method selects the best data and sends it to the next generation. In this so-called elitism, the best is always kept. This increases the speed of the GA [21].

GA has been used to solve many problems in various fields since it was first developed [37]. GA technique helps ANN provide reliable results [42,50]. GA-based models are effective techniques for solving optimization problems because they can produce practical and minimum-cost design solutions [71].

3.3. Particle swarm optimization

PSO is a population-based optimization approach that randomly selects a population of particles or solutions, and then searches for the optimum by updating the production at each iteration. Gheytanzadeh et al., [25]. The PSO technique can help ANFIS to provide more reliable results. The ANFIS-PSO technique has the advantage of being more flexible for a given network structure size. The model procedure in the ANFIS-PSO technique starts with the initialization of a set of particles and continues with the random selection of particles. It helps in determining the optimal weights and deviations in the final output [49].

3.4. Methods of comparing prediction

To rigorously evaluate the prediction accuracy of the proposed hybrid models, this study employed seven statistical metrics widely recommended in the recent literature [7,30,68,69]. These performance indicators include the Coefficient of Determination (R^2), Root Mean Squared Error (RMSE), Mean Biased Error (MBE), Mean Absolute Error

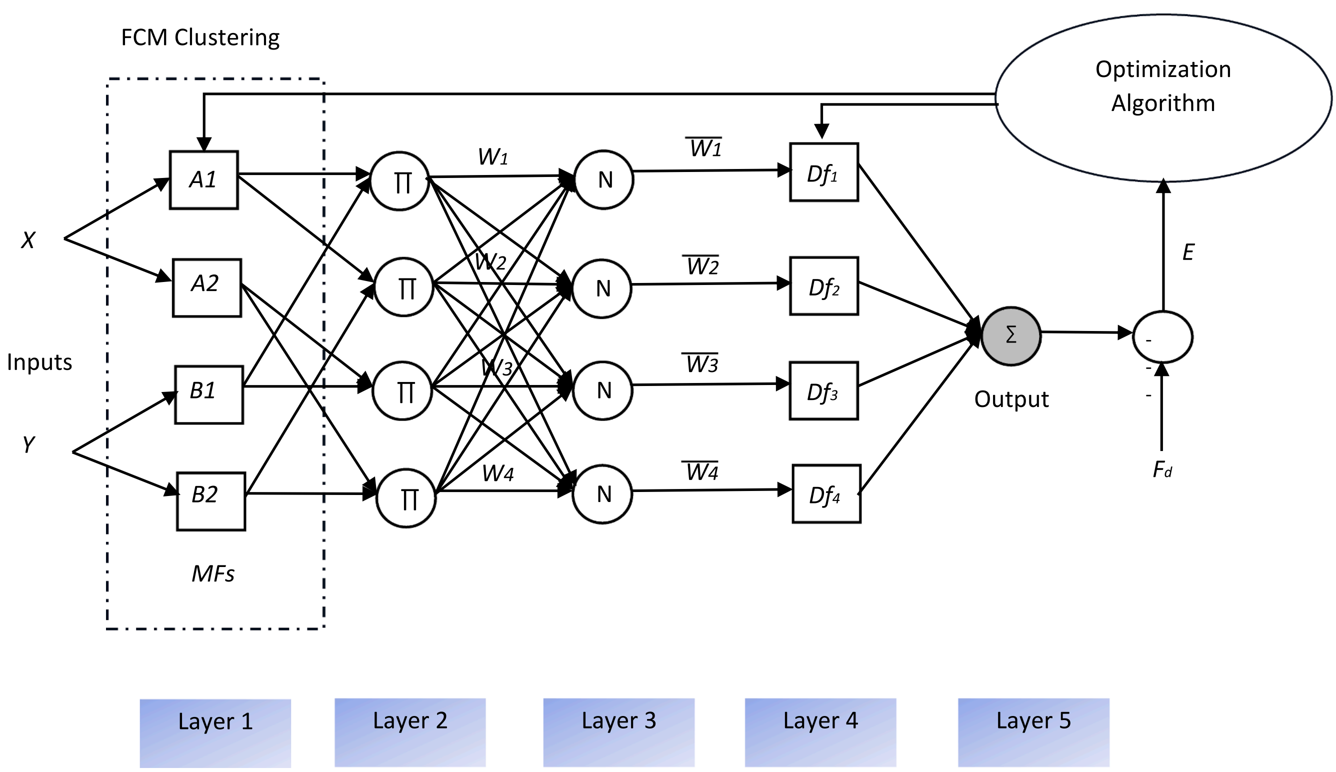

Fig. 1. Basic ANFIS structure with two inputs and optimization adaptation.

(MAE), Symmetric Mean Absolute Percentage Error (SMAPE), Mean Square Error (MSE), and Percent Bias (PBIAS). The mathematical notations and definitions of these measures are briefly explained below.

The R^2 method is commonly used in regression models to calculate the difference between dependent and independent variables. It determines how well the predicted data fits the observed data. The higher the Correlation coefficient, which is always less than 1, in other words, the closer it is to 1, the more accurate the model is [34,46]. The mathematical notation of the R^2 method is expressed in Eq. (3). where RSS is the sum of squares of residuals and TSS is the total sum of squares. The best value is 1, the worst value is -∞ .

$$R^2 = 1 - \frac{RSS}{TSS} \tag{3}$$

RMSE is one of the most commonly used methods in time series forecasting. It measures the amount of error between predicted and observed values. RMSE is calculated using Eq. (4). The best value is 0, the worst value is + ∞.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} (Act - Pred_i)^2}{N}} \tag{4}$$

MBE is used to estimate the average deviation in the model. It captures the average deviation in the model with positive and negative values. A positive deviation indicates an overestimation of the data, while a negative deviation indicates an underestimation of the data. The method is presented in Eq. (5).

$$MBE = \frac{1}{N} \sum_{j=1}^{N} (Pred_j - Act_j) \tag{5}$$

MAE provides a general and limited performance measure for the model by correcting all errors of possible outliers. MAE is formulated by Eq. (6). The best value in the MAE scale is 0, the worst value is + ∞ [13].

$$MAE = \frac{1}{N} \sum_{j=1}^{N} |Pred_j - Act_j| \tag{6}$$

Mean Absolute Error in Percent (MAPE), which calculates the percentage average of absolute errors between the predicted values and the actual values, provides specific information about the magnitude and distribution of errors. However, when the observation and prediction data set has a zero value, the use of the current MAPE scale gives errors. In this study, the SMAPE measure proposed by Flores [23] and Makridakis [47] was used to eliminate the disadvantages of the current MAPE scale. SMAPE, which shows how large the errors are in percentage, is explained by Eq. (7). The best value in the SMAPE scale is 0, the worst value is 2.

$$SMAPE = \frac{100\%}{N} \sum_{j=1}^{N} \frac{|Pred_j - Act_j|}{(|Pred_j| + |Act_j|)/2} \tag{7}$$

MSE is the method used to measure the performance of a prediction model. MSE is calculated as the mean of the squared differences between the true values and the predicted values. This measures the magnitude of the errors in the model's predictions. The MSE scale is formulated by Eq. (8).The best value is 0 and the worst value is + ∞ [13].

$$MSE = \frac{1}{N} \sum_{j=1}^{N} (Pred_j - Act_j)^2 \tag{8}$$

To assess the systematic bias of the best-performing model, PBIAS was calculated. PBIAS measures the average tendency of the predicted values to be higher or lower than the observed data. The metric is widely used to evaluate model reliability in forecasting and estimation studies [67].

$$PBIAS(\%) = 100 \times \frac{\sum (Obs_i - Pred_i)}{\sum Obs_i} \tag{9}$$

3.5. Data collection and preprocessing

The selection of input variables for estimating manufacturing value-added in this study was determined based on the principles of 'Modern Production Theory' and gaps identified in the recent literature. Unlike traditional production functions that rely solely on quantitative inputs such as labor and capital, this study constructs a multi-dimensional scenario focusing on three qualitative development pillars:

1. **Innovation (R&D Expenditures):** Selected based on the endogenous growth theory, which posits that technological advancement is the primary driver of value-added [64].
2. **Entrepreneurship (Number of Entrepreneurs):** Included to capture the economic dynamism and business creation capacity of the manufacturing sector [86].
3. **Environmental Indicators (CO_2 Emissions):** Selected to reflect the impact of the 'Green Economy' and sustainable manufacturing regulations on production outputs [59]. Therefore, this specific combination was chosen to test the hypothesis that developmental indicators are as significant as physical inputs in predicting macro-level manufacturing performance. The conceptual pattern of the research dimensions is illustrated in Fig. 2.

The dataset utilized in this study was obtained from the OECD Data Explorer database, with an annual frequency covering the period from 2015 to 2020. The input and output variables were derived by averaging these annual observations for 23 European countries.

Table 1 presents the descriptive statistics for the input variables (R&D, CO_2, Number of manufacturing enterprises) and the output variable (Value Added). The dataset comprises 23 observations, split into a training set of 16 samples (~70 %) and a testing set of 7 samples (~30 %) to evaluate model generalizability. An analysis of the statistical parameters in Table 1 reveals a heterogeneous structure within the dataset. The high Standard Deviation (SD) values relative to the means indicate significant variation across the variables. Notably, the positive Skewness values for all variables in the total dataset (e.g., R&D: 4.28; CO_2: 4.44; Value Added: 3.82) indicate a right-skewed distribution. Furthermore, the high Kurtosis values (e.g., R&D: 19.10; CO_2: 20.49) suggest that the data follow a leptokurtic distribution with heavy tails, deviating significantly from a normal distribution. This high variability and non-normality confirm the non-linear and complex nature of the problem, thereby justifying the utilization of robust artificial intelligence techniques, such as ANFIS, for accurate estimation.

To prove the suitability of the data used in the study and to support the accuracy of the analysis results, the relationship level between the variables was examined with Spearman correlation analysis. As can be seen in Table 2, a high relationship was generally observed between the variables. The high relationship between the variables is important in terms of the suitability of the data and the accuracy of the analysis results.

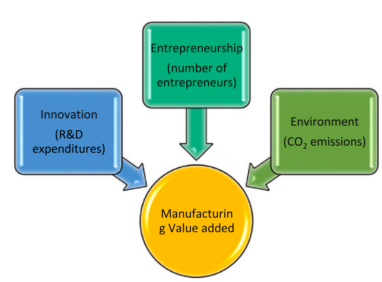

Fig. 2. Modeling variables.

Table 1
Descriptive statistics of data.

	Statistical parameters	Training set (16)	Testing set (7)	Total data set (23)
R&D ($ Million)	Min	45.6088	469.1075	45.6088
	Max	78344.3243	274065.8333	274065.8333
	Mean	8160.9168	41791.4300	18396.2904
	Kurtosis	13.4247	6.9862	19.1005
	Skewness	3.5893	2.6423	4.2867
	SD	19391.61181	102455.0001	58047.87025
CO_2 (Ton)	Min	1188207.2917	2641574.2783	1188207.2917
	Max	197020082.3133	971266666.6667	971266666.6667
	Mean	35040933.7909	165276150.5369	74677738.8875
	Kurtosis	6.9593	6.8638	20.4906
	Skewness	2.5179	2.6127	4.4432
	SD	50692855.66	356487856.9	200413409.5
Number of manufacturing enterprises	Min	7491.6667	19498.6667	7491.6667
	Max	377565.8333	341912.0000	377565.8333
	Mean	82430.0938	134009.9762	98128.3188
	Kurtosis	3.0440	0.4047	1.1347
	Skewness	1.8306	1.0734	1.4067
	SD	105272.647	114885.1664	108372.6659
Value added ($ Million)	Min	10183.9529	126.3308	126.3308
	Max	2149824.3303	5789192.1600	5789192.1600
	Mean	367213.0643	987546.2540	556010.1220
	Kurtosis	6.8630	6.7715	15.7596
	Skewness	2.5436	2.5906	3.8201
	SD	560322.7048	2128142.277	1238716.961

Table 2
Correlation matrix of data.

	R&D expenditures	CO2	Number of Manufacturing Enterprises	Value added
R&D expenditures -	1	,990**	,555**	,981**
CO_2		1	,614**	,982**
Number of Manufacturing Enterprises			1	,684**
Value added				1

**. Correlation is significant at the 0.01 level (2-tailed).

For the training of hybrid ANFIS models, based on previous successful studies [49,54,79], all data were randomly divided from the original dataset at a ratio of 70:30. In other words, 70 % of the dataset (16 data points) was used for training purposes to establish model parameters, and the remaining 30 % (7 data points) was used to test the model performance and validate generalization capability. Before creating ANFIS models, the data were normalized to increase the accuracy of the results and to ensure faster convergence by eliminating the scaling bias between variables. Eq. (10) was used in the normalization process of the data:

$$n_j = \frac{X_j - X_{\min}}{X_{\max} - X_{\min}} \tag{10}$$

Eq. (10) normalizes the data into the range of $[0,1]$. While some studies suggest a narrower range (e.g., $[0, 0.95]$) to avoid potential saturation in sigmoid-based activation functions, the Gaussian membership functions employed in this ANFIS structure performed robustly within the standard $[0,1]$ interval without convergence issues.

3.6. Hybrid modeling and implementation

Thanks to the integration of developments in computer science into business science, new approaches are used in estimating macro indicators. Fuzzy logic applications can provide successful solutions to problems in complex and uncertain environments by starting from the human mind. Oshodi [56]. In this study, ANFIS parameters were optimized and tested with GA and PSO to increase the manufacturing value-added estimation performance. The basic flow chart of the methodological approach used in the study is presented in Fig. 3. The implementation of the models was carried out in the Matlab R2023b environment. To achieve the purpose of the research, 70 % of the data was divided into the training set (16 data), and 30 % into the test set (7 data). The data was normalized and loaded. The model includes 3 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.

A Takagi-Sugeno type fuzzy inference system was utilized to establish the baseline ANFIS model structure. The initial fuzzy inference system (FIS) was generated using the Fuzzy C-Means (FCM) clustering technique to effectively identify the antecedent parameters and data patterns. The comprehensive specifications of the applied models, including the FCM settings (e.g., number of clusters) and the specific hyperparameters for both ANFIS-GA and ANFIS-PSO optimization algorithms, are consolidated in Table 3. During the optimization phase, the objective function—representing the error between model outputs and target values—was minimized iteratively until the maximum iteration count (100 iterations) was reached. Following the completion of the training process, the testing phase was initiated to evaluate the generalization capability of the hybrid models. Finally, the predicted results were systematically recorded and subjected to a rigorous comparative analysis based on the statistical error metrics defined in the methodology.

4. Results and discussion

To clarify the questions in this research, the classical ANFIS, ANFIS-GA, and ANFIS PSO models were tested on the data in the sample. GA and PSO learning algorithms were used to adapt the weights in the ANFIS model modified by Ghasemi et al. [24]. In this section, the results of the model proposed for the estimation of added value in manufacturing are presented. The fuzzy model rule surfaces showing the relationship between the inputs in the research (R&D expenditures, number of entrepreneurs, CO_2 emissions) and output (Manufacturing Value added) are displayed in Figs. 4, 5, and 6. It can be observed from the surface viewers that the increase in inputs is reflected in the outputs. The rule viewers show that the variables determined in the research provide reasonable results.

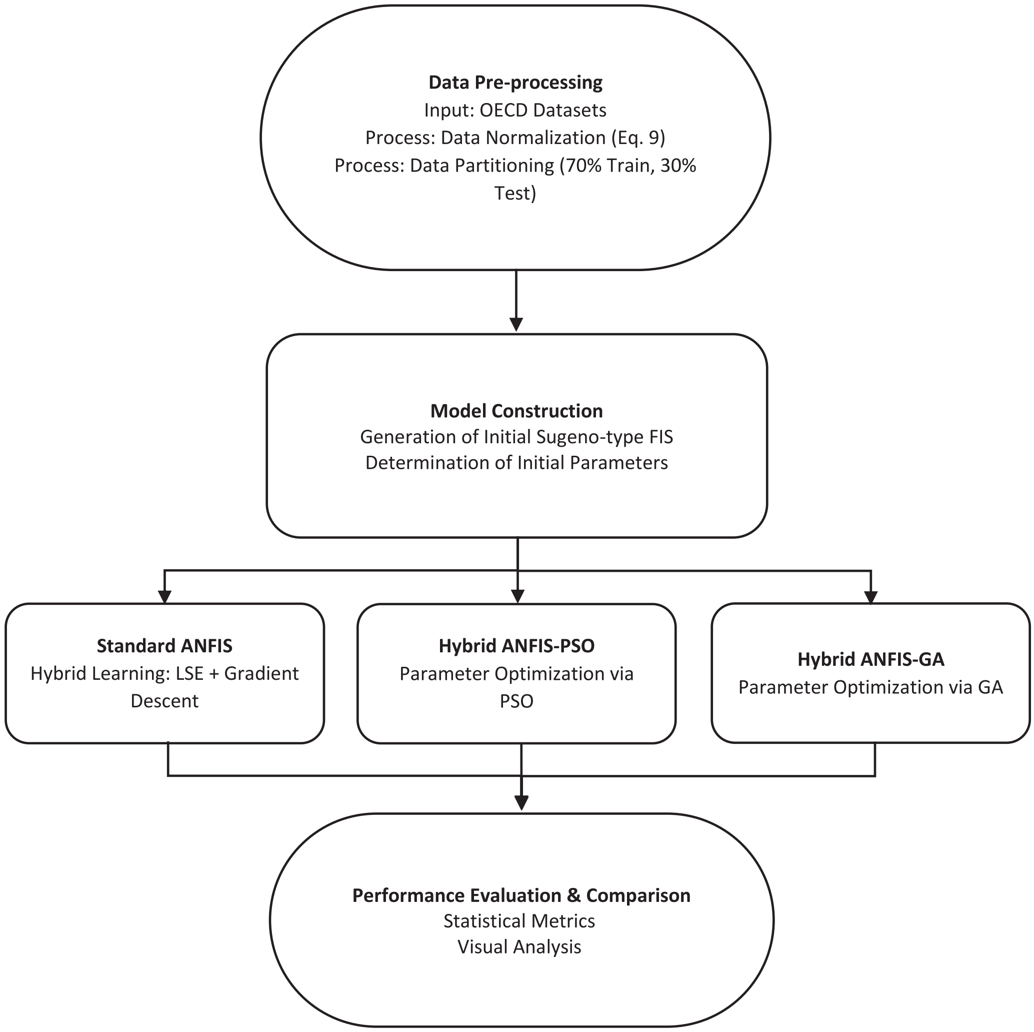

Fig. 3. Flow chart of methodological approach.

Table 3
Comprehensive parameter settings for the proposed ANFIS and Hybrid models.

Category	Parameter	Value / Setting
FIS Generation (Clustering)	Clustering Method	Fuzzy C-Means (FCM)
	Number of Clusters	4
	Exponent	2
	Max. Iterations	100
	Min. Improvement	1×10^{-15}
	FIS Type	Sugeno
ANFIS Training Settings	Initial Step Size	0.01
	Step Size Decrease Rate	0.9
	Step Size Increase Rate	1.1
	Number of Epochs	100
Genetic Algorithm (GA)	Population Size (N_{pop})	5, 25, 50
	Max. Iterations (*MaxIt*)	100
	Crossover Percentage (p_c)	0.4
	Mutation Percentage (p_m)	0.7
	Mutation Rate (μ)	0.15
	Selection Pressure (β)	8
	Gamma (γ)	0.7
	Selection Method	Roulette Wheel
Particle Swarm Opt. (PSO)	Population Size (N_{pop})	5, 25, 50
	Max. Iterations (*MaxIt*)	100
	Inertia Weight (w)	1
	Inertia Weight Damping Ratio	0.99
	Personal Learning Coeff. (c_1)	1
	Global Learning Coeff. (c_2)	2

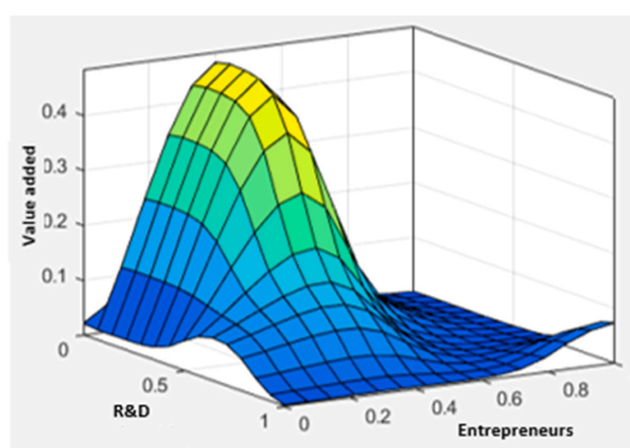

Fig. 4. Surfaces of ANFIS Model 1.

Optimization algorithms in hybrid ANFIS models were tested with different population parameters. Expert opinion was sought in determining the population parameters to be used in this study. According to expert opinions, models were run with 5, 25 and 50 population parameters. The evaluation of the regression graphs showing the training and test results of the optimized ANFIS models is presented in Figs. 7 and

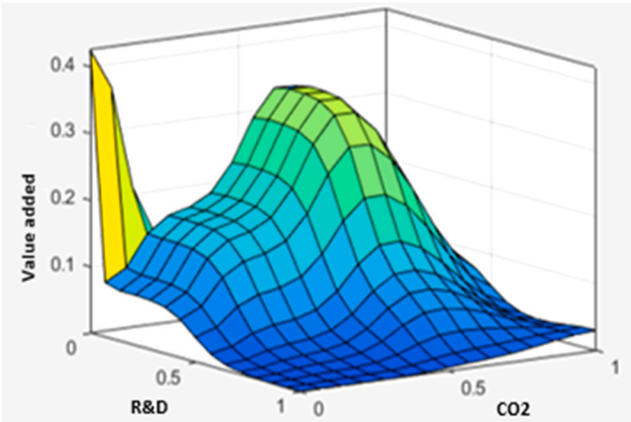

Fig. 5. Surfaces of ANFIS Model 2.

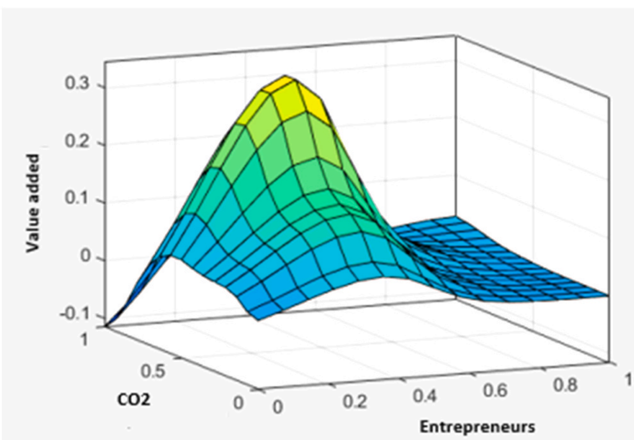

Fig. 6. Surfaces of ANFIS Model 2.

8. Fig. 7 shows that the training results of the ANFIS-GA model are successful in all of the different population parameters applied (R^2=0.9967). It is understood that the ANFIS-GA model exhibits the highest prediction performance (R^2=0.9080) in the test results for 25 population parameters. Fig. 8 presents the regression analysis for the ANFIS-PSO model. A critical scientific examination of Fig. 8 reveals a notable discrepancy between the training and testing performances. While the model achieves near-perfect fitting in the training phase ($R^2 \approx 0.9971$), the prediction accuracy drops significantly in the testing phase ($R^2 = 0.7878$ for 25 populations). This behavior, characterized by the scattering of test data points away from the regression line, indicates that the PSO algorithm tends to suffer from overfitting in this specific problem domain. Unlike the ANFIS-GA model (Fig. 7), which demonstrates a stable generalization capability, the ANFIS-PSO model struggles to predict unseen data with the same level of precision. Therefore, Fig. 8 is essential to visually demonstrate the comparative instability of the PSO optimization against the proposed GA approach.

The R^2 value alone may not be sufficient to show the success of the results obtained in the study. To ensure the validity and reliability of the research results, the performances of the prediction results were measured with various error comparison methods in this study. The error comparison results are presented in Table 4. It is understood that all models exhibited success with similar results in the error comparison results of the training data. However, the results of the test data are important to understand how accurate and successful the proposed models are in the manufacturing value-added prediction. When the error comparison results of the test data are examined;

- The optimal prediction result regarding MAE values was observed in the ANFIS-GA (25 pop) model (0.1455). The worst MAE value was determined in the ANFIS-PSO (5 pop) model.
- The most successful result in the SMAPE values, which show how large the prediction errors are relative to the real value, was determined in the ANFIS-GA (25 pop) model (0.1030). The classical ANFIS model has the least successful result (0.1379).
- The MSE value (0.0325) calculated in the ANFIS-GA (25 pop) model reflects the most appropriate estimation result. According to the MSE values, the worst result in estimation success (0.1462) is in the classical ANFIS model.

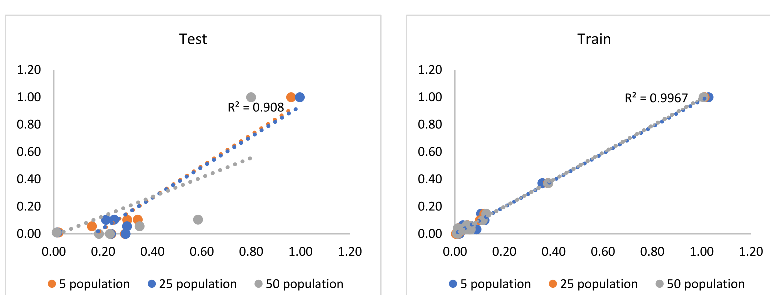

Fig. 7. ANFIS-GA.

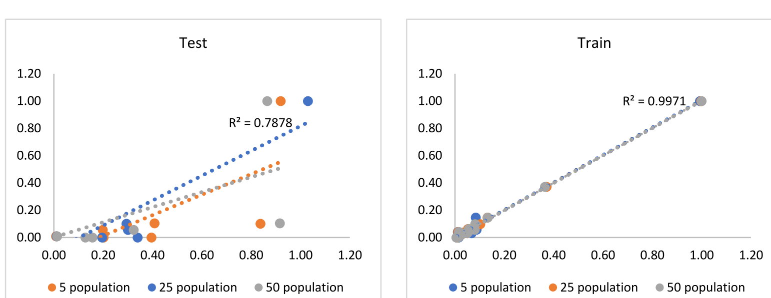

Fig. 8. ANFIS PSO.

Table 4
Results of performances for training and testing stages of models.

	Training							Testing						
	MAE	SMAPE	MSE	RMSE	MBE	R^2	PBIAS	MAE	SMAPE	MSE	RMSE	MBE	R^2	PBIAS
ANFIS	0.0034	0.0358	0.0000	0.0070	0.0000	0.9992	0.0000	0.1976	0.1379	0.1462	0.3824	-0.1310	0.0864	-0.7209
ANFIS PSO (5 Pop)	0.0148	0.0488	0.0005	0.0220	-0.0010	0.9918	-0.0083	0.2656	0.1152	0.1223	0.3497	0.2423	0.4925	1.3335
ANFIS PSO (25 Pop)	0.0076	0.0426	0.0001	0.0098	-0.0001	0.9984	-0.0011	0.1659	0.1217	0.0394	0.1985	0.1204	0.7878	0.6624
ANFIS PSO (50 Pop)	0.0115	0.0510	0.0002	0.0132	0.0015	0.9971	0.0120	0.2458	0.1352	0.1196	0.3458	0.1447	0.3833	0.7962
ANFIS GA (5 Pop)	0.0182	0.0549	0.0005	0.0233	0.0023	0.9914	0.0187	0.1570	0.1099	0.0346	0.1861	0.1460	0.8980	0.8037
ANFIS GA (25 Pop)	0.0110	0.0477	0.0002	0.0137	0.0021	0.9970	0.0168	0.1455	0.1030	0.0325	0.1801	0.1446	0.9080	0.7960
ANFIS GA (50 Pop)	0.0114	0.0474	0.0002	0.0144	0.0017	0.9967	0.0139	0.2455	0.1319	0.0790	0.2811	0.0926	0.4542	0.5097

• The ANFIS-GA (25 pop) model has the best RMSE value (0.1801). The worst RMSE estimation error value (0.3824) is observed in the classical ANFIS model.

• The highest estimation value (0.2423) according to MBE was determined in the ANFIS-PSO (5 pop) model. The lowest estimation value (0.0926) was measured in the ANFIS-GA (50 pop) model. An ideal MBE value (0.1446) is observed in the ANFIS-GA (25 pop) model.

• The manufacturing value-added estimation success of the ANFIS-GA (25 pop) model in the R^2 value (0.9080) is also supported by the results of other error comparison methods.

•According to the PBIAS analysis results for the testing phase, distinct differences were observed in the directional prediction performance of the models. The ANFIS- GA (50 Pop) model exhibited the lowest bias in terms of absolute magnitude, with a PBIAS value of 0.5097, indicating the most balanced distribution between observed and predicted values. Conversely, the ANFIS-PSO (5 Pop) model demonstrated the poorest performance with the highest deviation value of 1.3335. Regarding the directional tendency of the errors, the standalone ANFIS model showed a negative bias (-0.7209), indicating a tendency for underestimation. In contrast, the hybrid models optimized with GA and PSO generally displayed a slight tendency for overestimation (positive PBIAS). The ANFIS GA (25 Pop) model, which provided the best overall accuracy in this study, maintained a PBIAS value of 0.7960, demonstrating that its bias remains within acceptable limits.

ANFIS-GA is the most powerful model for manufacturing value-added estimation in 25 population parameters. It is followed by the ANFIS-PSO model. Classical ANFIS model has produced unsuccessful results in manufacturing value-added estimation.

To better elucidate the research findings, the training and testing graphs of the optimized hybrid ANFIS models are presented in Figs. 9 and 10. Upon examining these figures, it is observed that both hybrid ANFIS models exhibit similar performance in the training data prediction phase. However, it is evident that the ANFIS-GA model demonstrates superior success in predicting manufacturing value-added, particularly at a population size of 25.

A closer inspection of Fig. 9 (ANFIS-GA) reveals that the GA-optimized model exhibits a robust capability in capturing the non-linear dynamics of the manufacturing process. Specifically, in the test phase, the ANFIS-GA model accurately predicts the critical peak value (Point 4), which represents the maximum value-added point. Although minor deviations are observed in low-amplitude regions, the model's trajectory closely follows the target trend, indicating a strong generalization ability for the primary characteristics of the dataset.

In contrast, while the ANFIS-PSO model (Fig. 10) also demonstrates good training performance, its test results at the same population size (25) show slightly less stability compared to GA. The prediction curve of PSO tends to exhibit sharper fluctuations around the target values in the test set. This comparative visual analysis suggests that the genetic algorithm provides a more balanced optimization for this specific problem, avoiding the premature convergence often seen in particle swarm optimization.

To provide a multi-dimensional comparison of the proposed models, Radar Charts were generated for both statistical indicators (R^2, MBE, PBIAS) and error metrics (MAE, RMSE, MSE, SMAPE), as shown in Fig. 11. Fig. 11 (Right) illustrates the error metrics where the axes represent the magnitude of prediction error. In this representation, a model performs better if its corresponding polygon encloses a smaller area (closer to the center). As clearly observed, the Standard ANFIS model (Blue line) exhibits the largest expansion, particularly along the RMSE and MAE axes, indicating lower precision. In contrast, the ANFIS-GA (25 Pop) model (Grey line) forms the innermost shape, effectively minimizing the error across all four metrics (RMSE, MSE, MAE, SMAPE). This visual evidence confirms that the Genetic Algorithm optimization significantly reduces the deviation between predicted and observed values compared to the PSO and Standard ANFIS approaches. Fig. 11 (Left) presents the performance regarding correlation and bias. The ANFIS-GA and ANFIS-PSO models show a much stronger expansion towards the outer edge of the R^2 axis compared to the Standard ANFIS, visually confirming their higher determination coefficients. Simultaneously, the hybrid models maintain narrower deviations in MBE and PBIAS, suggesting a more balanced and unbiased prediction capability.

The Taylor Diagram (Fig. 12) provides a concise statistical summary of how well the models' patterns match the observed manufacturing value-added data. The diagram quantifies the degree of correspondence between the modeled and observed behavior in terms of the correlation coefficient (R), root-mean-square difference (RMSD), and standard deviation. As illustrated in Fig. 12, the position of the ANFIS-GA model (Red Circle) indicates a superior performance compared to the ANFIS-PSO model (Blue Square). Specifically:

Fig. 9. ANFIS-GA −25 population.

Fig. 10. ANFIS-PSO 25 population.

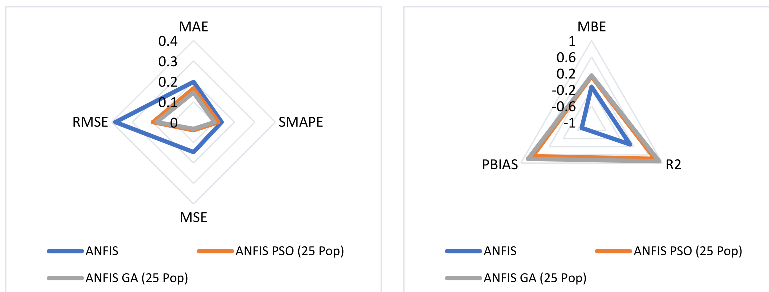

Fig. 11. Radar chart analysis of statistical consistency indicators and error measures of model performances during the testing phase.

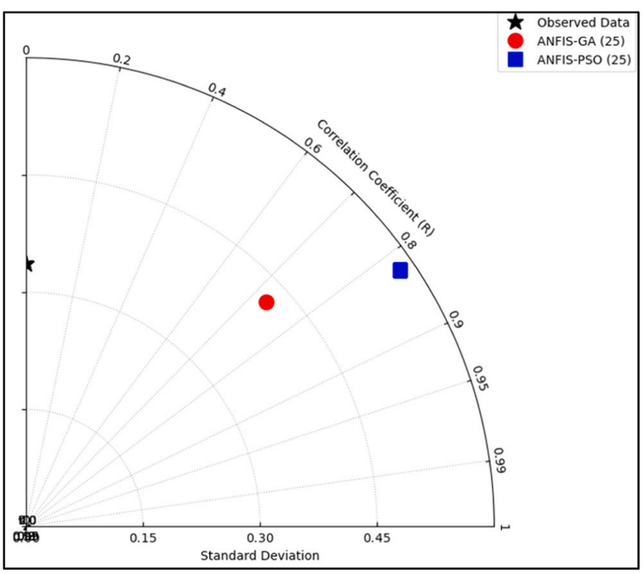

Fig. 12. Taylor diagram (Testing Phase).

4.1. Correlation

The ANFIS-GA point is located closer to the horizontal axis (representing perfect correlation, $R = 1$), aligning with a correlation coefficient greater than 0.90. In contrast, the ANFIS-PSO point is positioned higher up the arc, corresponding to a lower correlation ($R \approx 0.78$).

4.2. Standard deviation

The radial distance from the origin represents the standard deviation. The ANFIS-GA model exhibits a standard deviation (≈ 0.32) that is very close to that of the observed data, implying that the GA-optimized model correctly captures the amplitude of variations in the dataset. The ANFIS-PSO model, positioned further out radially (> 0.45), overestimates the variability of the target values.

4.3. Overall accuracy

In a Taylor Diagram, the distance from the reference point (ideal prediction) represents the centered RMSE. The closer proximity of the Red Circle to the ideal correlation zone confirms that ANFIS-GA achieves the lowest prediction error and highest structural consistency.

This superiority is further supported by Fig. 13 (Iteration). When the convergence curves for 25 populations (orange lines) are compared, the ANFIS-GA algorithm (left graph) achieves a lower final error rate and maintains a stable descent after the initial iterations. Conversely, the ANFIS-PSO algorithm (right graph), while converging quickly at the start, settles at a slightly higher error plateau. This confirms that at a population size of 25, ANFIS-GA offers a more precise and reliable prediction model for manufacturing value-added estimation.

Variations in population size significantly influenced the prediction performance. However, no linear correlation was observed between population size and accuracy; specifically, performance did not monotonically increase with population size. The prediction performance does not decrease in proportion to the decreasing population size. It is also stated that the calculation time is relatively shorter than that required for ANFIS-GA, which can be attributed to the decrease in population size due to the selection of the most suitable one.

4.3.1. Comparison with existing studies

To validate the robustness and prediction capability of the proposed ANFIS-GA model, a comparative analysis was conducted against recent studies in the literature focusing on economic and industrial forecasting. Table 5 summarizes the performance metrics of the proposed model alongside other relevant studies employing Machine Learning (Random Forest, XGBoost), Traditional (ARIMA), and Hybrid methods.

As observed in Table 5, Kaya & Özkan [40] utilized the traditional ARIMA model for GDP forecasting, achieving a high determination coefficient ($R^2 = 0.9003$) with low error rates. However, the proposed Hybrid ANFIS-GA (25 Population) model in this study surpassed this benchmark, achieving a higher R^2 value of 0.9080. This indicates that the optimized neuro-fuzzy approach provides a superior explanation of

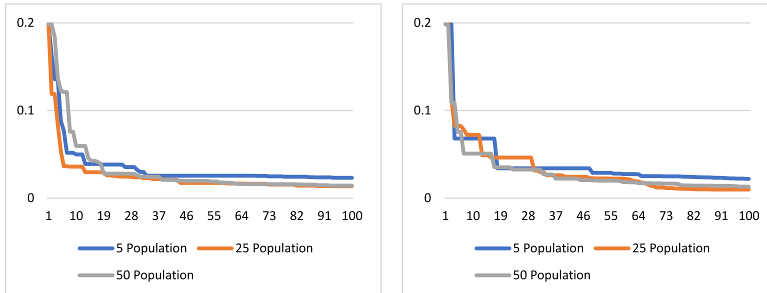

Fig. 13. ANFIS-GA (left) and ANFIS-PSO (right) Iteration.

Table 5
Comparison with existing studies.

Study	Method	Application Domain	Performance (R^2)	Performance (RMSE/MAE/MSE/MAPE)
Proposed Study	Hybrid ANFIS-GA (25 Pop)	Manufacturing Value-Added	0.9080	RMSE = 0.1801 MAE = 0.1455
Passarella et al. [57]	Random Forest / XGBoost	GDP/Economic Growth	0.116–0.111	RMSE = 2.032–2.037 MAE = 1.033–1.526
Kaya & Özkan [40].	ARIMA (Traditional)	GDP Forecasting	0.9003	RMSE = 0.0327 MAE = 0.0246 MSE = 0.0010
Chaudhary & Uprety [9].	Hybrids ARIMA-ANN	GDP Forecasting	-	RMSE = 0.0973–0.0663 MSE = 0.0094–0.0045 MAPE = 0.0034–0.0557

the non-linear variance in the dataset compared to linear traditional methods. Furthermore, when compared to the study by Passarella et al. [57], which employed Random Forest and XGBoost algorithms, the proposed ANFIS-GA model demonstrated significantly higher stability and predictive accuracy. While Chaudhary & Uprety [9] reported low error margins (MSE/RMSE) using Hybrid ARIMA-ANN, the direct comparison of R^2 highlights that our proposed method offers a competitive and reliable framework for manufacturing value-added estimation. Consequently, the results confirm that integrating Genetic Algorithms for parameter optimization enhances the model's generalization capability, making it a robust tool for macro-level predictions.

4.3.2. Advantages of the proposed model

The primary advantage of the proposed hybrid ANFIS-GA model lies in its ability to effectively handle the non-linear and complex nature of manufacturing value-added data. Unlike traditional statistical methods (e.g., linear regression or ARIMA), the the hybrid neuro-fuzzy structure effectively captures the inherent uncertainties and ambiguous patterns in the dataset. Furthermore, integrating the GA for parameter optimization significantly mitigates the risk of getting trapped in local minima, a common drawback of gradient-based learning algorithms. This results in higher prediction accuracy and better generalization capability, as evidenced by the superior R^2 values compared to standard methods.

5. Conclusions

This study proposes a novel hybrid soft-computing framework to estimate manufacturing value-added at the macro level by integrating innovation, entrepreneurship, and environmental indicators. This multi-dimensional perspective addresses a significant gap in the literature, as traditional econometric models often fail to capture the non-linear interactions, fuzzy uncertainties, and complex dynamics inherent in macroeconomic systems. By employing ANFIS-GA and ANFIS-PSO algorithms, this research contributes to the field by demonstrating how evolutionary meta-heuristic techniques can effectively solve high-dimensional economic forecasting problems where conventional gradient-based methods fall short.

Summary of Findings and Technical Contributions

The empirical analysis, conducted on the OECD dataset, revealed critical insights regarding model optimization and stability. The comparative results rigorously demonstrated that the ANFIS-GA model with a population size of 25 achieved the most robust performance, yielding the highest determination coefficient ($R^2 = 0.908$) and the lowest error rates ($RMSE = 0.180$, $MAE = 0.145$) in the testing phase. A key finding of this study is the identification of overfitting in the ANFIS-PSO model. While PSO showed high accuracy in training, its performance dropped significantly in the testing phase ($R^2 = 0.788$), indicating a limited generalization capability for this specific domain. In contrast, the ANFIS-GA model exhibited superior stability and consistency across both training and testing datasets. This confirms that the Genetic Algorithm provides a more effective global search mechanism for optimizing neuro-fuzzy parameters in manufacturing value-added estimation, preventing the model from getting trapped in local optima.

Theoretical Implications

Theoretically, this research challenges the sufficiency of single-factor production models. It establishes that qualitative developmental indicators (R&D expenditures and entrepreneurial activity) and environmental constraints (CO_2 emissions) are as critical as physical capital in value creation. The study validates the "Modern Production Theory" within an AI framework, proving that manufacturing value-added is a stochastic process driven by the synergy of innovation, business dynamism, and sustainability, rather than a linear accumulation of resources.

Practical Implications

From a managerial and policy-making perspective, the high predictive accuracy of the proposed model offers actionable insights:

For Policymakers: The strong correlation between the selected inputs and value-added suggests that policies incentivizing R&D and green manufacturing are direct drivers of economic growth. The model provides a reliable tool for simulating the economic impact of potential environmental regulations.

For Industrial Practitioners: Manufacturing firms can utilize this hybrid AI approach to optimize their resource allocation. By accurately forecasting value-added based on environmental and innovation inputs, companies can reduce waste, minimize unnecessary costs, and align their production strategies with sustainable development goals.

For Entrepreneurs: The model highlights the pivotal role of entrepreneurship in the manufacturing ecosystem, encouraging data-driven investment decisions and risk assessment.

Limitations and Future Scope

Despite its contributions, this study has certain limitations. The research focused on 23 OECD countries, which may limit the direct applicability of the findings to developing economies with different structural dynamics. It is important to acknowledge that the testing dataset utilized in this study is relatively small ($n = 7$ observations). While the hybrid models demonstrate high accuracy, this limited sample size introduces a potential risk of overfitting, suggesting that the model's generalization capability should be interpreted with caution and validated on larger datasets in future research. Additionally, the computational cost of hybrid algorithms is higher than traditional statistical methods. For future research, the scope can be expanded by investigating other advanced meta-heuristic algorithms, such as Grey Wolf Optimizer (GWO) or Ant Colony Optimization (ACO), to further fine-tune the ANFIS parameters. Incorporating deep learning models like Long Short-Term Memory (LSTM) networks could provide a benchmark against neuro-fuzzy approaches. Furthermore, expanding the dataset to include emerging markets and integrating more diverse macroeconomic indicators would offer a broader perspective on global manufacturing value-added prediction.

Nomenclature

Abbreviations

ABC	Artificial Bee Colony
Act	Actual
ACO	Ant Colony Optimization
ANFIS	Adaptive Neuro Fuzzy Inference System
ANN	Artificial Neural Network
CO_2	Carbon dioxide
DE	Differential Evolution
FCM	Fuzzy C-Mean
GA	Genetic algorithm
GP	Grid Partitioning
GWO	Grey Wolf Optimizer
LSTM	Long Short-Term Memory
MAE	Mean Absolute Error
MAPE	Mean Absolute Error in Percent
MBE	Mean Biased Error
MLP	Multilayer Perceptron
MSE	Mean Square Error
OECD	Organisation for Economic Co-operation and Development
PBIAS	Percent Bias
Pop	Population
Pred	Prediction
PSO	Particle Swarm Optimization
R2	R-squared
RMSE	Root Mean Square Error
RSS	sum of squares of residuals
R&D	Research and development
SC	Subtractive Clustering method
SMAPE	Symmetric Mean Absolute Percentage Error
TLBO	Teaching-Learning-Based Optimization
TSS	total sum of squares

Symbols

Symbol	Description
R^2	Coefficient of Determination
α	Learning rate / Crossover parameter
β	Selection pressure parameter
σ	Standard deviation
θ	Model parameters
N_{pop}	Population size
$MaxIt$	Maximum number of iterations
p_c	Crossover probability
p_m	Mutation probability
y_{act}	Actual value
y_{pred}	Predicted value
$\bar{y}$	Mean of observed data
w_i	Firing strength of the i-th rule
n	Total number of samples

Ethical approval

This article does not contain any studies with human participants or animals performed by any of the authors.

Funding

Not applicable

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A

Algorithm 1 Pseudo-code of the proposed Hybrid ANFIS-GA Model

Input:

Training Data set (D_{train})

Initial FIS structure (Sugeno-type)

GA Parameters:

Population Size ($N_{pop} = 25$)

Maximum Iterations ($MaxIt = 100$)

Crossover Rate ($p_c = 0.4$)

Mutation Rate ($p_m = 0.7$)

Selection Pressure ($\beta = 8$)

Output: Optimized ANFIS Parameters (θ_{best})

Initialization:

1: Extract initial parameters θ_0 from FIS structure.

2: **for** $i = 1$ to N_{pop} **do**

3: Generate initial population P_i randomly within bounds $[Var_{min}, Var_{max}]$.

4: Evaluate Cost $J_i = MSE(ANFIS(P_i, D_{train}))$.

5: **end for**

6: Sort population based on Cost values.

7: Store the Best Solution (Sol_{best}).

Main Loop (Optimization):

8: **while** $t < MaxIt$ **do**

9: Calculate Selection Probabilities using Boltzmann distribution: $P = \exp(-\beta \times Costs/Cost_{worst})$.

10: **Crossover Step:**

11: Select parent pairs using Roulette Wheel Selection.

12: Apply Arithmetic Crossover to generate offspring (P_{cross}).

13: Evaluate Cost for offspring.

14: **Mutation Step:**

15: Select individuals randomly based on mutation rate p_m.

16: Apply Gaussian Mutation:$x_{new} = x + \sigma \times \mathcal{N}(0,1)$.

17: Evaluate Cost for mutants P_{mut}).

18: **Selection & Update:**

19: Merge populations: $P_{total} = [P_{current}; P_{cross}; P_{mut}]$.

20: Sort P_{total} and select top N_{pop} individuals (Elitism).

21: Update Sol_{best} if a better solution is found.

22: $t = t + 1$.

23: **end while**

Finalization:

24: Map best parameters (Sol_{best}) to ANFIS structure.

25: **Return** Optimized ANFIS Model.

Data availability

The data used in this study can be obtained through the Eurostat data platform or shared with researchers upon request.

References

[1] A.V. Adejumo, Foreign direct investments and manufacturing sector performance in Nigeria,(1970-2009), Aust. J. Bus. Manag. Res. 3 (4) (2013) 39, https://doi.org/10.52283/NSWRCA.AJBMR.20130304A05.

[2] I.M. Alarifi, H.M. Nguyen, A. Naderi Bakhtiyari, A. Asadi, Feasibility of ANFIS-PSO and ANFIS-GA models in predicting thermophysical properties of Al2O3-MWCNT/oil hybrid nanofluid, Materials 12 (21) (2019) 3628, https://doi.org/10.3390/ma12213628.

[3] J.C. Anyanwu, Does human capital matter in manufacturing value added development in Africa, Asian J. Econ. Model. 6 (3) (2018) 294–317, https://doi.org/10.18488/journal.8.2018.63.294.316.

[4] E. Aydın, Impact of capital intensity and R&D spending on manufacturing industry value added in Industry 4.0 process: panel data analysis, J. Manag. Econ. Res. 16 (1) (2018) 303–314, https://doi.org/10.11611/yead.416806.

[5] A.A. Behroozpour, D. Jafari, M. Esfandyari, S.A. Jafari, Prediction of the continuous cadmium removal efficiency from aqueous solution by the packed-bed column using GMDH and ANFIS models, Desalin. Water Treat. 234 (2021) 91–101, https://doi.org/10.5004/dwt.2021.27591.

[6] J.P. Bharti, P. Samui, Predicting slope failure with intelligent hybrid modeling of ANFIS with GA and PSO, Multiscale Multidiscip. Model. Exp. Des. (2024) 1–17, https://doi.org/10.1007/s41939-024-00492-6.
[7] C. Biswakalyani, S. Samantaray, D.P. Satpathy, Assessment of spatio-temporal characteristics of groundwater quality at Khordha District, India, Discov. Civ. Eng. 1 (1) (2024) 28.
[8] N. Cantore, M. Clara, A. Lavopa, C. Soare, Manufacturing as an engine of growth: which is the best fuel? Struct. Change Econ. Dyn. 42 (2017) 56–66, https://doi.org/10.1016/j.strueco.2017.04.004.
[9] S. Chaudhary, D. Uprety, Hybrids ARIMA-ANN models for GDP forecasting in Nepal, NRB Econ. Rev. 35 (1-2) (2023) 22–53.
[10] W. Chen, X. Chen, J. Peng, M. Panahi, S. Lee, Landslide susceptibility modeling based on ANFIS with teaching-learning-based optimization and Satin bowerbird optimizer, Geosci. Front. 12 (1) (2021) 93–107, https://doi.org/10.1016/j.gsf.2020.07.012.
[11] X. Chen, Z. Liu, Q. Zhu, Reprint of" Performance evaluation of China's high-tech innovation process: analysis based on the innovation value chain, Technovation 94 (2020) 102094, https://doi.org/10.1016/j.technovation.2019.102094.
[12] X. Chen, N. Wang, A DNA based genetic algorithm for parameter estimation in the hydrogenation reaction, Chem. Eng. J. 150 (2-3) (2009) 527–535, https://doi.org/10.1016/j.cej.2009.03.016.
[13] D. Chicco, M.J. Warrens, G. Jurman, The coefficient of determination R-squared is more informative than SMAPE, MAE, MAPE, MSE and RMSE in regression analysis evaluation, Peerj Comput. Sci. 7 (2021) e623, https://doi.org/10.7717/peerj-cs.623.
[14] Cuneo, P., & Mairesse, J. (1983). Productivity and R&D at the firm level in French manufacturing (No. w1068). National Bureau of Economic Research. https://doi.org/10.3386/w1068.
[15] H. Djulius, W.G. Choi, J. Juanim, R. Dwi Santy, Nexus of foreign direct investment, domestic investment, and manufacturing industry value added in Indonesia, Signifikan J. Ilmu Ekon. 8 (1) (2019), https://doi.org/10.15408/sjie.v8i1.9520.
[16] M. Dolatabadi, M. Mehrabpour, M. Esfandyari, H. Alidadi, M. Davoudi, Modeling of simultaneous adsorption of dye and metal ion by sawdust from aqueous solution using of ANN and ANFIS, Chemom. Intell. Lab. Syst. 181 (2018) 72–78, https://doi.org/10.1016/j.chemolab.2018.07.012.
[17] M. Esfandyari, M. Amiri, M.K. Salooki, Neural network prediction of the Fischer-Tropsch synthesis of natural gas with Co (III)/Al2O3 catalyst, Chem. Eng. Res. Bull. 17 (1) (2015) 25-33, https://doi.org/10.3329/cerb.v17i1.22915.
[18] M. Esfandyari, A.A. Delouei, A. Jalai, Optimization of ultrasonic-excited double-pipe heat exchanger with machine learning and PSO, Int. Commun. Heat. Mass Transf. 147 (2023) 106985, https://doi.org/10.1016/j.icheatmasstransfer.2023.106985.
[19] M. Esfandyari, M. Esfandyari, D. Jafari, Prediction of thiophene removal from diesel using [BMIM][AlCl4] in EDS Process: GA-ANFIS and PSO-ANFIS modeling, Pet. Sci. Technol. 36 (16) (2018) 1305–1311, https://doi.org/10.1080/10916466.2018.1471500.
[20] P.E. Febriani, Green manufacturing strategy as a pillar of sustainable innovation a SWOT analysis, Clean. Sustain. Bus. 1 (1) (2025) 57–68.
[21] M. Ferdosian, H. Abdi, S. Karimi, S. Kharrati, Short-term load and spinning reserve prediction based on LSTM and ANFIS with PSO algorithm, J. Eng. 2024 (3) (2024) e12356, https://doi.org/10.1049/tje2.12356.
[22] N. Fernando, L. Seneviratne, N. Weerasinghe, N. Rathnayake, Y. Hoshino, Efficient hotspot detection in solar panels via computer vision and machine learning, Information 16 (7) (2025) 608.
[23] B.E. Flores, A pragmatic view of accuracy measurement in forecasting, Omega 14 (2) (1986) 93–98, https://doi.org/10.1016/0305-0483(86)90013-7.
[24] M.R. Ghasemi, M. Ghasri, A.H. Salarnia, ANFIS-TLBO hybrid approach to predict compressive strength of rectangular FRP columns, Int. J. Optim. Civ. Eng. 12 (3) (2022) 399–410.
[25] M. Gheytanzadeh, A. Baghban, S. Habibzadeh, K. Jabbour, A. Esmaeili, A. H. Mashhadzadeh, A. Mohaddespour, Intelligent route to design efficient CO2 reduction electrocatalysts using ANFIS optimized by GA and PSO, Sci. Rep. 12 (1) (2022) 20859, https://doi.org/10.1038/s41598-022-25512-8.
[26] J.H. Holland, Adaptation in natural and artificial systems, The University of Michigan Press, Ann Arbor, 1975, p. 1.
[27] J.H. Holland, Adapt. Nat. Artif. Syst. Introd. Anal. Appl. Biol. Control Artif. Intell. MIT Press (1992), https://doi.org/10.7551/mitpress/1090.001.0001.
[28] Y. Hoshino, K. Yoshimi, T.L. Dang, N. Rathnayake, Controlling heterogeneous multi-agent systems under uncertainty using fuzzy inference and evolutionary search, Information 16 (9) (2025) 732.
[29] C.R. Houck, J. Joines, M.G. Kay, A genetic algorithm for function optimization: a Matlab implementation, Ncsuie Tr. 95 (09) (1995) 1–10.
[30] W. Hussain, J.M. Merigó, M.R. Raza, H. Gao, A new QoS prediction model using hybrid IOWA-ANFIS with fuzzy C-means, subtractive clustering and grid partitioning, Inf. Sci. 584 (2022) 280–300, https://doi.org/10.1016/j.ins.2021.10.054.
[31] M.M. Irwanto, O. Rosalia, F. Firayani, J. Chin, The impact of technological innovation on the productivity of the manufacturing industry. NOMICO Учредители, Pt. Anagata Sembagi Educ. 2 (1) (2025) 38–50.
[32] A. Jadidi, R. Menezes, N. de Souza, A.C. de Castro Lima, Short-term electric power demand forecasting using NSGA II-ANFIS model, Energies 12 (10) (2019) 1891, https://doi.org/10.3390/en12101891.
[33] J.S. Jang, ANFIS: adaptive-network-based fuzzy inference system, IEEE Trans. Syst. Man Cybern. 23 (3) (1993) 665–685, https://doi.org/10.1109/21.256541.
[34] K.T. Kabengele, I.O. Olayode, L.K. Tartibu, Analysis of the performance of a hybrid thermal power plant using adaptive neuro-fuzzy inference system (ANFIS)-based approaches, Appl. Sci. 13 (21) (2023) 11874, https://doi.org/10.3390/app132111874.
[35] N. Kaldor, N. Kaldor, Causes of growth and stagnation in the world economy, Cambridge University Press, Cambridge, 1996, pp. 55–70, https://doi.org/10.1017/CBO9780511559709.
[36] D. Karaboga, B. Akay, A modified artificial bee colony (ABC) algorithm for constrained optimization problems, Appl. soft Comput. 11 (3) (2011) 3021–3031, https://doi.org/10.1016/j.asoc.2010.12.001.
[37] D. Karaboga, E. Kaya, Adaptive network based fuzzy inference system (ANFIS) training approaches: a comprehensive survey, Artif. Intell. Rev. 52 (2019) 2263–2293, https://doi.org/10.1007/s10462-017-9610-2.
[38] A. Kaveh, Advances in metaheuristic algorithms for optimal design of structures, Springer International Publishing, Switzerland, 2017, pp. 9–40, https://doi.org/10.1007/978-3-319-46173-1.
[39] A. Kaveh, T. Bakhshpoori, Metaheuristics: outlines, MATLAB codes and examples, Springer Nature Switzerland AG, 2019, https://doi.org/10.1007/978-3-030-04067-3.
[40] H. Kaya, B. Özkan, Comparative analysis of machine learning and traditional methods in Turkey's gross domestic product forecasting, J. Econ. Forecast. 3 (2025) 110–127.
[41] J. Kennedy, R. Eberhart, Particle swarm optimization (November), in: In Proceedings of ICNN'95-international conference on neural networks, 4, IEEE, 1995, pp. 1942–1948 (November).
[42] M. Khandelwal, A. Marto, S.A. Fatemi, M. Ghoroqi, D.J. Armaghani, T.N. Singh, O. Tabrizi, Implementing an ANN model optimized by genetic algorithm for estimating cohesion of limestone samples, Eng. Comput. 34 (2018) 307–317, https://doi.org/10.1007/s00366-017-0541-y.
[43] L.O. Lara-Cerecedo, J.F. Hinojosa, N. Pitalúa-Díaz, Y. Matsumoto, A. González-Angeles, Prediction of the electricity generation of a 60-kW photovoltaic system with intelligent models ANFIS and optimized ANFIS-PSO, Energies 16 (16) (2023) 6050, https://doi.org/10.3390/en16166050.
[44] J. Li, G. Yan, L.H. Abbud, T. Alkhalifah, F. Alturise, M.A. Khadimallah, R. Marzouki, Predicting the shear strength of concrete beam through ANFIS-GA-PSO hybrid modeling, Adv. Eng. Softw. 181 (2023) 103475, https://doi.org/10.1016/j.advengsoft.2023.103475.
[45] G. Libanio, S. Moro, Manufacturing industry and economic growth in Latin America: a Kaldorian approach (December), Second Annu. Conf. Dev. Change (2006) 2–5.
[46] V. Mahakur, V.K. Mahakur, S. Samantaray, D.K. Ghose, Prediction of runoff at ungauged areas employing interpolation techniques and deep learning algorithm, HydroResearch 8 (2025) 265–275.
[47] S. Makridakis, Accuracy measures: theoretical and practical concerns, Int. J. Forecast. 9 (4) (1993) 527–529, https://doi.org/10.1016/0169-2070(93)90079-3.
[48] I. Mansouri, O. Kisi, P. Sadeghian, C.H. Lee, J.W. Hu, Prediction of ultimate strain and strength of FRP-confined concrete cylinders using soft computing methods, Appl. Sci. 7 (8) (2017) 751, https://doi.org/10.3390/app7080751.
[49] H. Moayedi, M. Raftari, A. Sharifi, W.A.W. Jusoh, A.S.A. Rashid, Optimization of ANFIS with GA and PSO estimating α ratio in driven piles, Eng. Comput. 36 (2020) 227–238, https://doi.org/10.1007/s00366-018-00694-w.
[50] E.T. Mohamad, R.S. Faradonbeh, D.J. Armaghani, M. Monjezi, M.Z.A. Majid, An optimized ANN model based on genetic algorithm for predicting ripping production, Neural Comput. Appl. 28 (2017) 393–406, https://doi.org/10.1007/s00521-016-2359-8.
[51] M. Mohammadi Behboud, A. Ramezanzadeh, B. Tokhmechi, M. Mehrad, S. Davoodi, Estimation of geomechanical rock characteristics from specific energy data using combination of wavelet transform with ANFIS-PSO algorithm, J. Pet. Explor. Prod. Technol. 13 (8) (2023) 1715–1740, https://doi.org/10.1007/s13202-023-01644-z.
[52] M. Motameni, M. Abdi Seyyedkolaee, S. Nasrnejad, Manufacturing added value and economic growth nexus in selected countries, Macroecon. Res. Lett. 16 (32) (2021) 7–22.
[53] M. Niknam Shahrak, M. Esfandyari, M. Karimi, Efficient prediction of water vapor adsorption capacity in porous metal-organic framework materials: ANN and ANFIS modeling, J. Iran. Chem. Soc. 16 (1) (2019) 11–20, https://doi.org/10.1007/s13738-018-1476-y.
[54] I.P. Okokpujie, J.E. Sinebe, An overview of the study of ANN-GA, ANN-PSO, ANFIS-GA, ANFIS-PSO and ANFIS-FCM predictions analysis on tool wear during machining process, J. Eur. éEn. Des. Syst. èMes. Autom. éS. 56 (2) (2023) 269, https://doi.org/10.18280/jesa.560212.
[55] R.N. Ongachi, P.M. Ngatia, E.N. Makokha, j Miroga, Entrepreneurial innovation and performance of small and medium paper wood manufacturing firms in Kenya, Eur. J. Bus. Manag. 17 (4) (2025) 1–19.
[56] A.F. Oshodi, Backward integration policy and manufacturing firms value added in Nigeria, Econ. Cult. 19 (1) (2022) 5–16, https://doi.org/10.2478/jec-2022-0001.
[57] R. Passarella, M.I. Setiawan, Z. Yamani, Comparative analysis of machine learning models for predicting Indonesia's GDP Growth, Acadlore Trans. AI Mach. Learn. 4 (3) (2025) 157–173.
[58] J. Pazhoohan, H. Beiki, M. Esfandyari, Experimental investigation and adaptive neural fuzzy inference system prediction of copper recovery from flotation tailings by acid leaching in a batch agitated tank, Int. J. Miner. Metall. Mater. 26 (2019) 538–546, https://doi.org/10.1007/s12613-019-1762-4.
[59] M.E. Porter, C.V.D. Linde, Toward a new conception of the environment-competitiveness relationship, J. Econ. Perspect. 9 (4) (1995) 97–118.
[60] R. Radfar, P. Jahangir, A suitable innovation type to improve the added value in entrepreneurship, Int. J. Manag. Bus. Res. 1 (3) (2011) 139–150.

[61] R.V. Rao, V.J. Savsani, D.P. Vakharia, Teaching-learning-based optimization: a novel method for constrained mechanical design optimization problems, Comput. Aided Des. 43 (3) (2011) 303–315, https://doi.org/10.1016/j.cad.2010.12.015.
[62] M. Rezakazemi, A. Dashti, M. Asghari, S. Shirazian, H2-selective mixed matrix membranes modeling using ANFIS, PSO-ANFIS, GA-ANFIS, Int. J. Hydrog. Energy 42 (22) (2017) 15211–15225, https://doi.org/10.1016/j.ijhydene.2017.04.044.
[63] M. Robert, Manufacturing innovation and the role of entrepreneurship. MPRA Paper, No. 124608, University of Munich, 2025.
[64] P.M. Romer, Endogenous technological change, J. Political Econ. 98 (5, Part 2) (1990) S71–S102.
[65] Salehi, H., Amiri, M., & Esfandyari, M. (2011). Using artificial neural network (ANN) for manipulating energy gain of nansulate coating. https://doi.org/10.1115/1.4003500.
[66] M.K. Salooki, M. Shokouhi, H. Farahani, M. Keshavarz, M. Esfandyari, J.S. Ahari, Experimental and modelling investigation of H2S solubility in N-methylimidazole and gamma-butyrolactone, J. Chem. Thermodyn. 135 (2019) 133–142, https://doi.org/10.1016/j.jct.2019.03.031.
[67] S. Samantaray, A. Sahoo, S. Paul, D.K. Ghose, Prediction of bed-load sediment using newly developed support-vector machine techniques, J. Irrig. Drain. Eng. 148 (10) (2022), 04022034.
[68] S. Samantaray, A. Sahoo, Prediction of flow discharge in Mahanadi River Basin, India, based on novel hybrid SVM approaches, Environ. Dev. Sustain. 26 (7) (2024) 18699–18723.
[69] S. Samantaray, A. Sahoo, Groundwater level prediction using an improved ELM model integrated with hybrid particle swarm optimisation and grey wolf optimisation, Groundw. Sustain. Dev. 26 (2024) 101178.
[70] N. Samargandi, Sector value addition, technology and CO2 emissions in Saudi Arabia, Renew. Sustain. Energy Rev. 78 (2017) 868–877, https://doi.org/10.1016/j.rser.2017.04.056.
[71] A.B. Senouci, M.S. Al-Ansari, Cost optimization of composite beams using genetic algorithms, Adv. Eng. Softw. 40 (11) (2009) 1112–1118, https://doi.org/10.1016/j.advengsoft.2009.06.001.
[72] M. Shafiullah, M.I.H. Pathan, M.S. Shahriar, A. Ali, M.I. Hossain, M.S. Alam, Real-time solution of PSS parameter tuning by GA-ANFIS in stabilizing the electrical power system, Arab. J. Sci. Eng. 48 (5) (2023) 6925–6938, https://doi.org/10.1007/s13369-023-07666-3.
[73] D. Shefer, A. Frenkel, R&D, firm size and innovation: an empirical analysis, Technovation 25 (1) (2005) 25–32, https://doi.org/10.1016/S0166-4972(03)00152-4.
[74] M. Shokouhi, M.K. Salooki, J.S. Ahari, M. Esfandyari, Thermodynamical and artificial intelligence approaches of H2S solubility in N-methylpyrrolidone, Chem. Phys. Lett. 707 (2018) 22–30, https://doi.org/10.1016/j.cplett.2018.07.032.
[75] R. Storn, K. Price, Differential evolution-a simple and efficient heuristic for global optimization over continuous spaces, J. Glob. Optim. 11 (1997) 341–359, https://doi.org/10.1023/A:1008202821328.
[76] H. Taan, H.V. Alam, S. Rukayah, Y.L. Ismail, N.F. Arsyad, The impact of entrepreneurial orientation and company innovation on the business performance of manufacturing SMEs, Int. J. Manag. Sustain. 12 (3) (2023) 419–434.
[77] T. Takagi, M. Sugeno, Derivation of fuzzy control rules from human operator's control actions, IFAC Proc. Vol. 16 (13) (1983) 55–60, https://doi.org/10.1016/S1474-6670(17)62005-6.
[78] M.A. Takassi, M.K. Salooki, M. Esfandyari, Fuzzy model prediction of Co (III) Al2O3 catalytic behavior in Fischer-Tropsch synthesis, J. Nat. Gas. Chem. 20 (6) (2011) 603–610, https://doi.org/10.1016/S1003-9953(10)60240-X.
[79] B. Tanhaei, M. Esfandyari, A. Ayati, M. Sillanpää, Neuro-fuzzy modeling to adsorptive performance of magnetic chitosan nanocomposite, J. Nanostructure Chem. 7 (2017) 29–36, https://doi.org/10.1007/s40097-016-0211-4.
[80] M. Unanoğlu, Ç. Özarı, Assessing the level of manufacturing value added of G-20 and its relation to innovation inputs and outputs, Kent. Akad. Kent. K. ültüR. ü ve Yönetimi Derg. 17 (2) (2024) 592–605, https://doi.org/10.35674/kent.1417436.
[81] M. Vaez, S.K. Tayebi, A.A. Ghanbari, The role of the (R&D) expenditures in the high-tech manufacturing value added, J. Quant. Econ. (Q. J. Econ. Rev.) 4 (4) (2008) 53–72. ⟨https://sid.ir/paper/110691/en⟩ (SID).
[82] A. Vajrapatkul, Cross-country manufacturing value added improvement in the quantile regression model. Proceedings of the 2023 International Conference on Economics, Management and Engineering (ICEME, Association for Computing Machinery, 2023.
[83] C.M. Van Praag, P.H. Versloot, What is the value of entrepreneurship? A review of recent research, Small Bus. Econ. 29 (4) (2007) 351–382, https://doi.org/10.1007/s11187-007-9074-x.
[84] D. Vuković, A. Dukić, A. Urošević, B. Ilić, The impact of product and process innovation and technological dimensions on the sustainable competitive advantage of manufacturing companies, Econ. Agric. 72 (1) (2025) 241–254 [2].
[85] Z. Wang, C. Feng, A performance evaluation of the energy, environmental, and economic efficiency and productivity in China: An application of global data envelopment analysis, Appl. Energy 147 (2015) 617–626, https://doi.org/10.1016/j.apenergy.2015.01.108.
[86] S. Wennekers, R. Thurik, Linking entrepreneurship and economic growth, Small Bus. Econ. 13 (1) (1999) 27–56.
[87] I.Y. Wulansari, S.I. Oktora, A.F. Yuniasih, The impact of information and communication technology on the value added of manufacturing sector: comparing Asian countries by income group levels, J. Crit. Rev. 7 (16) (2020) 596–607.
[88] H. Yang, M. Hasanipanah, M.M. Tahir, D.T. Bui, Intelligent prediction of blasting-induced ground vibration using ANFIS optimized by GA and PSO, Nat. Resour. Res. 29 (2020) 739–750, https://doi.org/10.1007/s11053-019-09515-3.
[89] A. Yonar, H. Yonar, Modeling air pollution by integrating ANFIS and metaheuristic algorithms, Model. Earth Syst. Environ. 9 (2) (2023) 1621–1631, https://doi.org/10.1007/s40808-022-01573-6.
[90] L.A. Zadeh, Fuzzy logic, neural networks and soft computing, Saf. Eval. Based Identif. Approaches Relat. TimeVar. Nonlinear Struct. (1993) 320–321, https://doi.org/10.1007/978-3-322-89467-0_19.
[91] Z. Zahoor, M.I. Latif, I. Khan, F. Hou, Abundance of natural resources and environmental sustainability: the roles of manufacturing value-added, urbanization, and permanent cropland, Environ. Sci. Pollut. Res. 29 (54) (2022) 82365–82378, https://doi.org/10.1007/s11356-022-21545-8.
[92] M. Zanganeh, A. Chaji, A new aspect of the ApEn application to improve the PSO-ANFIS model to forecast Caspian Sea levels, Reg. Stud. Mar. Sci. 69 (2024) 103347, https://doi.org/10.1016/j.rsma.2023.103347.