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The reduction of polynomial degrees based on moving average filter and derivative approach to decrease the computational load in polynomial classifiers

Dewi Agustini Santoso[1,*], Gutama Indra Gandha[2]
[1,2]Faculty of Engineering, Universitas Dian Nuswantoro
[1,2]Nakula 1 No. 5-11, B Building, Semarang, Central Java 50131, Indonesia
[*]Coresponding email: dewi@dsn.dinus.ac.id

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Abstract — Carbon monoxide has huge benefits in the industrial field. The measurement of carbon monoxide concentration is required to achieve the required dose in the industrial process. The measurement of carbon monoxide levels is not easy moreover with low-cost sensors. The usage of four sensors namely TGS2611, TGS2612, TGS2610, and TGS2602 have been used along with the feature extractor. The polynomial classifier is required to interpret the feature vector into the amount of substance concentration. The common classifier methods suffer fatal limitations. The polynomial classifiers method offers lower complexity in solution and lowers computational effort. Since the involvement of a huge number of data points in the modeling process leads to a high degree in the polynomial model. The occurrence of Runge's phenomenon is highly possible in this condition. This phenomenon affects the accuracy level of the generated model. The degree reduction algorithm is required to prevent the occurrence of Runge's phenomenon. The combination of the Mean Average Filter (MAF) and derivative approach as a degree reduction algorithm has succeeded in reducing the polynomial model degree. The greater the number of degrees in the model means the greater the computational load. The model degree reduction algorithm has succeeded to reduce the computational load by 96.6%.

Keywords – carbon monoxide sensing, polynomial classifier, polynomial degree reduction

I. Introduction

Carbon monoxide is a colorless, odorless gas that is categorized as stable gas and able to survive 2-4 months in the atmosphere [1]. Carbon monoxide has huge benefits, especially for industrial matters such as in the food packaging industries. It has also been used to produce hydrogen, propionate and formic acid on an industrial scale [2]–[4]. The measurement of carbon monoxide concentration is required especially for industries that involve carbon monoxide in their production process. The measurement of carbon monoxide concentration involved four sensors namely TGS2611, TGS2612, TGS2610, and TGS2602. The sensor configuration was adopted from research conducted by Fonollosa [5]. The feature extraction process has also been done by using Principal Component Analysis (PCA) with the dimensional reduction method. The feature extraction process results in a feature vector. The classifiers method is required to determine the carbon monoxide concentration based on the feature vector.

The classification for scattered data could be solved with polynomials. The polynomial allowed the extraction of the polynomial curve within simulation data or experimental data [6], [7]. Polynomial is a well-known modeling method used in many fields such as biomedical engineering, sensor engineering, robotic application, etc. Easy to implement in computational platforms, simple model structure, and well-known properties were the advantages of polynomial-based modeling [8]. Since the vector feature consists of hundreds of data points, it leads to high-degree model polynomials in the final model. The Runge's phenomenon was highly possible in the high degree polynomial model [9]. The appearance of oscillation in the edge of the interval point was the effect of Runge's phenomenon [10]. The nonlinear models were highly likely to be affected by this phenomenon [11]. The

implementation of high-degree polynomials affected the computational load directly. The more degree in the polynomial model leads to more load in computation. The higher requirement of the processing platform would be required to process more computational load [12]. This research focused on the reduction of the polynomial degree to decrease the computational load on feature vector processing to determine the carbon monoxide concentration level.

II. Research Method

The determination of carbon monoxide concentration level based on the feature vector is the most critical point in this research. A comparative study between four common supervised machine learning methods for classification has been done, namely Support Vector Machine (SVM), Artificial Neural Network, K-Nearest Neighbor, and Decision Tree [13]. SVM was introduced in the 1990s. SVM was introduced in the 1990s. The construction of an optimal hyperplane is the main foundation of SVM. The classification of linearly separable patterns was the aim of SVM. SVM only uses the objects (samples) on the edges of the margin (called support vectors) to separate objects (samples) rather than using the differences in class means. Since the separating hyperplane is supported (defined) by the vectors (data points) nearest the margin, therefore the algorithm is called SVM. SVM is one of the most efficient machine learning algorithms, which is mostly used for pattern recognition since its introduction in the 1990s. On the other hand, there are several drawbacks regarding SVM algorithms such as SVM is not suitable for large datasets, low performance to a dataset with noise, unavailability of probabilistic explanation, and computationally expensive [14].

K-Nearest Neighbors (KNN) is a standard machine-learning method. It has been used for various projects. It also has been extended to large-scale data mining efforts. The concept is that a vast amount of training data is used, with each data point being defined by a collection of factors. Each point is conceptually represented in a high-dimensional space, with each axis corresponding to a single variable. Assume we have a fresh (test) data point and want to know who our K closest neighbors are. The square root of N, the total number of points in the training data set, is commonly used as the number K. KNN is a simple method and beneficial for being nonparametric. This method also can be used for variables that are categorized by categorical. The challenge came from the huge number of data handling. When the number of data is categorized as a high amount of data, special methods must be used to perform certain actions such as searching for certain data The disadvantages of the KNN algorithm were slow algorithm for large datasets, no rules setting available, and a large amount of memory allocation is required [15].

A decision tree is a flowchart-like tree structure in which each internal node represents an attribute test, each branch represents a test outcome, and each leaf node represents a class label (or terminal node). The attribute values of a tuple X are evaluated against the decision tree given a tuple X. A path is traced from the root to a leaf node that contains the tuple's class prediction. Decision trees are simple to translate into categorization rules. A decision tree is used as a predictive model in decision tree learning. It translates observations about an object to conclusions about the item's goal value. In statistics, data mining, and machine learning, it is one of the predictive modeling methodologies [16]. The disadvantages of decision tree algorithms lie in the low level of accuracy, specificity, and sensitivity [13].

Artificial neural networks are a fresh take on logistic regression, the statistical technique with which they have the most in common. Neural networks are algorithms that are modeled after the human brain's structure. They are made up of a set of mathematical equations that are used to replicate biological processes like learning and memory. Among other things, neural networks have been designed to diagnose acute myocardial infarction, and acute pulmonary embolism, and forecast Intensive Care Unit (ICU) resource consumption after cardiac surgery. The purpose of a neural network is similar to that of logistic regression modeling: to predict an outcome based on the values of some predictor variables. Artificial neural networks have a number of advantages, including the ability to detect complex nonlinear relationships between dependent and independent variables without requiring formal statistical training, the ability to detect all possible interactions between predictor variables, and the availability of multiple training algorithms. Its "black box" character, higher computing cost, proclivity for over-fitting, and empirical nature of model creation are all disadvantages [17].

KNN, Decision Tree, Artificial Neural Network, and SVM were used to evaluate the performance of the four classification algorithms. Accuracy, specificity, sensitivity, and kappa were all examined in the performance evaluation. Accuracy is a metric that measures how well an algorithm classifies unseen cases. The ratio of correctly categorized positive examples is called sensitivity. The ratio of correctly recognized negative examples is known as specificity. The kappa statistic compares a classifier's performance to a classifier that solely makes predictions based on random guessing [13].

According to Table 1, the SVM algorithm has superiority in the accuracy performance, sensitivity performance, and kappa statistic. However, the SVM has limitations such as SVM is not suitable for large datasets, low performance to a dataset with noise, and computationally expensive. Those limitations were

crucial, since a large amount of data size of the sensor and full of noise. This algorithm is not suitable for the requirement. From a computational perspective, the SVM also required more computation effort. The more computation effort means the greater the computation load.

Since the SVM's issues then finding a more appropriate solution is required. The polynomial classifiers method offers lower complexity in solution and lowers computational effort. Polynomial classifiers are a well-known and common method in engineering interests. The excellent properties made polynomials utilized as classifiers. The emergence of the Weierstrass theorem made polynomials to be used as universal approximators to the optimal Bayes classifier. The statistical method or minimizing mean-squared error criterion as the type of training polynomial classifiers [19]. Polynomial classifiers have been used in various projects such as signal modulation classification project, voice recognition project and word recognition project [18]–[21].

An automatic modulation classification has been conducted using a polynomial classifier to classify the modulation constellations. This project involved signal input, feature extractor, and polynomial classifier. The feature extractor extracted the features from the input signal. The polynomial classifier determines the modulation constellations based on classifier weight. The proposed system has succeeded to classify BPSK, QPSK, 8-PSK, 16-QAM, and 64-QAM constellations. The other advantages of the polynomial classifier are low computational complexity and being more suited for real-time applications [18].

Table 1. The Index Result of Classifiers Performance [13]

Algorithms	Accuracy	Specificity	Sensitivity	Kappa
Support Vector Machine (SVM)	0.763	0.487	0.881	0.3948
Artificial Neural Network	0.709	0.507	0.796	0.3038
Decision Tree	0.739	0.487	0.847	0.3495
K- Nearest Neighbor	0.713	0.253	0.91	0.1929

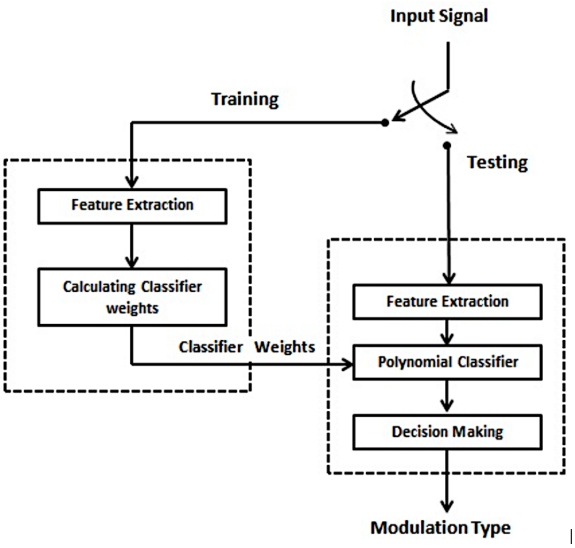

Fig. 1. Automatic modulation classification system model [18].

The polynomial classifiers offer low complexity in computations. The hierarchical classification using polynomial classifiers has been done. To calculate their second-order polynomial expansion, the suggested system uses high-order cumulants of the received signal to a polynomial network. Then, as a feature selection system, a step-wise regression model is utilized, with relevant characteristics being discovered and used for the classification issue, and inconsequential features being rejected. The complexity of the classifier is greatly decreased as a result of this optimization step, yet classification accuracy is maintained [20].

The polynomial classifiers have also been used for isolated word recognition projects. Speech recognition applications required cheap complexity and storage space in addition to high accuracy, which the polynomial classifier provided. The well-known mel-frequency cepstral coefficient is one of the speech features used (MFCC). The performance of the aforementioned classifier is evaluated for MFCC sizes 12 to 22 and the best one is chosen for further investigation. Polynomial classifier identification is proven to be faster than Vector Quantizer (VQ) and Dynamic Time Warping (DTW) and requires less storage space [21].

Polynomial classifiers offer lower complexity in solution, robustness, and lower computational requirements [18]. In this research, the implementation of polynomials as vector feature classifiers would be applied. The most efficient polynomial type is required to obtain the lowest computational load. Srivastava has conducted research regarding performance comparison between Langrange's polynomial and Newton's polynomial. The result shows that Newton's polynomials have better performance than Lagrange's polynomials. Newton's polynomials result in lower error than Langrange's polynomial. The other advantages of Newton's polynomial are easy to implement in the computational platform, simple model structure, suitable for low-cost microprocessors and well-known properties [8], [22].

The proposed system of the polynomial classifiers-based carbon monoxide meter is shown in Fig. 2. The proposed consist of two parts of the subsystem namely the training sub system and testing sub system. Since polynomial classifiers are categorized as supervised learning, the training subsystem is used to generate models as a result of training activity. When the training model has been generated by the training subsystem, the testing sub-system performs testing activity to measure

carbon monoxide levels using a polynomial classifier. Since this paper focused on the degree reduction method, the discussion other than degree reduction is not discussed in depth.

The feature extraction generated the feature vector as the result of the extraction process. The degree reduction method reduces the data points using moving average filters and a derivative approach. The output of the degree reduction method was a feature vector with fewer data points.

Based on the experiment data, the feature extraction process generated a feature vector with a total of 58597 data points. The number of data points is categorized as large data points. Without the degree reduction method, this condition leads to the occurrence of Runge's phenomenon when modeling using polynomial-based Automatic Model Generator (AMG) was done [23]. The AMG would generate a polynomial model with an $n-1$ degree. Where n is the number of data points. The Runge's phenomenon is highly possible in the high degree polynomial model [9]. The appearance of oscillation in the edge of the interval point was the effect of Runge's phenomenon [10]. The utilization of the degree reduction method is expected to overcome the occurrence of Runge's phenomenon.

A. Moving Average Filter for Noise Removal

As shown in Fig. 2, the input signal is a raw signal. The raw data material has been adopted from data used by Fonolossa [5]. This signal is generated directly from sensor outputs. There were four sensors involved in this research namely TGS2611, TGS2612, TGS2610, and TGS2602. The 5-dimensional vector has been generated as the sensor output, namely time, TGS2611, TGS2612, TGS2610, and TGS2602. The PCA (Principal Component Analysis) generated the feature vector and reduce the feature vector dimension to decrease the complexity [5]. The schematic of the carbon monoxide level meter using polynomial classifiers is shown in Fig. 3.

The presence of the noise in the feature vector was hard to avoid since the raw signal highly possible contains noise. The example of a feature vector is shown in Fig. 4. It represents data acquisition results for carbon monoxide concentration by 10 ppm, 20 ppm, 30 ppm, and 40 ppm. The x represents the feature values of four sensors and y represents the frequency. Both variable values are generated from the feature extraction process. As seen in Fig. 4, the feature vector may be contaminated with noise. The filter is required to minimize the presence of noise in the feature vector. Moving Average Filter (MAF) is a common filter in digital signal processing. The MAF filter was effective to reduce random noise and high-frequency noise. The other advantages of MAF filters are simple in the form, low complexity in the algorithm, and low computation cost. [24], [25]. The Gaussian filter is also commonly

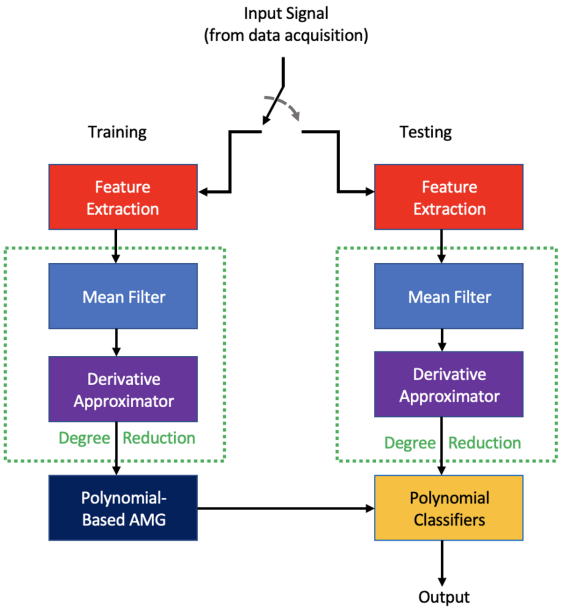

Fig. 2. The proposed system for carbon monoxide meter.

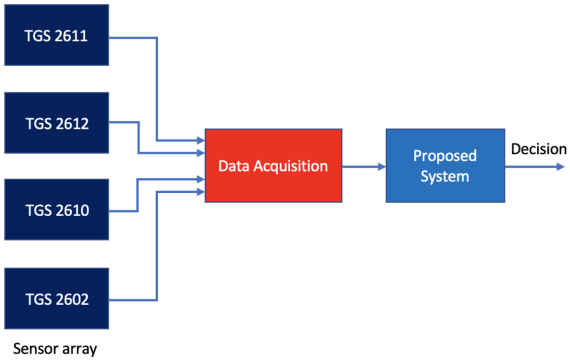

Fig. 3. The schematic of carbon monoxide level meter using polynomial classifiers.

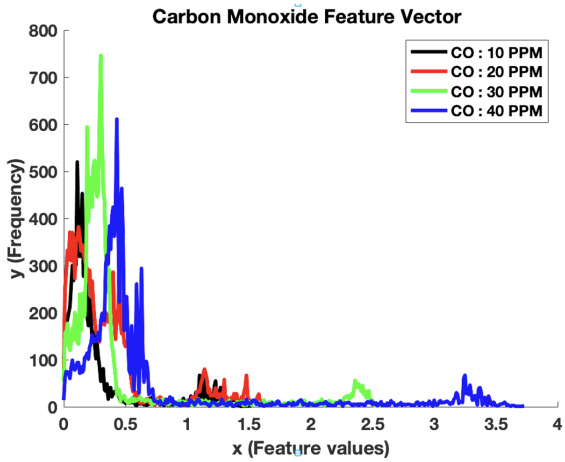

Fig. 4. The example of feature vector.

used to overcome high-frequency noise. This filter is categorized as a low pass filter by nature. The Gaussian filter required a large amount of computation effort and was not suitable for real-time applications [26]. To maintain simplicity in the algorithm and keep the computational complexity still low, the MAF filter has been used in this research.

B. Derivative Approach for Minimizing Runge's Phenomenon Occurrence

The aim of the usage of the derivative method was to eliminate the unnecessary data point as the result of moving average filtering. The number of data points affected the degree number of the generated model. The degree of the polynomial model would be generated for data points [23]. The unnecessary data point increases the degree number of the model. The high degree number of the model has a risk for Runge's phenomenon occurrence [10]. Therefore, it is important to remove the unnecessary data points to maintain the degree of the polynomial model.

C. Computational Load Measurement

The measurement of the computational load has been done by using MATLAB with TOC and TIC functions. The measurement involved two scenarios. Firstly, the measurement of the computational load on the resulting model without the degree reduction method. Then, the measurement of the computational load on the generated model with the degree reduction method. As a reference, this experiment involved a 2.3 GHz dual-core Intel Core i5 processor with 64 MB of eDRAM, 8 GB of Random Access Memory (RAM), and MAC OS for the operating system.

III. Result

The moving average filtering is the first step for feature vector processing. In this part, the one sample data has been taken from feature extraction results at carbon monoxide measurement of 10 ppm. The result of moving average filtering is shown in Fig. 5. The moving average filter has succeeded in removing noise while maintaining the signal trajectory. The green line represents the original feature vector. The red line represents the filtered feature vector. The original feature vector contains 58597 data points. After the filtering process using a moving average filter, the data points shrank to 8838 data points. In addition to eliminating noise, the utilization of moving average filters also has the effect of reducing the number of data points. This effect made the moving average filter very suitable for degree reduction purposes in polynomial models.

The moving average filter results in horizontal line elements in the filtering result as shown in Fig. 6. There are two reasons regarding horizontal line elements are considered unnecessary data points. Firstly, the horizontal line elements increase the number of data points. More data points increase the possibility of Runge's phenomenon occurring. Secondly, the nature of polynomials was based on oscillation [27]. The more horizontal line elements increase the oscillation between the edge of data points of the horizontal line. The oscillation leads to a decreased accuracy level of the model result [23].

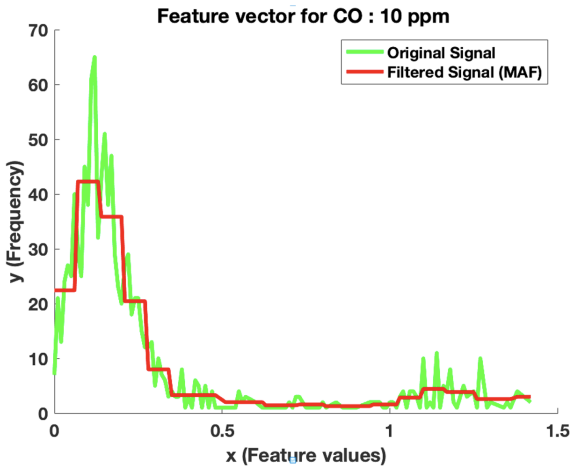

Fig. 5. The comparison between original feature vector and filtered feature vector using moving average filter.

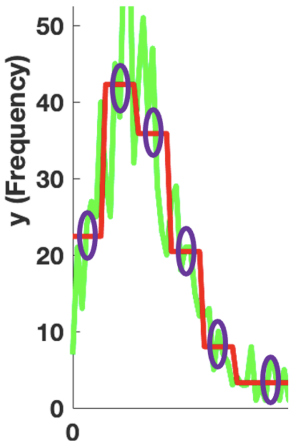

Fig. 6. Horizontal line elements (marked with purple circle) as the result of moving average filter.

For both reasons regarding horizontal line elements, therefore horizontal line element removal is required. The removal involves a derivative approach to automatically remove the horizontal lines. The result is shown in Fig. 7. The usage of the derivative approach also decreases the number of data points by 90%.

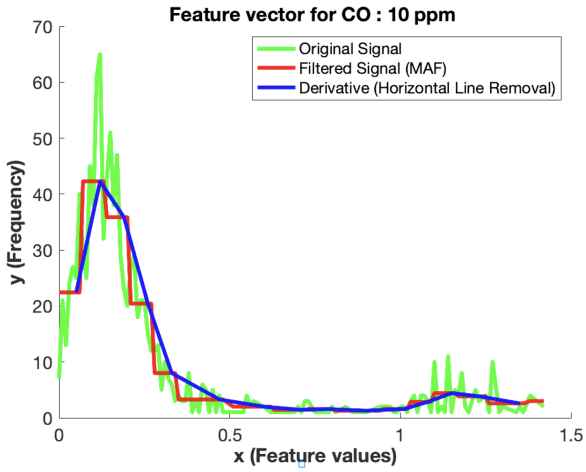

Fig. 7. The result of the feature vector using moving average filter (red line) and horizontal line removal (blue line).

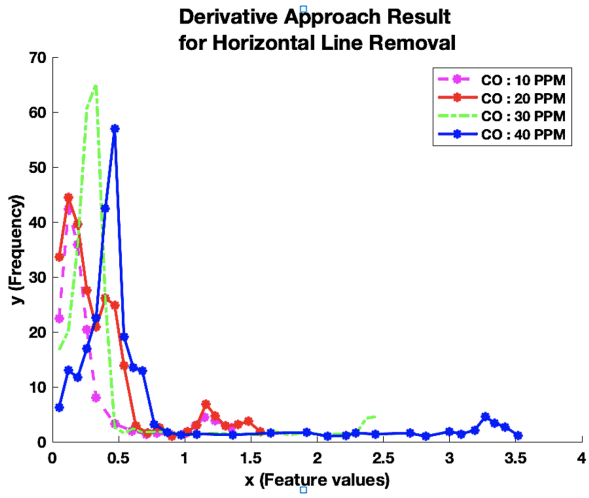

Fig. 8. The result of horizontal line removal using derivative approach in various carbon monoxide concentration.

The complete result of the degree reduction process using moving average and derivative approaches for various carbon monoxide concentrations is shown in Fig. 8.

The result of the feature vector that has been processed must be confirmed regarding the occurrence of Runge's phenomenon. The verification process involves the AMG kernel engine that was proposed by Gandha [23]. This kernel engine automatically generates a polynomial model based on a set of data points. In this case, the processed feature vector roles as an input set of data point to the AMG kernel engine.

As seen in Fig. 9, Runge's phenomenon did not occur in the data reconstruction that was performed by the AMG kernel engine. The measurement of fit level between original data and reconstructed data is represented by MSE (Mean Squared Error) shown in Table 2. The lower MSE level leads to higher accuracy of the generated model [22]. The MSE level for each experiment was categorized as low-level MSE.

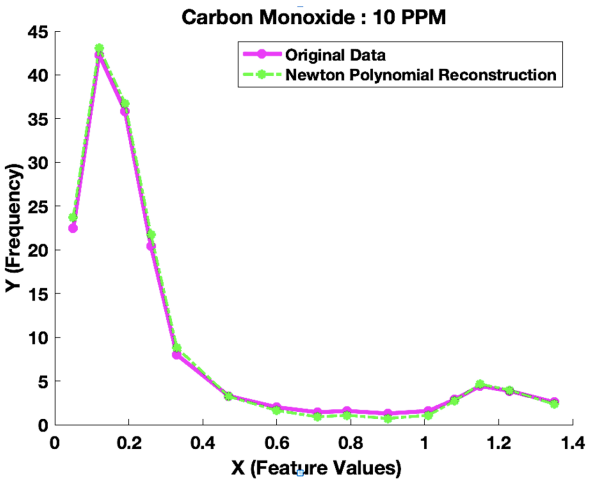

Fig. 9. Newton polynomial-based data reconstruction for feature vector of carbon monoxide concentration by 10 ppm.

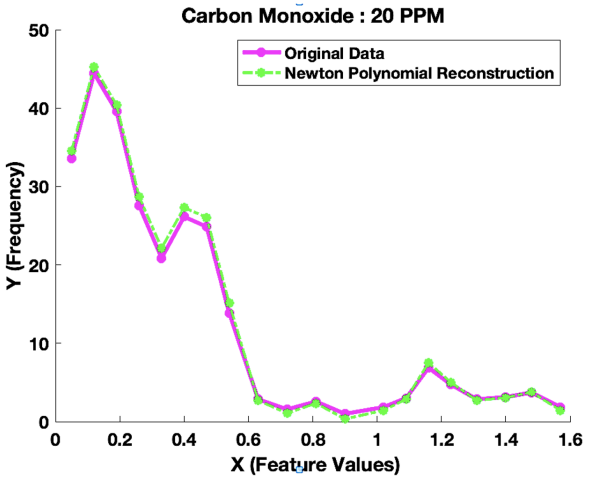

Fig. 10. Newton polynomial-based data reconstruction for feature vector of carbon monoxide concentration by 20 ppm.

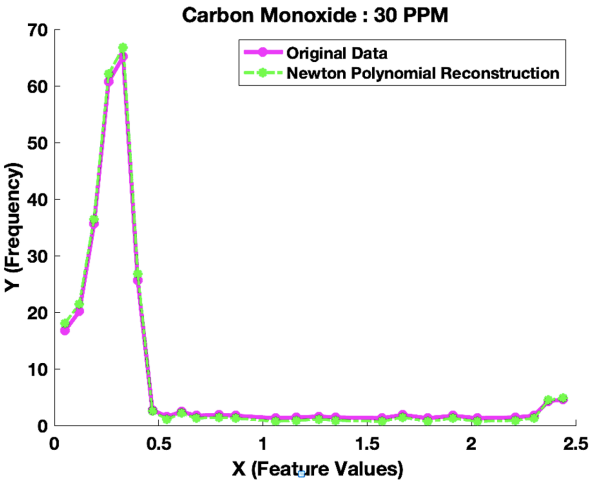

Fig. 11. Newton polynomial-based data reconstruction for feature vector of carbon monoxide concentration by 30 ppm.

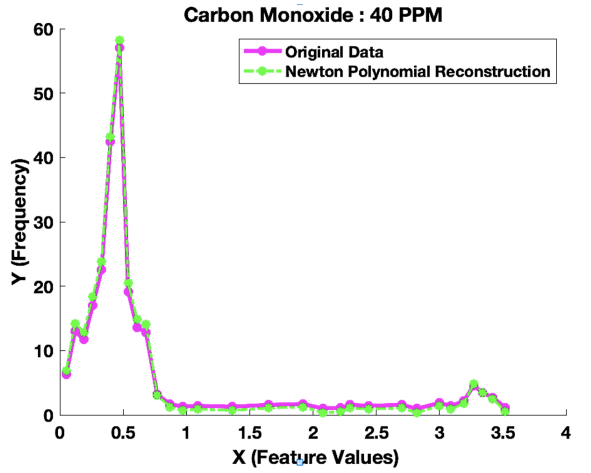

Fig. 12. Newton polynomial-based data reconstruction for feature vector of carbon monoxide concentration by 40 ppm.

Table 2. The Comparison of MSE Level for Various Carbon Monoxide Concentration

CO Concentration	10 ppm	20 ppm	30 ppm	40 ppm
MSE	0.442	0.55	0.5618	0.59

Table 3. The Execution Time Various Model of Carbon Monoxide Concentration

CO Concentration	Using Degree Reduction Algorithm	Without Degree Reduction Algorithm
10 PPM	0.95 s	5.11s
20 PPM	0.73 s	4.13 s
30 PPM	0.68 s	6.14 s
40 PPM	0.66 s	7.12 s

The computational load has been measured from the execution time of the generated model. Table 3 shows the comparison of model execution time in two scenarios. Firstly, the execution time of the model using a degree reduction algorithm. Secondly, the execution time of the model without a degree reduction algorithm. The utilization of the degree reduction algorithm improved the execution time faster by 96,6%.

IV. Discussion

The discussion focused on the degree reduction algorithm for the polynomial model in polynomial classifiers. The discussion regarding the AMG engine kernel is optional. This research discussion focused on the degree reduction algorithm for polynomial models in polynomial classifiers. The discussion regarding the AMG engine kernel is optional. This research adopts a similar polynomial AMG kernel engine that was proposed by Gandha [23].

A. The Polynomial Degree Reduction using MAF and Derivative Approach

The polynomial degree reduction algorithm divides into two parts namely MAF for noise removal and unnecessary data points removal using a derivative approach. The usage of MAF has beneficial effects such as removing noise and decreasing the data points of the feature vector. The moving average filter produces each point in the output signal by averaging a number of points from the input signal. The equation is shown in (1).

$$y[i] = \frac{1}{M} \sum_{j=0}^{M-1} x[i+j] \tag{1}$$

Where x[] is the input signal, y[] is the output signal, and M is the moving average's number of points. This algorithm only calculates points from one side of the output sample [24]. The number of points that are used in the moving average has a side effect on the data points. The higher number of points used in the moving average leads to a low level of model accuracy since this algorithm scrapes the data points. The value of 3 has been used in this research for the M variable. The occurrence of horizontal lines is the other effect of the M variable as shown in Fig 6. However, this effect is unavoidable. The scrapping process of data points is the basic principle of how the MAF algorithm works. The horizontal line as the effect of MAF was considered an unnecessary data point. The number of data points is critical in polynomial modeling. The more data points increase the occurrence of Runge's phenomenon possibility. Runge's phenomenon leads to a decrease in model accuracy [10].

The removal of horizontal lines as the scrapping effect of the MAF algorithm can be performed by using a derivative approach. The basic operation of the horizontal line removal algorithm is adopted from the derivative method. The derivative formula is shown in (2).

$$\frac{dy}{dx} = \frac{\Delta y}{\Delta x} = \frac{y_2 - y_1}{x_2 - x_1} \tag{2}$$

The algorithm indexes the first point until the end of the point of the curve with a certain interval point. The interval point by 2 points has been used in this research. This method checks the angle based on the slope along the curve per 2-point interval. The formula is shown in (3).

$$\Theta = \arctan(\frac{y_2 - y_1}{x_2 - x_1}) \tag{3}$$

While the indexing process is running, the algorithm marks a certain point as a removal point when is equal to 0. After the indexing process has been done, this algorithm removes the unnecessary data point automatically. The result is shown in Fig. 7. It shows that the horizontal line has been eliminated by using a derivative approach. The elimination also has a beneficial effect to minimize the number of data points in the polynomial model.

B. Polynomial Classifier

In the training mode, the proposed system minimizes the number of data points using the degree reduction method and then generates the polynomial model. The generation of the polynomial model has been done by using a polynomial-based AMG kernel engine. This engine converts the processed data points into a polynomial model. The basic idea of a polynomial-based AMG kernel engine is Newton's polynomial. Newton's polynomial computation is divided into two parts. The first part is the computation for model coefficients as pre-processing computation. Secondly, the model determination. The pre-processing step of Newton's polynomials was computed in this step. This computation involved the matrix. The computation formula is shown in (4).

$$f[z_k] = f(z) \tag{4}$$

$$f[z_0, z_k] = \frac{f[z_0] - f[z_k]}{z_0 - z_k}$$

$$f[z_0, z_1, \cdot, z_i, z_k] = \frac{f[z_0, z_1, \cdot, z_i] - [z_0, z_1, \cdot, z_{i-1}, z_k]}{z_i - z_k}$$

The pre-processing step results in the coefficient values arranged in Table 2. The coefficient table was turned into a matrix form called T Matrix for computing purposes. The vacant columns of the T Matrix were replaced with zero values. The polynomial approximation stage produces the T Matrix.

When the matrix has been obtained, it would be stacked into model stacks in the polynomial classifier. The schematic of the polynomial classifier is shown in Fig. 13. The number of the model in the model stack block depends on the number of training data. For example, the training has been done for CO concentration by 10 ppm, 20 ppm, 30 ppm, and 40 ppm. Then it would be four models in the model stack block. The decision maker block uses the models in the model stack block to perform model matching. Commonly, the model matching used the MSE algorithm to compute the fit level between two or more datasets [19].

$$\begin{aligned} T = [f[z_0]000f[z_1]f[z_0,z_1]00f[z_2]f[z_1,z_2] \\ f[z_0,z_1,z_2]0f[z_i]f[z_{i-1},z_i] \\ f[z_{i-2},z_{i-1},z_{i-0}]f[z_0,z_1,z_2,\cdot z_i] \end{aligned} \quad (5)$$

The Means Squared Error (MSE) method has been used as the principle of model matching in the polynomial classifiers. The MSE level represents the closeness level to the target value. The lower MSE value leads to a lower error level. The equation of MSE is shown in the Eq 6.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(\hat{X} - X_i)^2 \quad (6)$$

The number of data quantities represented by n, the n number of true values represented by $\hat{X}_i$, the number of measurement values represented by $\hat{X}$ [28]. The MSE threshold value of 3 has been used in this research. When the MSE level of the model is generated by the model builder resulting in an MSE level of more than 3, then it would be assumed as no model matched.

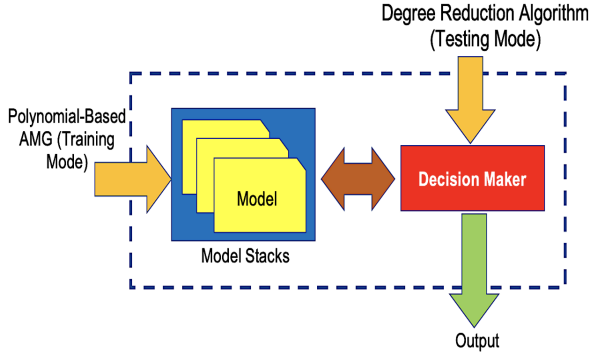

Fig. 13. Polynomial classifier schematic diagram.

C. Computational Load Measurement

The simple method has been used to measure the computational load. The measurement was based on execution time. The longer execution time has been assumed as the greater the computational load. On the other hand, the faster execution time means the lighter the computational load. The result of the execution time is shown in Table 3. As seen in Table 3, the degree reduction algorithm results in a faster execution time. It means the degree reduction algorithm has succeeded in reducing the computational load and made the execution time 96.6

Basically, dataset transformation into polynomial form can be developed in the form of recursive operations in the computing platform [29]. In the Newton-based polynomial form, the more data points in a dataset lead to the more degree in the generated polynomial model. It also affects the number of tasks in the transformation process [8]. The more tasks for coefficient determination means the greater number of recursive operations efforts. The greater number of recursive operations leads to a longer execution time. The duration of execution time is proportional to the computational load [30].

D. Future Works

In this project, the measurement of carbon monoxide was based on the polynomial model. Since polynomial classifiers are categorized as supervised learning, the requirement of the number of samples is required for training. The accuracy level depends on the number of samples in training mode. A particular method is required to improve the measurement without adding more samples.

V. Conclusion

The combination of the Mean Average Filter (MAF) algorithm and derivative approach can be developed as a polynomial degree reduction. The MAF algorithm has beneficial effects on degree reduction algorithms such as noise removal effect and data points reduction. However, the MAF algorithm has drawbacks, namely the occurrence of unnecessary data points. It affects the number of degree models. The elimination of unnecessary data points can be done with a derivative approach. The result shows the utilization of the polynomial degree reduction algorithm has succeeded to reduce 96.6% of the computational load in polynomial classifiers.

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