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A Hybrid Model High-Order Hesitant Fuzzy Time Series and Multilayer Perceptron with Mean Aggregated Membership Value for Enhanced Air Pollutant Concentration Forecasting

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ABSTRACT

This study introduces an advanced hybrid model integrating High-Order Hesitant Fuzzy Time Series (HOHFTS) with a Multilayer Perceptron (MLP) to improve the accuracy of air pollutant concentration forecasting. The model utilizes Hesitant Fuzzy Sets to define fuzzy sets, mean aggregated membership values to handle hesitant fuzzy elements, and MLP neural networks to capture complex relationships. A distinguishing feature is the determination of the optimal fuzzy time series (FTS) order, set to 24 in this study, to effectively capture daily temporal dependencies in the hourly air pollutant data. A case study using Semarang City's air pollution dataset demonstrates the model's effectiveness, with preprocessing addressing missing values and interval-based discretization. Performance evaluation with Mean Absolute Error (MAE) and Symmetric Mean Absolute Percentage Error (SMAPE) indicates outstanding accuracy, with SMAPE values below 10% for most pollutants. Further exploration of hyperparameter optimization and order determination is recommended to enhance generalization and computational efficiency.

KEYWORDS: Fuzzy Time Series, Multilayer Perceptron, Hesitant Fuzzy Set, High-Order Hesitant Fuzzy Time Series, Air Pollution Forecasting, Accuracy Metric

I. INTRODUCTION

Fuzzy concept introduced by Lotfi Zadeh in 1965 is a mathematical framework for dealing with uncertainty, vagueness and imprecision which are often present in real-world. Unlike classical set theory where an element belongs to a set or doesn't, fuzzy set allow for partial membership where an element belong to a set to a certain degree that can be represented by a membership value between 0 and 1. Fuzzy concept also developed to forecast and known as Fuzzy Time Series introduced by Song and Chissom is a forecasting technique that applies fuzzy principles by modelling time series data as a sequence of fuzzy sets [1], [2]. In 2002, Chen introduced high-order fuzzy time series concept which involves two or more sequential data in time series to model Fuzzy Logic Relation (FLR) [3]. To define the fuzzy set, many techniques has been developed by researchers. One of the concept in defining fuzzy set is the concept of Hesitant Fuzzy Set (HFS) that allows each element of data point has multiple membership value [4]. Beside in defining the fuzzy set, fuzzy time series concept can be developed in the defuzzification not only using certain defuzzification technique but also another algorithms including machine learning and deep learning algorithms. In previous research, Pattanayak [5], [6] use Support Vector Machine to models the FLR to get the forecasted value without using any defuzzification techniques, where this approach is one of interesting as the machine learning algorithm are used to models and resulting the forecasting result. Inspired by this, instead of using a machine learning algorithm, a deep learning algorithm could be used to models and forecast based on the constructed FLR. One of deep learning algorithms is Multilayer Perceptron (MLP) that is a feedforward neural network that consist of one input and output layer and one or more hidden layer and capable to solve non-linear problems approximating continuous function [7]. MLP categorized as supervised learning that learn input-output patterns and approximate non-linear function mapping from input space into output space [8]. Motivated by this, in this research the fuzzy time series concept will be developed by using hesitant fuzzy set to define its set along with high-order fuzzy time series concept to record more data points and the MLP will be used to models and forecast the forecasting result.

Substances or energy introduced into the environment that cause harmful effects of negatively impact the value of resources called as pollutants[9]. Air pollution encompassed various gases, particles and toxins present in the air and organism at high concentration that could lead into health risks and also respiratory problems [10]. Particulate matter (PM_{10} and $PM_{2.5}$), carbon monoxide (CO), nitrogen dioxide (NO_2), sulfur dioxide (SO_2), ozone (O_3) and hydrocarbon (HC) are common air pollutant especially in Indonesia. This kind of pollution come from many source which primarily from industries, vehicle emissions and natural sources and could risk human respiratory [11]Major pollutants impacting human health include nitrogen oxides, sulfur compounds and suspended particulate matter [12] Air pollution remains a critical global issue due to its significant impact on human health. According to World Health Organization (WHO), approximately 4.2 million premature deaths annually are linked to air pollution, with estimates suggesting this number may rise to 6.7 million deaths per year [13], [14] Monitoring air pollution in urban areas is essential, requiring the measurement of pollutant concentrations and comparison against global air quality standards. Forecasting the Air Quality Index (AQI) and air pollutant concentrations supports decision-making processes for mitigation and preventive measures. Time series data of air pollutant concentrations and AQI, often recorded on an hourly or daily basis can help predict pollution levels, identify trends and recognize patterns. Thus, in its turn enables the development of effective environmental policies and strategies.

Numerous studies related with air pollution and quality prediction have been conducted. Saini *et al.* [15] utilized the Long Short- Term Memory (LSTM) model to predict air pollution parameters in Amravati, India using data from 2008 to 2018. Marinov *et al.* [16] employed the Auto-Regressive Integrated Moving Average (ARIMA) model to forecast pollutants such as ozone and nitrogen dioxide at varying time intervals in Sofia, Bulgaria. Hasnain *et al.* [17] applied the Prophet Forecasting Method (PFM) to predict air pollution levels across multiple monitoring stations in Jiangsu, China. Reikard [18] investigated the effects of volcanic emissions from Kilauea in Hawaii on air quality and public health, using ARIMA and regression models to forecast pollutant concentrations.

Motivated by those past research, this research aims to develop a prediction model by integrating High-Order Hesitant Fuzzy Time Series (HOHFTS) with Multilayer Perceptron (MLP). The proposed model will be applied to a pollutant concentration dataset from Semarang City, and its performance will be evaluated using Mean Absolute Error (MAE) and Symmetric Mean Absolute Percentage Error (SMAPE) to measure the model's accuracy.

II. PROPOSED MODEL

In traditional Fuzzy Time Series (FTS) analysis, forecasting typically involves seven key steps: defining the Universe of Discourse (UOD), partitioning the UOD into intervals, defining fuzzy sets, fuzzifying the time series data, establishing Fuzzy Logical Relationships (FLRs), constructing Fuzzy Logical Relationship Groups (FLRGs), and defuzzifying the results to produce the forecasted value. However, this research proposes a novel hybrid model that combines three advanced approaches to overcome the limitations of traditional FTS techniques.

First, Length-Based Discretization (LBD) is employed to dynamically determine the Number of Intervals (NOI) and construct two Universes of Discourse (UODs). Next, High-Order Hesitant Fuzzy Time Series (HOHFTS) is utilized to model complex relationships between sequential data points by leveraging hesitant fuzzy sets for a more nuanced definition of fuzzy sets and FLRs. Finally, a Multilayer Perceptron (MLP) is integrated to refine the forecasting process, replacing the need for conventional defuzzification techniques by learning directly from the data, thereby there is no certain defuzzification technique and the proposed model called High Order Hesitant Fuzzy Time Series- Multilayer Perceptron (HOHFTS-MLP) and hereby its model architecture

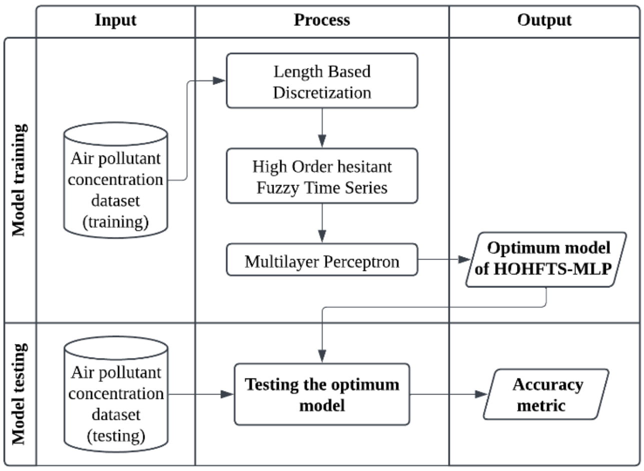

Figure 1 Model architecture of HOHFTS-MLP

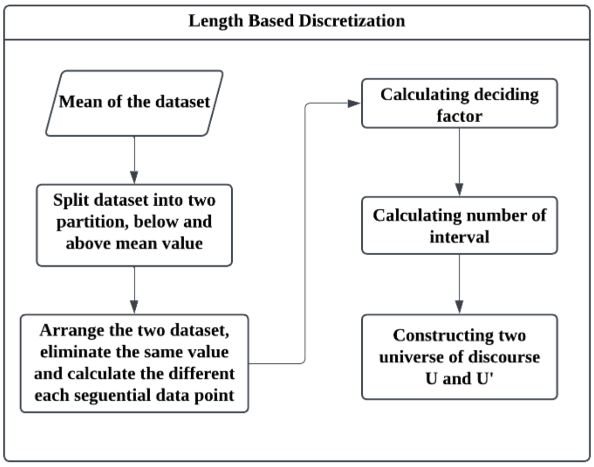

Figure 2 Algorihtm of LBD approach

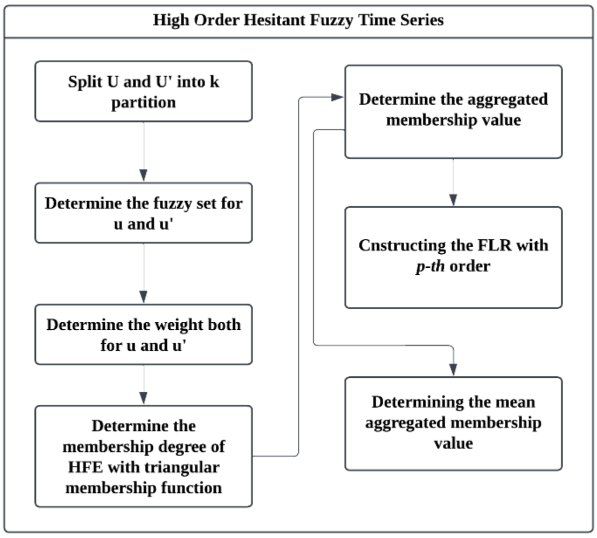

Figure 3 Algorihtm of HOHFTS approach

In high order fuzzy time series, the FLR can be constructed from two or more data point in the past [19]. For example, if $F(t)$ is caused by the sequence of $F(t-1), F(t-2), F(t-3), \dots, F(t-m)$, then the FLR can be constructed as $F(t-m), \dots, F(t-3), F(t-2), F(t-1) \rightarrow F(t)$, and can be called as the m[th] order of Fuzzy Time Series model. The hesitant fuzzy set, is a generalization of a fuzzy set that allows the membership degree of an element to be represented as a set of possible values, rather than a single value [20]. A Hesitant Fuzzy Set (HFS) H on a universe of discourse X dan be defined as $H = \{\langle u, h_H(u)\rangle | \forall u \in U\}$, where $h_H(u)$ is a set of possible membership degrees of u in H and called as Hesitant Fuzzy Element (HFE). To obtain the representative of HFE that may various, an aggregation operator will be used to simplify using this formula [21]

$$h = 1 - \prod\nolimits_{i=1}^{v} (1-u_i)^{w_i}$$

where v represents the number of subsets formed for each observation of membership degree in range [0,1] of each interval in the fuzzy set and for each u_i, the weight represented as w_i $\forall i | i = 1,2,3, \dots, v$ such that $\sum_{i=1}^{v} w_i = 1$.

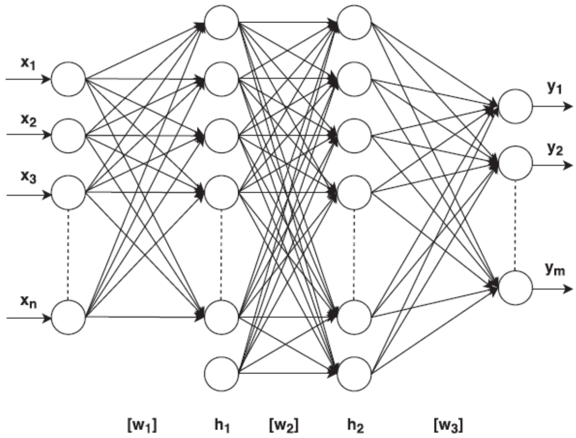

Figure 4 Basic structure of MLP [22]

MLP that basically consist of 3 layers, in this research the input layer is the past data based on the number of the obtained order and its FLR. Generally, if the order of FLR is m^{th} then the obtained FLR is $F(t-m), \dots, F(t-3), F(t-2), F(t-1) \rightarrow F(t)$ the input layer would be all of the m number of past data points. The number of hidden layer and its number of neurons is flexible, even adding more layer could bring better accuracy but they don't always lead into it, for complex data the hidden layers often require at least two or three hidden layers or can be more with regularization to avoid model to overfit [23], [24], [25]. To prevent resulting overfiting model, L2 regularization will be used add weight penalties without eliminating weights entirely [26], [27].

Accuracy metrics, Mean Absolute Error (MAE) and Symmetric Mean Absolute Percentage Error (SMAPE), are used to evaluate the performance of the proposed model. Lower values of MAE and SMAPE indicate better forecasting accuracy. MAE can be expressed as follows [28]

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |y_i - \hat{y}_i|$$

SMAPE can avoid problem of large errors when the actual value is very close to zero and large difference between the absolute error of actual and predicted value and can be expressed mathematically as follows [29]

$$SMAPE = \frac{1}{n}\sum_{i=1}^{n} \frac{|y_i - \hat{y}_i|}{(y_i + \hat{y}_i)/2} . 100\%$$

III. RESULT AND DISCUSSION

The air pollutant concentration dataset includes $PM_{2.5}$, PM_{10}, SO_2, CO, O_3, NO_2 and HC recorded at 30 minutes intervals from January 1[st], 2023 to September 4[th],2024 resulting 29,424 data points with the number of missing value are shown in Table 1. To handle missing values in dataset, four-step process applied:

1. Missing value will be filled based on the average of the same hour in the same week,
2. For remaining missing values will be filled using the average from same hour in previous and next week,

3. Any further missing values will be filled using the average from the same hour in same month, and
4. Finally, use the average for the same hour in the previous and next month for any remaining gaps.

Table 1 Number of missing values from each air pollutant

Air Pollutant	*Number of Missing Value*
$\mathbf{PM_{10}}$	9899
$\mathbf{PM_{2.5}}$	17055
$\mathbf{SO_2}$	4831
CO	5883
$\mathbf{O_3}$	10569
$\mathbf{NO_2}$	6399
HC	14725

Before applying the HOHFTS-MLP model, the dataset was aggregated into hourly intervals by averaging every two consecutive 30-minute records for the same hour. This process reduced the original 29,424 data points to 14,712 hourly data points.

Table 2 Descriptive statistic from each air pollutant

Air Pollutant	*Mean*	*Range*	*Standard Deviation*
$\mathbf{PM_{10}}$	30.137	186.5	17.215
$\mathbf{PM_{2.5}}$	8.138	93	8.49
$\mathbf{SO_2}$	36.281	145	13.315
CO	1392.185	5292	718.552
$\mathbf{O_3}$	34.575	226	42.463
$\mathbf{NO_2}$	31.394	164.5	25.884
HC	32.132	98.5	21.69

Following the preprocessing phase to prepare the dataset, the Length-Based Discretization (LBD) method was applied to each air pollution concentration dataset. This process determined the Number of Intervals (NOI) along with two universes of discourse (UOD), U and U'. The outcomes are as follows:

Table 3 NOI and two UODs from each air pollutant

Air Pollutant	*NOI*	*U*	*U'*
$\mathbf{PM_{10}}$	6	[0.99, 188.0]	[0.99, 220.0]
$\mathbf{PM_{2.5}}$	4	[0.99, 94.5]	[0.99, 120.0]
$\mathbf{SO_2}$	6	[4.49, 151.0]	[4.49, 172.5]
CO	6	[0.99, 5296.46]	[0.99, 6136.5]
$\mathbf{O_3}$	11	[8.99, 235.5]	[8.99, 256.5]
$\mathbf{NO_2}$	110	[14.49, 179.5]	[14.49, 180.5]
HC	201	[0.99, 100.0]	[0.99, 100.0]

Based on the result of LBD approach, the HOHFTS approach can be deployed. Based on the two universe of discourse U and U', the interval partition can be determined by dividing the range of the universe of discourse to the number of intervals. For example, $PM_{2.5}$ has 4 number of interval, hereby the length of every interval in universe of discourse U and U' that denoted by b and b' can be calculated b$=\frac{94.5-0.99}{4}=23.3775$ and $b'=\frac{120.000-0.990}{4}=29.7525$ and this result can be used to determine the weight both for u and u' that denoted by w and w' can be calculated w$=\frac{23.3775}{23.3775+29.7525}=0.44001$ and $w'=\frac{29.7525}{23.3775+29.7525}=0.55999$ and this calculation of length of interval and weight of interval also applied in other air pollutant. After the length of interval and its weight for both U and U' are obtained, each data points in air pollutant dataset will be determined its HFE value. In this research, each data points will have two HFE as it come from universe of discourse U and U'. To determine the membership degree of each data points, triangular membership function will be used, for example the first data point of $PM_{2.5}$ is 6.5 $\mu g/m^3$ located in first interval both for U and U', then the membership degree for u_1 can be calculated $\mu_{(6.5)}(u_1)=\frac{6.5-0.99}{12.67875-0.99}=0.471393$ where 0.99 is the lower bound of the first interval partition and 12.67875 is the midpoint of the first interval in UOD of U' and with same technique, the membership degree for u'_1 can be calculated $\mu_{(6.5)}(u'_1)=\frac{6.5-0.99}{15.86625-0.99}=0.370389$, therefore the HFE of 6.5 are 0.473063 and 0.370389. The two memberships degree obtained then aggregated using aggregation operator, thus the aggregated membership value can be calculated as $h_{1(6.5)}=1-[(1-0.471393)^{0.44001}.(1-0.370389)^{0.55999}]=0.417014$.
Since 6.5 was located in the first interval both for U and U', it means that the membership value for other interval partition will be 0, thus the aggregated value also 0, which means $h_{2(6.5)}=h_{3(6.5)}=h_{4(6.5)}=0$ and the mean aggregated membership value can be calculated $\bar{h}_{(6.5)}=\frac{0.417014+0+0+0}{4}=0.104254$. The obtained mean aggregated membership value of each data points will be used along with its normalized value to construct Fuzzy Logic Relation (FLR). For example, if the order of the high-order fuzzy time series is 4, then the FLR can be constructed as $y_1,\bar{h}_1,y_2,\bar{h}_2,y_3,\bar{h}_3,y_4\bar{h}_4\rightarrow y_5$ where y is the value of each datapoints and $\bar{h}$ is the mean aggregated membership value related with each datapoints. This step in HOHFTS algorithm also deployed in all air pollution dataset and in each datapoints. In this study, a high-order fuzzy time series model of order 24 was selected, aligning perfectly with the hourly data recording frequency over a 24-hour period, capturing the daily patterns.
To optimize the HOHFTS-MLP model, extensive hyperparameter tuning was performed to balance accuracy and generalization while avoiding overfitting. Key parameters, such as the number of hidden layers, activation functions, and solvers, were tailored for each pollutant to

reflect its unique characteristics. This meticulous process, detailed in Table 4, ensured the model captured underlying patterns effectively and maintained high forecasting accuracy across diverse pollutants. The result is a robust and adaptable model capable of delivering precise air pollutant concentration predictions.

Table 4 Hyperparameter from each air pollutant

Air Pollutant	*Hyperparameter*
PM_{10}	hidden_layer_sizes=(1024,512), solver='adam', max_iter=1000, activation='relu'
$PM_{2.5}$	hidden_layer_sizes=(1024,1024), solver='adam', max_iter=1000, activation='relu'
SO_2	hidden_layer_sizes=(64,128), solver='adam', max_iter=1000, activation='relu'
CO	hidden_layer_sizes=(1024,1024,1024,1024, 1024), solver='adam', max_iter=1000, activation='relu'
O_3	hidden_layer_sizes=(1024,1024), solver='adam', max_iter=1000, activation='relu'
NO_2	hidden_layer_sizes=(256,128), solver='adam', max_iter=1000, activation='relu'
HC	hidden_layer_sizes=(256,512), solver='adam', max_iter=1000, activation='relu'

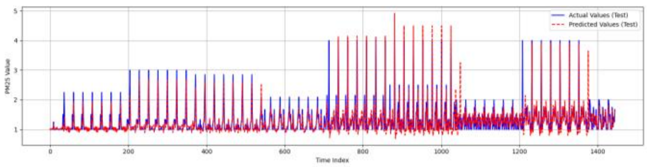

Figure 5 Comparison of actual and predicted $PM_{2.5}$ value in testing

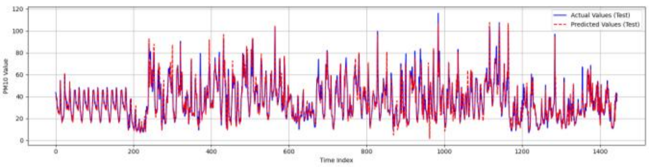

Figure 6 Comparison of actual and predicted PM_{10} value in testing

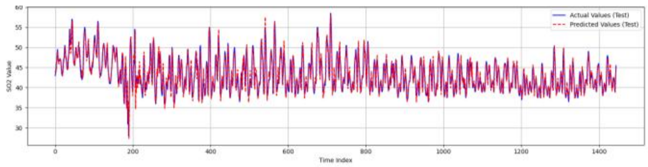

Figure 7 Comparison of actual and predicted SO_2 value in testing

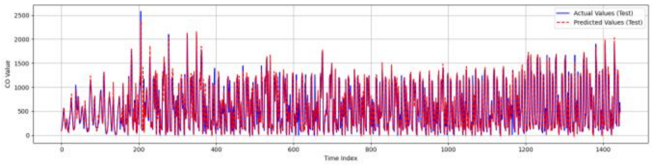

Figure 8 Comparison of actual and predicted CO value in testing

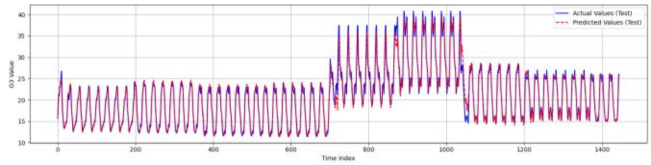

Figure 9 Comparison of actual and predicted O_3 value in testing

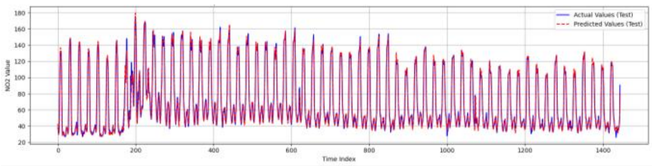

Figure 10 Comparison of actual and predicted NO_2 value in testing

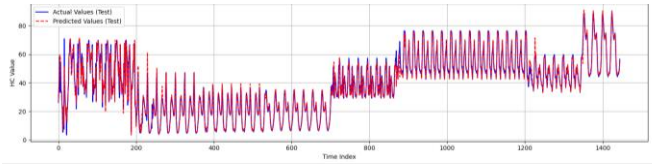

Figure 11 Comparison of actual and predicted HC value in testing

The proposed method, applied to the air pollutant dataset, achieved varying accuracy metrics in testing, as shown in

Table *5*. The dataset was split into 90% for training, 10% for validation, and the remaining 10% for testing. The accuracy metrics, including Mean Absolute Error (MAE) and Symmetric Mean Absolute Percentage Error (SMAPE), highlight the model's performance across different air pollutants. The validation data was used to fine-tune the model's hyperparameters, ensuring a balance between accuracy and generalization while avoiding overfitting during the training process. This split allows for a comprehensive evaluation of the model's robustness and reliability in forecasting air pollutant concentrations.

Table 5 Accuracy metric resulted in testing from each air pollutant

Air Pollutant	*MAE*	*SMAPE (%)*
PM_{10}	2.9436	9.00
$PM_{2.5}$	0.1197	9.05

SO_2	1.1324	2.63
CO	58.345	18.99
O_3	0.8842	4.13
NO_2	2.8211	4.55
HC	1.3545	4.36

While the proposed HOHFTS-MLP model demonstrates strong accuracy for most air pollutants, a deeper sensitivity analysis is required, particularly in determining the FTS order and fine-tuning the MLP hyperparameters. These factors play a pivotal role in the model's ability to capture temporal dependencies and non-linear relationships within the data.

For instance, SO_2 forecasting with an FTS order of 168-corresponding to weekly periodicity and an MLP architecture comprising two hidden layers with 512 and 256 neurons, coupled with the Adam solver and ReLU activation function, achieves impressive results, an SMAPE of 2.44% and an MAE of 1.0482. However, exploring alternative configurations, such as varying the FTS order or adjusting the MLP's architecture, could further optimize performance.

Sensitivity analysis allows for a systematic evaluation of how these parameters influence accuracy, helping to identify the most effective configurations for different pollutants. This process ensures that the model remains robust, adaptable, and capable of delivering high-precision forecasts across diverse environmental scenarios. By refining these parameters, the HOHFTS-MLP model can achieve even greater reliability and efficiency in practical applications.

IV. CONCLUSIONS

The HOHFTS-MLP model developed in this research showcases exceptional performance in forecasting air pollutant concentrations by seamlessly integrating Hesitant Fuzzy Sets (HFS), Multilayer Perceptron (MLP), and an optimal determination of the FTS order for high-order fuzzy time series. By leveraging the strengths of these methodologies, the model effectively captures the inherent complexities of air pollutant data, including non-linear patterns, temporal dependencies, and uncertainties.

Setting the FTS order to 24, which corresponds to hourly recordings over a 24-hour cycle, proved highly effective in capturing daily temporal patterns. This alignment significantly enhanced the model's ability to identify trends and make accurate predictions. The results underscored the model's reliability, with Symmetric Mean Absolute Percentage Error (SMAPE) values consistently below 10% for most pollutants, demonstrating its superior accuracy and adaptability across varying datasets.

Despite its success, the model's performance can be further optimized through refined hyperparameter tuning and advanced exploration of FTS order selection. Future research should delve deeper into adaptive methods for selecting the FTS order, allowing the model to dynamically adjust to different data frequencies and pollutant behaviors. Additionally, the hyperparameter optimization process could benefit from automated approaches, such as Bayesian optimization or grid search, to identify optimal configurations more efficiently.

Overall, the HOHFTS-MLP model represents a groundbreaking tool for air quality monitoring and management. Its innovative design not only enhances forecasting accuracy but also supports informed decision-making and policy development. By addressing critical environmental challenges, this model contributes significantly to sustainable urban planning, health risk mitigation, and the formulation of effective air pollution control strategies.

The HOHFTS-MLP model developed in this research demonstrates exceptional capability in forecasting air pollutant concentrations by combining Hesitant Fuzzy Sets, MLP, and optimal order determination for high-order fuzzy time series. Setting the FTS order to 24 aligns with the hourly recording frequency and captures daily temporal patterns, significantly improving model performance. Results highlight superior accuracy, with SMAPE values below 10% for most pollutants. While the model is highly effective, future work should focus on refining the hyperparameter tuning process and further exploring the role of FTS order selection to maximize accuracy and efficiency. This innovative approach provides a powerful tool for air quality management and environmental decision-making, enabling better forecasting and policy development.

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