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ENHANCING WEIGHTED FUZZY TIME SERIES FORECASTING THROUGH PARTICLE SWARM OPTIMIZATION

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ABSTRACT

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Climate change is a complex process that has far-reaching consequences for daily living. Temperature is one of the climatic features. Knowing its future value through a forecasting model is critical, as it aids in earlier strategic decision-making. Without considering spatial factors, this study investigates an Air Temperature variable forecasting. Weighted Fuzzy Time Series (WFTS) is one of the forecasting techniques. Furthermore, the length of the interval and the extent to which previous values (Order length) are utilized in predicting the subsequent value are pivotal factors in WFTS modelization and its forecasting accuracy. Therefore, this research investigates the interval length and the Order length of the WFTS through the Particle Swarm Optimization (PSO) approach. The variable used is the air temperature in Malang, Indonesia. The dataset is taken from BMKG-Indonesia. The forecasting performance of classical WFTS is enhanced by setting an appropriate order level and employing Particle Swarm Optimization (PSO) to determine the optimal interval fuzzy length. As indicated by the Evaluation matrices in the result section, the proposed optimization overtaken the classical WFTS in term of accuracy. The evaluation indicates a Mean Absolute Percentage Error (MAPE) value of 1.25 and a Root Mean Square Error (RMSE) of 0.32 for the Proposed model. In contrast, the classical WFTS demonstrates a MAPE of 2.26 and RMSE of 0.58. The implementation of the PSO provides solid insights for Air temperature forecasting accuracy.

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1. INTRODUCTION

Accurate weather and climate data are crucial in various fields. Temperature tremendously impacts the environment and social well-being, including generating electricity, planting, manufacturing, etc. Modeling and predicting daily temperature are vital for early decisions on adapting to future air temperatures. System modeling is a comprehensive domain with various research fields, including time series forecasting. According to [1], the primary aim of time series forecasting is to derive latent patterns from data and generate projections on future values based on the model's learning and historical observations. Time series forecasting is frequently used across several industries, including weather, climate, healthcare, finance, social studies, and others [2], [3]. The existing literature elucidates the application of time series analysis techniques and modeling methodologies to predict and offer valuable insights for strategic decision-making. Those methodologies empower decision-makers to deal with potential risks and get more favorable outcomes efficiently.

There exist multiple methodologies for conducting forecasting. According to [4], the Autoregressive Integrated Moving Average (ARIMA) model is commonly employed in linear time series forecasting methodologies and realizes application in several domains like business, agriculture, and social sciences. Research has demonstrated that ARIMA models reasonably predict time series data with relative stationarity. Further, a Seasonal ARIMA (SARIMA) model is employed to analyze univariate time series exhibiting trend and seasonal components [5]. Nevertheless, the methodologies mentioned earlier assumed that the given time series is devoid of any missing data and exhibits stationary patterns [6]. However, it is important to acknowledge that many real-world time series data contain complex nonlinear patterns that the ARIMA and SARIMA modeling techniques may need to improve.

In recent years, there has been a growing recognition of the potential of machine learning methods in tackling the issues associated with time series approximation. These methodologies utilize past time-series data to estimate the value of forthcoming data points. The Fuzzy Times series (FTS) subject matter has attracted considerable interest in current scholarly investigations. As a forecasting technique, fuzzy time series employs fuzzy sets to effectively capture and represent the inherent ambiguity and vagueness included in time series data. The process of FTS forecasting methodology has four main stages: fuzzification, relational analysis, forecasting, and defuzzification [7]. The research by [8] presents an innovative method for predicting fuzzy time series data that considers seasonal variations within the framework of seasonal fuzzy time series forecasting. The approach outlined in the study above involves partitioning the realm of communication into intervals that demonstrate a gradual increase in time, ascertained through an optimization procedure. The suggested approach was applied to two data sets, and a comparative examination was conducted. The optimized seasonal Fuzzy time-series model has lower root mean square error (RMSE) and mean absolute percentage error (MAPE) compared to SARIMA and other models when applied to time-series data exhibiting seasonality and trend.

Along with the efficacy of the FTS in various contexts, its inbuilt limitations must be recognized. One of the main limitations of conventional fuzzy time series is that it treats previous data points as equivalent entities, disregarding their relative importance in forecasting future values [9]. Predicting future values may lead to improper performance in scenarios where certain historical data points are more valuable than others. Weighted fuzzy time series (WFTS) is a predictive technique that builds upon fuzzy time series (FTS) by integrating the importance of past data elements into its model. In weighted fuzzy time series, weights are assigned to past data points according to their predictive value in predicting future values. Many research has been devoted to evaluating the effectiveness of weighted fuzzy time series in various applications through comparisons with common fuzzy time series models and traditional time series models [10]. Furthermore, according to [11], the effectiveness of the fuzzy time series model in making predictions is influenced by two factors: the length of the intervals and the order involved in predicting the subsequent value.

Determining the optimal approach for partitioning the intervals is a challenging task. The practicality of establishing parameter values through trial and error is limited because there are thousands of possible combinations of values. Consequently, it is necessary to employ an optimization approach to choose parameter values that minimize the number of tests and need a reasonable duration. Metaheuristic methodologies have exhibited notable effectiveness in providing solutions at realistic computational costs. According to [11], Particle Swarm Optimization (PSO) is a metaheuristic technique that efficiently determines the optimal interval length. Thus, the proposed studies introduced a forecasting model using the Particle Swarm Optimization (PSO) approach. The PSO technique aims to efficiently determine the best interval lengths not just within the classical Fuzzy Time Series (FTS) models as studied by [12] but using FTS with weight (WFTS). The proposed model will deal with finding the optimum length and the order/lag of the WFTS model.

On the other hand, the scientific community has recently shown considerable interest in global warming, primarily due to its observed association with rising air temperatures. Increased atmospheric temperature changes climatic patterns, such as rising sea levels, intensified extreme weather events, and the worsening of global warming. These changes ultimately negatively impact human well-being [13], [14]. Accurately forecasting air temperature is significant in weather prediction, as it plays a crucial role in safeguarding human lives and conserving valuable assets. Significant fluctuations in air temperature can elicit detrimental effects on both plant and animal organisms. Accurate forecasting of atmospheric temperature holds significant importance due to its considerable influence on multiple sectors [15]. Various factors, including air temperature, influence the weather. An accurate forecast of air temperature in Malang is crucial because the region is located in the equatorial zone, which results in the reception of solar energy and, therefore, high temperatures [16]. Plus, the Air temperature has a role in stimulating the potential extension of drought-prone areas in the region, combined with variations in rainfall [17]. Hence, having insight into future air temperature values is essential for making timely and informed decisions to mitigate its adverse effects on society.

Thus, this work aims to predict the Average Air Temperature in Malang using an optimized Weighted Fuzzy Time Series model. The optimization steps involve finding the optimum value of the interval length of the WFTS using the Particle Swarm Optimization (PSO) technique while simultaneously searching for optimum order values by considering many prior observations simultaneously at a higher order. We gathered the data from the online database BMKG in Indonesia over three years ago. The findings of this study are expected to provide a significant point of reference for future research on forecasting models and related events in Malang allied with Air Temperature.

2. RESEARCH METHODS

Forecasting is a systematic methodology that envisions forthcoming occurrences or results by analyzing pertinent historical data and information [3]. As defined by [18], time-series forecasting models are utilized to generate predictions regarding the future values of a target variable, represented as yt, at a specific time t. Models for one-step-ahead forecasting can be expressed in their most fundamental form as:

$$y_{t+1}=f(y_t\text{-}k) \tag{1}$$

where y_{t+1} is the model forecast, y_t - k is the observations of the targets over a look-back window k, and $f(\ldots)$ is the forecast function learned by the model.

Figure 1 reflects the workflow of the project. There exist three primary stages: The initial step involves pre-processing the data. Afterward, the best order for forecasting the air temperature variable will be determined. Next, identify the optimal interval length for the fuzzy model using the Particle Swarm Optimization (PSO). Subsequently, the best fuzzy interval length is input for the optimized WFTS model. In the end, the evaluation process is performed to determine which of the two models, the classical WFTS and the optimized WFTS, has the slightest error.

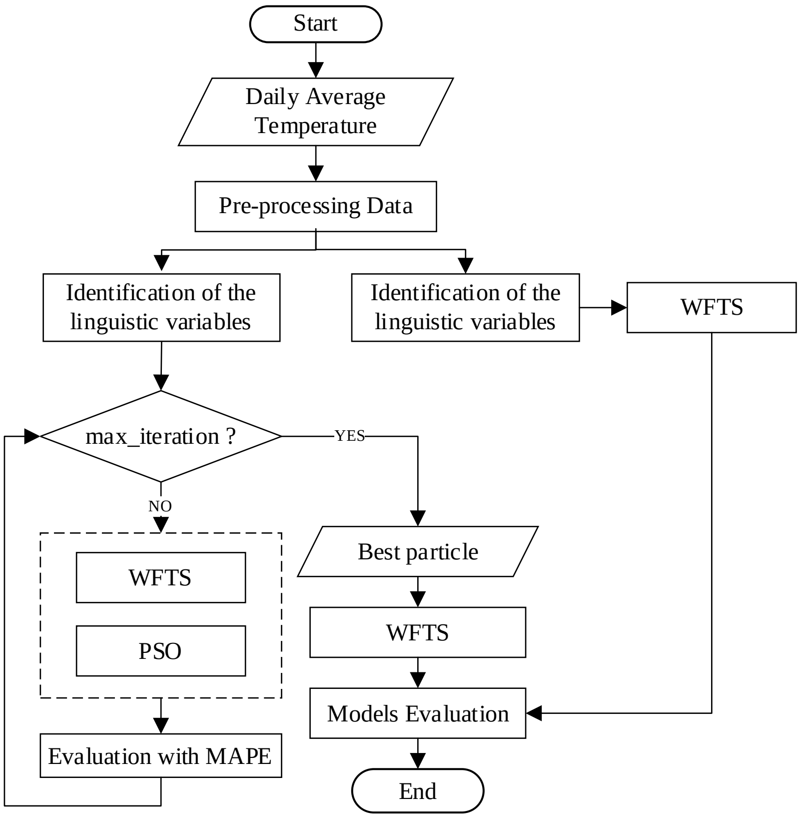

Figure 1. Research flow diagram

2.1 Dataset and Pre-processing

The main purpose of the research is to build a model trained by a univariate Air temperature. The case study of this study is air temperature in Malang because of its equatorial position, which leads to elevated temperatures and drought. The data on average daily temperatures in Celsius is obtained from the online data of the Meteorology, Climatology, and Geophysics Agency. The dataset ranges from July 1, 2020, to June 1, 2023, encompassing 1066 rows of Average temperature data collected over nearly three years. One of the primary pre-processing procedures is handling the missing values. This study utilizes the 'rolling mean' strategy with a window size of 7. This implies computing the average seven days before and after the missing values. A subsequent step involves partitioning the dataset into separate training and testing sets.

2.2 The Weighted Fuzzy Time Series

Song and Chissom initially proposed the notion of fuzzy time series in 1993 [7]. Fuzzy Time Series (FTS) is a method utilized in prediction and decision-making wherein predictions regarding future values are generated by combining historical data with fuzzy functions. This fuzziness is a result of the datasets' inherent ambiguity. As an extension of the FTS method, the Weighted Fuzzy Time Series (WFTS) technique was created [10]. It is by assigning weight to individual fuzzy relationships. The WFTS highlights the diverse importance of the sequence of fuzzy relations. The procedure for generating forecasts utilizing Chen's algorithm comprises the subsequent stages [18]:

Step 1. Establishing the Universe of Discourse (U) by utilizing the maximum (D_{min}) and minimum (D_{max}) values obtained from the dataset and two positive integers d1 and d2.

$$U = [D_{min} - d_1,\ D_{min} - d_2] \tag{2}$$

Step 2. Partitioning the Universe of Discourse into multiple subsets of identical range size and subsequently constructing a fuzzy set from the subsets $u_1, u_2, \ldots, u_n$.

$$sturges = 1 + 3.322 \log n \tag{3}$$

Step 3. Defining fuzzy sets A_i, formed by dividing the Universe of Discourse into subsets. The **Equation (4)** demonstrates the fuzzification of one set:

$$A_1=\frac{a_{11}}{u_1}+\frac{a_{12}}{u_2}+\ldots+\frac{a_{1n}}{u_n},$$
$$A_2=\frac{a_{21}}{u_1}+\frac{a_{22}}{u_2}+\ldots+\frac{a_{2n}}{u_n},$$
$$\ldots$$
$$A_k=\frac{a_{k1}}{u_1}+\frac{a_{k2}}{u_2}+\ldots+\frac{a_{kn}}{u_n}. \quad (4)$$

The membership degree value, denoted as A_i, is defined as follows: $A_{ij} \in [0,1]$, $1 \leq i \leq k$, and $1 \leq j \leq n$. A data point is considered to be part of a fuzzy set A_i when its degree of membership in A_i is the highest.

Step 4. Development of the Fuzzy Logical Relationships Group (FLRG). The classification is established based on the current states in respect to its future state fuzzy logical connections; as an illustration: For example, $A_i \to A_b$, $A_i \to A_d$, $A_i \to A_e$ then $A_i \to A_b, A_d, A_e$.

Step 5. Determining the predicted values. Suppose F(t-1) =A_i, so the value of F(t) is calculated by considering the following cases:

a. If the fuzzy logical sequence consists of only a single logical relationship, such as $A_i \to A_j$, then the predicted value F(t) is A_j.
b. If the fuzzy logical sequence consists of many logical relationships, such $A_i \to A_a, A_b, \ldots, A_k$, then F(t) is taken from $(n_1+n_2+\ldots+n_p)/p$, where $n_1, n_2, \ldots, n_p$ were the midpoints of the intervals $u_a, u_b, \ldots, u_k$, respectively.
c. If the fuzzy logical sequence does not exist, then the F(t) equals with the current fuzzy logical.

Step 6. Defuzzification step. If the prediction of F(t) were $A_1, A_2, \ldots, A_k$, then the defuzzified values are the same with midpoints value of $A_1, A_2, \ldots, A_k$.

$$M(t) = [m_1, m_2, \ldots, m_{jk}] \quad (5)$$

Step 7. Assigning the weights **[10]**.

$$w(t) = [w'_1, w'_2, \ldots, w'_k] = \left[\frac{w_1}{\sum_{h=1}^{k} w_h}, \frac{w_2}{\sum_{h=1}^{k} w_h}, \ldots, \frac{w_k}{\sum_{h=1}^{k} w_h}\right] \quad (6)$$

Step 8. Calculating the weighted values for the forecast. The prediction value is calculated by multiplying the defuzzified matrix with the transpose of the weight matrix, resulting in the weighted model. **[11]** proposes using a differencing technique to compare the observed data and the midpoint values created within each interval class.

$$\hat{F}(t) = M(t) \times w(t)^T, \text{ and} \quad (7)$$
$$\hat{F}(t+1) = F(t+1) \pm |diff(X(t), m_i) \quad (8)$$

where $m_1, m_2, \ldots, m_n$ is the midpoints of fuzzy interval.

2.3 The Particle Swarm Optimization

The Particle Swarm Optimization (PSO) algorithm was introduced by James Kennedy and Russell Ebenhart in 1995. The aforementioned technique is among various metaheuristic methods that can be utilized to tackle optimization challenges **[19]**. The researcher stated that this optimization technique is based on the collective behavior observed in flocks of birds and schools of fish as they navigate and solve complicated nonlinear issues. In order to achieve an optimal outcome, the particles experience two specific forms of learning. In addition to its individual trajectory, every particle will gain instruction from the experiences of other particles. Particles retain the memory of the optimal solution (Personal best), denoted as P_{best}, as a result of cognitive learning. G_{best} denotes the optimal outcome (Global best) within the context of social learning. The subsequent equation to calculate the displacement of particles into a new location:

$$x_{i,j}^{t+1} = x_{i,j}^{t} + v_{i,j}^{t+1} \quad (9)$$

where $x_{i,j}^t$ is the actual position of the particle i and dimension j in the iteration t. And $v_{i,j}^t$ represents the velocity of particle i of dimension j in the iteration t. The velocity and the position will always be updated. The **Equation (10)** is used to update the velocity.

$$v_{i,j}^{t+1} = \omega . v_{i,j}^t + c_1 . r_1 \left(P_{best}{}_{i,j}^t - x_{i,j}^t \right) + c_2 . r_2 (G_{best}{}_{g,j}^t - x_{i,j}^t) \quad (10)$$

where,

ω : the inertia weight,
c_1 : the self-cognition,
c2 : the social cognition,
r_1 and r_2 : random numbers between 0 and 1,
$P_{best}{}_{i,j}^t$: personal best position of particle i and dimension j in the iteration t,
$G_{best}{}_{g,j}^t$: global best position of particle i and dimension j in the iteration t.

2.4 Performance Evaluation

After constructing the models, their predicted results are evaluated and compared using assessment metrics. In this work, two error measures were utilized to assess the models. They are Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE). The formulas for calculating the error metrics MAPE and RMSE are represented by **Equations (11)** and **(12)**, respectively **[20]**:

$$MAPE = \frac{1}{n} \sum_{t=1}^{n} \left| \frac{x_t - \hat{x}_t}{x_t} \right| \times 100\% \quad (11)$$

$$RMSE = \sqrt{\left(\frac{1}{n}\right) \sum_{i=1}^{n} (x_t - \hat{x}_t)^2} \quad (12)$$

where,

n : number of data,
x_t : the observed value at time t,
$\hat{x}_t$: the predicted value at time t.

3. RESULTS AND DISCUSSION

This section overviews the results and evaluates the model's effectiveness. The average daily temperatures are forecasted in this study using Chen's Fuzzy Time Series model as the basis. Chen's fuzzy model is optimized by employing weight and Particle Swarm Optimization (PSO) techniques to determine the optimal fuzzy interval length.

3.1 Experiment Model Training

The study is performing a univariate analysis of time series data. The feature is the average Air Temperature time series. The model's development process commences with pre-processing, followed by setting the initial hyperparameters to get the most optimal forecasting model. The first step in building the model is establishing the universe of discourse. Chen's conventional fuzzy time series model applies an equal-length fuzzy interval to every fuzzy set. However, by implementing the PSO later, the primordial step generates uniform random numbers within the range of the Universe of Discourse. The value of the Universe of Discourse based on **Equation (2)** is U = [19.1, 27.9]. The hyperparameters for the PSO, which are obtained through a random search, are as follows:

- Number of particles = 5
- Number of iterations = 15
- Dimension of particles = 9
- c_1 = 1
- c_2 = 1.5
- w = 0.5
- r_1 and r_2 = Random variables that change through iteration.

The chosen hyperparameter values yield an ideal model that avoids under and overfitting. Given the number of particles, which is 5, i.e., there are five distinct linguistic variable sets between each particle. Specifically, each particle possesses a unique A_1-A_9 values (value of the interval points). A_1-A_9 is the fuzzy sets of a particle. Subsequently, the optimized Weighted Fuzzy Time Series is executed using the particle with the lowest Mean Absolute Percentage Error (MAPE) value.

3.2 Identification of the Optimum Order length

Chen's fuzzy model with weight is implemented to identify the best order value. The Universe of Discourse is primordial to building a fuzzy time series model, i.e., using **Equation (2)**. Since a conventional Chen's fuzzy time series utilizes an interval with equal length, the maximum conceivable interval length within the range of the Universe of Discourse is 1. Hence, the WFTS encompasses a total of 9 linguistic variables. The next step is the evaluation process based on their MAPE and RMSE within different order values. The scenarios of order value are order 1, order 2, and order 3. Those three scenarios will give a solid foundation for a more comprehensive understanding of the temporal relationships in the data. Note that, in high-order fuzzy time series forecasting, the model incorporates several prior observations simultaneously (higher-order relationships) instead of simply evaluating immediate past data (first-order relationships). **Table 1** displays the evaluation of each order related to the train and test sets. It is noticed that order 2 surpasses all the other order values in test sets. It is also seen that order-3 leads to overfitting, i.e., it has the lowest error on training data but does not perform well on the test set. Thus, it is noticed that the optimum order value for predicting future values is not always based on the higher order.

Table 1. Evaluation Result Based on Different Order Values

Sets	Orders	MAPE	RMSE
Train	1^{st} order	2.3922	0.6178
	2^{nd} order	2.0944	0.5235
	3^{rd} order	2.0211	0.5036
Test	1^{st} order	2.5205	0.6689
	2^{nd} order	**2.2603**	**0.5822**
	3^{rd} order	2.3014	0.5973

3.3 Identification of the Best Particle

The value of the best order, which is 2nd-order, from the previous step is used to identify the best particle. Note that each particle has different interval values; thus, uniform randomization within the range of Universe of Discourse U = [19.1, 27.9] is required to generate the initial interval values. The number of interval point values is the number of dimension+1, i.e., a total number of 10 fuzzy interval point values. There are five particles, and each particle is incorporated into iterations of the WFTS model using the PSO function.

Suppose we calculate the fuzzy interval from the first iteration of *Particle 1*. Bellows are the fuzzy interval and the MAPE before the first iteration of PSO:

- Particle 1: A_1= [19.1, 19.61), A_2= [19.61, 20.47), A_3= [20.47, *21.48*), A_4= [*21.48*, 22.39), A_5= [22.39, 24.36), A_6= [24.36, 25.54), A_7= [25.54, 26.72), A_8= [26.72, 27.46), A_9= [27.46, 27.9]. MAPE = 1.7422
- Particle 2: A_1= [19.1, 19.28), A_2= [19.28, 20. 70), A_3= [20.70, 21.08), A_4= [21.08, 21.96), A_5= [21.96, 24.38), A_6= [24.38, 25.33), A_7= [25.33, 26.42), A_8= [26.42, 27.63), A_9= [27.63, 27.9]. MAPE = 2.3688
- Particle 3: A_1= [19.1, 20.32), A_2= [20.32, 21.66), A_3= [21.66, 21.77), A_4= [21.77, 22.39), A_5= [22.39, 22.90), A_6= [22.90, 23.71), A_7= [23.71, 24.48), A_8= [24.48, 26.26), A_9= [26.26, 27.9]. MAPE = 1.7577
- Particle 4: A_1= [19.1, 19.50), A_2= [19.50, 20.60), A_3= [20.60, *20.85*), A_4= [*20.85*, 23.11), A_5= [23.11, 23.62), A_6= [23.62, 24.31), A_7= [24.31, 25.44), A_8= [25.44, 26.00), A_9= [26.00, 27.9]. **MAPE = 1.0316**
- Particle 5: A_1= [19.1, 19.67), A_2= [19.67, 19.95), A_3= [19.95, 21.78), A_4= [21.78, 22.97), A_5= [22.97, 25.12), A_6= [25.12, 26.21), A_7= [26.21, 27.45), A_8= [27.45, 27.59), A_9= [27.59, 27.9]. MAPE = 2.1791

Let us calculate the velocity and the next position of the particle 1.
At dimension 4:
To calculate the next position, it is required to determine its velocity toward its next position first. The equation bellow describes the calculation of $v_{1,4}^{t+1}$. Note that its velocity before the PSO iteration is 0 ($v_{1,4}^{t}$=0).

We have:
- The random numbers: r_1 = 0.82, and r_2 = 0.37,
- The personal best position of the Particle 1 at dimension 4: $P_{best}{}_{1,4}^{t}$ = 20.48,
- The Global best of the first run at dimension 4: $G_{best}{}_{g,4}^{t}$= 20.85

  Thus, by using **Equation (10)**, we have the velocity needed of the particle 1 at dimension 4 to move toward to the best position:

$$v_{1,4}^{t+1} = 0.5 \times 0 + 1 \times 0.82(20.48 - 20.48) + 1.5 \times 0.96(20.85 - 20.48) = 0.20 \tag{13}$$

  And by using **Equation (9)**, we get the next position of the particle 1 at dimension 4:

$$x_{1,4}^{t+1} = 21.48 + 0.20 = 20.67 \tag{14}$$

By using the same process, the followings are the results of velocity calculation and the next position of the other dimensions of Particle 1.
At dimension 1: r_1 = 0.05, and r_2 = 0.77. ➔ $v_{1,1}^{t+1} = 0$ ➔ $x_{1,1}^{t+1} = 19.1$
At dimension 2: r_1 = 0.09, and r_2 = 0.56. ➔ $v_{1,2}^{t+1} = -0.09$ ➔ $x_{1,2}^{t+1} = 19.51$
At dimension 3: r_1 = 0.50, and r_2 = 0.45. ➔ $v_{1,3}^{t+1} = 0.08$ ➔ $x_{1,3}^{t+1} = 20.55$
At dimension 5: r_1 = 0.06, and r_2 = 0.80. ➔ $v_{1,5}^{t+1} = 0.86$ ➔ $x_{1,5}^{t+1} = 23.25$
At dimension 6: r_1 = 0.39, and r_2 = 0.06. ➔ $v_{1,6}^{t+1} = -0.06$ ➔ $x_{1,6}^{t+1} = 24.29$
At dimension 7: r_1 = 0.48, and r_2 = 0.22. ➔ $v_{1,7}^{t+1} = -0.40$ ➔ $x_{1,7}^{t+1} = 25.13$
At dimension 8: r_1 = 0.91, and r_2 = 0.44. ➔ $v_{1,8}^{t+1} = -1.50$ ➔ $x_{1,8}^{t+1} = 25.21$
At dimension 9: r_1 = 0.71, and r_2 = 0.87. ➔ $v_{1,9}^{t+1} = -1.90$ ➔ $x_{1,9}^{t+1} = 25.55$

Therefore, the Particle 1 becomes: A_1= [19.1, 19.51), A_2= [19.51, 20.55), A_3= [20.55, *20.67*), A_4= [*20.67*, 23.55), A_5= [23.55, 24.29), A_6= [24.29, 25.13), A_7= [25.13, 25.21), A_8= [25.21, 25.55), A_9= [25.55, 27.9]. MAPE = 1.40.

Table 2 displays the MAPE before implementing the PSO and at the final PSO iteration using the train set. It is noted that initially, Particle 4 had the lowest error, but at the last iteration, Particle 5 had the lowest error. Besides, it is noticed that all the particles tend towards the least error values at the previous iteration. Here is the fuzzy set of the particle five after the last iteration, that considered as the best parameters for training model, and used for performing testing: A_1= [19.1, 19.50), A_2= [19.50, 20.60), A_3= [20.60, 20.85), A_4= [20.85, 23.10), A_5= [23.10, 23.64), A_6= [23.64, 24.31), A_7= [24.31, 24.47), A_8= [24.47, 25.99), A_9= [25.99, 27.9].

Table 2. Evaluation Result of PSO Iteration on Train Set

Particles	MAPE	
	Before the First iteration	After the Last iteration
Particle 1	1.7422	0.9808
Particle 2	2.6988	0.9653
Particle 3	1.7577	0.9890
Particle 4	**1.0316**	0.9654
Particle 5	2.1791	**0.8798**

3.4 Model Evaluation

To evaluate the proposed model, particle 5 with order 2 is used as it delivers the most negligible error value after implementing the PSO. Then, the comparison of it with the conventional Chen's Fuzzy time series model with 2nd order is conducted. The MAPE and RMSE evaluation matrices are used to perceive the goodness of the model.

Table 3. Forecasting Evaluation Based on the Proposed model

Models	MAPE	RMSE
WFTS	2.2603	0.5822
WFTS-PSO	1.2551	0.3196

Table 3 displays the evaluation matrices for the conventional and the proposed model based on the testing set. It is noticed that the proposed model has the lowest MAPE compared with the traditional WFTS, 1.2551 and 2.2603, respectively. The MAPE values indicate that the proposed model deviates 1.22% from the actual data, whereas the conventional is 2.26%. The proposed model overcomes the conventional WFTS based on the Root Mean Square Error values, 0.3196 and 0.5822, respectively.

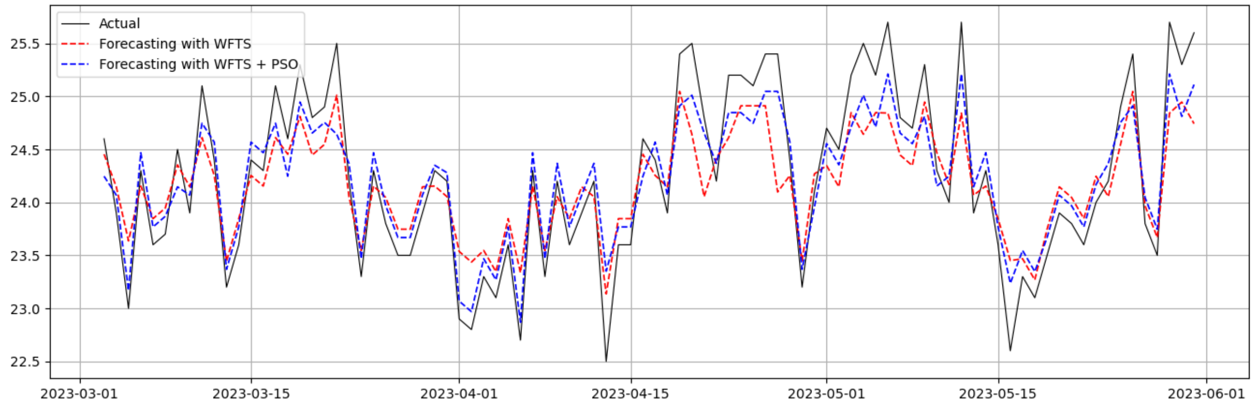

Figure 2. Forecasting over 30 days based on the proposed models

Moreover, **Figure 2** shows the qualitative performance of the two models compared with the actual data set. The plot shows that the proposed model has a more substantial correspondence with the actual test set than the conventional WFTS. The proposed model needs to be stronger in capturing the extremum (the highest and lowest) value due to the estimated weight from the training process. The frequency of the extreme value from the historical data must be increased for an adequate weight estimation value. Nevertheless, the prediction values follow the actual data pattern, i.e., the proposed model can capture the pattern of the average Air Temperature correctly. Therefore, the proposed model outperforms the classical WFTS in predicting future Air temperature values, i.e., the forecasting of Air temperature variables is more accurate when the PSO techniques are applied to the data set. On the other hand, it serves as a valuable benchmark for future research on forecasting models and associated encounters in Malang, specifically regarding Air Temperature. Besides, as the Air Temperature can vary significantly from location to location due to factors such as topography, proximity of bodies of water, etc., it is crucial to consider the spatial factors, i.e., using spatial data. It can assist in capturing the diversity within a particular region and generating more accurate temperature forecasting.

4. CONCLUSIONS

A precise model to predict Air Temperature is crucial for making timely and appropriate decisions in the future. The optimized WFTS model with PSO optimizer surpasses the classical weighted Chen's fuzzy model while predicting future average Air Temperature values. Updating the WFTS interval length using PSO and lag-2 produces a more accurate Air temperature forecasting than the classical Chen's WFTS. An unequal interval length on the fuzzy sets improves the weight values and the model's accuracy. Based on the Evaluation metrics, the proposed model has error values of 1.25 and 0.32, whereas the classical weighted fuzzy time series model has 2.26 and 0.58 for the MAPE and RMSE, respectively. The difference between the conventional weighted fuzzy time series model and the optimized model is slight. Companies can also rely on the proposed model to predict future air temperature; precisely, the proposed model can accurately predict the pattern of air temperature change. Aside from further research, it is recommended that dual optimization be implemented and other variables related to air temperature be considered to have better accuracy in air temperature forecasting or to capture the upper and the lower extreme values.

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