ISSN 2409-2665
Journal of Logistics, Informatics and Service Science
Vol. 11 (2024) No. 12, pp. 373-387
DOI:10.33168/JLISS.2024.1218

Bridging Economic Integration and Trade Forecasting: An ANFIS Model for Predicting Intra-ASEAN Trade Growth

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Abstract. This study investigates the application of the Adaptive Neuro-Fuzzy Inference System (ANFIS) modeling approach in predicting intra-ASEAN trade growth. Using a panel dataset spanning 16 years and covering all ASEAN member countries, the research employs Vector Error Correction Model (VECM) analysis and ANFIS modeling to examine the factors influencing trade dynamics and forecast trade growth. The findings demonstrate the high accuracy and robustness of the ANFIS model in predicting intra-ASEAN trade growth, with accuracy rates ranging from 70.14% to 99.88% across different countries. The study contributes to the understanding of economic integration challenges in ASEAN and showcases the potential of machine learning techniques in trade forecasting and policy decision-making.

Keywords: Economic, Intra-ASEAN, ANFIS

1. Introduction

Trade is the process of transferring resources, goods, or services between individuals, businesses, or countries. These transactions occur because each party has different advantages in producing or accessing certain resources, allowing them to more effectively acquire the commodities or services needed than if they tried to produce them themselves (Citci, Sadettin Haluk and Kaya, 2023). Trade theory is a set of principles, concepts, and models used to understand and study the phenomenon of international trade between countries. This theory attempts to explain why countries trade, what they trade, and how they benefit from such trade (da Silva, João Carlos Garzel Leodoro and de Souza Maciel, 2022).

International trade has a significant impact on a country's economic growth. When a country exports more than it imports, its national income increases, positively affecting overall economic growth. The benefits of engaging in international trade include increased national income, higher foreign exchange reserves, greater capital transactions, and more job opportunities (Yuni, 2021). Moreover, economic growth resulting from international trade also positively impacts the production and consumption sectors. Increased real income benefits both producers and consumers. Producers face decisions related to production processes during increases in production factors or technological changes, while consumers decide how to allocate the additional real income (Soyres & Gaillard, 2022).

In Southeast Asia, intra-ASEAN trade has become a crucial pillar in achieving deeper economic integration and sustainable growth. ASEAN (Association of Southeast Asian Nations), consisting of ten member countries, has been strengthening economic cooperation through various initiatives, such as the formation of the ASEAN Economic Community (AEC) aimed at creating a single market and integrated production base. Globalization introduces new dynamics in international economic relations, broadly opening markets beyond geographical and territorial boundaries. Since the beginning of economic integration, intra-ASEAN goods trade has seen significant growth. Various initiatives, such as tariff elimination, trade facilitation, and policy harmonization, have been implemented to enhance accessibility and efficiency in regional trade. Despite these advancements, challenges and opportunities remain to further increase intra-ASEAN trade growth. Global trade in the past five years has been influenced by the US-China trade war, the COVID-19 pandemic, WTO policies, and commodity price fluctuations. However, efforts for global economic recovery are expected to boost world trade (Ang, James, & Wang, 2023).

Market access and economies of scale for diverse products tend to benefit ASEAN countries with a variety of innovative products. Conversely, countries with less diverse product offerings may experience reduced trade volumes, suboptimal GDP impact, and uncertain economic growth. Some ASEAN countries have not fully utilized product diversification, limiting their presence in international markets and economies of scale. Enhancing product diversification and modification can boost economies of scale, GDP, and economic growth in these countries. Declining trade growth threatens economic growth in the region (Sreenath, S., 2022). Over the past few decades, ASEAN has undergone significant economic transformation. With a population of over 650 million and a combined GDP reaching trillions of dollars, ASEAN is one of the most dynamic economic regions in the world. Intra-ASEAN trade has been a key element in supporting economic growth. Through free trade agreements and tariff elimination, ASEAN member countries strive to create a conducive environment for increasing intra-regional goods trade.

However, despite many advancements, challenges remain in intra-ASEAN trade. Shanran Yang et al. state that trade agreements, tariffs, trade barriers, and regional economic integration influence ASEAN trade flows. Import tariffs can increase goods prices, affect global competitiveness, trigger trade wars, and harm consumer welfare. Protectionism can hurt global competitiveness, investment, and international trade. Although sometimes used to protect domestic markets, tariffs can impede trade and harm all parties involved in international trade (S. Yang et al., 2023). Non-tariff barriers, regulatory differences between countries, and infrastructure and logistics issues often hinder smooth trade.

Therefore, an in-depth analysis of intra-ASEAN goods trade growth is needed to identify areas requiring further attention and to formulate effective strategies to overcome these barriers.

Despite substantial progress in fostering intra-ASEAN trade, significant gaps remain in understanding the nuanced factors influencing trade growth and the uneven distribution of trade benefits among ASEAN member states. While prior studies have largely focused on qualitative assessments of economic integration and trade facilitation, there is limited research employing predictive quantitative models to analyze trade growth trends and identify underlying drivers and inhibitors. Specifically, the dynamic interplay between market access, product diversification, economies of scale, and regional economic integration requires further exploration. To address these gaps, this study aims to develop a predictive model for intra-ASEAN goods trade growth using the Adaptive Neuro-Fuzzy Inference System (ANFIS) method, leveraging trade data from the past 16 years. The research objectives include analyzing growth trends and trade patterns in intra-ASEAN trade, identifying key factors influencing trade growth such as policy and structural variables, assessing the extent of economic integration achieved within ASEAN, and providing actionable insights for overcoming trade barriers and enhancing opportunities for growth.

Artificial intelligence (AI) has revolutionized various fields of study, demonstrating its transformative power in addressing complex challenges and enhancing decision-making. In engineering, AI optimizes design processes, predicts equipment failures, and automates production systems, improving efficiency and innovation (Turnip & Hong, 2012; Turnip, et al., 2012; Suhaeni, Wulandari, Turnip, & Deliana, 2023). In medicine, AI-driven tools are used for disease diagnosis, personalized treatment, and medical imaging analysis, significantly advancing healthcare outcomes. Social sciences, including economics, have also embraced AI for analyzing large datasets, forecasting trends, and modeling human behavior. In economics, AI applications enable precise trade forecasting, market analysis, and policy evaluation, offering new insights to tackle global challenges. This versatility underscores AI’s growing influence across disciplines, reshaping research and practical applications alike. Machine learning techniques are increasingly applied in international trade forecasting, offering advanced tools to capture complex patterns and enhance prediction accuracy. Akpan and Isihak (2023) provide a comprehensive review of machine learning applications in trade, highlighting their potential to improve forecasting precision compared to traditional models. Chen and Zhang (2021) demonstrate the effectiveness of artificial neural networks in forecasting bilateral trade flows, using the case of China and the United States to illustrate the method's ability to model non-linear relationships. Similarly, Sharma and Chakraborty (2022) explore the use of machine learning to predict regional trade integration in ASEAN, emphasizing its role in identifying key drivers and supporting economic policymaking. These studies underline the transformative impact of machine learning on trade analysis, particularly in regions like ASEAN, where economic integration is a priority.

The study is anchored in international trade theory, particularly the principles of comparative advantage and economies of scale, which explain why countries trade and how they derive mutual benefits. Additionally, it incorporates modern trade theories that emphasize the role of regional integration, global supply chains, and trade facilitation measures. These include understanding how differences in production capabilities and resource endowments influence trade flows within ASEAN (comparative advantage), exploring the impact of economies of scale and market size on intra-regional trade (new trade theory), and evaluating the success of ASEAN initiatives like the AEC in reducing trade barriers and fostering economic cooperation. By developing a quantitative ANFIS-based model, this study contributes to existing knowledge by bridging the gap between qualitative and quantitative analyses of trade growth within ASEAN. It offers a predictive framework for policymakers to anticipate trends and make informed decisions while highlighting actionable strategies to overcome trade barriers, enhance product diversification, and optimize economies of scale for sustained economic growth. Through its innovative approach, this research not only sheds light on current challenges and opportunities in intra-ASEAN trade but also lays a foundation for future studies on regional economic integration and its broader implications for global trade dynamics.

This study aims to develop a predictive model for intra-ASEAN goods trade growth based on trade data from the past 16 years using the ANFIS method. Modeling trade growth is crucial to understanding the extent to which economic integration has been achieved and the factors influencing this growth. Additionally, this model can provide insights into the challenges and opportunities faced in deepening economic cooperation in ASEAN in the future. Through a quantitative approach, this research will identify growth trends, trade patterns, and factors contributing to the increase or decrease of intra-ASEAN trade. The structure of this paper is as follows: Section 2 presents the methodology, including data collection and analysis. Section 3 discusses results and findings. Section 4 concludes with implications, limitations, and suggestions for future research.

2. Method

This research is a quantitative study that utilizes secondary data. The data is obtained from the official websites of the World Bank and the ASEAN Statistics YearBook. The dataset is a time series spanning 16 years, from 2007 to 2022. The dependent variable in this study is Intra-ASEAN Trade (PRD_IN). The independent variables used in this research are Inflation (INF), Foreign Direct Investment (FDI), Market Size (MSZ), Economic Growth (GDP), Tariffs (TRF), and Exchange Rate (KURS). The relationships among these variables are evaluated using the Panel Vector Error Correction Model (PVECM). Subsequently, the output PRD_IN against the six inputs is modeled using the Adaptive Neuro-Fuzzy Inference System (ANFIS) method.

To ensure data quality and reliability, trade data spanning 16 years was preprocessed with meticulous steps. Missing values were handled using interpolation for numerical data and mode imputation for categorical data, while extensive gaps led to variable exclusion. Outliers were identified through Z-scores and IQR methods and either capped or removed based on their impact. Data normalization or standardization ensured equal contribution of variables, and time-series consistency was verified through cross-referencing with reliable ASEAN sources. Transformations, such as logarithmic scaling, were applied where needed, and fuzzy sets were created for integration into the ANFIS model. Despite its advantages in capturing non-linear relationships, ANFIS has limitations, including computational complexity from fuzzy rule generation, reliance on high-quality training data, and challenges in handling non-stationary trends. These were mitigated by feature selection to reduce dimensionality, k-fold cross-validation for robust training, and inclusion of external shock variables (e.g., pandemic effects) to stabilize predictions. Sensitivity analysis was conducted to enhance interpretability, and optimized training algorithms addressed computational intensity. While data gaps and region-specific constraints remain limitations, the comprehensive preprocessing steps and methodological adjustments ensure the model’s robustness and reliability for intra-ASEAN trade forecasting.

PVECM is used to capture both the long-term and short-term dynamics between the variables in the panel data. VECM is a special form of Vector Autoregression (VAR) used when the data exhibits cointegration properties. Cointegration indicates a long-term equilibrium relationship among the variables in the model. By combining the cointegration vector and VAR dynamics, VECM provides a more comprehensive view of the relationships between variables. In this study, the VECM approach is employed to analyze the relationship between intra-ASEAN trade and other economic variables, as well as to understand how changes in one variable affect the others in both the long and short term. The VECM model for the variable with two other variables Y_t X_1tand X_2t can be written as follows:

$$\Delta Y_t = \alpha_0 + \alpha_1 ECT_{t-1} + \sum_{i=1}^{p-1} \beta_i \Delta Y_{t-i} + \sum_{i=1}^{p-1} \gamma_i \Delta X_{1,t-i} + \sum_{i=1}^{p-1} \delta_i \Delta X_{2,t-i} + \epsilon_t$$

where, represents the difference operator, Δα is the intercept term, β1and β2 are short-term coefficients, γ1is the speed of adjustment coefficient, Yt−1, X1t−1, and X2t−1 are lagged values, δ1and δ2 are long-term coefficients, and is error term.ϵt

ANFIS is an approach that combines neural networks with fuzzy inference to model complex and non-linear systems. The main goal of ANFIS is to create a model that can learn from provided input data and generate accurate output based on applied fuzzy rules. Generally, ANFIS consists of several layers or stages representing the data processing steps. In the initial stage, each input variable is linked to fuzzy membership functions to determine its fit with existing sets such as "low," "medium," or "high." These membership functions can take forms such as triangular, trapezoidal, or other shapes depending on the problem at hand. The next stage, known as the inference phase, involves combining pre-determined rules to generate output from fuzzy inference. These rules consist of IF-THEN conditions that connect input variables with output variables using fuzzy logic operators like AND, OR, and NOT. The fuzzy inference results obtained from the previous layer are normalized to produce the weight or strength of each rule. In the composition phase, all contributions from the fuzzy rules producing the ANFIS output are combined using various methods such as minimum or maximum. The final stage in ANFIS is defuzzification, where the aggregated values from the previous stage are converted into concrete or actual output values. Mathematically, the membership functions in ANFIS can be described by the following equations:

$$\mu A(x) = \frac{1}{1 + (\frac{x - c}{a})^{2b}}$$

where C is the center or centroid, A controls the width of the membership function, and B controls the shape of the curve. For example, a rule can be written as:

If x1 is A1 AND x2 is A2 THEN y is B

where A1 and A2 are the fuzzy sets of the input variables x1, x2, and B are the fuzzy sets of the output variables y. By integrating artificial neural networks and fuzzy inference, ANFIS can address complex problems that are difficult to model linearly. This makes ANFIS very useful in a variety of applications such as prediction, system control, and data analysis where the relationships between variables are very complex and non-linear.

3. Results and Discussion

Stationary tests are conducted to ensure that the data used in the analysis does not contain root units, which means that the data is stationary and has constant variance and mean over time. In this context, the stationary test was carried out using Augmented Dickey-Fuller (ADF) with the Fisher Chi-square and Choi Z-stat methods. The results of the Stationary Test for each variable can be seen in Table I.

Table 1. Results of the Stationary Test of each Variable

Method	**Statistics**						
	PRD_INT	X1_INF	X2_FDI	X3_MSZ	X4_PDB	X5_TRF	X6_KURS
Fisher Chi-square	7.73347	49.0962	45.3689	16.9518	73.9157	67.1517	32.6692
Play Z-stat	5.26695	-3.64500	-1.43126	0.59042	-5.51389	-4.16181	-0.21676
Method	**Probabilities**						
Fisher Chi-square	0.9935	0.0003	0.0010	0.6561	0.0000	0.0000	0.0367
Play Z-stat	1.0000	0.0001	0.0762	0.7225	0.0000	0.0000	0.4142

For the PRD_INT and X3_MSZ variables, the results of the stationary test showed that the statistical values of ADF-Fisher Chi-square tended to be low and ADF-Choi Z-stat tended to be high with high probability, respectively. This high probability indicates that the null hypothesis (H0) cannot be rejected, so the variables PRD_INT and X3_MSZ contain root units and are not stationary at the level of the original data. However, when the data were first differentiated (D(PRD_INT) & D(X3_MSZ)), the test results using the ADF-Fisher Chi-square method showed statistical values (for each variable) of 56.6063 and 55.6246 with a probability of 0.0000, while using the ADF-Choi Z-stat method were obtained of -3.83805 and -4.19646 with a probability of 0.0001 and 0.0000, respectively. This suggests that after the first differentiation, the data becomes stationary because a very low probability indicates the rejection of the null hypothesis.

Meanwhile, the tests for other variables (X1_INF, X2_FDI, X4_PDB, X5_TRF, X6_KURS) were obtained that the statistical values using ADF-Fisher Chi-square tended to be high and tended to be low with the ADF-Choi Z-stat method with a very low probability of 0.which was very low. This very low probability (below 0.05) suggests that we can reject the null hypothesis that there is a root unit, so that each of those variables can be declared stationary at the level of the original data. In addition, the intermediate ADF test results for each cross-section also support this result, where most cross-sections have a low probability, indicating a null hypothesis rejection. Although there are some cross-sections with higher probability, the majority show that the data on those cross-sections are stationary. Thus, it can be concluded that each variable tested contains no root unit and is stationary, making it eligible for use in advanced analysis without the need for differentiation

Determining the lag length in the VECM model is an important step to ensure that the model can accurately describe the dynamic relationships between variables. Based on the test results in Table 2, several criteria are used to determine the optimal lag length, namely Likelihood Ratio (LR), Final Prediction Error (FPE), Akaike Information Criterion (AIC), Schwarz Information Criterion (SC), and Hannan-Quinn Information Criterion (HQ). The results of the lag length selection show that the LR, FPE, and AIC criteria all indicate optimal lag at the 3rd lag. Meanwhile, the SC and HQ criteria choose the optimal lag in the 1st lag. Although there are differences between the SC and HQ criteria and the others, three of the five criteria that are more widely used in the econometric literature show that the optimal lag is the 3rd lag. Therefore, in this analysis, the selected lag length is the 3rd lag, given the consistency of the results of several criteria that generally provide more reliable results in the VECM model.

Table 2. Results of Lag length determination

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-6644.328	NA	1.44e+36	103.1214	103.2766	103.1844
1	-5655.200	1855.574	6.73e+29	88.54574	89.78720*	89.05017*
2	-5592.430	110.9416	5.47e+29	88.33225	90.66001	89.27807
3	-5515.342	127.8835*	3.60e+29*	87.89677*	91.31081	89.28396

The results of Johansen's cointegration test on the variables PRD_INT, X1_INF, X2_FDI, X3_MSZ, X4_PDB, X5_TRF, and X6_KURS in Table 3 show varying results. The v-Statistic panel and the rho-Statistic panel have a probability value greater than 0.05, so the null hypothesis stating the absence of cointegration cannot be rejected. This suggests that there is not enough evidence to support the existence of cointegration based on these statistics. However, the weighted PP-Statistic Panel and ADF-Statistic Panel show a very low probability (0.0000), so the null hypothesis can be rejected and there is a strong indication of cointegration. On the other hand, the rho-Statistic Group shows a probability of 1.0000, indicating the absence of cointegration, while the PP-Statistic Group with a probability of 0.0000 supports the existence of cointegration. The ADF-Statistic group with a probability of 0.0515 shows some evidence of cointegration. Thus, although there is evidence to suggest a long-term relationship between these variables, these results are inconsistent across the statistics used.

Table 3. Results of the Johansen Variable Cointegration Test

PRD_INT X1_INF X2_FDI X3_MSZ X4_PDB X5_TRF X6_KURS
Included observations: 160
Cross-sections included: 10

	Statistics	Prob.	Weighted Statistics	Prob.
V-Statistic Panel	0.446403	0.3277	-2.880622	0.9980
rho-Statistic Panel	2.693746	0.9965	2.871089	0.9980
Panel PP-Statistic	1.545483	0.9389	-4.620385	0.0000
Panel ADF-Statistic	1.495374	0.9326	-4.044357	0.0000
	Statistics	Prob.		
Group rho-Statistic	4.470637	1.0000		
Group PP-Statistic	-6.901002	0.0000		
Group ADF-Statistic	-1.630095	0.0515		

The results of the Engle-Granger causality test show several significant causal relationships between economic variables in the sample data from 2007 to 2022 with a lag of 3. Industrial production (PRD_INT) has a significant influence on foreign direct investment (X2_FDI), but not the other way around. Gross domestic product (X4_PDB) also has a significant effect on industrial production. Market size (X3_MSZ) affects foreign direct investment and tariffs (X5_TRF), but the opposite does not apply. No significant causal relationship was found between inflation (X1_INF) and other variables, as well as between exchange rates (X6_KURS) and most other variables.

The results of the Vector Error Correction estimation show a long-term relationship between the variables analyzed. The coefficient of cointegration indicates a significant positive relationship of D(PRD_INT(-1)) with several variables and a significant negative relationship with D(X1_INF(-1)), D(X3_MSZ(-1)), D(X4_PDB(-1)), and D(X6_KURS(-1)). The error coefficient of the correction term (CointEq1) is significant for several variables, indicating the existence of an adjustment mechanism towards long-term equilibrium. Inflation, GDP, and exchange rates have a significant impact on industrial production in the short term, while foreign direct investment and tariffs have not shown significant effects. The model explains the data variation well for most variables, but there are some variables with lower R-squared values, indicating the presence of other influential factors that are not included in the model. The results of the VEC show a complex relationship between the economic variables analyzed, with some variables showing significant influence in the short and long term.

The impulse response function (IRF) analysis of the VECM shows the dynamics of complex economic variable interactions. Shocks in industrial production (D(PRD_INT)) were initially significant but declined over time, with other variables such as inflation (D(X1_INF)), foreign direct investment (D(X2_FDI)), market size (D(X3_MSZ)), Gross Domestic Product (D(X4_PDB)), transfers (D(X5_TRF)), and exchange rates (D(X6_KURS)) indicating a diverse influence that tended to be negative. Inflation (D(X1_INF)) experienced significant initial fluctuations with long-term negative impacts from variables such as D(X2_FDI) and D(X4_PDB). Foreign direct investment (D(X2_FDI)) is particularly sensitive to economic changes, while other variables show varying influences. The market size (D(X3_MSZ)) increases significantly initially but then fluctuates, influenced by D(X2_FDI) and D(X4_PDB). GDP (D(X4_PDB)) showed a negative response overall, greatly affected by D(PRD_INT) and D(X1_INF). Transfer (D(X5_TRF)) shows a long-term positive response despite significant initial fluctuations, with a strong influence from the rate (D(X6_KURS)). The exchange rate (D(X6_KURS)) increased significantly initially but fluctuated, with a positive response from transfers (D(X5_TRF)) and other economic variables. The IRF describes the dynamic interaction of economic variables, showing the significant impact of changes in one variable on another over a period of time.

Variance Decomposition (VD) in the VECM model shows the relative contribution of variables in explaining variability over various time periods. Initially, the variability of each variable is largely explained by itself. However, over time, the contribution of other variables increased. In the 10th period, industrial production (D(PRD_INT)) was significantly influenced by GDP, exchange rate, and transfers; inflation (D(X1_INF)) by GDP, industrial production, and exchange rates; foreign direct investment (D(X2_FDI)) by industrial production, market size, and inflation; market size (D(X3_MSZ)) by industrial production, inflation, and exchange rates; GDP (D(X4_PDB)) by industrial production, inflation, and foreign direct investment; transfer (D(X5_TRF)) by exchange rate, industrial production, and inflation; and the exchange rate (D(X6_KURS)) by transfer. GDP, inflation, and industrial production play important roles in the economic system, with the contribution of other variables increasing over time.

The VECM highlights both short-term dynamics and long-term relationships in intra-ASEAN trade. Impulse response functions (IRFs) show that GDP growth and tariff reductions significantly boost trade volumes, emphasizing the importance of economic interdependence and policy measures like those under the ASEAN Economic Community. Exchange rate shocks have mixed effects, with short-term export gains for depreciating currencies but potential long-term disruptions to regional trade balances. Variance decomposition (VDC) reveals that GDP growth is the primary driver of trade variance over the long term, while exchange rate fluctuations dominate in the short term. Trade policies, including tariff reductions, gain importance over time, reflecting their cumulative impact. These findings underscore the need for sustained economic growth and consistent trade policies to enhance regional trade. Addressing short-term exchange rate volatility through monetary coordination could improve trade stability. The results also highlight the benefits of long-term economic integration, where infrastructure and policy harmonization play vital roles. Lastly, the interconnected dynamics revealed by VECM stress the importance of coordinated regional strategies to optimize collective trade growth.

Table 4. Variance Decomposition results of each variable

Period	S.E.	D(PRD_INT)	D(X1_INF)	D(X2_FDI)	D(X3_MSZ)	D(X4_PDB)	D(X5_TRF)	D(X6_KURS)
Variance Decomposition of D(PRD_INT):								
1	12109.26	100.0000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
…	…	…	…	…	…	…	…	…
10	27133.35	73.65548	0.628751	2.173110	0.112494	9.525611	3.483793	10.42077
Variance Decomposition of D(X1_INF):								
1	2.548162	0.230689	99.76931	0.000000	0.000000	0.000000	0.000000	0.000000
…	…	…	…	…	…	…	…	…
10	3.901908	3.367444	66.68995	0.770631	0.930637	14.82898	4.151256	9.261102
Variance Decomposition of D(X2_FDI):								
1	6489.006	0.936577	0.429003	98.63442	0.000000	0.000000	0.000000	0.000000
…	…	…	…	…	…	…	…	…
10	10400.70	17.27167	1.669147	66.78087	7.710005	1.383917	0.834189	4.350195
Variance Decomposition of D(X3_MSZ):								
1	2073.423	11.54005	0.022280	0.007830	88.42984	0.000000	0.000000	0.000000
…	…	…	…	…	…	…	…	…
10	4873.223	9.355697	1.680667	4.484437	75.17374	1.978522	0.862244	6.464689
Variance Decomposition of D(X4_PDB):								
1	3.294334	7.315225	0.972025	1.019779	0.596894	90.09608	0.000000	0.000000
…	…	…	…	…	…	…	…	…
10	5.363779	16.69847	8.243619	4.449857	1.282592	65.33662	3.034982	0.953870
Variance Decomposition of D(X5_TRF):								
1	0.898245	0.005132	2.051941	2.103240	0.254888	0.647239	94.93756	0.000000
…	…	…	…	…	…	…	…	…
10	1.775268	3.592681	2.819175	0.942565	0.664709	4.750137	83.55119	3.679546

Variance Decomposition of D(X6_KURS):								
1	482.5907	0.192783	0.069919	0.561746	0.453034	0.001987	6.698687	92.02185
…	…	…	…	…	…	…	…	…
10	1457.347	0.104620	0.738359	0.620162	0.292104	0.236442	5.686963	92.32135

The ANFIS modeling process starts by getting a dataset of different data types to load into the system which includes training and testing datasets. The data entered into modeling is input data and output data. In this research, input data includes inflation (INF), Foreign Direct Investment (FDI), Market Size (MSZ), Economic Growth (GDP), Import Tariffs (TRF), and currency exchange rates (KURS). The output data is the value of international trade growth (PRD_INT). In system modelling, the Grid Partition method used to produce FIS. The main advantage of using a partition grid in FIS is that there are no dimension restrictions, meaning that when we increase the number of input variables the number of rules also increases. Six input variables have three Member Functions (MF) for each input variable, so the number of rules formed is 36 which also present the relationship between input and output. Each data input has the same membership function, namely the Triangle Member Function (trimf) type and the data output has a constant membership function. After setting Generate FIS, the ANFIS architecture will be formed as in Figure.1.

The Train FIS method used by the hybrid learning algorithm combines the Least-square method and the Back-propagation gradient descent method to train the resulting FIS. Training is carried out to adjust the MF parameters produced by FIS and achieve Root Mean Square Error. Through a hybrid learning algorithm, the training process is carried out by choosing the number of iterations. The number of epochs is the number of training iterations to get the smallest error value. This model uses 4 epochs with RMSE value obtained 4 is about 386.6. After the FIS (Fuzzy Inference System) training process, validation of the FIS output is carried out to ensure model accuracy using a test data set which is part of the training data set as in Figure 2. Fig. 3 shows a comparison of the results between the actual output value (true value) and the ANFIS prediction results in the model training process. Based on Fig. 3, the ANFIS model training results show a very good similarity between the predicted value (ANFIS Value) and the actual value (True Value). This indicates that the ANFIS model has a high prediction accuracy of 94.3%.

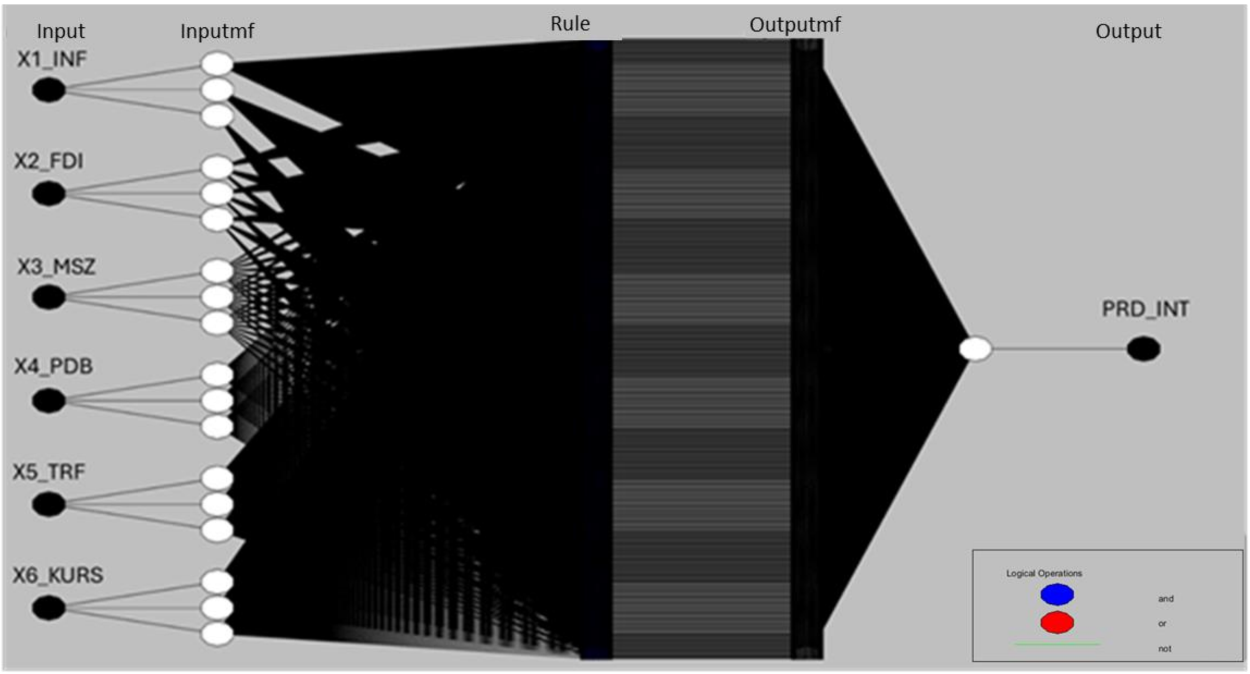

Fig. 1. ANFIS architecture after membership function initiation

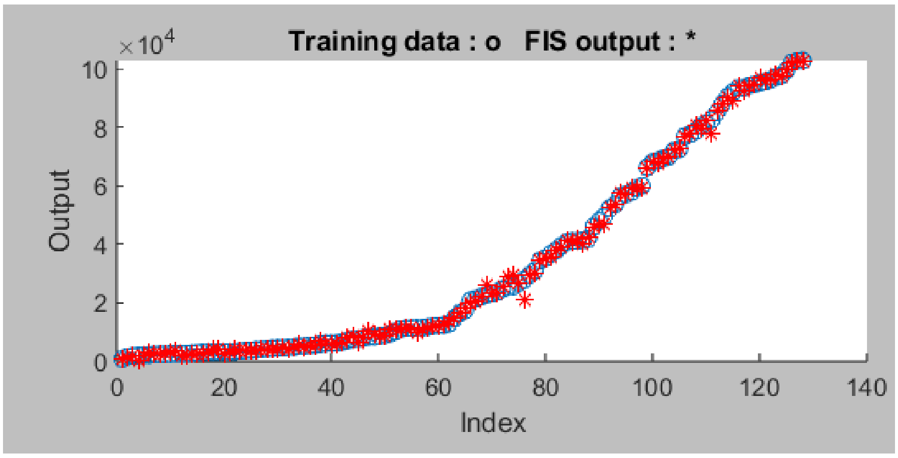

Fig. 2. Training data testing results

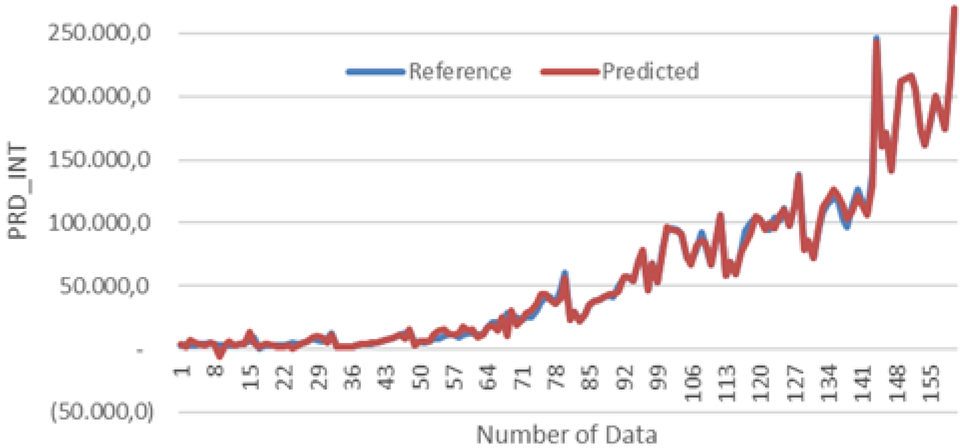

Fig.3. ANFIS Modeling Test Results: Comparison of Model Output and Reference in the form of Measurement Data

Apart from high accuracy, the model also shows good stability in predicting values, both in the low and high value ranges. The model is able to follow the data growth trend consistently, which is an important indicator in evaluating the performance of predictive models. The model's ability to maintain prediction accuracy over a wide range of data conditions indicates that the ANFIS model is well trained and reliable for practical applications. Overall, the ANFIS model was trained effectively, producing highly accurate and stable predictions throughout the training period. Fig. 4 shows the error values for each prediction during the training process, which can be used to analyze error patterns and better understand the model performance. The consistently low error pattern strengthens the evidence that this model is not only accurate but also robust to variations in the training data. This analysis confirms that ANFIS is a highly effective tool for complex prediction problems, offering high accuracy and stability in a wide range of data conditions. Further research could focus on applying this model across different domains to test its generalizability and identify potential for further improvements.

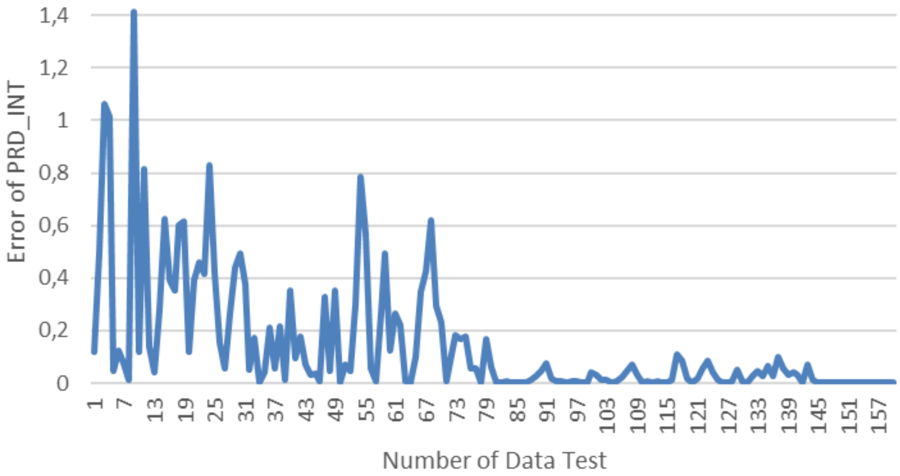

Fig. 4. The error values for each prediction during the training process

Figure. 5-7 are the comparison of ANFIS Modeling accuracy when tested for each Country. The ANFIS model's predictions (Fig. 5) for Brunei show an average error of approximately 0.22, with an accuracy of 77.82%. The error rates vary significantly, indicating inconsistencies in the model's performance. For example, the model predicted a value of 3577 for a reference value of 3192.8, resulting in an error of 0.1203. Conversely, for a reference value of 6276.3, the model predicted 6328, yielding a minimal error of 0.0082. The variation in error rates suggests the model performs better with certain values but struggles with others, particularly lower ones. In Cambodia, the ANFIS model exhibits a lower average error of approximately 0.116 and a higher accuracy of 88.40%. The model performs well with several values, such as predicting 1836 for a reference value of 1836.2, resulting in an error of almost zero. However, the model also shows significant errors, such as predicting 4427 for a reference value of 3278, yielding an error of 0.3505. Despite these discrepancies, the overall higher accuracy indicates a relatively reliable model performance. The ANFIS model achieves impressive accuracy in Indonesia, with an average error of 0.018 and accuracy of 98.22%. The model demonstrates remarkable precision, with errors consistently low across the dataset. For instance, the model predicted 46370 for a reference value of 46084.2, resulting in an error of 0.0062. Even the highest errors, such as predicting 82160 for a reference value of 78686.7, yield a relatively low error of 0.0441. This high level of accuracy suggests the model is exceptionally effective in predicting values for Indonesia. The model's performance in Laos is less accurate, with an average error of 0.299 and an accuracy of 70.14%. The model struggles significantly, particularly with lower and mid-range values. For example, it predicted 1065 for a reference value of 833.9, resulting in an error of 0.2771, and predicted 4002 for a reference value of 2478.1, yielding a high error of 0.6149. The high error rates indicate that the model needs substantial adjustments to improve its prediction accuracy for Laos

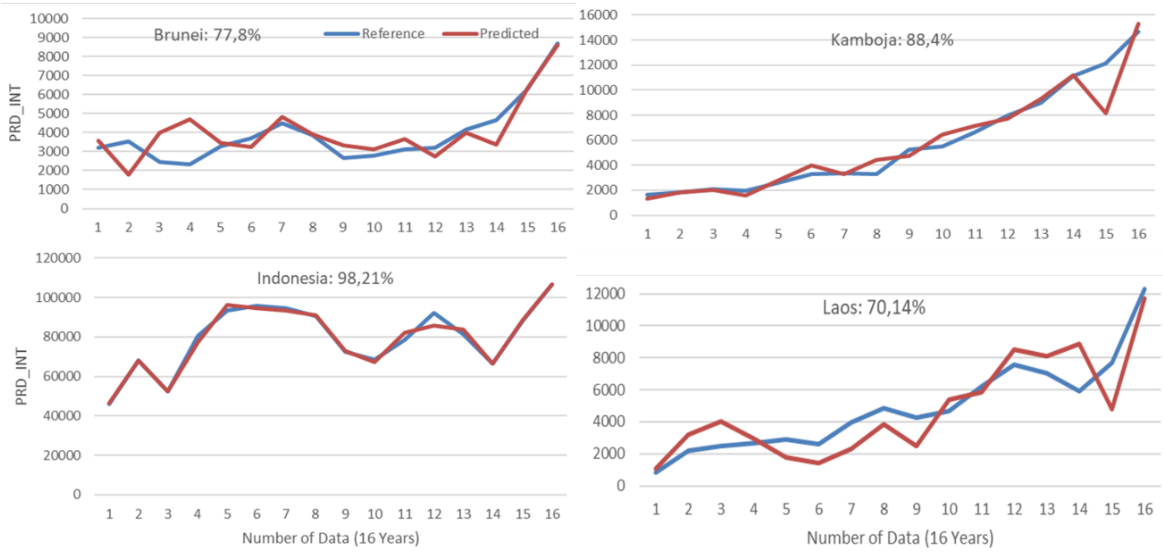

Fig. 5. Accuracy of ANFIS Modeling Testing for each Country: Brunei, Kamboja, Indonesia, and Laos.

In Malaysia (Fig. 6), the model shows a low average error of approximately 0.037 and high accuracy of 96.31%. The model performs well, with predictions such as 85620 for a reference value of 85076.7, resulting in an error of 0.0064. However, there are some higher errors, such as predicting 113230 for a reference value of 102847.8, yielding an error of 0.1009. Overall, the model demonstrates strong reliability and accuracy in Malaysia. The ANFIS model's performance in Myanmar is less reliable, with an average error of 0.223 and accuracy of 77.72%. The model struggles with some values, such as predicting 3096 for a reference value of 4804.8, resulting in an error of 0.3556, and predicting 14984 for a reference value of 8391.9, yielding a high error of 0.7855. The inconsistencies and high error rates suggest that the model needs refinement for better accuracy in Myanmar. For the Philippines, the model shows an average error of approximately 0.158 and accuracy of 84.18%. The model performs reasonably well with some values, such as predicting 22665 for a reference value of 22786.2, resulting in an error of 0.0053. However, there are significant errors, such as predicting 19023 for a reference value of 24758.3, yielding an error of 0.2317. The mixed performance indicates a need for model adjustments to improve accuracy. The ANFIS model demonstrates exceptional accuracy in Singapore, with an average error of 0.0012 and accuracy of 99.88%. The model's predictions are highly precise, such as predicting 160610 for a reference value of 160853.6, resulting in an error of 0.0015, and predicting 269010 for a reference value of 269012.6, yielding an almost negligible error of 0.00001. The consistently low errors indicate a highly reliable model for Singapore.

In Thailand (Fig. 7), the model shows a low average error of approximately 0.029 and high accuracy of 97.13%. The model performs well, with predictions such as 58220 for a reference value of 57886.8, resulting in an error of 0.0058. However, there are some higher errors, such as predicting 83170 for a reference value of 93508, yielding an error of 0.1106. Overall, the model demonstrates strong reliability and accuracy in Thailand. The ANFIS model achieves impressive accuracy in Vietnam, with an average error of 0.013 and accuracy of 98.72%. The model's predictions are highly precise, such as predicting 23146 for a reference value of 23175.3, resulting in an error of 0.0013, and predicting 269010 for a reference value of 269012.6, yielding an almost negligible error of 0.00001. The consistently low errors indicate a highly reliable model for Vietnam.

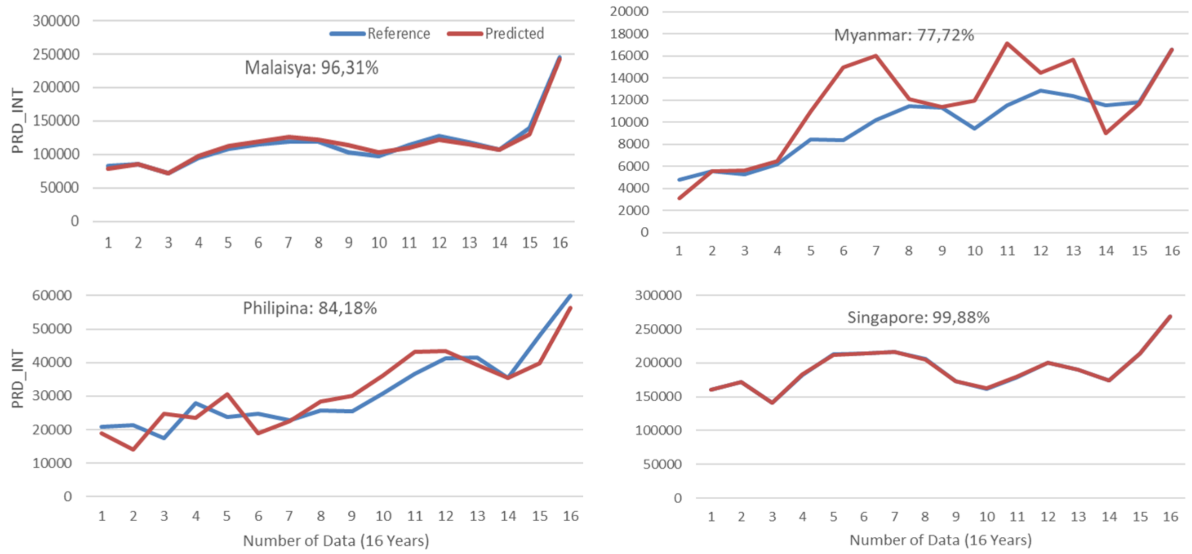

Fig. 6. Accuracy of ANFIS Modeling Testing for each Country: Malaysia, Myanmar, Philipina, and Singapore

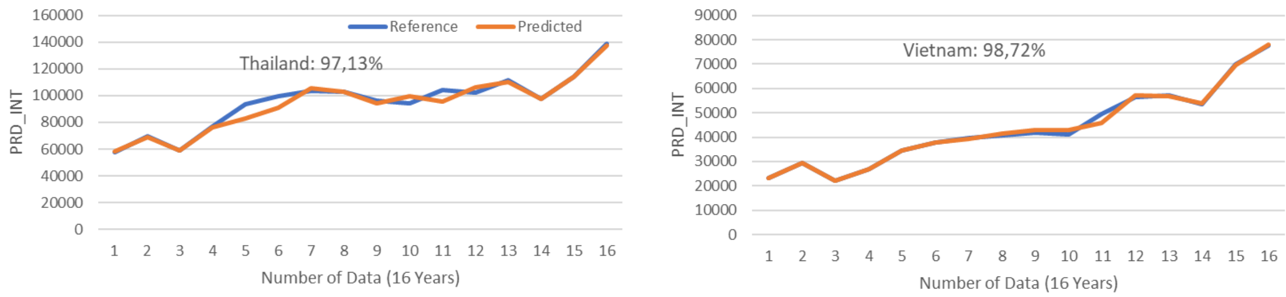

Fig. 7. Accuracy of ANFIS Modeling Testing for each Country: Thailand and Vietnam

The performance of the ANFIS model varies significantly across the ten countries. It achieves the highest accuracy in Singapore and Vietnam, followed by Indonesia, Thailand, Malaysia, Cambodia, the Philippines, Brunei, Myanmar, and Laos. The findings suggest that while the model is highly effective in certain regions, it requires refinement and optimization to achieve consistent accuracy across different datasets. Enhancing the model parameters, increasing training data, and conducting detailed error analysis could improve the ANFIS model's overall prediction accuracy and reliability.

4. Conclusions

The analysis confirms that most variables are stationary after differentiation and indicates a significant long-term relationship among key economic variables. The optimal lag length for VECM analysis is three, and the model effectively captures the dynamics of these variables. The ANFIS model achieved high prediction accuracy of 94.3% during the training process across different datasets, showcasing its ability to closely follow the actual data trends. The model exhibited strong stability and robustness in predicting values over a wide range of data conditions. This was evident from the consistently low error patterns observed during the training process, indicating the model's reliability in practical applications. The ANFIS model's performance varied across different countries: Indonesia (98.22%), Singapore (99.88%), Thailand (97.13%), Vietnam (98.72%), Cambodia (88.40%) and Malaysia (96.31%) showed exceptional accuracy, with low average errors, indicating the model's strong predictive power in these regions; Lower accuracy in countries like Laos (70.14%) and Myanmar (77.72%), the model's performance was less reliable, with higher average errors indicating the need for further refinement and adjustments to improve prediction accuracy. The ANFIS model has proven to be a highly effective tool for predicting economic variables, offering high accuracy, stability, and robustness across diverse data conditions. Its application potential extends beyond economic forecasting to various other domains requiring complex data analysis and prediction capabilities. The study's limitations include reliance on historical data that may overlook structural changes and external shocks, and the potential oversimplification of trade dynamics by the chosen methods. For policymakers, the research emphasizes coordinated efforts to enhance GDP growth, stabilize exchange rates, and harmonize policies. It highlights the importance of infrastructure investment and strategies to reduce trade barriers, offering insights to strengthen intra-ASEAN trade and economic integration.

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