Forecasting Indonesia's Export Values Using SETAR-GA and SETAR-Tree

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ABSTRACT

This study employs two advanced nonlinear time series models, SETAR-GA and SETAR-Tree, to forecast Indonesia's export values. The SETAR-GA model integrates a genetic algorithm to optimize parameters within a self-exciting threshold autoregressive framework, while the SETAR-Tree model combines SETAR with a recursive partitioning approach to capture regime changes more flexibly. The nonlinearity in the export data was confirmed using the Terasvirta test. The performance of both models is evaluated using in-sample and out-of-sample forecasting accuracy, assessed through MAPE and RMSE. The results indicate that both models are capable of capturing nonlinear patterns in export data, with SETAR-GA showing superior forecasting performance. These findings highlight the potential of nonlinear models to improve export forecasting in emerging economies.

Keywords-genetic algorithm; forecasting; nonlinear; SETAR-Tree; accuracy

I. INTRODUCTION

Exports connect countries through international trade, enabling the exchange of goods and services while addressing challenges such as enhancing trade competitiveness, promoting economic stability, and strengthening global cooperation, particularly for developing economies navigating the uncertainties of an increasingly integrated global market [1]. Exports are divided into direct and indirect, with the former involving producers selling their products directly to international markets and the latter occurring through domestic intermediaries that export the products abroad. Analysis of Belgian firm-level data reveals that only 12% of firms engage in direct exporting, while the majority (88%) participate indirectly by supplying domestic buyers who subsequently trade internationally [2]. For exporting countries, exports play a pivotal role in driving economic growth by increasing income, generating foreign exchange, enhancing welfare, expanding markets, and fostering innovation. For importing countries, exports address demands for goods and services that are challenging to produce domestically, improve product quality, and facilitate technology transfer. As a resource-rich country, Indonesia holds a strategic position in the global market. Its export sector, encompassing both oil and gas and non-oil and gas products, underscores its substantial potential to contribute to international trade and economic development [3]. Accurate export data is essential for the government to establish appropriate trade, investment, and infrastructure policies, making export trend forecasting crucial for future planning.

Indonesia's export data from 2007 to 2023 show fluctuations influenced by global economic dynamics and the country's internal conditions. Significant declines occurred in 2009 due to the global economic crisis and in 2020 due to the impact of the COVID-19 pandemic on international trade. These fluctuations indicate the presence of nonlinear components in Indonesia's export values, necessitating the use of appropriate nonlinear models to forecast future export trends. As highlighted in [4], the COVID-19 pandemic severely impacted global trade sectors, with energy- and resource-dependent economies experiencing sharp demand shocks and declining investments, underlining the importance of adaptive strategies for economic recovery. Similarly, the role of diversification and non-linear modeling becomes vital in managing trade uncertainties, as evidenced by research into non-oil export contributions to economic growth in Saudi Arabia and other resource-driven economies [5]. In 2022, Indonesia's export sector contributed more than 20% to its GDP, highlighting the strategic role of international trade in national economic resilience and growth. With this level of contribution, reliable forecasting of export values is essential for supporting policy decisions and market planning.

Despite extensive efforts to model export behaviors, traditional linear models often fall short of capturing the inherent nonlinearities present in economic time series. The volatility of Indonesia's export data, influenced by global commodity prices, trade policies, and external shocks, calls for more advanced modeling approaches. Although several studies have explored ARIMA, VAR, and machine learning techniques, few have explicitly addressed threshold behavior or regime-switching patterns that are common in real-world export dynamics. This study addresses this gap by applying nonlinear methods capable of modeling asymmetric responses in export trends.

Nonlinear time series models, such as Threshold Autoregressive (TAR), Self-Exciting Threshold Autoregressive (SETAR), Markov chain, and Artificial Neural Networks (ANNs), are often used to capture nonlinear patterns in data [6]. For example, the SETAR model uses a step transition function to differentiate patterns based on certain conditions (regimes) and applies different autoregressive models in each one [7]. However, manual selection of thresholds and delays remains a significant limitation, as this process is often time-consuming, computationally demanding, and susceptible to overfitting.

To overcome these issues and improve the accuracy of the SETAR model, Genetic Algorithm (GA) methods are often used as an optimization tool. GA is an effective metaheuristic method for finding global optimum solutions to complex nonlinear problems [8]. Previous research has shown that GA is more accurate than conventional methods in identifying and estimating parameters in the SETAR model, such as in stock return forecasting [9, 10]. Further enhancing nonlinear modeling, the SETAR-Tree model has been developed as a variation of SETAR, using a tree-based approach to find the optimal lag and threshold that divide the data into nodes. In each leaf node, a linear AR model is applied to analyze the time series in more detail. Previous studies have shown that although SETAR-Tree performs less well in in-sample forecasting, it outperforms conventional SETAR models in out-of-sample forecasting [11].

Given the need to predict nonlinear fluctuations in Indonesia's export data, this study compares the performance of the SETAR-GA and SETAR-Tree models in forecasting Indonesia's export values. Performance evaluation of these two models uses error measures such as the Mean Absolute Percentage Error (MAPE) and the Root Mean Square Error (RMSE). Through this research, it is hoped that the government and business actors will obtain more accurate information to formulate more appropriate trade and investment policies in the future.

II. METHODOLOGY

The rationale for selecting the following models is grounded in their proven ability to handle complex, nonlinear time series data.

A. Self-Exciting Threshold Autoregressive (SETAR) Model

SETAR is a special case of the TAR model. In the SETAR model, the transition between regimes is controlled by a variable called the threshold, similar to the TAR model. What differentiates SETAR is that its threshold is endogenous, meaning it is determined by the lagged values of the time series itself, rather than an exogenous variable as in the TAR model [12]. In general, the SETAR model with two regimes is described as:

$$y_t = \begin{cases} \phi_0^{(1)} + \sum_{i=1}^{p_1} \phi_i^{(1)} y_{t-i} + \varepsilon_t^{(1)} & if \ \ y_{t-d} \le r_1 \\ \phi_0^{(2)} + \sum_{i=1}^{p_2} \phi_i^{(2)} y_{t-i} + \varepsilon_t^{(2)} & if \ y_{t-d} > r_1 \end{cases} \quad (1)$$

where y_t is the value of the variable at time t, k denotes the number of regimes in the model, p_k is the autoregressive order in the k-th regime, d is the delay of the threshold variable, and r_k represents the threshold for the k-th regime. The threshold values satisfy the boundary condition $-\infty = r_0 < r_1 < \cdots < r_{k-1} < r_k = \infty$. Within each regime, the error term ε_t is assumed to follow a normal distribution $\varepsilon_t \sim \mathrm{N}(0, \sigma^2)$.

B. Genetic Algorithm (GA)

GA is an optimization algorithm developed by John Holland in 1975, inspired by Darwin's theory of evolution. It uses a population-based approach, where solutions are represented as chromosomes, and parameters are genes. The algorithm applies selection, crossover, and mutation to evolve solutions, with a fitness function evaluating their quality. Selection mechanisms such as random or roulette wheel help prioritize better solutions while maintaining diversity to avoid local optima [13]. In GA, chromosomes represent the solutions to the problem in the form of individuals in a population. The process of searching for an optimal solution is carried out through selection, mutation, and crossover to produce a new generation (offspring). Chromosomes with better objective function values have a higher chance of becoming parents to the new offspring. In general, the stages of the algorithm in GA are as follows [14]:

- Generate an initial population.
- Set the iteration with $i = 1$.
- Select the best individuals for replication (elitism).
- Select parents for crossover.
- Perform crossover on the selected parents.
- Determine the individuals to undergo mutation.
- If not converged, continue the iteration with $i = i + 1$.
- Return to step 2 and repeat the process

C. Self-Exciting Threshold Autoregressive-Tree (SETAR-Tree)

SETAR-Tree is a new tree-based algorithm that uses the basic concept of SETAR in defining model splits (nodes). Specifically, this method determines the nodes with optimal lag and optimal threshold, identified using a grid search approach without considering each split used by the linear regression tree model [15]. In SETAR-Tree, the node splitting criteria are divided into two: linearity tests and/or error reduction. A node will only be further split if there is a significant nonlinear residual. The hypothesis used in the F-test is as follows:

- H_0: There is no significant nonlinear residual in the training instance.
- H_1: There is significant nonlinear residual in the training instance.

The test statistic is calculated as:

$$F^* = \left(\frac{SSE(P)-SSE(C)}{df_P-df_C}\right)\left(\frac{df_C}{SSE(C)}\right) \tag{2}$$

where $SSE(P)$ is the Sum of Squared Errors (SSE) of the parent node, $SSE(C)$ is the SSE of the child node, $df_P = N - L - 1$ are the degrees of freedom for the parent node, and $df_C = N - 2L - 2$ are the degrees of freedom for the child node. The decision to reject the H_0 is if $F^* > F_{(\alpha;\, df_P, df_C)}$ or if the p-value is less than the significance level α. In this case, the null hypothesis is rejected, and the node is divided into a child node.

D. Error Reduction

The SETAR-Tree method uses error reduction as a criterion to decide whether a node should be further split. Specifically, a node will only be split if the percentage of error reduction is greater than or equal to a predefined error threshold, denoted as ε. If the error reduction does not reach this threshold, the node is considered a leaf node, and no further splitting is performed. The error threshold value ε has been empirically determined through experiments in [15], with a default setting of 3%.

E. Model Building, Optimization, and Validation

This study employs two nonlinear time series models, SETAR-GA and SETAR-Tree, to forecast Indonesia's export values. The modeling process involves several key steps: testing for nonlinearity, parameter estimation, model optimization, and performance evaluation. For both SETAR-GA and SETAR-Tree models, the first step is to test for nonlinearity using the Terasvirta neural network test. If the test indicates nonlinearity, modeling proceeds with the nonlinear approach.

1) SETAR-GA Modeling Procedure

The structure of the SETAR model is first determined by selecting the optimal lag order using PACF plots and identifying the best delay and threshold parameters via a grid search based on the Akaike Information Criterion (AIC). The initial parameter estimation is performed using Ordinary Least Squares (OLS). To enhance accuracy, GA is applied to optimize parameters for both the low and high regimes. The GA process includes initializing a population of chromosomes, evaluating their fitness using the inverse of MAPE, and applying selection, crossover, mutation, and elitism strategies across generations to evolve toward optimal parameter sets. The final SETAR-GA model is validated using both in-sample and out-of-sample forecasts, with performance measured using MAPE and RMSE.

2) SETAR-Tree Modeling Procedure

The SETAR-Tree model begins similarly with the selection of optimal lag and threshold parameters via AIC-guided grid search. OLS is used for initial estimation. A recursive partitioning process based on F-tests is employed to split nodes further if significant nonlinearity remains. The splitting continues until no additional gain in accuracy is achieved or the error falls below a predefined threshold (e.g., 3%). Forecast performance is again evaluated using MAPE and RMSE for both in-sample and out-of-sample data.

3) Model Selection

To determine the best-performing model, SETAR-GA and SETAR-Tree results are compared based on their MAPE and RMSE values. The model with the lowest forecasting error is selected for final prediction.

F. Simulation of SETAR-GA and SETAR-Tree

The simulation is based on data generated from the SETAR model. Scenarios in this simulation include variations in model parameters and the amount of data to evaluate the performance of two models, SETAR-GA and SETAR-Tree, under varying scenarios. Specifically, the scenarios include different autoregressive orders $(p = 2, 3, 4)$ and the number of regimes $(k = 1, 2)$. These scenarios are designed to test the model's ability to forecast export data with varying levels of accuracy. The first scenario utilizes a SETAR (2; 2, 2; 1) model, represented in (3), based on the method described in [16].

$$y_t = \begin{cases} 16 + 0.3y_{t-1} - 0.1y_{t-2} + \varepsilon_t^{(1)}, & if\ y_{t-1} \le 20 \\ 12 + 0.6y_{t-1} - 0.3y_{t-2} + \varepsilon_t^{(2)}, & if\ y_{t-1} > 20 \end{cases} \quad (3)$$

This model consists of two regimes, where the regime change is determined by a threshold value of 20 with lag 1 (y_{t-1}) as the threshold variable. The first regime applies when y_{t-1} is less than or equal to 20, while the second regime applies when y_{t-1} is more than 20.

The second scenario applies a SETAR (2; 3, 3; 1) model, as described in:

$$y_t = \begin{cases} 20 + 0.6y_{t-1} + 0.2y_{t-2} - 0.2y_{t-3} + \varepsilon_t^{(1)}, & if\ y_{t-1} \le 30 \\ 10 + 0.4y_{t-1} - 0.2y_{t-2} + 0.1y_{t-3} + \varepsilon_t^{(2)}, & if\ y_{t-1} > 30 \end{cases} \quad (4)$$

This model introduces a higher order autoregressive (3) and uses a threshold value of 30 to divide between the two regimes, using the same threshold variable, lag 1 (y_{t-1}). This setting is intended to test the performance of the model with additional lagged variables in the autoregressive structure.

The third scenario involves a SETAR (2; 4, 4; 1) model, as expressed in:

$$y_t = \begin{cases} 25 + 0.4y_{t-1} + 0.3y_{t-2} + 0.2y_{t-3} - 0.1y_{t-4} + \varepsilon_t^{(1)}, & \text{if } y_{t-1} \le 40 \\ 20 + 0.4y_{t-1} + 0.3y_{t-2} - 0.3y_{t-3} - 0.2y_{t-4} + \varepsilon_t^{(2)}, & \text{if } y_{t-1} > 40 \end{cases} \quad (5)$$

In this scenario, the autoregressive order is further increased to 4, and the threshold change is increased to 40 with the same variable threshold of lag 1 (y_{t-1}). This model aims to evaluate the forecasting ability with higher complexity in the autoregressive structure and different threshold values.

In the simulation of the SETAR-GA model, the GA specifications used to optimize the SETAR model include a population size of 200, a crossover probability of 0.7, a mutation probability of 0.1, 3000 generations, and a fitness function aimed at minimizing the MAPE value. From the three previously determined SETAR model equations, 20 sets of simulation data are generated. Each set of data consists of two sizes: small data with 200 data points and large data with 500 data points. This simulation data is used to calculate the MAPE and RMSE values for the two models, SETAR-GA and SETAR-Tree. For each model, 20 MAPE and RMSE values are produced for each data size, small and large. Furthermore, the average MAPE and RMSE values for each model are calculated for both data sizes, which are then compared to determine the model with the best performance, where the model with the smallest MAPE and RMSE values is considered to have better performance for both small and large data.

III. RESULTS AND DISCUSSION

A. Simulation of SETAR-GA and SETAR Tree

The simulations were conducted on two sample sizes: small datasets with 200 observations and large datasets with 500 observations. The data generation process is based on the first scenario using a SETAR (2; 2, 2; 1) model (3). In addition, the estimated parameters and structural characteristics of each model are examined to evaluate the consistency and precision of the estimation procedures.

Table I presents a summary of the simulation results obtained from the application of the SETAR-GA model, conducted with more than 20 replications for both small and large datasets. The table includes estimated parameters across different regimes. The predictive performance of the model, as evaluated by MAPE and RMSE, varies slightly depending on the size of the dataset. For smaller datasets, MAPE values range from approximately 3.71% to 4.63%, while for larger datasets, these values lie between 3.84% and 4.34%. Similarly, RMSE values fall within the range of 0.92 to 1.08 for small datasets and 0.94 to 1.05 for large datasets. These results indicate that both dataset sizes yield comparable predictive accuracy, although the variability suggests a potential sensitivity to the initial parameter settings in the optimization process. Additionally, the computational time required for parameter optimization is notably higher for larger datasets, with average runtimes of approximately 49,339.97 seconds for small datasets and 69,929.79 seconds for large datasets, highlighting the increased complexity and computational burden associated with scaling the model.

TABLE I. RESULTS OF SETAR-GA

Rep.	n	$\phi_0^{(1)}$	$\phi_1^{(1)}$	$\phi_2^{(1)}$	$\phi_0^{(2)}$	$\phi_1^{(2)}$	$\phi_2^{(2)}$	MAPE	RMSE
1	200	18.254	0.245	-0.166	8.494	0.642	-0.162	3.75	0.93
	500	17.521	0.249	-0.133	9.783	0.690	-0.283	4.11	1.01
2	200	17.504	0.293	-0.174	18.86	0.24	-0.279	4.64	1.07
	500	14.148	0.358	-0.059	11.329	0.676	-0.351	4.30	1.03
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
20	200	10.726	0.501	-0.022	10.425	0.477	-0.084	4.14	0.98
	500	14.288	0.357	-0.068	9.035	0.740	-0.305	4.15	0.99

Table II illustrates the results of the SETAR-Tree simulations for both small and large datasets under Scenario 1. The table reports the structural characteristics of the resulting models, including the depth of the tree (the number of hierarchical splits) and the total number of leaf models, which correspond to the distinct regimes identified by the algorithm. The performance metrics (MAPE and RMSE) are also presented for both dataset sizes ($n = 200$ and $n = 500$) using the same replication setup as in the previous simulations. These results allow for a comparative evaluation of the model's complexity and forecasting accuracy across different data sizes, offering insights into how data size may influence both the model structure and its predictive capabilities.

TABLE II. RESULTS OF SETAR-TREE

Rep	n	Depth	Leaf Model	MAPE	RMSE
1	200	2	4	3.88	0.97
	500	3	7	4.13	1.02
2	200	3	7	4.19	1
	500	4	8	4.21	1.01
⋮	⋮	⋮	⋮	⋮	⋮
20	200	3	5	4.18	0.98
	500	4	7	4.19	0.99

These results show that larger datasets ($n = 500$) result in deeper trees with more leaf models, indicating that the SETAR Tree method captures more complex nonlinear structures in the data as sample size increases. However, the MAPE and RMSE values are relatively stable across dataset sizes, demonstrating the robustness of the SETAR-Tree model. To facilitate comparison between the SETAR-GA and SETAR Tree models, Figure 1 presents a visual representation of the MAPE and RMSE values obtained across 20 simulation replications for Scenario 1. This plot highlights the differences in model performance across dataset sizes and illustrates the relative advantages of each approach.

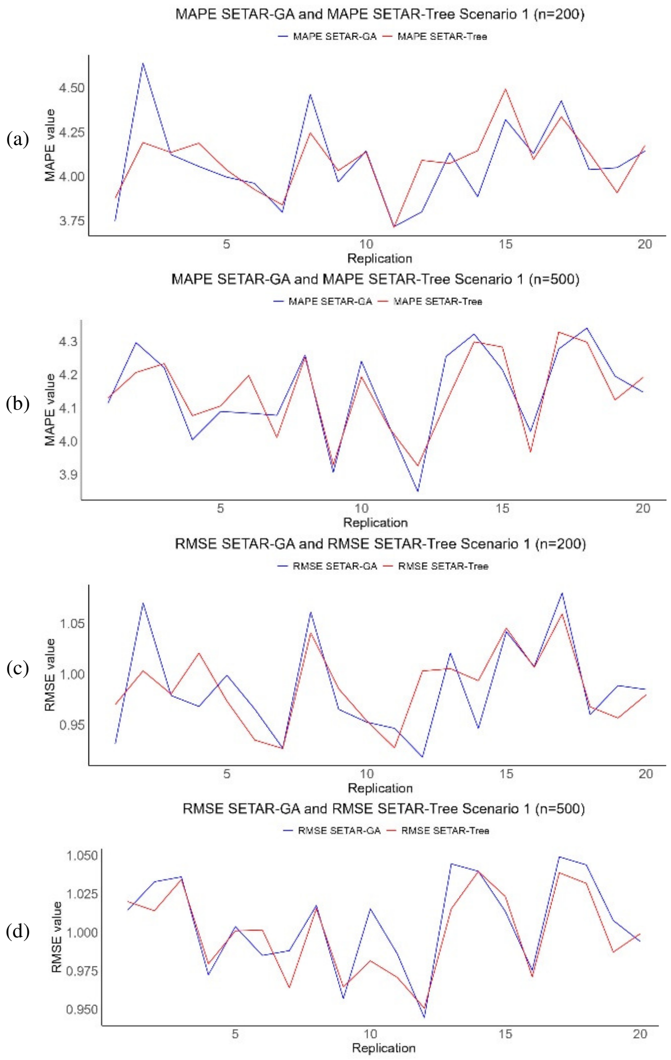

Fig. 1. (a) MAPE SETAR-GA dan SETAR-Tree Scenario 1 (n=200), (b) MAPE SETAR-GA dan SETAR-Tree Scenario 1 (n=500), (c) RMSE SETAR-GA and SETAR-Tree Scenario 1 (n=200), (d) RMSE SETAR-GA and SETAR-Tree Scenario 1 (n=500).

For smaller datasets (Figure 1a), the SETAR-GA model yields slightly lower and more stable MAPE values, ranging from 3.71% to 4.64%, compared to SETAR-Tree, which ranges from 3.71% to 4.49%. However, for larger datasets (Figure 1b), SETAR-Tree outperforms SETAR-GA with lower MAPE values and reduced variability, in the range of 3.92% to 4.33%, while SETAR-GA ranges from 3.84% to 4.34%. Regarding RMSE, both models perform comparably. For smaller datasets, SETAR-GA slightly outperforms, while for larger datasets, SETAR-Tree shows marginally better and more consistent RMSE values. The differences, however, remain small across scenarios. Overall, SETAR-GA tends to perform better on smaller datasets, whereas SETAR-Tree shows greater stability and improved accuracy with larger samples. The narrow performance gap suggests that both models are viable for nonlinear time series analysis, with model selection depending primarily on data size. The simulation results in Figure 1 compare the performance of the models across 20 replications for the two dataset sizes.

Table III summarizes the average evaluation results for Scenario 1 based on (3). These results include the mean and standard deviation of MAPE and RMSE for both models, highlighting their performance differences across dataset sizes. In Scenario 1, the SETAR-GA model produces lower mean MAPE on small samples ($n = 200$), though with greater variability. In contrast, SETAR-Tree results in lower RMSE and more consistent predictions. For large samples ($n = 500$), SETAR-Tree performs better in both MAPE and RMSE, with more stable outcomes across replications. Overall, both models deliver similar accuracy, but SETAR-GA is more effective for small data, while SETAR-Tree offers better stability and handles larger datasets more efficiently.

TABLE III. AVERAGE RESULTS FOR SCENARIO 1

Scenario	n	Model	MAPE		RMSE	
			Mean	St. Dev.	Mean	St. Dev.
1	200	SETAR-GA	4.0775	0.2434	0.9857	0.0479
		SETAR-Tree	4.0891	0.1778	0.9867	0.0375
	500	SETAR-GA	4.1486	0.1373	1.0061	0.0302
		SETAR-Tree	4.1457	0.1242	1.0002	0.0275

With the same treatment, the average evaluation results for the scenarios in (4) and (5) are shown in Table IV.

TABLE IV. AVERAGE RESULTS FOR SCENARIOS 2 AND 3

Scenario	n	Model	MAPE		RMSE	
			Mean	Standard deviation	Mean	Standard deviation
2	200	SETAR-GA	2.7129	0.1572	0.9790	0.0519
		SETAR-Tree	2.7309	0.1855	0.9749	0.0375
	500	SETAR-GA	2.7782	0.0958	1.0043	0.0299
		SETAR-Tree	2.7637	0.0962	0.9909	0.0287
3	200	SETAR-GA	2.1284	0.1365	0.9719	0.0502
		SETAR-Tree	2.1357	0.1502	0.966	0.0514
	500	SETAR-GA	2.1890	0.0738	1.0009	0.0293
		SETAR-Tree	2.1785	0.0846	0.9921	0.0344

In Scenario 2, with small data, SETAR-GA has a lower average MAPE and less variability, while SETAR-Tree has a lower RMSE with more consistent errors. With large data, SETAR-Tree performs better in both MAPE and RMSE, although the difference is not significant. Both models show balanced performance in terms of average prediction error.

In Scenario 3, SETAR-GA has a lower average MAPE value compared to SETAR-Tree, as well as a smaller variability in prediction error on small data. The SETAR-Tree performs better in RMSE but with greater variability. On large data, SETAR-Tree shows improved results in both metrics, though with increased error spread. Overall, both models performed well in terms of the average prediction error.

Overall, the three scenarios in the SETAR-GA and SETAR-Tree models show balanced performance in terms of average prediction error on both small and large datasets.

B. Modelling Indonesia's Export Values

Data on Indonesia's export values in this study cover the period from January 2007 to December 2023, obtained from the Central Bureau of Statistics website (bps.go.id). The data is divided into two subsets: in-sample (January 2007-December 2022) and out-of-sample (January 2023-December 2023), to test the model's performance on observed and unobserved data. Figure 1 presents the time plot of the entire dataset, illustrating the overall trend and seasonal fluctuations in Indonesia's export values throughout the study period.

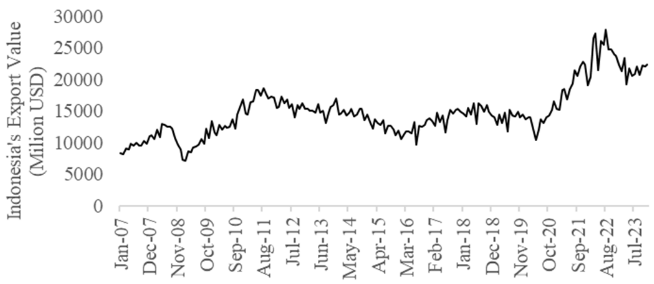

Fig. 2. Plot of Indonesia export values.

Stationary data exhibiting nonlinear characteristics were used in modeling Indonesia's export values. The model identification process was carried out using lags 11 and 12, based on Partial Autocorrelation Function (PACF) analysis, which indicated significant patterns in the data. The two identified SETAR-GA models are SETAR(2; 3, 2; 5) and SETAR(2; 4, 3; 12), with the GA specifications used including a population size of 300, a crossover probability (P_c) of 0.85, a mutation probability (P_m) of 0.1, and a total of 3000 generations. The fitness function was defined to minimize the MAPE value.

TABLE V. IN-SAMPLE EVALUATION OF SETAR-GA MODEL

Model with GA	MAPE	RMSE
SETAR(2; 3,2; 5)	6.739244%	1354.48
SETAR(2; 4,3; 12)	6.534935%	1351.05

Based on Table V, it is known that the best SETAR model with GA optimization is the SETAR(2; 4, 3; 12) model, achieving a MAPE of 6.5349% and an RMSE of 1351.05. Subsequently, the SETAR (2; 4, 3; 12) model with GA optimization was used for out-of-sample forecasting of Indonesia's export values. Furthermore, Table VI provides the configuration of SETAR-Tree models with their corresponding parameters. The selection of lag order, threshold values, and delay parameters was guided by both data characteristics and model performance metrics. Specifically, the maximum lag order was informed by Partial Autocorrelation Function (PACF) plots, while threshold and delay values were optimized via grid search based on Akaike Information Criterion (AIC). This systematic approach ensures that the chosen parameters reflect the nonlinear nature of Indonesia's export data and lead to robust forecasting performance.

TABLE VI. SETAR-TREE CONFIGURATION

Model	Depth	Opt. lag	Opt. threshold	Leaf model	Lag	Parameter
Lag 11	1	1	4.21	1	1	0.868
					2	1.310
					3	-2.239
					4	0.866
					5	0.089
					6	2.551
					7	-2.507
					8	-2.668
					9	1.976
					10	1.966
					11	-1.209
				2	1	0.450
					2	0.322
					3	0.121
					4	0.121
					5	0.077
					6	-0.032
					7	0.031
					8	0.019
					9	-0.014
					10	-0.088
					11	-0.006
Lag 12	0	-	-	0	1	0.520
					2	0.392
					3	0.084
					4	0.036
					5	0.018
					6	-0.075
					7	-0.015
					8	0.014
					9	-0.033
					10	-0.130
					11	-0.084
					12	0.271

In the SETAR-Tree model with lag 11, two leaf nodes are produced, while the model with lag 12 produces one leaf node or the root node itself. The predicted values are obtained from these leaf nodes. The evaluation values of the resulting model are as follows.

TABLE VII. IN-SAMPLE EVALUATION OF SETAR-TREE MODEL

SETAR-Tree	MAPE	RMSE
Lag 11	6.598746%	1281.55
Lag 12	6.981042%	1304.39

Based on Table VII, the SETAR-Tree model with lag 11 is the best model among the two models evaluated. Therefore, this model with lag 11 was used for out-of-sample forecasting of Indonesia's export values. Table VIII shows the out-of-sample forecast evaluation results.

TABLE VIII. OUT-SAMPLE EVALUATION OF SETAR-GA AND SETAR-TREE MODEL

Model	MAPE	RMSE
SETAR(2; 4, 3; 12) with GA	5.11703%	1351.05
SETAR-Tree with Lag 11	5.90989%	1670.8

Based on the evaluation results, the SETAR-GA model shows better performance compared to the SETAR-Tree model, both on in-sample and out-of-sample data. In the MAPE evaluation, the SETAR-GA model has a lower value, indicating a smaller prediction error. Although the RMSE value of the SETAR-GA model is slightly higher on in-sample data, its out-of-sample performance is better with a lower RMSE value. Overall, the SETAR-GA model is more accurate and stable compared to the SETAR-Tree model, especially in out-of-sample data, as shown in Figure 3. Although SETAR-GA demonstrated slightly higher predictive accuracy, SETAR-Tree may be more interpretable and easier to implement in contexts where model transparency is essential. For instance, SETAR-Tree is better suited for real-time decision support in trade monitoring systems, while SETAR-GA may be preferred in data-rich environments where optimization accuracy is prioritized. Thus, the choice of model should be aligned with the specific objectives and constraints of the end-user.

Figure 3 presents the in-sample and out-of-sample forecasts generated by the SETAR-Tree model with lag 11 and the SETAR(2;4,3;12) model optimized with a GA. The plot spans the entire data period from January 2007 to June 2024. During the in-sample phase (January 2007-December 2022), both models closely align with the actual data, although SETAR-GA provides slightly more precise fits at turning points and during periods of sharp fluctuation. SETAR-Tree captures general trends but displays greater deviations around abrupt changes, suggesting that the GA-optimized model handles nonlinear dynamics better.

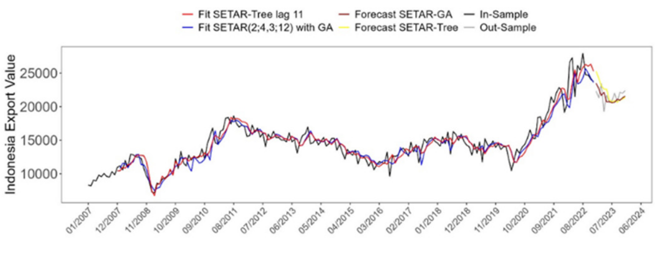

Fig. 3. Plot of forecasting for in-sample and out-of-sample data.

In the out-of-sample period (January 2023–December 2023), both models continue the trajectory of past trends. The SETAR-GA model generates smoother and more consistent forecasts, while the SETAR-Tree model shows greater variability, particularly in the early months of the forecast. However, predictions from both models begin to converge over time, reflecting their comparable long-term tracking capability. Overall, the figure demonstrates that both models are effective in modeling the nonlinear structure of Indonesia's export values, with the SETAR-GA model exhibiting better forecast smoothness and accuracy. The best model chosen to forecast Indonesia's export values for the next six months is SETAR (2; 4, 3; 12) with GA.

Table IX shows the forecasting results using the SETAR-GA model for the period from January to June 2024. Overall, the forecast shows a fluctuating pattern with a peak at the beginning of the period, lower values in the middle, and a slight increase toward the end of the forecast period.

TABLE IX. OUT-OF-SAMPLE EVALUATION OF SETAR-GA AND SETAR-TREE MODEL

Month/Year	SETAR(2; 4, 3; 12) with GA
01/2024	21655.19
02/2024	20924.43
03/2024	19772.14
04/2024	20533.71
05/2024	20242.81
06/2024	20806.44

IV. CONCLUSION

This study offers a novel contribution by systematically comparing two advanced nonlinear time series forecasting approaches, SETAR-GA and SETAR-Tree, applied to Indonesia's export data. Although previous research has focused on either threshold models or tree-based methods independently, this study is among the first to benchmark their forecast performance within a single framework, using both simulated and real-world economic data. The integration of a GA into the SETAR framework (SETAR-GA) represents a methodological innovation that improves optimization accuracy, especially in capturing regime-switching behavior in volatile economic time series. Meanwhile, the application of the relatively new SETAR-Tree model offers interpretability and structural insights, which are critical for policy decision-making. These contributions not only fill a methodological gap in export forecasting, but also provide practical tools for policymakers and analysts working in dynamic trade environments.

The simulation results demonstrate that the SETAR-GA model outperforms the SETAR-Tree model in terms of MAPE for small datasets, while SETAR-Tree exhibits superior performance for large datasets. Additionally, the SETAR-Tree model shows lower RMSE values for both small and large datasets. Despite these differences, the overall performance gap between the two models is minimal, indicating that they offer comparable performance.

In terms of forecasting Indonesia's export values, the best model identified is SETAR(2; 4, 3; 12) optimized using a GA. This model yields lower MAPE and RMSE values compared to the SETAR-Tree model, particularly in the out-of-sample data, thereby indicating its higher accuracy and stability. The SETAR(2; 4, 3; 12) with GA forecasts a fluctuating pattern for Indonesia's export values from January to June 2024, with the highest value predicted for January, followed by a gradual decline through March, and slight fluctuations in the following months.

These results indicate that the SETAR-GA model outperforms the SETAR-Tree in terms of in-sample and out-of-sample forecasting accuracy. This has important implications for Indonesian policymakers and trade analysts. A more accurate export forecast enables better planning of trade policies, import-export regulations, and resource allocation. For businesses, these forecasts can guide production scheduling, inventory management, and investment decisions.

The practical implications of this study are noteworthy for policymakers and trade analysts. By accurately capturing the nonlinear and regime-switching behavior of Indonesia's export values, the SETAR-GA and SETAR-Tree models can support more informed decision-making in international trade planning and economic forecasting. These models, especially when optimized using evolutionary algorithms and recursive partitioning, provide flexible and adaptive forecasting tools that are capable of adjusting to structural breaks and abrupt changes common in trade data.

For future research, several directions are recommended. First, incorporating multivariate frameworks that include external macroeconomic variables, such as exchange rates, global commodity prices, and trade partner indices, could improve the accuracy and interpretability of the model. Second, hybrid models, combining SETAR with other machine learning methods such as LSTM or random forest, can capture both temporal dependencies and complex nonlinear interactions [17-19]. Lastly, applying the methodology to other developing countries with similar export characteristics could validate the generalizability of the findings and offer comparative insights across regions. Future studies could also explore the incorporation of additional modeling components, such as applying the GA to the SETAR-Tree model to further improve accuracy. Additionally, comparisons could be made with advances in SETAR-Tree models, such as the Multivariate SETAR-Tree and SETAR-Forest, to assess the potential for enhanced forecasting performance.

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