Prediction of Carbon Monoxide (CO) Atmospheric Pollution Concentrations with Machine Learning and Time Series Analysis in Langkawi, Malaysia

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Carbon monoxide (CO) is a non-irritant toxic and odourless gas produced from the incomplete combustion of fossil fuels. Long-term exposures to lower levels of carbon monoxide have wide implications for human health. Thus, an early warning system for CO atmospheric concentration with an accurate and reliable forecasting method is crucial. Studies for predicting CO atmospheric concentration are still limited in Malaysia especially using data science approaches. This study aims to develop and predict future CO concentration for the next few hours by using the statistical time series approach and machine learning approach. The data used for the project is the air quality data of the monitoring station in Langkawi, Malaysia. The data mining tool used for this project is RapidMiner Studio. Based on the results, it showed that Time Series analysis with deep learning gave a reasonably good CO concentration prediction for the next 3 hours with a relative error of approximate 10%. The model developed in this project can be used by authorities as public health’s protection measure to provide an early alarm for alerting the Malaysian populations on the air pollution issue.

Keywords: machine learning; Time series analysis; carbon monoxide; prediction

I. INTRODUCTION

Clean air is a basic requirement to sustain life. Human beings need an essential continuous supply of air at 10 m3–20 m3 per day. “All people should have free access to clean air as one of the fundamental human rights”, as said by the World Health Organisation (WHO) Director-General during the closing of a three-day global conference on air pollution and health (Clean air is a human right: WHO, 2018). Clean air in nature may have more components difference than pure air from a scientific perspective, and thus it is quite complicated to precisely define clean air. Figure 1 shows a list of gaseous components of natural pure air (Baumbach, 1996).

Air pollution is caused by pollutants in the atmosphere in a certain concentration and period, which can cause an unwanted effect on humans, plants, animal life or property. Human activities or even certain natural phenomena can become the root cause of the unfavourable concentrations of air pollutants. Some examples of traditional pollutants are carbon monoxide, hydrogen sulphide, nitrogen oxides, sulphur dioxide and haze.

| Volume content in % related to dry air |
|---------------------------------------|
| Oxygen (O2) | 20.93 |
| Nitrogen (N2) | 78.10 |
| Argon (Ar) | 0.9325 |
| Carbon dioxide (CO2) | 0.03-0.04 |
| Hydrogen (H2) | 0.01 |
| Neon (Ne) | 0.0018 |
| Helium (He) | 0.0005 |
| Krypton (Kr) | 0.0001 |
| Xenon (Xe) | 0.000009 |

Figure 1. Natural Composition of Air (Baumbach, 1996)

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WHO has provided guidelines for public health with regard to risks that can occur from several chemicals that are commonly present in the air (Penney et al., 2010; Ambient (outdoor) air pollution, 2018). Carbon monoxide (CO) is one of the pollutants that need to be given attention. Carbon monoxide (CO) is a non-irritant toxic gas that is odourless. It is produced from fossil fuels, such as diesel and kerosene in the combustion of Otto or Diesel engines, which is mainly from automobiles in the street traffic.

Baumbach (1996) claimed that it is quite impossible to eliminate CO in exhaust gas emissions because the complete combustion process of carbon to CO2 (carbon dioxide) requires an ignition temperature of at least 717°C for a certain period. Most of the time this condition cannot be achieved because the automobile engines will not be operated with a constant number of revolutions and constant load. Therefore, automobiles are the main contributors of carbon monoxide in the atmosphere.

Berg et al. (2002) explained that Oxygen (O2) appears as oxyhaemoglobin (HbO2) in blood transportation and is attached weakly to Fe2+ in haemoglobin. Blood oxygen-carrying capacity is reduced by CO as it forms a stable carboxyhaemoglobin (COHb) by merging with haemoglobin.

The affinity of haemoglobin for CO is around 200–250 times stronger than for oxygen (Higgins, 2005). CO can poison the haemoglobin oxygen transport system as it cannot regenerate the COHb, and thus making haemoglobin unavailable for oxygen transport (Vesilind et al., 2013). COHb level is determined by variables, such as CO in the inhaled air and the exposure period (Penney et al., 2010). In Malaysia, the number of studies to predict CO atmospheric concentration is still limited, especially by using data science approaches.

This study aims to develop and predict CO concentration in the future. The study objectives are: (1) to determine the characteristics of CO and its relationship with other meteorological parameters by using descriptive statistics and data visualisation, (2) to develop a model for CO prediction concentration by using time series approach (ARIMA), machine learning techniques and deep learning techniques, and (3) to determine the best model for predicting CO concentration in Langkawi Island, Malaysia.

The model developed in this project will be a localised model that suits Malaysia's topography and could be implemented for public health protection in providing an early alarm to alert the Malaysian population on the air pollution issue.

In the next section of this paper, some related works are presented. This is followed by the methods used, wherein the analytical techniques and data selection are presented in the third section. The fourth section discusses further about data preparation, which is followed by evaluation in the fifth section. Results are further discussed with the help of some visualisation in the sixth section. In the seventh section, subsequent discussion is presented, focusing on the two different approaches used for prediction and the prediction with the best model built. In the eighth section of the paper, the conclusion is presented.

## II. RELATED WORKS

UK AIR (2021) presents a frequently updated air pollution forecast and the latest measured air quality, but it is limited to the United Kingdom only. READY (2019) is a system which displays meteorological data products by using a dispersion model on their Air Resources Laboratory’s web server. The prediction of air pollutants can be considered as a key component in environmental monitoring, for instance, to help identify possible trends and as a guideline for environmental policies. This can be seen in a report presented by Tonellato (2001) on the Italian law which required short-term forecasts by public authorities at some locations of monitoring stations.

Hamid et al. (2017) carried out a study to predict the CO concentration at two locations in Malaysia, which are Kuala Terengganu (in Terengganu) and Bachang (in Melaka). Statistical time series models were used. Findings showed that in Bachang, the most suitable model was ARIMA (1,0,1) whereas, in Kuala Terengganu, the ARIMA (1,0,2) was found to be the most appropriate model.

A study carried out by Shaadan (2019) showed that several industrial sites in peninsular Malaysia had different temporal behaviour of CO levels. Each industrial site had a different best-appropriate model. Therefore, a specified model is needed to be developed for a specific location, such as Langkawi Island. This model can be used by authorities
as a public health protection measure to provide early alerts to Malaysia’s population concerning the air pollution issue. For instance, the model can be used to alert the tourists on the CO forecast in Langkawi Island and help them in their planning, i.e., suitability alert for outdoor activities.

In 2005, Venkatasubramanian (2019) reported on three significant ideas that emerged in Data Science, which were reinforcement learning, deep or convolutional neural networks (CNNs), and statistical machine learning (ML). Exploring further in Data Science and air quality prediction, techniques like the support vector machine (SVM), mixture model and artificial neural network (ANN), had grown to be favourable (Heo & Kim, 2004; Lu & Wang, 2008).

This project used a systematic project life cycle approach known as Cross-Industry Standard Process for Data Mining (CRISP-DM). It is broadly used in industry (James, 2019) (Figure 2). CRISP-DM comprises six phases, which are initialised by the phase of (1) business understanding (2) data understanding, (3) data preparation, (4) modelling, (5) evaluation and, (6) deployment. It iterated as a cyclical process. In each phase of the CRISP-DM process, there are a few second-level generic activities with specialised operations. CRISP-DM methodology phase is not a one-direction flow. Some phases are two-way and iterative.

Figure 2. The CRISP-DM process Model (James, 2019)

III. DATASET DESCRIPTIONS AND ANALYTICAL TECHNIQUES

The data used for the project is the air quality data from a monitoring station in Langkawi Island, which is an island in Kedah, Malaysia. Langkawi Island was selected as the case study area because it is a tourist area with very few industrial activities. Therefore, very few air pollution studies were carried out. The data were acquired from the Department of Environment (DOE), Malaysia. The data were presented in excel worksheet format. The dataset contained data collection for the year 2004 taken at every hour interval.

The dataset comprised 8 attributes: 1) date, 2) time, 3) carbon monoxide concentration (CO Conc), 4) air pollution index (API), 5) wind speed (WS), 6) wind direction (WD), 7) relative humidity (Humidity) and 8) temperature (Temp). All data were in a numerical format and chronological order. There were 8,784 records in 2004, which were taken from 1 January at 1:00 am to 31 December at 24:00 am. The 2004 data was selected to train the model because it contained fewer missing values as compared to the data of other years, which had a large amount of missing values and outliers (for instance temperature with negative value).

The data selection approach was also aligned with the recommendation by Pyle (2003), who stated fundamental principles for the right selection of data which select relevant and redundant attributes and ensure that the records cover the complete range of between-attributes and within attributes behaviours. Figure 3 shows the partial dataset for 24 hours on 1 January 2004.

Besides dataset selection, the selection of a suitable learning algorithm is crucial, but this cannot be achieved without understanding the data characteristic and advantages and limitations of each learning algorithm. For this project, the dataset contained the labelled output variable for the research project goals - CO concentration. In this project, the output was focused on numerical attributes with the goal to discover changes in each of the predictor meteorological variables that will trigger a change in the output variable (CO concentration), and thus a prediction that will estimate a numerical value.

One of the key characteristics of the dataset is that the CO concentration is a set of quantitative observations arranged in chronological order in the same regularity of the observation frequency (every hour). Therefore, the analytical techniques used in the project were based on the time series approach.

RapidMiner was used for data visualisation and data analysis. RapidMiner was selected because of its ease of use and did not require any coding. Therefore, the work can be
focused on the analytical methodology rather than on programming.

Alongside with RapidMiner, MATLAB was used for plotting a chart for data visualisation. Time series forecasting in RapidMiner was based on the Windowing concept. Windowing is terminology for RapidMiner time series data which is converted into a generic cross-sectional dataset, whereby the target variable and the next time steps are predicted by applying ARIMA, Machine Learning or Deep Learning algorithms.

### Figure 3. Partial of the Dataset for the year 2004

| Row No. | Date     | Time | WS | WD | API | COConc | Temp | Humidity |
|---------|----------|------|----|----|-----|--------|------|----------|
| 1       | 2004/01/01 | 0600| 7.89| 115| 41  | 0.341 | 26.600| 69.550   |
| 2       | 2004/01/01 | 0900| 0.438| 112| 39  | 0.336 | 26.100| 69.660   |
| 3       | 2004/01/01 | 1200| 0.765| 104| 38  | 0.284 | 25.900| 71.350   |
| 4       | 2004/01/01 | 1500| 0.560| 113| 38  | 0.223 | 25.300| 71.750   |
| 5       | 2004/01/01 | 1800| 7.800| 109| 37  | 0.189 | 25.100| 72.160   |
| 6       | 2004/01/01 | 2100| 0.438| 112| 39  | 0.163 | 24.400| 74.650   |
| 7       | 2004/01/01 | 0600| 7.670| 100| 38  | 0.163 | 24.350| 75.160   |
| 8       | 2004/01/01 | 0900| 7.860| 102| 39  | 0.159 | 24.500| 74.250   |
| 9       | 2004/01/01 | 1200| 7.165| 96  | 39  | 0.216 | 25.900| 72.200   |
| 10      | 2004/01/01 | 1500| 7.855| 128| 37  | 0.234 | 28.100| 67.660   |
| 11      | 2004/01/01 | 1800| 0.414| 102| 37  | 0.285 | 37.200| 52.650   |
| 12      | 2004/01/01 | 2100| 133.9| 147| 37  | 0.237 | 34.650| 56.560   |
| 13      | 2004/01/01 | 1600| 10.166| 156| 37  | 0.183 | 37.700| 52.760   |
| 14      | 2004/01/01 | 1500| 10.796| 113| 38  | 0.302 | 25.900| 51.51     |
| 15      | 2004/01/01 | 1600| 0.564| 123| 38  | 0.349 | 36.100| 49.49     |
| 16      | 2004/01/01 | 1700| 7.386| 107| 39  | 0.338 | 36.700| 48.48     |
| 17      | 2004/01/01 | 1800| 7.106| 116| 38  | 0.350 | 25.900| 50.250    |
| 18      | 2004/01/01 | 1900| 7.406| 96  | 38  | 0.376 | 32.500| 55.800    |
| 19      | 2004/01/01 | 2000| 7.806| 101| 39  | 0.381 | 28.000| 63.800    |
| 20      | 2004/01/01 | 2100| 7.800| 115| 33  | 0.415 | 20.000| 66.660    |
| 21      | 2004/01/01 | 2200| 0.246| 114| 41  | 0.431 | 28.100| 59.09     |
| 22      | 2004/01/01 | 2300| 0.806| 104| 42  | 0.438 | 27.100| 70.800    |
| 23      | 2004/01/01 | 2400| 7.866| 93  | 43  | 0.452 | 25.600| 71.450    |

### IV. DATA PREPARATION

#### A. Treating Missing Value

The dataset contained records with attributes that have no measured values, which is often termed as “missing value” in data mining terminology. The possible reasons for missing value can be from errors during the gathering process, measuring sensor malfunction, and data corruption in the way data is processed. When data are missing in a variable of a particular case, it is very important to fill this attribute with some intuitive data for those algorithms that require one, especially for time series forecasting. Although the best way to eliminate missing values is to fill them through own further research, it is most time-consuming and it is not possible for the historical data in this context.

Therefore, a reasonable estimate of a suitable data value for missing data is required rather than leaving it blank. The methodology of replacing missing values depends on criteria without adding or removing any information from the data set and depends on the assumption about the dataset pattern.

One common replacement method is by choosing the variable’s mean value as a replacement. Kolehmainen et al. (2001) presented a solution for missing data items, whereby the data were filled by using the weighted nearest-neighbour method for applications of neural networks in the NO2 time-series, whereby the average of the neighbouring values in the series were used as a replacement. For time series analysis in this project, forward or backward filled missing value by nearest neighbours’ data was more appropriate, it may be closer to the true value as compared to mean substitution.

#### B. Features Selection

Features selection is aimed to identify important features in the dataset and discard any other features which are irrelevant and redundant. The process of feature selection is a very important strategy, especially for algorithms that are computationally intensive when dealing with large datasets. Although additional attributes are added to a model, it may be able to predict a number better, but it will lead to the problem of slow convergence on those solutions either during the iterative learning process or the error minimisation process. Therefore, before the data set is used for modelling, those attributes to be used as predictors need to be selected.

The features selection for this project was based on domain knowledge rather than an analytical approach. From the research dataset, there were five independent attributes to be selected for modelling, which are wind speed (WS), wind direction (WD), relative humidity (Humidity), temperature (Temp) and air pollution index (API). The air pollutant index (API) is an indicator used to represent air quality status in the area under study. It is determined by the sub-index values computed based on the average concentration (for air pollutants, namely SO2, NO2, CO, O3, and...
PM$_{2.5}$ and PM$_{10}$). The maximum sub-index of all six pollutants will be chosen as the API, and thus, it is not independent and related to the target variable to be studied – CO concentration. Therefore, the API variable was excluded as a predictor variable.

V. EVALUATION

After building a model from the dataset, the quality of the model needs to be examined. In the CRISP-DM process model, the evaluation phase is one of the major steps. For this research project, the historical data of past CO concentration experience with its corresponding meteorological parameters were given, and the objective was to predict the CO concentration when only other meteorological parameters were known. A few questions need to be answered before the model can be used. For example, “Are its predictions sufficiently accurate that makes its future application worthwhile?” If the predicted CO concentration is not accurate, the data is useless to the public and will affect the authorities reputation, which is the DOE of Malaysia. There are several different performance benchmarks to assess the relative merits of models, such as goodness-of-fit, robustness, forecasting accuracy and others.

Several model metrics can be used to evaluate the “goodness” of a model. Yeganeh et al. (2012) used root mean squared errors, relative mean errors and mean absolute relative error to evaluate model performance in the hourly CO concentrations prediction by using SVM (support vector machine) regression. Kolehmainen et al. (2001) applied root mean squared error (RMSE) to produce the numerical description of the goodness of the model estimates. In this paper, the selected statistical indicators which produced the numerical description of the goodness of estimates, are presented as follows: 1) Root mean squared error (RMSE) 2) Absolute error 3) Relative Error 4) Akaike Information Criterion.

A. Root Mean Squared Error

The Mean square error (MSE) is often used as an error metric. In MSE, the difference in predicted and expected values in the records are observed and the value, which is then squared to retain the numerical quantity as well as eliminate the negative signs. RMSE on the other hand, will convert back the mean-squared error to the original data scale. RMSE is seen to have a more practical comparison because it appears in the same unit as the data.

B. Absolute Error

The absolute error sums up positive and negative errors to quantify the accuracy of the overall model, but without a clear indication of how the error varies. For example, it may seem that the error is almost balanced when both the positive and negative values are quite large. For accuracy, the performance of the model is reflected for the whole scored population. Therefore, this measure can be beneficial when one dimension of the error is considered.

C. Relative Error

By using a simple predictor, the relative error correlates the total error to the error. A simple model is utilised to be the baseline, taking the average value of all the expected values. The relative error will then show the difference between the model and the simple model.

D. Akaike Information Criterion

To determine how a trained ARIMA model defines a time series, indicators such as Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) can be used.

These performance measures are calculated with the help of the ArimaTrainer operator in RapidMiner, and the calculated values are generated as a performance vector. The Akaike Information Criterion (AIC) measure is used extensively for the statistical model, whereby it measures the “goodness” of a model. In a comparison carried out between two models, the lower value of AIC showed that it was better than the one with a higher value.

VI. RESULTS AND DATA VISUALISATION

The data for the year 2004 was selected for model training. This was because the year 2004 data contained less missing value as compared to data of other years (Figure 4). There was no outlier detected as the minimum and maximum values were observed within a common range. There were missing data of 26 datapoints of wind speed (WS), 26
datapoints of wind direction (WD), 32 datapoints of API, 31 datapoints of Temperature and 26 datapoints of Relative Humidity (Humidity) were imputed. The missing values were imputed by filling the missing value with the nearest neighbour’s data (Figure 5).

In Figure 6, it is shown that CO concentration was approximately normally distributed. From the scatter plot matrix in Figure 7, it was shown that there was no linear correlation between CO concentration and meteorological variables. In Figure 8, the polar plot also showed that the wind direction recorded were random and did not come from a particular direction. Therefore, it could be concluded that the data quality was good and comply with the assumptions of the parametric statistical model as below.

A. Assumption of Independence

Each variable in the documented effects was independent of each other. This was in line with the variable independency that was stated in Fisher’s mathematics (Nisbet et al., 2018).

B. Assumption of Normality

Nisbet et al. (2018) explained that based on Fisher’s mathematics, each variable’s distribution of values in a dataset will keep on a normal distribution around the mean value. The assumptions of normality and independency can be made when a classical parametric statistical procedure is applied. False assumptions can occur when there are significant departures from a normal distribution. These significant departures can cause the results to be biased and thus become untrustworthy. When some predictor variables are firmly linked to one another, it can cause significant departures from the assumption of independency, which will trigger more issues.

C. Assumption of Stationary

Stationary is a prerequisite before times series data can be applied with most statistical forecasting methods. Before the modelling starts, it is advised that the trends and seasonality found in time series datasets be eliminated. This is because trends and seasonality identify time series as non-stationary. Eventually, the mean value in trends can be varied, whereby there can be changing variance in seasonality.

A stationary time series has constant statistical properties, for instance, mean, variance and so on. The future values in stationary time series tend to become more predictable over time, and thus making this series simpler to model. To identify whether the time series is stationary or not, the line plot of series can be observed over time. To identify non-stationary series, the signs can be observed in series, on obvious trends, seasonality, or even some other systematic structures.
Figure 6. Histogram for CO concentration for the year 2004

From Figure 9 and Figure 10, the time series for the year 2004 CO concentration over time was stationary. This was also confirmed by the study by Hamid et al. (2017) on the study of CO concentration time series for Bachang, Melaka and Kuala Terengganu, in which after being tested by Augmented Dickey Fuller test, it indicated that they were stationary.

Figure 7. Scatter Plot CO concentration vs meteorological variables

Figure 8. Polar coordinate plot wind direction vs wind speed

VII. DISCUSSION

In this section, the discussion is divided into two sections, which discuss the two different approaches used for the prediction. The first sub-section shows the time series with ARIMA approach, and the second subsection will discuss the machine learning and deep learning approach.

A. Time Series Approach (ARIMA)

The CO concentration is a set of quantitative observations arranged in chronological order and the same regularity of every hour, and thus time series analysis with ARIMA was used for the prediction. In the ARIMA model, the target variable was the CO concentration, and the predictor variable was the CO concentrations of the previous hour and time. In order to identify the best-fit parameters, various window sizes of window operator and ARIMA $p,d,q$ parameters were explored, where some different combinations of terms were tried out to determine which combinations work best in the RapidMiner.
ARIMA with \( p=2, d=0, q=1 \) is the most suitable model to predict the CO concentration in Langkawi Island as its AIC was lowest amongst other ARIMA (Table 1). The small AIC statistic values indicated the most appropriate model with the smallest error. ARIMA \((2,0,1)\) or \((AR, I, MA)\) means that the model described some response variable (Y). The value "0" embodies the 'I' or "Integrative" part of the model, can be ignored in the model, especially for stationary data.

Table 1 also shows that ARIMA \((1,0,1)\) and ARIMA \((1,0,2)\) is also a good model for prediction, these findings also aligned with the study by Hamid et al. (2017) in that the best model for CO concentration prediction for Bachang, Melaka was ARIMA \((1,0,1)\) and the best model for CO concentration prediction for Kuala Terengganu was ARIMA \((1,0,2)\). Table 2 shows the ARIMA prediction with new few hours’ prediction. Figure 11 shows the time series plot of predicted CO concentration. From Figure 12, it is shown that CO concentration in Langkawi Island can be modelled as shown in Equation (1).

\[
X_t=0.428+1.652X_{(t-1)}-0.744X_{(t-2)}+0.243e_{(t-1)}+e_t
\]  

(1)

The best model ARIMA \((2,0,1)\) with a window size of 60 gives prediction ability similar or slightly better than the best model reported by Hamid et al. (2017), which are ARIMA \((1,0,1)\) and ARIMA \((1,0,2)\) from the study for Bachang and Kuala Terengganu, respectively. The results reported in Hamid et al. (2017) is shown in Table 3 as reference.

### Table 1. ARIMA with various \(p,d,q\) settings

| Window size | 60  | 60  | 60  | 60  | 60  |
|-------------|-----|-----|-----|-----|-----|
| \(p,d,q\)   | 1,0,1 | 1,0,1 | 2,0,1 | 1,1,1 | 1,0,2 |
| AIC         | -209.74 | -212.06 | -228.49 | -213.01 | -219.17 |
| BIC         | +51.30 | +55.03 | +55.33 | +55.43 | +53.07 |
| Root Mean   | +0.035 | +0.685 | +0.030 | +0.569 | +0.033 |

### Table 2. ARIMA prediction with new few hours prediction

| Prediction | Next 1 hour | Next 2 hours | Next 3 hours |
|------------|-------------|--------------|--------------|
| AIC        | -228.497    | -228.484     | -228.472     |
| BIC        | +55.338     | +55.329      | +55.321      |
| Root Mean  | +0.030      | +0.050       | +0.068       |

### B. Time series approach (Windowing with Machine Learning and Deep Learning)

In the time series with windowing, the target variable was CO concentration. Five predictor variables used to train the time series model were CO concentration of previous hour, Wind Speed, Wind Direction, Temperature and Humidity. Amongst a few algorithms used in prediction for the data
year 2004 in the Windowing, deep learning gave the most accurate result, as shown in Table 4. RapidMiner deep learning operator was based on H2O open-source platform, a multi-layer feed-forward artificial neural network that is trained with stochastic gradient descent by using back propagation. It can contain a large number of hidden layers consisting of neurons with various activation functions.

After further optimised the parameters (window = 24 hours, Epochs = 20, with rectifier activation function), deep learning gave a relative error of 5.02 % for the next one-hour prediction, as shown in Table 5. It is shown that time series analysis with deep learning gave reasonably good CO concentration prediction for the next 3 hours with a relative error of less than or approximate 10%.

Figure 11. ARIMA (2,0,1) CO prediction for next 1 hour

VIII. PREDICTION WITH THE BEST MODEL BUILT

The result was reproducible from the model trained for the year 2004 data, applied to the data from the year 2006, giving a similar performance. After the optimum model of deep learning was built by using the year 2004 data; data from the year 2006 with a few purposely deleted values was fed into the model to test the model performance, as shown in Figure 13. The results were found to be satisfactory, as shown in Figure 14 and Figure 15, where the prediction for the next 1 hour and the next 3 hours gave a satisfactory result. However, for more the next 24 hours, the model was unable to give an accurate result, as shown in Figure 16.

Figure 12. ARIMA (2,0,1) model performance result and parameters

Table 3. CO prediction with ARIMA for Bachang and Kuala Terengganu, Malaysia (Hamid et al., 2017)

| Location          | Performance Indicator (Error Measure) |
|-------------------|---------------------------------------|
|                   | RMSE       | NAE        | MAPE      |
| Bachang, Melaka   | 0.1119     | 0.0845     | 17.074    |
| Kuala Terengganu  | 0.0773     | 0.0641     | 13.131    |

Table 4. Comparison of algorithm in Windowing

| Algorithm          | Gradient Boosted Tree | Generalised Linear Model | Decision Tree | Deep Learning | Random Forest | SVM          |
|--------------------|-----------------------|--------------------------|---------------|---------------|---------------|--------------|
| Root Mean Error    | ±0.001                | ±0.001                   | ±0.001        | ±0.001        | ±0.003        | ±0.003       |
| Squared Error      | ±0.027                | ±0.027                   | ±0.038        | ±0.026        | ±0.064        | ±0.101       |
| Absolute Error     | ±0.00                  | ±0.001                   | ±0.001        | ±0.001        | ±0.002        | ±0.003       |
| Relative Error     | 5.93                  | 5.75                     | 8.20          | 5.61          | 14.91         | 22.73        |
Table 5. Deep learning prediction with new few hours

| Prediction | Next 1 hour | Next 2 hours | Next 3 hours |
|------------|-------------|--------------|--------------|
| Root Mean  | 0.032 ± 0.001 | 0.050 ± 0.002 | 0.063 ± 0.002 |
| Squared Error | 0.023 | 0.037 | 0.047 |
| Absolute Error | ± 0.001 | ± 0.001 | ± 0.01 |
| Relative Error | 5.02% | 7.89% | 10.13% |
| Error | ± 0.29% | ± 0.20% | ± 0.42% |

IX. CONCLUSION

It is very important to design air pollution forecasting models appropriately, as the models can help improve the management of air quality. Together with the implementation of such models, the efforts to improve the techniques of forecasting accuracy are also very significant. The temporal elements (time series) are the important variable to make an accurate CO concentration prediction.

From this study, both time series approaches in RapidMiner- (1) ARIMA and (2) Windowing with deep learning gave satisfactory results, where Windowing with deep learning was more superior. Regardless, time series with ARIMA gave more interpretable results where the model can be translated into mathematics equations.

However, Windowing with deep learning was more superior not only in terms of low relative error but also in terms of more variables that can be used in the model building. In ARIMA, only a univariate variable (CO concentration at a particular time) was used in model
building. But for Windowing with deep learning, besides CO concentration and time, other variables such as wind direction, wind speed, temperature and humidity parameters were also used as the predictor variables. This gave a more accurate and generalised model. In this work, it was demonstrated that RapidMiner Studio is a useful tool for CO prediction. Therefore, in future work, model deployment features in RapidMiner Studio can be further explored.

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