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Application Of Multi-Sensor Data Fusion Method with Fuzzy Time Series Model to Improve Indoor Water Prediction Accuracy Quality

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Abstract−There is a lot of indoor air pollution, especially from cigarette smoke, wall paint, air fresheners and gas. With this situation, the room uses Air Box WP6003 air quality detection device by transmitting information about air quality through visualization index. This study aims to improve prediction accuracy with fuzzy time series methods processed through 2 naïve and moving average models using forecast transformers and without transformers. The level of prediction accuracy is calculated through several metrics, namely Mean Absolute Percentage Error (MAPE), Sum of Squares Error (SSE), Mean Square Error (MSE), Root Mean Square Error (RMSE) and Mean Absolute Error (MAE). These results can be calculated between the actual value and the predicted value. The data used is 204584 data from 4 parameters including Temperature, TVOC, HCHO and CO2. The test results with the difference from the forecast transformer and without transformer are comparable. Temperature value obtained using naïve with transformer from RMSE of 0.158866 and naïve without transformer of 0.782397, data using moving average with transformer obtained by 0.147546 and moving average without transformer of 0.772570. This can be explained by the error analysis that was tried, where the error rate continued to increase so that the experimental results continued to be far from the actual number. From the test results it can be concluded that the accuracy of air quality prediction using naïve forecast transformer is pretty accurate.

Keywords: Air Quality; Fuzzy Time Series; Naive; Moving Average

1. INTRODUCTION

About 91% of the world's population breathes air containing pollutants, exceeding the limits set by the World Health Organization (WHO). This pollution is caused by household activities and the burning of solid fuels. 40% of the world's population dies from respiratory diseases. The main causes of pollution in Indonesia are forest fires, garbage burning, motor vehicle activity, and industrial activity, resulting in deaths 6 times faster than life expectancy. industrial activity resulting in deaths faster than life expectancy. The consequences have spread to neighboring countries, and the combustion gases emitted into the atmosphere (such as CO2) which has an impact on global warming [1].

Air quality gets worse, air quality meters are needed. Temperature measuring devices are very needed in certain cases [2]. Temperature is one of the most important things in terms of the smoothness and quality of the server room network. The most effective obstacle is the increase in temperature and humidity in the server room. Servers with high temperature and humidity slow down each other in network processes. The suboptimal effect of suboptimal network quality is a slow network, requiring devices to maintain temperature and humidity levels. Device can predict upcoming events or forecast the future by measuring temperature and humidity and sending a data recording system when the temperature exceeds a predetermined limit [3].

Jenkinsh Box method, the data used must have seasons over a long period of time, so it requires polydata. Fuzzy method This method must first be transformed into a qualitative qualitative form that has the equivalent of a time series over an infinitely long period of time. such as genetic solution methods and artificial neural networks, of course, it is easier to develop. This method can also be used to solve historical network prediction problems in the form of linguistic values. FST research has been developed by several researchers including using the FST method to solve the problem of predicting historical data according to linguistic values [4] , research using the interval partition method, namely H. partition based on frequency density, which forms more accurate forecasting results compared to the regular interval partition method in the fuzzy time series method. FST also used for sales forecasting, stock price forecasting, inflation forecasting to use electricity load forecasting [5]. By making predictions we can also do with the fuzzy time series method [6]. The fuzzy time series method can capture patterns from data and predict future data [2]. Fuzzy time series is suitable for long-term prediction or short-term prediction with short values. short-term predictions with good accuracy [7].

Research on fuzzy time series by Abdullah (2011) describes the prediction of the Kuala Lumpur composite index using fuzzy time series. Prediction of the Kuala Lumpur composite index using fuzzy time series, this method produces an MSE value of 42.44, RMSE 6.52 and AFER 0.389%. Further research by Abdullah and Taib [8] predicted the Malaysian Ringgit exchange rate against the United States Dollar using FTS which in its application produced a practical MSE value of 0.000225796. Chou's research (2012) discusses the use of FTS to predict the steel price index in Asia. steel price index in Asia shows an average forecast error value of 3.90%. further research by Liu, Niu, He and Li (2016) predict words that are often searched on the Weibo site with the fuzzy time series method and the MAPE accuracy value of 2.32%. and the MAPE accuracy value is 2.32%. Research by S Suryono et al, explaining the use of FTS to predicting ambient temperature and relative humidity where this research produces a MAPE value of 4.6% for ambient temperature and 2.76% for relative humidity. for ambient temperature and 2.76% for relative humidity [9].

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In this study with the estimated data accuracy, it can improve the accuracy of indor quality prediction. Calculating the accuracy and reliability of time series data indoor air quality model [7].

Helmi et al. conducted research in 2020 using the MLX-90614 body temperature sensor with the Journal of Final Projects Faculty of Informatics. An accumulation of ultrasonic sensors for action detection and measurement of For the body temperature to work optimally using a statement, if the body temperature is above 37.5% °C, the buzzer will be filled and the magnetic lock door will not open and send information to the telegram. The result is the creation of a prototype body temperature measuring device automatically without the need to involve people.[10].

This research aims to build an IoT-based tool using the Air Box WP6003 sensor as a gas and temperature sensor. then a fuzzy logic sensor with a fuzzy time series forecasting method used to forecast air quality parameters in the room for a certain period.

2. RESEARCH METHODOLOGY

2.1 Research Stages

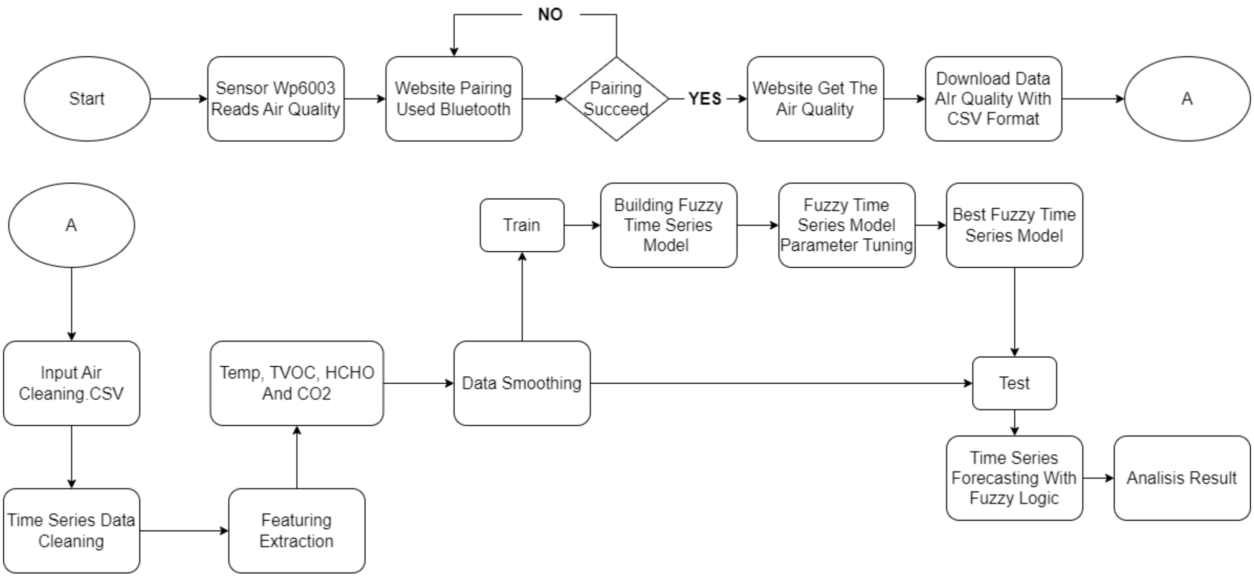

Figure 1. System Design

In designed system, starting from the Air Box WP6003 device which functions to measure air quality in a room, as for the air elements measured are Temperature, HCHO, TVOC, and CO2. after the Air Box WP6003 device is turned on, the device will measure the previous air quality. The website that has been created will pair with the device using Bluetooth communication, if the website cannot pair with the device, then the website will try to pair continuously until it is successfully paired with the device. until it is successfully installed with the device. The device is equipped with a Bluetooth module so that it cannot be connected to the internet connection, the device can send air quality measurement data, after the website is installed on the device, the website will retrieve and store data from the device and display it in a table. Train csv data contains air quality data for some time, csv files will be trained so that they are able to predict air quality values using fuzzy time series with naïve forecasting and moving average forecasting models to improve air quality prediction accuracy. The algorithm built can predict the possibility that will occur in the next few times. Data that has "feature extraction" from a form of value will later be analyzed and processed in a classification manner through calculations and comparisons, after which the data is filtered to eliminate data randomness [11]. The data will be processed and divided into two parts: data training and testing [12]. The data train will be built using the "Building Fuzzy Time Series model" model, after which the parameter data is tuned to obtain an optimal model, and the best value is taken from the FTS model. The data is then tested and produces a predicted value from processing time series forecasting. After the training process is considered good, the predicted results will be visualized.

2.2 Overview of The System

The general description of the system contains the overall design of the system that will be used in the research conducted. system design used in this study:

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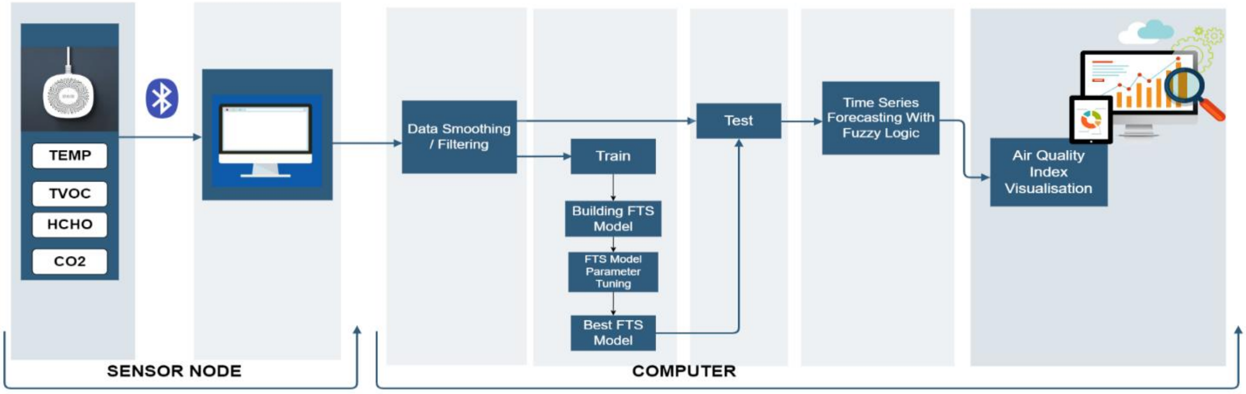

Figure 2. Overview of the system

a. Air Box WP6003 Sensor
   Air Box WP6003 is a TVOC, HCHO, CO2 gas sensor unit and a temperature sensor unit.
b. Data Smoothing
   Filtered data to remove the randomness of time series data to get a forecast of the future era.
c. Fuzzy Logic Inference Engine
   The system that can perform machine learning reasoning [13].
d. Model Parameter Tuning
   Obtain controller parameters that are similar to the required reaction and require a relatively short duration [14].
e. Fuzzy Time Series Forecasting
   A way of estimating information that uses fuzzy principles as its basis. Predictions using fuzzy time series summarize patterns from past information and then use them to predict future statistics [15].
f. Air Quality Index Visualization
   To display time series information with geographic recommendations, and can be applied in controlling other area information (Temperature, TVOC, HCHO, and CO2.) Through several layers [16].

2.3 Tool Design

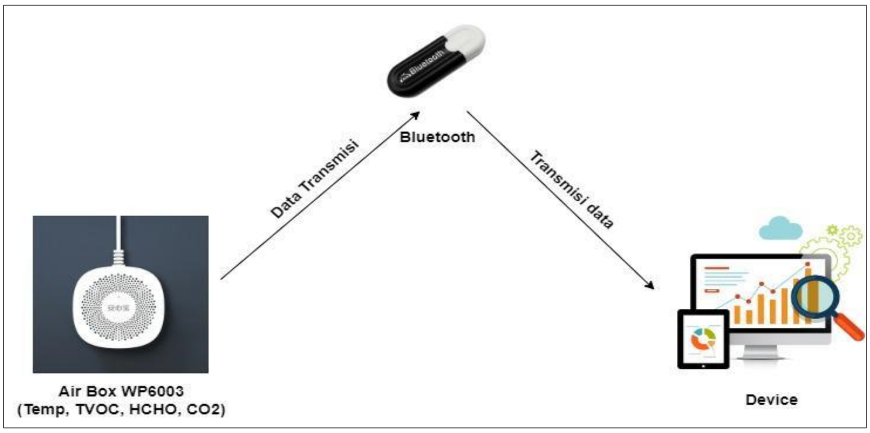

Figure 3. Tool Design

Connecting the WP6003 Air Box sensor to the website via Bluetooth, then after that the sensor will read the data for several weeks, then the data results are downloaded in the form of csv. read data for several weeks, then the data results are downloaded in csv form. The data is successfully processed and gets an accuracy value then the data is uploaded to the database and displayed on the Website. And displays the monitoring results of each content that has been obtained in the room.

2.4 Dataset

In this research, using air quality datasets obtained indoors by measuring Temperature, TVOC, HCHO, CO2 using the Air Box WP6003 tool that has recorded for a month from November 19, 2022 to December 20, 2022 with a total of 204584 data.

2.5 Fuzzy Time Series

Fuzzy time series (FTS), a way of predicting information using a fuzzy time series design as the origin of the calculation. oncept as the basis for its calculations. Forecasting systems using this method work by capturing patterns

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from historical data and using them to project future data. In addition, This method uses complex data so it is easy to apply and refine [17].

2.6 Time Series

Time series is a set of data observations ordered in time. Time series analysis is a Quantitative Forecasting method to determine the pattern of data in the past which is collected based on time sequence or called time series data. Forecasting a time series data need to pay attention to type or data pattern. In general, there are four types of time series data patterns, namely horizontal, trend, seasonal, and cyclical [17].

2.7 Multi Sensor Data Fusion

This method is characterized by continuously assessed improvements and assessments of the need for extra resources or changes to the method itself to achieve better results. Fusion of multi-sensor information can also be attempted in 4 different processing levels according to how the fusion takes place: signal level, pixel level, feature level, and resolution level [18].

2.8 Naïve Method

naive method this method is often used as a comparison because of the ease of obtaining forecasting results. Formulas that can be applied to the Naive method include:

$$\text{Naive Method} = X_{t\text{ -1}} \tag{1}$$

X t = actual data in period t. The forecasting value for the next data is the same as the previous actual data [19].

2.6 Moving Average Method

Methods related to gathering, linking and combining information and data from one base, and multiple bases to achieve position estimates, refine identities, complete and timely calculation of conditions, danger, and significance. This method is called moving average because every time each time new observation data is available, a new average number is calculated and used as a forecast value [19]. Formulas that can be applied in the Simple Moving Average method include:

$$\text{SMA} = \frac{Xt \quad Xt\ 1 \quad Xt\ 2 \ \ldots \ Xt\ n\ 1}{n} \tag{2}$$

Description:
X = actual data at a certain period (t) t
n = a lot of data

2.6 Model Fit Statistics

Model Fit statistics are used to see the goodness of the model used in fitting the behavior of historical time series data. historical time series data. In other words, the statistics of fit can be used to evaluate of the model used with the aim of getting a better model [20]. Some criteria statistics of fit that are available and can be used in TSFS include:

Sum of Squares Error (SSE) : $SSE = {}_{t}^{n}{=}1\ (y_t - \hat{y}_t)^2$ (3)

Mean Square Error (MSE) : $RMSE = {}^{1}{}_{n}\ {}_{t}^{n}{=}1\ (y_t - \hat{y}_t)^2$ (4)

Root Mean Square Error (RMSE) = $\sqrt{\frac{\sum_{i=1}^{n}(X_t - F_t)^2}{n}}$ (5)

Mean Absolute Error (MAE): MAE $= {}^{1}{}_{n}\ {}_{t}^{n}{=}1$ (6)

Mean Absolute Percent Error (MAPE) : MAPE = MAPE = $(\frac{1}{n})\sum_{t-1}^{n} | \frac{X_t - F_t}{X_t} |$ (7)

3. RESULT AND DISCUSSION

This study uses a dataset that has been collected totaling 204584 data, air quality obtained in the room by measuring the temperature of TVOC, HCHO, CO2 using the Air Box tool. obtained in the room by measuring the temperature of TVOC, HCHO, CO2 using the Air Box tool. WP6003 which has been recorded for one month starting from November 19, 2022 to December 20, 2022.

3.1 Test Results

Dataset

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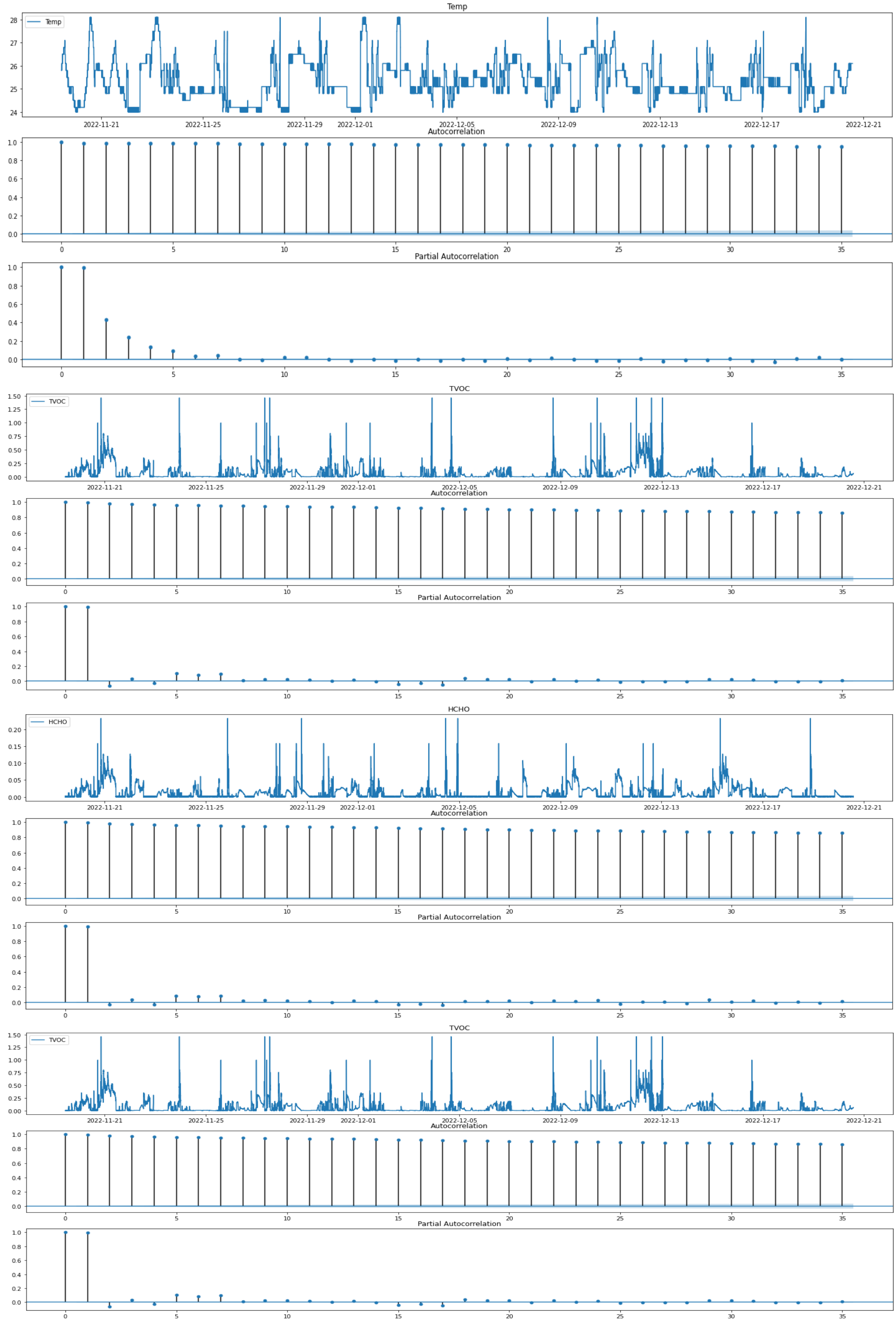

Figure 4. Graph Dataset

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Graph of the dataset obtained consisting of Temperature, TVOC, HCHO and CO2 from the WP6003 device for a month. The results on the graph show that each sensor can function properly. and there is no missing data from the sensor readings.

3.1.2 Test Results Naïve Forecasting

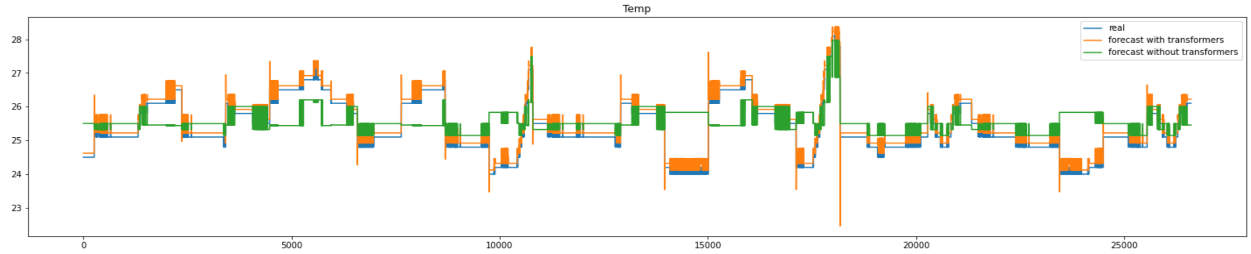

Figure 5. Temperature Prediction Results

Temperature prediction results obtained from the sensor reading data training process, the graph shows the total temperature readings by the device during the period from November 19, 2022, to December 20, 2022. in the figure there is a blue graph which is the original data from the device and the orange line is the prediction of device readings with the transformer method, as well as the green one without transformer. the prediction results using naïve forecasting are good enough with the prediction results with transform better than those without using transform.

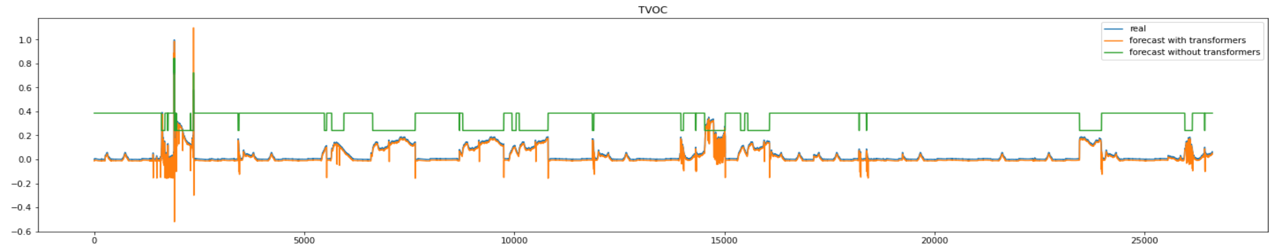

Figure 6. TVOC Prediction Results

TVOC prediction results obtained from the sensor reading data training process. the graph shows the total TVOC readings for November 19, 2022, to December 20, 2022. the blue line graph is the original data, orange prediction data using transformers and green lines of prediction data without transformers. prediction using the naïve forecasting transform method is quite good compared to without using transformers.

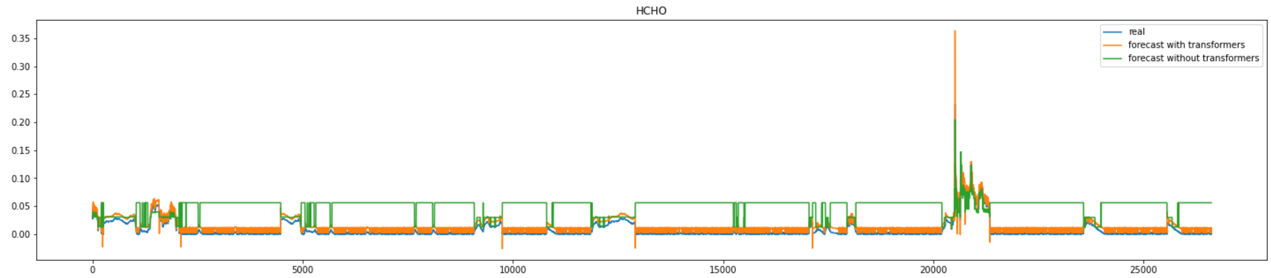

Figure 7. HCHO Prediction Results

HCHO prediction results obtained from the data training process and sensor readings show the total HCHO readings for November 19, 2022, to December 20, 2022. the original data shows almost the same as the prediction data using the naive forecast transformer compared to the data without the forecast transformer. the prediction of the naive forecast transformer method is better than without the forecast transformer.

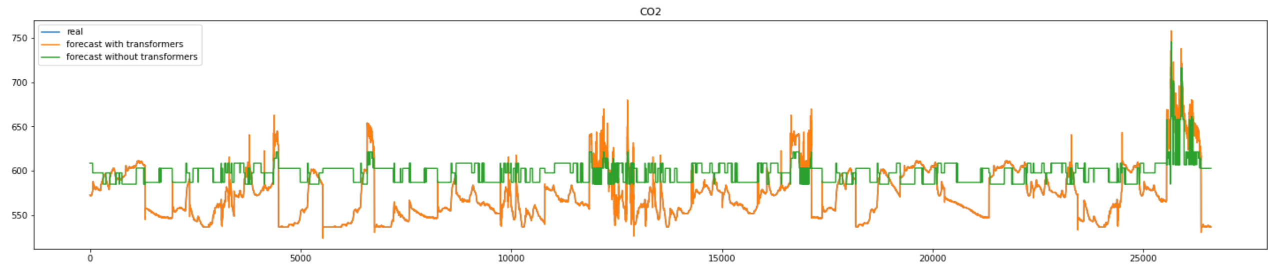

Figure 8. CO2 Prediction Results

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CO2 prediction results obtained from the sensor reading data training process. The graph shows the total CO2 readings by the device during the period from November 19, 2022, to December 20, 2022. The blue graph is the original data from the device and the orange line is the prediction of device readings with the transformer method, as well as the green one without transformers. The prediction results using naïve forecasting are good enough with the prediction results without transform better than using transform.

3.1.3 Moving Average Forecasting

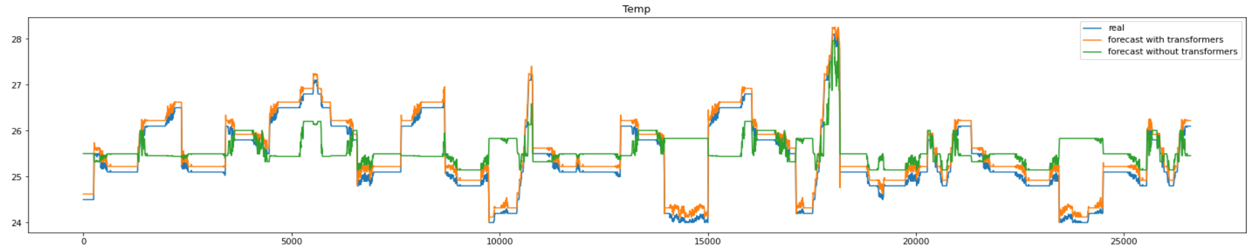

Figure 9. Temperature Prediction Results

Temperature prediction results obtained from training data and sensor readings. sensor readings. The graph shows the total temperature readings for November 19, 2022 to December 20, 2022. December 2022. On the graph, the blue line is the original data, the orange prediction data using transformers and green line prediction data without transformers. The picture above can be concluded that predictions using moving average forecasting transform method is quite good compared to without using transformers.

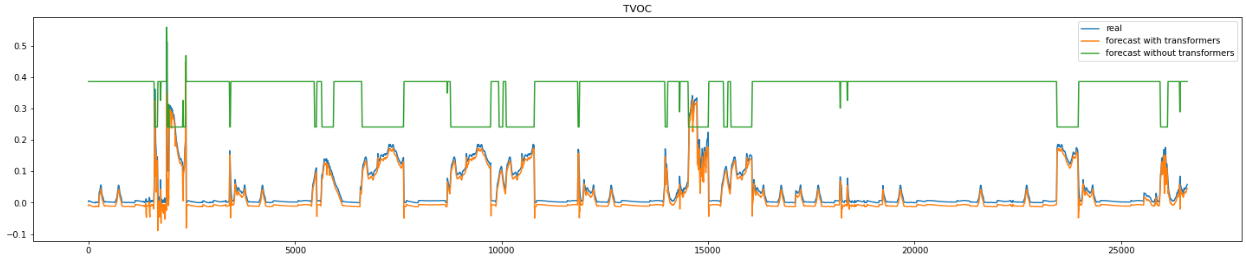

Figure 10. TVOC Prediction Results

A graph of the TVOC obtained from the training data and sensor readings. The graph is obtained from sensor readings from November 19, 2022 to December 20, 2023. Data that data obtained is quite significant between data using forecast transformers and data without a transformer. transformer. The original data is even more or less the same as the forecast transformer data. It is concluded that using the Moving Average method is quite satisfactory for the value obtained from the forecast transformer.

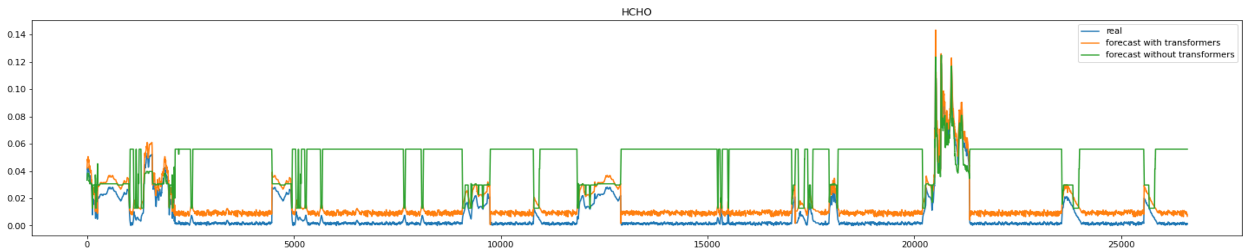

Figure 11. HCHO Prediction Results

The graphical display of HCHO is quite significant away from the real and forecast transformer data. The graph can be directly concluded that using the moving average method is quite good for transformer forecasts than forecasts without transformers whose values are quite far away.

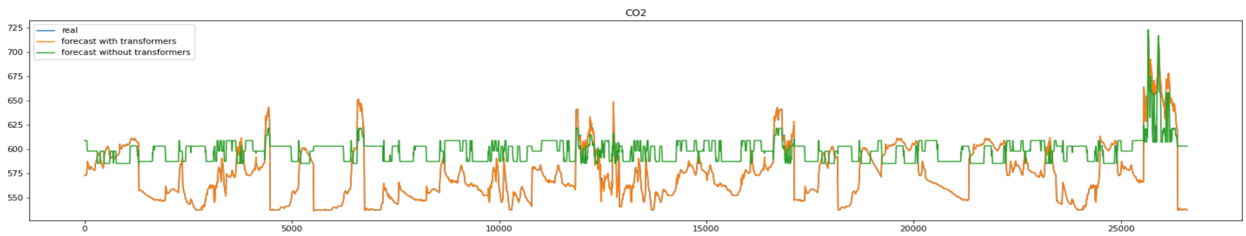

Figure 12. CO2 Prediction Results

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Graphical display of CO2 obtained from the training data process and sensor readings. It can be seen that only two are visible, namely the results of the moving average method using forecast transformers and without transformers. The original data graph is overlaid or overwritten by the forecast transformer chart because the data is the same as the forecast transformer's data. It was concluded from these results that using the moving average method of forecast transformers is better than forecast without transformers.

3.2 Discussion

Table 1. Temperature Prediction

	ME	MAE	MSE	RMSE	MPE	MAPE	U1	U2
Naïve Without Transformer	-0.186311	0.622014	0.612145	0.782397	-0.818700	2.471306	0.015354	6.778615
Naïve Transformer	-0.142460	0.143628	0.158865	0.158866	-0.562292	0.566984	0.003120	1.351492
Moving Average Without Transformer	-0.186314	0.605506	0.772570	0.772570	-0.817759	2.406810	0.015162	55.227464
Moving Average Transformer	-0.142469	0.142777	-0.562405	0.147546	-0.562405	0.563581	0.002898	10.352290

The results in temperature obtained results from 2 methods, namely naïve and moving average with using transform or not using transform. looking for the smallest MAPE value 0.563581. The appropriate method for predicting temperature is the moving average method using transformers.

Table 2. Result TVOC

	ME	MAE	MSE	RMSE	MPE	MAPE	U1	U2
Naïve Without Transformer	-0.315483	0.317209	0.113350	0.336675	-31.037737	31.168575	0.140371	46.832879
Naïve Transformer	0.014510	0.014635	0.000509	0.022567	1.390116	1.398280	0.010907	2.814542
Moving Average Without Transformer	-0.315466	0.317086	0.113149	0.336377	-31.027086	31.150905	0.140253	188.108325
Moving Average Transformer	0.014511	0.014559	0.000314	0.017731	1.387435	1.391099	0.008570	9.250362

the results on TVOC obtained results from 2 methods, namely naïve and moving average using transform or not using transform. From these results, it can be calculated from several metrics, for example from the smallest RMSE value of 0.017731 that the moving average method using transformers is better than without transformers. better than without transformers

Table 3. Result HCHO

	ME	MAE	MSE	RMSE	MPE	MAPE	U1	U2
Naïve Without Transformer	-0.041443	0.042177	0.002204	0.046948	-4.137326	4.206366	0.022822	34.259553
Naïve Transformer	-0.007818	0.007904	0.000069	0.008285	-0.775995	0.784277	0.004094	5.995955
Moving Average Without Transformer	-0.041449	0.042140	0.002191	0.046804	-4.137661	4.202793	0.022752	145.626784
Moving Average Transformer	-0.007818	0.007831	0.007831	0.000062	-0.776228	0.777434	0.003903	24.443332

The results on HCHO obtained results from 2 methods, namely naïve and moving average using transform or not using transform. From these results can be calculated from several metrics, for example the smallest U1 value is 0.004094 and 0.003903 that the value can be calculated better using transformers and for the naïve method can be smaller than moving average.

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Table 4. Result CO2

	ME	MAE	MSE	RMSE	MPE	MAPE	U1	U2
Naïve Without Transformer	-24.482399	31.776349	1328.096034	36.443052	-4.480171	5.659474	0.031076	20.707344
Naïve Transformer	0.012650	0.175059	3.159044	1.777370	0.002158	0.028919	0.001547	0.935410
Moving Average Without Transformer	-24.471508	31.617072	1312.315087	36.225890	-4.476333	5.631485	0.030891	64.383112
Moving Average Transformer	0.012655	0.139282	0.352819	0.000062	-0.776228	0.023025	0.000517	0.96902

The results on CO2 are quite significantly high between the values of the results using transformers and without transformers. transformer. This value can be calculated from several metrics, for example from the smallest RMSE values 1.777370 and 0.000062 that from these values it is still better to use transformers even though the moving average value is the smallest. The moving average value is obtained the smallest.

4. CONCLUSION

According to the results of the research that was attempted, The conclusion that can be taken from this research is the system architect that was formed on moving average forecasting using transform gets the best results with a MAPE value at temperature of 0.563581, TVOC of 1.391099, HCHO of 0.777434, and CO2 of 0.023025. of 0.023025. This result is beyond ability of the naïve forecasting model using the best transforms performed in this study, with a MAPE value at temperature of 0.566984, TVOC of 1.398280, HCHO 0.784277, co2 0.028919. The number of identities in each perspective and the variety of perspective tokens have a significant impact on system training. The more diverse the perspectives of a token, the more difficult it is to classify that token on trial statistics. In this experiment, the hyperparameter has been shown to result in better accuracy. It is effective in improving prediction accuracy, However, naïve forecasting still gives worse performance than moving average forecasting. The MAPE for naïve forecasting without transform tends to be the highest in each test. This can be explained by the error analysis error analysis, where the higher the error value, the farther the test result is from the actual value. Further research is needed to produce a model that performs better by increasing the dataset that can affect the distribution of labels in the experimental data and training data to improve the prediction results of the system created.

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