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INDONESIA'S GDP FORECAST: EVIDENCE FROM FUZZY TIME SERIES MODEL USING PARTICLE SWARM OPTIMIZATION ALGORITHM

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ABSTRACT. Gross Domestic Product (GDP) is a principal indicator used to measure the economic condition of a country. Indonesia's GDP growth from 2017 to 2019 was approximately 6 percent; however, it experienced a decline in 2020 and 2021, with rates of only -0.02 percent and 2.41 percent, respectively. In the process of economic development planning, a forecasting system is required to determine GDP in the future. The forecasting method employed in this research is fuzzy time series optimized using Particle Swarm Optimization (PSO), to enhance the accuracy and convergence of forecasted values. The dataset used comprises secondary data, specifically 54 sets of Indonesian GDP data spanning from the first quarter of 2010 to the second quarter of 2023. The analysis results indicate that the proposed method is better than the conventional fuzzy time series approach. The former method provides a predictive value for one period in the future with a Mean Absolute Percentage Error (MAPE) value of 4.40%. In contrast, the latter yields higher predictive values with a MAPE value of 7.93%.

Key words and phrases: Forecasting model; Gross domestic product; Fuzzy time series; Particle swarm optimization.

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1. INTRODUCTION

Gross Domestic Product (GDP) is one of the indicators used to measure the economic condition of a country. GDP includes the amount of goods and services produced by a nation's production units based on prevailing prices or constant prices. Growth with redistribution can lead to poverty and national inequality, as observed in other countries, such as the Philippines, between 2000 and 2018. Over the same 20-year period, nearly the entire territory of the country experienced growth. The growth rate experienced between 2012 and 2019 exceeded that of previous years. Economic expansion, however, has manifested unevenly across the region, with two conspicuous outliers. The National Capital Region (NCR) stands out as the most consistent economic player, maintaining a real GDP per capita of approximately 457,000 pesos (or around 8,823 USD) in 2019 [1]. One of the studies conducted in Nigeria [2] that aims to analyze or conduct studies on gross domestic income (GDI) and GDP, can reduce carbon emissions in the country. A substantial body of empirical and theoretical literature exists focusing on the impact of natural disasters, including forest fires, on GDP growth [3]. GDP serves as a prominent metric in economic accounting, commonly employed to assess the economic performance of countries and regions worldwide [4]. However, GDP lacks consideration for inclusivity and fails to furnish insights into the sustainability of economic growth [5]. The feature of providing broad consideration of the consequences of economic growth on a small (local) or global scale is needed to replace GDP in the SDG 8 indicators set to increase its coherence with the overall SDGs Agenda [6].

In planning economic development, it is essential to implement a forecast calculation system to project future GDP as a benchmark for the Indonesian economy. One applicable forecasting method is the fuzzy time series method. Through this forecasting approach, policymakers can develop and formulate more effective policies, thereby fostering a positive impact on development. This strategic use of forecasting facilitates economic development aimed at enhancing the population's welfare.

Forecasting in macroeconomics generally refers to the sequence of data related to the same statistical variable based on its chronological occurrence. The objective is to identify intrinsic relationships within the data through historical data analysis, enabling the prediction of future data points. The majority of time series modeling and forecasting involve the utilization of statistical regression models for continuous time series. Additionally, widely employed analysis models include Autoregressive Moving Average (ARMA) and Autoregressive Integrated Moving Average (ARIMA). For non-stationary time series, the initial step involves rendering it stationary through successive differencing. This process is commonly represented as a combination of white noise and moving average [7]-[11]. While these methods are widely recognized in economic forecasting, employing linear models, they may yield suboptimal results when applied to complex non-linear systems that aim to simulate real-life scenarios [12].

A method to address the aforementioned issue is the fuzzy time series-particle swarm optimization algorithm. Fuzzy time series are widely applied for forecasting in various cases, such as in the application of forecasting of air pollution time series data, with a new hybrid forecasting model that integrates fuzzy time series into Markov chains and C-Means clustering techniques with an optimal number of clusters [13], forecasting of weather, earthquakes, stock fluctuations and any phenomenon indexed by variables that change unexpectedly in time, given that classical time series methods cannot handle forecasting problems where time series values are linguistic terms represented by fuzzy sets [14], forecasting is therefore used as a new approach to present large time pools in a cluster, taking into account the dependencies of successive threads between times to obtain fuzzy partitions from pool observations [15], [16], forecasting subjective performance in engineering and construction management (CEM) issues, with a variety of suitable fuzzy hybrid techniques [17], forecasting coal mining production based on fuzzy-neural models [18], and in the application of fuzzy clustering to determine the distance between ordinal time series.

The proposed Fuzzy Time Series-Particle Swarm Optimization (FTS-PSO) algorithm introduces a novel approach to economic forecasting by seamlessly integrating two powerful techniques. The hybridization of Fuzzy Time Series (FTS) and Particle Swarm Optimization (PSO) leverages the strengths of each method to address critical challenges in forecasting. FTS, known for its adept handling of linguistic variables in representing qualitative information, forms the foundational component, allowing for nuanced interpretations of complex economic indicators. The PSO algorithm, operating synergistically, dynamically tunes key partitioning parameters of the FTS model during the optimization process. This adaptability not only enhances the accuracy of forecasting but also ensures the model's responsiveness to changes in the economic landscape. Importantly, FTS-PSO is explicitly designed to tackle the non-linear intricacies inherent in economic time series data, providing a more realistic representation of economic systems compared to traditional linear models. The algorithm's transparency and interpretability are preserved, allowing researchers and practitioners to trace each step of the decision-making process. Furthermore, the FTS-PSO algorithm showcases its versatility by demonstrating successful applications beyond GDP forecasting, spanning domains such as air pollution, weather, and stock fluctuations. In summary, FTS-PSO stands as an innovative and adaptive solution, contributing to the advancement of economic forecasting methodologies and offering a robust framework for addressing the complexities of diverse forecasting scenarios.

2. METHOD

The accuracy levels examined in this paper include the mean absolute percentage error (MAPE) and the Akaike information criterion (AIC). MAPE is commonly employed in modeling accuracy assessments due to its relatively straightforward interpretation of relative error. The merit of using the MAPE accuracy measure lies in its ease of comprehension and communication. It facilitates the presentation of results depicting the extent to which the estimate deviates from the actual average value, expressed in percentage terms. Consequently, MAPE assists in comparing model performance over a given timeframe, as long as the actual value does not approach zero closely. While the drawback is that MAPE can be affected by outliers or extreme values. For example, if there is an observation with a significantly large percentage of error, this can increase the accuracy value of MAPE [19]-[21]. Meanwhile, AIC serves as a criterion for selecting the optimal model, with the best model being characterized by the smallest AIC value.

The steps of forecasting for the fuzzy time series method are as employed by [22], [13]. This method decomposes the set of universes U into an equal number of intervals, $u_1, u_2, \ldots, u_n$. Through this step, fuzzy sets can be determined and fuzzified time series, which ultimately performs fuzzy logic relationship (FLR) modeling in fuzzification time series. The same steps are described [23].

- Describe the set of universes, U, and divide them into intervals of equal length. Assume $D_{\min}$ and $D_{\max}$ are the minimum and maximum residuals, respectively. Define $U = [D_{\min} - D_1, D_{\max} + D_2]$ where D_1 and D_2 are sustable positive numbers. When U is partitioned into n equal intervals

$u_1, u_2, \ldots, u_n$, the length of the interval l, can be defined as $l = (D_{\max} + D_2 - (D_{\min} - D_1)$
n

- Determine fuzzy sets $A_1, A_2, \ldots, A_n$, as linguistic values of linguistic variables on the observed time series. Each A_i, where $i = 1, \ldots, n$ is defined by the intervals obtained in the step above and can be written as:

$A_i = \ldots + 0/ u_i -2 + 0.5/ u_i -1 + 1/ u_i + 0.5/ u_i +1 + 0/ u_i +2 + \ldots$ (1).

In Equation (1), the maximum membership value of A_i is contained in the interval u_i and so on.

- Calculate the forecast value for residuals based on FLR according to several methods, such as the method used by Chen, Yu, Cheng, and Lee.
- Calculate the final forecast value according to the forecast value obtained with the fuzzy model.

The steps of the calculation process are shown in the flowchart [24]. In this paper, the steps are carried out according to the following flowchart in Figure 1.

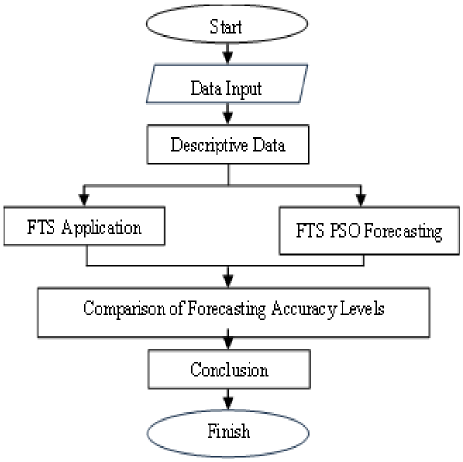

Figure 1: Flowchart of FTS PSO Forecasting Process Steps.

- Data Input: This stage involves collecting and organizing relevant data, such as historical time series data related to the phenomenon being studied. The quality and completeness of the input data play a crucial role in the accuracy of the forecasting model.
- Descriptive Data Analysis: Before applying any forecasting method, it's essential to analyze the descriptive statistics of the data. This includes measures like mean, median, standard deviation, and other statistical properties. Understanding the characteristics of the data helps in choosing appropriate modeling techniques.
- FTS Application: Fuzzy Time Series (FTS) involves capturing the uncertainty and fuzziness inherent in time series data. The application of FTS typically includes defining linguistic terms (e.g., low, medium, high), constructing fuzzy sets, and developing fuzzy rules that represent the patterns observed in the historical data.
- FTS PSO Forecasting Process Steps:

Initialization: PSO starts with the initialization of a population of particles, each representing a potential solution. These particles are assigned random positions and velocities in the solution space.

Objective Function Evaluation: The fuzzy time series model with PSO optimizes an objective function, which quantifies the accuracy of the forecasting model. This function takes into account the difference between the predicted values and the actual values from the historical data.

Updating Particle Positions: PSO updates the position and velocity of each particle based on its own best-known position and the best-known position of the entire swarm. This is done to search for the optimal solution in the solution space.

Fuzzy Rule Optimization: FTS, in combination with PSO, optimizes the fuzzy rules to enhance the forecasting accuracy. This step involves adjusting the parameters of the fuzzy rules to better fit the historical data patterns.

Iterative Optimization: The PSO algorithm iteratively refines the particle positions and fuzzy rule parameters to converge towards an optimal solution. This iterative process continues until a stopping criterion is met.

- Comparison of Forecasting Accuracy Levels: After applying the FTS with PSO forecasting method, the results are compared with other forecasting methods, presumably including standard FTS. This comparison is essential to assess the effectiveness and improvement achieved through the integration of Particle Swarm Optimization.
- Conclusion: The conclusion summarizes the findings, highlighting the strengths and weaknesses of the FTS with PSO forecasting approach. It may discuss the identified improvements in accuracy and provide insights into the practical implications of using this method for future predictions.
- Finish: The concluding section wraps up the study, potentially suggesting avenues for further research and application of the FTS with PSO forecasting model in different contexts. It may also discuss any limitations of the study and propose recommendations for future enhancements.

The proposed fuzzy time series model for forecasting Indonesia's GDP, incorporating a particle swarm optimization (PSO) algorithm, reveals notable limitations that impact its robustness and generalizability. Challenges arise from the model's susceptibility to partitioning parameters and the assumption of linearity in the relationship between linguistic variables and GDP within the complex economic landscape. The handling of outliers during the fuzzy logic relationship (FLR) modeling lacks explicit consideration, introducing uncertainties about the model's resilience to economic shocks. Additionally, dependence on a specific FLR method and subjective linguistic variable definitions may introduce biases, affecting forecast accuracy. Limited transparency in detailing the integration of the PSO algorithm raises concerns about the model's overall robustness.

To address these concerns, the study suggests an extension to explore alternative metaheuristic algorithms, emphasizing the importance of a judicious selection and explicit justification. The extended methodology incorporates a broader range of forecasting models commonly used in economic prediction studies, such as autoregressive integrated moving average (ARIMA), exponential smoothing methods (e.g., Holt-Winters), and machine learning algorithms (e.g., regression models, support vector machines, or neural networks). This addition enables a more comprehensive evaluation of the performance of the fuzzy time series (FTS) and fuzzy time series with particle swarm optimization (FTSPSO) models. A rigorous evaluation strategy, employing performance metrics like mean absolute percentage error (MAPE) or root mean square error (RMSE) and statistical tests such as t-tests or ANOVA, is introduced to quantitatively assess the accuracy of each model. This enhanced methodology broadens the scope of the analysis, providing a more robust comparison and facilitating a clearer understanding of the relative strengths and weaknesses of the fuzzy time series models compared to other established forecasting techniques. The inclusion of explicit details on the alpha-cut type further contributes to a nuanced understanding of the methodology's intricacies, enhancing scholarly rigor.

3. RESULT AND DISCUSSION

The dataset employed in this study comprises Indonesia's quarterly Gross Domestic Product (GDP) data, measured in Billion Rupiahs at Current Market Prices by Industry. The data is sourced directly from the publication of the Central Bureau of Statistics. Specifically, the dataset spans from the first quarter of 2010 to the second quarter of 2023, covering a comprehensive timeframe for economic analysis. Table 1 provides a detailed breakdown of the quarterly GDP figures, offering a structured representation of the economic data used for the forecasting of Indonesia's GDP in this study.

Table 1. Indonesia's Quarterly GDP (Billion Rupiahs)

Index	Period	GDP Value	Index	Period	GDP Value
1	Q- I 2010	1,603,771.90	28	Q-IV 2016	3,193,903.80
2	Q-II 2010	1,704,509.90	29	Q- I 2017	3,228,172.20
3	Q-III 2010	1,786,196.60	30	Q-II 2017	3,366,787.30
4	Q-IV 2010	1,769,654.70	31	Q-III 2017	3,504,138.50
5	Q- I 2011	1,834,355.10	32	Q-IV 2017	3,490,727.70
6	Q-II 2011	1,928,233.00	33	Q- I 2018	3,510,363.10
7	Q-III 2011	2,053,745.40	34	Q-II 2018	3,686,836.40
8	Q-IV 2011	2,015,392.50	35	Q-III 2018	3,842,343.00
9	Q- I 2012	2,061,338.30	36	Q-IV 2018	3,799,213.50
10	Q-II 2012	2,162,036.90	37	Q- I 2019	3,782,618.30
11	Q-III 2012	2,223,641.60	38	Q-II 2019	3,964,074.70
12	Q-IV 2012	2,168,687.70	39	Q-III 2019	4,067,358.00
13	Q- I 2013	2,235,288.50	40	Q-IV 2019	4,018,606.20
14	Q-II 2013	2,342,589.50	41	Q- I 2020	3,923,347.90
15	Q-III 2013	2,491,158.50	42	Q-II 2020	3,690,742.20
16	Q-IV 2013	2,477,097.50	43	Q-III 2020	3,897,851.90
17	Q- I 2014	2,506,300.20	44	Q-IV 2020	3,931,411.20
18	Q-II 2014	2,618,947.30	45	Q- I 2021	3,972,769.60
19	Q-III 2014	2,746,762.40	46	Q-II 2021	4,177,970.80
20	Q-IV 2014	2,697,695.40	47	Q-III 2021	4,327,358.00
21	Q- I 2015	2,728,180.70	48	Q-IV 2021	4,498,592.40
22	Q-II 2015	2,867,948.40	49	Q- I 2022	4,508,597.80
23	Q-III 2015	2,990,645.00	50	Q-II 2022	4,897,942.90
24	Q-IV 2015	2,939,558.70	51	Q-III 2022	5,066,994.30
25	Q- I 2016	2,929,269.00	52	Q-IV 2022	5,114,910.60
26	Q-II 2016	3,073,536.70	53	Q- I 2023	5,072,370.10
27	Q-III 2016	3,205,019.00	54	Q-II 2023	5,226,670.10

The above data plot can be shown in Figure 2.

Figure 2 presents a graphical representation of Indonesia's GDP data at Current Market Prices by Industry, measured in Billion Rupiahs, spanning from the first quarter of 2010 to the second quarter of 2022. The observed trend in the data pattern, as illustrated in the figure, indicates a discernible directional movement over the specified timeframe. This trend pattern provides valuable insights into the overall trajectory of Indonesia's economic output.

The minimum recorded data value occurred in the first quarter of 2010, registering at 1,603,771.90 billion Rupiahs. In contrast, the maximum value was documented in the second quarter of 2023, reaching IDR 5,226,670.10 billion. These extrema highlight the dynamic range of the GDP data, showcasing both the lowest and highest values within the given period.

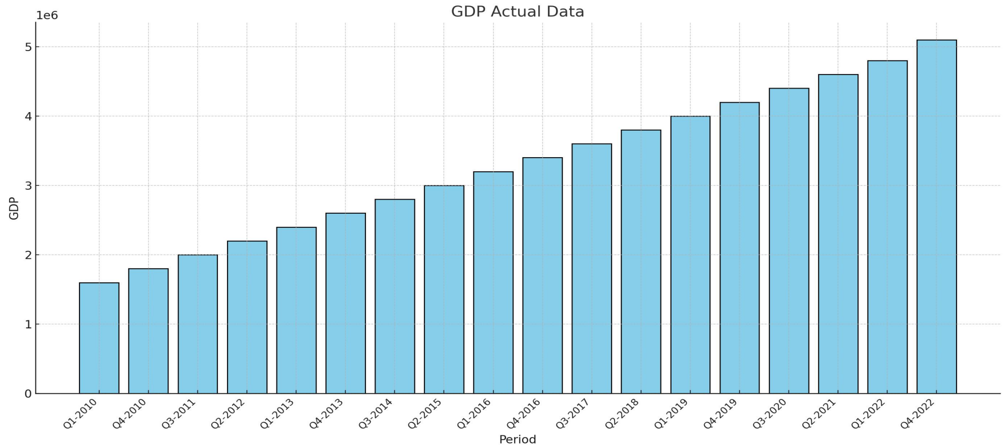

Figure 2: Indonesia's GDP Chart

The recognition of a discernible trend in the GDP data pattern serves as a rationale for considering the application of fuzzy time series for forecasting. The distinct fluctuations and directional movements in the data offer a foundation for exploring the potential of fuzzy time series methodology in capturing and predicting the intricate dynamics of Indonesia's economic output.

3.1. **Fuzzy Time Series Analysis.** The set of universes is derived from historical data through the establishment of minimum and maximum data bounds for the universes. In this context, specific parameters are defined to shape the universes: d_1 = 0,d_2 = 100, D_{min} = 1,603,771.90, and D_{max} = 5,226,670.10. These parameters lead to the formation of the universe set, denoted as U = [1,603,771.90; 5,226,670.10].

To determine the number of intervals, *K*, the formula $K = 1 + 3.3 \cdot log(54)$ is utilized, resulting in

$K \approx 6.7168$, rounded to 7. Subsequently, fuzzy sets are derived by dividing the sum of intervals within U into K equal parts. Table 2 provides a clear representation of these fuzzy sets, delineating the intervals and corresponding linguistic values obtained from the historical data.

This systematic approach ensures a transparent explanation of the process involved in forming the set of universes, specifying the parameters used and how the intervals are determined. The subsequent representation in Table 2 further enhances the clarity of the derived fuzzy sets, establishing a foundation for the subsequent steps in the fuzzy time series modeling methodology.

Interval	Lower Bound	Upper Bound	Middle Value	Fuzzy Set
U_1	1,603,771.90	2,121,343.07	1,862,557.49	A_1
U_2	2,121,343.07	2,638,914.24	2,380,128.66	A_2
U_3	2,638,914.24	3,156,485.41	2,897,699.83	A_3
U_4	3,156,485.41	3,674,056.59	3,415,271.00	A_4
U_5	3,674,056.59	4,191,627.76	3,932,842.17	A_5
U_6	4,191,627.76	4,709,198.93	4,450,413.34	A_6
U_7	4,709,198.93	5,226,770.10	4,967,984.51	A_7

Table 2. Fuzzy set

After conducting a fuzzy time series analysis based on intervals, the set of speech universes and fuzzy sets obtained forecasting results, as shown in Table 3.

Table 3. Results of Indonesia's GDP Forecasting (Billion Rupiahs)

Period	**GDP Value**	**Forecasting**	**Period**	**GDP Value**	**Forecasting**
Q- I 2010	1,603,771.90	NA	Q-IV 2016	3,193,903.80	3,489,209.74
Q-II 2010	1,704,509.90	1,920,065.39	Q- I 2017	3,228,172.20	3,489,209.74
Q-III 2010	1,786,196.60	1,920,065.39	Q-II 2017	3,366,787.30	3,489,209.74
Q-IV 2010	1,769,654.70	1,920,065.39	Q-III 2017	3,504,138.50	3,489,209.74
Q- I 2011	1,834,355.10	1,920,065.39	Q-IV 2017	3,490,727.70	3,489,209.74
Q-II 2011	1,928,233.00	1,920,065.39	Q- I 2018	3,510,363.10	3,489,209.74
Q-III 2011	2,053,745.40	1,920,065.39	Q-II 2018	3,686,836.40	3,747,995.32
Q-IV 2011	2,015,392.50	1,920,065.39	Q-III 2018	3,842,343.00	3,972,655.34
Q- I 2012	2,061,338.30	1,920,065.39	Q-IV 2018	3,799,213.50	3,972,655.34
Q-II 2012	2,162,036.90	2,178,850.98	Q- I 2019	3,782,618.30	3,972,655.34
Q-III 2012	2,223,641.60	2,437,636.57	Q-II 2019	3,964,074.70	3,972,655.34
Q-IV 2012	2,168,687.70	2,437,636.57	Q-III 2019	4,067,358.00	3,972,655.34
Q- I 2013	2,235,288.50	2,437,636.57	Q-IV 2019	4,018,606.20	3,972,655.34
Q-II 2013	2,342,589.50	2,437,636.57	Q- I 2020	3,923,347.90	3,972,655.34
Q-III 2013	2,491,158.50	2,437,636.57	Q-II 2020	3,690,742.20	3,972,655.34
Q-IV 2013	2,477,097.50	2,437,636.57	Q-III 2020	3,897,851.90	3,972,655.34
Q- I 2014	2,506,300.20	2,437,636.57	Q-IV 2020	3,931,411.20	3,972,655.34
Q-II 2014	2,618,947.30	2,437,636.57	Q- I 2021	3,972,769.60	3,972,655.34
Q-III 2014	2,746,762.40	2,696,422.15	Q-II 2021	4,177,970.80	3,972,655.34
Q-IV 2014	2,697,695.40	2,962,396.23	Q-III 2021	4,327,358.00	4,231,440.92
Q- I 2015	2,728,180.70	2,962,396.23	Q-IV 2021	4,498,592.40	4,622,937.07
Q-II 2015	2,867,948.40	2,962,396.23	Q- I 2022	4,508,597.80	4,622,937.07
Q-III 2015	2,990,645.00	2,962,396.23	Q-II 2022	4,897,942.90	4,881,722.65
Q-IV 2015	2,939,558.70	2,962,396.23	Q-III 2022	5,066,994.30	4,967,984.51
Q- I 2016	2,929,269.00	2,962,396.23	Q-IV 2022	5,114,910.60	4,967,984.51
Q-II 2016	3,073,536.70	2,962,396.23	Q- I 2023	5,072,370.10	4,967,984.51
Q-III 2016	3,205,019.00	3,221,181.81	Q-II 2023	5,226,670.10	4,967,984.51

Referring to Table 3, the forecasted value for Indonesia's GDP in the upcoming period is projected to be 4,967,984.51 billion Rupiahs. This forecast is generated through the application of the fuzzy time series model, incorporating historical data and linguistic variables. The forecasted value provides an estimation of the economic output for the forthcoming period based on the established patterns and relationships identified in the historical GDP data.

Additionally, the Mean Absolute Percentage Error (MAPE) is calculated as 7.93%. MAPE is a measure of the accuracy of the forecasting model, representing the average percentage difference between the predicted and actual values. In this context, a MAPE of 7.93% suggests that, on average, the forecasted GDP values deviate by approximately 7.93% from the actual observed values. Lower MAPE values generally indicate a higher level of accuracy in the forecasting model.

Interpreting these results, the forecasted GDP value provides insight into the expected economic performance for the specified period, while the MAPE metric offers a quantitative measure of the accuracy of the forecasting model. A lower MAPE value indicates a more accurate forecast, implying that the fuzzy time series model has demonstrated a relatively precise ability to capture and predict the patterns in Indonesia's GDP data. However, it's essential to consider the specific context and requirements of the forecasting application when evaluating the adequacy of the model's performance.

3.2. **Fuzzy Time Series using Particle Swam Optimization.**

3.2.1. *Initial Parameter.* The PSO parameters include the number of particles, commonly chosen within the range of multiples of 5 to 100, the number of iterations, the weight of iterations (w) starting from 0.5 to 1, and a combination of c1 and c2, subject to the condition that $c1 + c2 \leq 4$. This paper adopts the PSO parameters as outlined in Table 4.

Table 4. PSO Parameter

• No.	PSO Parameter	Value
• 1	Number of iteration	50
• 2	Number of particles	10
• 3	Weight of iteration	0.5
• 4	c_1	1.5
• 5	c_2	1.5
• 6	r_1	0.3
• 7	r_2	0.2

Position and initial velocity of particles

The initial velocity of each particle is assumed to be zero. The number of dimensions for the particles is determined by subtracting one from the total number of particles, i.e., 7 – 1 = 6 dimensions. The initial velocities of the particles are presented in Table 5.

Table 5. The Initial Velocity of The Particle

• No.	• d_1	• d_2	• d_3	• d_4	• d_5	• d_6
• 1	• 0	• 0	• 0	• 0	• 0	• 0
• 2	• 0	• 0	• 0	• 0	• 0	• 0
• 3	• 0	• 0	• 0	• 0	• 0	• 0
• 4	• 0	• 0	• 0	• 0	• 0	• 0
• 5	• 0	• 0	• 0	• 0	• 0	• 0
• 6	• 0	• 0	• 0	• 0	• 0	• 0
• 7	• 0	• 0	• 0	• 0	• 0	• 0
• 8	• 0	• 0	• 0	• 0	• 0	• 0
• 9	• 0	• 0	• 0	• 0	• 0	• 0
• 10	• 0	• 0	• 0	• 0	• 0	• 0

The initial positions of each particle in the particle swarm optimization (PSO) algorithm are determined through a random generation process. The generated positions are constrained within the historical data bounds, specifically ranging from 1,603,771.90 to 5,226,770.10. It's worth noting that the values of both lower and upper bounds (1,603,771.90 and 5,226,770.10, respectively) are fixed and not included in the randomly generated positions.

Table 6 presents a detailed overview of these initial positions for each particle. The values listed in the table represent the randomly generated positions within the specified data bounds. The initial positions play a crucial role in initiating the PSO algorithm, influencing how particles explore the solution space in search of optimal parameter values for the fuzzy time series model.

Table 6. The Initial Position of The Particle

• No.	d_1	d_2	d_3	d_4	d_5	d_6
• 1	1,776,329.23	2,263,802.21	3,073,536.70	4,007,008.01	4,167,338.76	4,072,169.66
• 2	1,776,329.23	2,117,436.47	3,105,219.27	4,008,606.11	4,018,555.28	4,117,270.83
• 3	1,821,067.72	2,078,418.32	3,187,813.82	4,023,347.91	3,923,347.14	4,027,458.72
• 4	1,869,224.63	2,272,514.26	3,238,273.42	3,690,742.24	3,890,732.21	4,328,512.42
• 5	1,831,747.26	2,723,541.26	3,476,787.64	3,897,851.97	4,067,358.14	4,408,398.63
• 6	1,977,333.08	2,216,768.82	3,476,787.64	3,978,611.23	4,218,006.32	4,897,942.61
• 7	1,869,224.63	2,352,344.53	3,476,787.64	4,009,678.03	4,013,447.33	5,102,124.13
• 8	1,879,114.12	2,352,344.53	3,523,363.12	4,118,504.22	4,190,732.29	5,111,211.64
• 9	1,872,671.12	2,352,344.53	3,523,363.12	4,254,348.54	4,767,458.44	5,272,381.41
• 10	1,946,373.10	2,486,123.61	3,847,443.37	4,093,642.25	4,518,706.18	5,204,113.14

3.2.2. *Fuzzy time series PSO.* Optimum results of wide fuzzy time series intervals with PSO with the help of *Rstudio software.*

```
> pso_fts <- psoptim(fts_function, n=10, max.loop=50, w, c1, c2, xmin=xmin, xmax=xmax, vmax=c(2, 2), seed=5, anim=TRUE)
There were 50 or more warning (use warning() to see the first 50)
>
> pso_fts
$sol
           x1
[1,] 3625478.38

$val
[1] 5013524.47

>
> opt_interval <- sort(fts_function(fts_function(pso_fts$sol))
> opt_interval
[1] 1632199.23  2250184.80  2776079.46  3424865.36  3719698.16  4748846.20
>
```

Figure 3: Output Interval PSO

In Figure 3, the Particle Swarm Optimization (PSO) algorithm yields an optimum solution for the fuzzy time series model, resulting in a forecasted GDP value of 3,625,478.38. This optimal solution corresponds to a fitness value of 5,013,524.47. Additionally, the PSO algorithm identifies an optimal set of intervals for the fuzzy time series model, which is determined as follows: 1,632,199.23; 2,250,184.80; 2,776,079.46; 3,424,865.36; 3,719,698.16; 4,748,846.20.

These optimal intervals are then used to form fuzzy sets denoted as $A_1, A_2, ..., A_7$. Each fuzzy set interval is defined based on the identified optimum values and is represented as

$A_1 = (D_{\min} - d_1, x_1)$, $A_2 = (x_1, x_2)$, ..., $A_7 = (x_6, D_{\max} + d_2)$, where x_1 to x_6 is the determined interval boundaries. The resulting fuzzy sets, along with their respective intervals, are organized and presented in Table 7.

Table 7. Fuzzy Set Interval

Fuzzy set	Lower Bound	Upper Bound	Middle Value
A_1	1,603,771.90	1,632,199.23	1,617,985.57
A_2	1,632,199.23	2,250,184.80	1,941,192.02

Fuzzy set	Lower Bound	Upper Bound	Middle Value
A_3	2,250,184.80	2,776,079.46	2,513,132.13
A_4	2,776,079.46	3,424,865.36	3,100,472.41
A_5	3,424,865.36	3,719,698.16	3,572,281.76
A_6	3,719,698.16	4,748,846.20	4,234,272.18
A_7	4,748,846.20	5,226,670.10	4,987,758.15

After conducting fuzzy time series analysis based on fuzzy set intervals PSO forecasting results are shown in Table 8.

Table 8. Fuzzy Time Series_PSO Forecasting Results

Period	**GDP Value**	**Forecasting**	**Period**	**GDP Value**	**Forecasting**
Q- I 2010	1,603,771.90	NA	Q-IV 2016	3,193,903.80	3,221,181.81
Q-II 2010	1,704,509.90	1,812,287.65	Q- I 2017	3,228,172.20	3,221,181.81
Q-III 2010	1,786,196.60	2,246,097.50	Q-II 2017	3,366,787.30	3,221,181.81
Q-IV 2010	1,769,654.70	2,246,097.50	Q-III 2017	3,504,138.50	3,221,181.81
Q- I 2011	1,834,355.10	2,246,097.50	Q-IV 2017	3,490,727.70	3,982,655.34
Q-II 2011	1,928,233.00	2,246,097.50	Q- I 2018	3,510,363.10	3,982,655.34
Q-III 2011	2,053,745.40	2,246,097.50	Q-II 2018	3,686,836.40	3,982,655.34
Q-IV 2011	2,015,392.50	2,246,097.50	Q-III 2018	3,842,343.00	3,982,655.34
Q- I 2012	2,061,338.30	2,246,097.50	Q-IV 2018	3,799,213.50	3,982,655.34
Q-II 2012	2,162,036.90	2,246,097.50	Q- I 2019	3,782,618.30	3,982,655.34
Q-III 2012	2,223,641.60	2,246,097.50	Q-II 2019	3,964,074.70	3,982,655.34
Q-IV 2012	2,168,687.70	2,246,097.50	Q-III 2019	4,067,358.00	3,982,655.34
Q- I 2013	2,235,288.50	2,246,097.50	Q-IV 2019	4,018,606.20	3,982,655.34
Q-II 2013	2,342,589.50	2,246,097.50	Q- I 2020	3,923,347.90	4,444,340.92
Q-III 2013	2,491,158.50	2,246,097.50	Q-II 2020	3,690,742.20	4,444,340.92
Q-IV 2013	2,477,097.50	2,246,097.50	Q-III 2020	3,897,851.90	4,444,340.92
Q- I 2014	2,506,300.20	2,772,645.24	Q-IV 2020	3,931,411.20	4,444,340.92
Q-II 2014	2,618,947.30	2,772,645.24	Q- I 2021	3,972,769.60	4,444,340.92
Q-III 2014	2,746,762.40	2,772,645.24	Q-II 2021	4,177,970.80	4,444,340.92
Q-IV 2014	2,697,695.40	2,772,645.24	Q-III 2021	4,327,358.00	4,444,340.92
Q- I 2015	2,728,180.70	2,772,645.24	Q-IV 2021	4,498,592.40	4,743,338.12
Q-II 2015	2,867,948.40	2,772,645.24	Q- I 2022	4,508,597.80	4,743,338.12
Q-III 2015	2,990,645.00	2,772,645.24	Q-II 2022	4,897,942.90	4,743,338.12
Q-IV 2015	2,939,558.70	2,772,645.24	Q-III 2022	5,066,994.30	5,116,852.62
Q- I 2016	2,929,269.00	2,772,645.24	Q-IV 2022	5,114,910.60	5,116,852.62
Q-II 2016	3,073,536.70	3,221,181.81	Q- I 2023	5,072,370.10	5,116,852.62
Q-III 2016	3,205,019.00	3,221,181.81	Q-II 2023	5,226,670.10	5,116,852.62

Referring to Table 8, the forecasted value for Indonesia's GDP in the upcoming period (Q-III 2023) is projected to be 5,116,852.62 billion Rupiahs. This forecast is derived from the fuzzy time series model, which incorporates the optimized parameters obtained through the Particle Swarm Optimization (PSO) algorithm. The forecasted value represents an estimate of the economic output for the specified future period, based on the identified patterns and linguistic representations in the historical GDP data.

The fuzzy time series model, with the optimized intervals determined by PSO, contributes to a more accurate and refined forecasting process. The forecasted GDP value of 5,116,852.62 billion Rupiahs provides valuable insights for decision-makers, analysts, and stakeholders, aiding in anticipating and planning for the economic performance of Indonesia in Q-III 2023. This output represents the culmination of the fuzzy time series modeling and optimization efforts, offering a quantified projection for the specified period.

3.3. **Comparison of fuzzy time series and fuzzy time series PSOs.** The comparison of the accuracy of fuzzy time series and fuzzy time series PSO forecasting are the AIC and MAPE. The results of AIC and MAPE values can be seen in Table 9.

Table 9. Comparison of Forecasting Results

Method	AIC	MAPE
Fuzzy time series	2773.32	7.93%
Fuzzy time series PSO	2137.21	4.40%

Based on the findings in Table 9, it is evident that the fuzzy time series method combined with PSO outperforms the conventional fuzzy time series, as indicated by its smaller error value (MAPE). A representation of the accuracy comparison between fuzzy time series and fuzzy time series forecasting with PSO is presented in Figure 4.

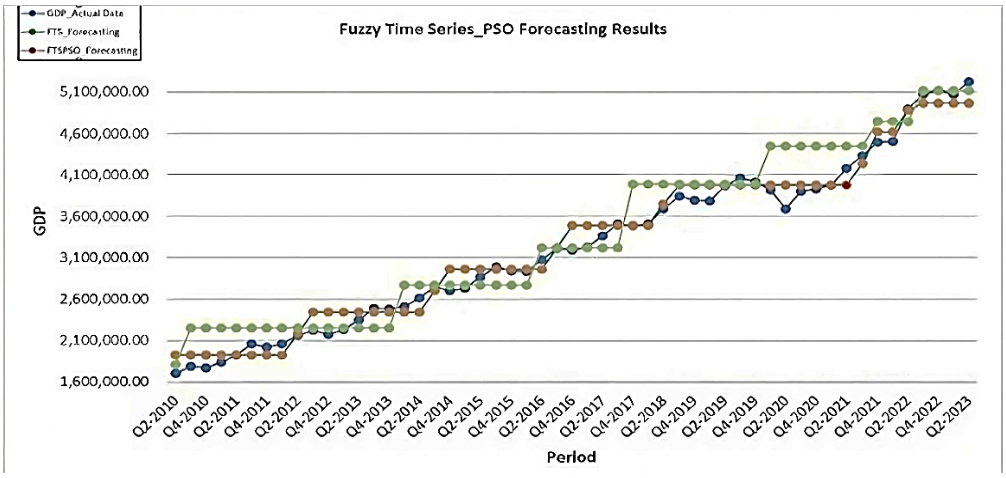

Figure 4: Fuzzy time series PSO Forecasting of Indonesia's GDP

3.4. **Figure 4. Fuzzy time series PSO Forecasting of Indonesia's GDP.** Figure 4 illustrates that the integration of the Particle Swarm Optimization (PSO) algorithm with the fuzzy time series method leads to an enhanced performance compared to the standard fuzzy time series alone. The plot demonstrates a closer alignment between the forecasted values obtained through the fuzzy time series method with PSO optimization and the actual Indonesia's GDP data. This closer alignment signifies that the optimized parameters, obtained through the PSO algorithm, contribute to a more accurate representation of the underlying patterns in the GDP data.

The overall conclusion drawn from this observation is that the combined approach, incorporating PSO for parameter optimization, improves the forecasting accuracy of the fuzzy time series model. The enhanced alignment between the forecasted values and the actual data suggests that the optimized parameters allow the model to capture and represent the complex dynamics of Indonesia's GDP more effectively. This outcome reinforces the value of meta-heuristic optimization techniques, such as PSO, in refining the fuzzy time series methodology for robust economic forecasting.

In summary, the results and discussions affirm that the integration of PSO with the fuzzy time series model is a promising approach for improving the accuracy of GDP forecasts. This finding holds significance for practitioners, policymakers, and researchers involved in economic forecasting, providing insights into effective methodologies for capturing and predicting the intricate dynamics of Indonesia's economic landscape.

4. CONCLUSION

Based on the comprehensive results and discussions, a robust conclusion can be drawn regarding the fuzzy time series predictions for Indonesia's GDP using particle swarm optimization (FTS-PSO). The model, optimized through the particle swarm optimization algorithm, successfully identified seven intervals that span the dynamic range from the lower limit of 1,603,771.90 to the upper limit of 5,226,770.10 in the historical data. The forecasted GDP value using FTS-PSO is 5,116,852.62 billion Rupiahs, with a remarkably low Mean Absolute Percentage Error (MAPE) value of 4.40%.

In comparison, the forecasting results for Indonesia's GDP using the standard fuzzy time series alone yielded a predicted value of 4,967,984.51 billion Rupiahs, accompanied by a higher MAPE value of 7.93%. This stark difference in MAPE values underscores the superiority of the FTS-PSO approach, as it demonstrates a significantly lower percentage deviation between the predicted and actual values.

The original theoretical and technical contributions of this paper lie in the successful integration of particle swarm optimization with fuzzy time series for GDP forecasting. The FTS-PSO model outperforms the standard fuzzy time series model, providing a more accurate representation of Indonesia's economic dynamics. This research contributes to the field by showcasing the effectiveness of meta-heuristic optimization, particularly PSO, in refining fuzzy time series models for enhanced accuracy in economic forecasting. The identification of optimized intervals and the subsequent reduction in MAPE value highlight the practical implications of this approach for policymakers, analysts, and researchers engaged in economic prediction. Overall, this paper adds valuable insights to the methodology of economic forecasting, emphasizing the potential of combining fuzzy time series with meta-heuristic algorithms for superior predictive performance.

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