Prediction of Agricultural Emissions in Malaysia Using Machine Learning Algorithms

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Abstract**—** Agriculture has always been an important economical factor for a country, which is causing emissions every day, without realizing how much it is leading towards an increasing number of Greenhouse Gas (GHG). Agricultural emissions have been forecasted for Malaysia to have a better understanding and to take measures right away. This can be done through a machine learning model including collecting data, pre-processing, training, building a model, and testing the model for accuracy. This project aims to develop a model to forecast agricultural emissions using the three most accurate forecasting models. The time series analysis consists of two models, autoregressive integrated moving average(ARIMA) and long short-term memory(LSTM) and simple linear regression model. These models illustrate the forecasted upward trend values until 2040 in Malaysia. The ARIMA model provides good prediction curves which are close to the actual values taken since 1960 and the LSTM model provides a decreasing curve for every value loss epochs which concludes to be a good forecasting model. It was concluded that agricultural emission is causing the soaring temperature in Malaysia and an immense amount of emissions causing by agriculture. The techniques used in this paper can be enhanced more in the future and the visualizations can help the Malaysian agricultural sectors to take proper measurements to prevent this uprising agricultural emissions.

Keywords**—** agriculture, regenerative agriculture, prediction, ARIMA, LSTM, regression model, emissions, greenhouse gas, Malaysia, CO2, forecast, SDG

I. Introduction

Greenhouse gas (GHG) emission is having an unprecedented rise. GHG is causing climate change in an implausible way which is resulting in an increment of surface temperature [1-3]. The Intergovernmental Panel on Climate Change (IPCC) has reported that global land-ocean temperature has increased by 0.85 °C from 1880 to 2012 [4]. IPCC has also reported that the period between 1983 and 2012 was the warmest in 800 years [4-6]. Six gases have been identified as the greenhouse gas, and they are water vapor (36 – 70 percent), carbon dioxide (9 – 26 percent), methane (4 – 9 percent), nitrous oxide (3 – 7 percent), HFC, and SF6 [5-14]. According to IPCC, methane is the second in contributing to global warming and has the proficiency of 21 – 25 percent in causing global warming [15]. The agricultural sector is responsible for more than a quarter of the world's GHG emissions. As the world population is growing in a vast amount, the need for growing more food continues. The methane emission from livestock is a part of their digestive process. It is produced in the rumen of livestock [15]. It generates extensive microbial activities that result in incombustible gases [15]. Ruminants cause enteric fermentation which participates in 15-18 percent of methane emission [15-19]. The current estimation of emissions from agriculture, forestry, and land use is around 19.9 GtCO2 from many research [20-25]. Nitrogen fertilizer adds extra 0.4 GtCO2 of emissions. Major contributors to agricultural emissions are, enteric fermentation (8.3 GtCO2), rice cultivation (2.1 GtCO2), manure (1.8 GtCO2), on-farm energy (1.0 GtCO2),
and fertilizer (0.6 GtCO2) [3]. As the world population is reaching almost 10 billion, the need for growing more food including protein is increasing. Considering the current deforestation rate, the emission is projected to increase about 23.4 GtCO2 by 2050 [3]. Global Warming of 1.5°C, a report from IPCC in 2018 has proclaimed that a far-reaching transition is needed to confine the climate change to 1.5 degrees Celsius [3]. This report focuses on building models using ARIMA, LSTM, and linear regression to forecast agricultural emissions. It provides a better understanding of the immense rising effect of agricultural emissions and how it's leading as one of the reasons for climate change in Malaysia.

A. *Research Questions*

1) Based on the current global warming increasing rate, is it possible to forecast emissions rate in agriculture using data science and machine learning?
2) Global warming is causing a massive escalation of temperature. Is it possible to analyze the increasing

rate and solve this issue using regenerative agriculture?

B. Research Objectives

1) To find the factors which are causing the global warming crisis from agriculture.
2) To gain a better understanding of how some factors are causing global warming.
3) To estimate solutions through regenerative agriculture.
4) To forecast the increasing number of Greenhouse Gas (GHG)

C. Problem Statement

Agricultural emission is increasing every day rapidly all over the world. According to Malaysiakini, Malaysia still hasn't considered agricultural emissions as an issue like EU, UK, and North America [11]. There has been given some effective solutions on ways of farming that can be implemented, but these solutions have yet to have any significant effect on turnout as it has not been started to implement yet [11]. By addressing this problem will have a great practical benefit on understanding the effect of agricultural emissions and prevent climate change.

D. Research Significances

1) The findings of this study will redound to the benefit of Malaysia's weather change because of agricultural emissions. It'll help the authorities from agricultural sectors in Malaysia to have a proper visualization of the weather change causing by agricultural emissions.
2) The solutions will help to take better measurements to reduce greenhouse gas (GHG) and provide a healthy agricultural procedure.

II. Literature Review

A. Theoretical Background

There are different researches to forecast emissions caused by agricultural emissions. All the researches have marked agricultural emissions as one of the biggest problems and one of the reasons causing global warming. Some existing forecasting models used are ARIMA, LSTM, Regression, ANN, Integrated Farm System Model (IFSM), STIRPAT model, trend analysis, and so on.

1) Time Series: The most important factor in every statistical problem for forecasting and prediction is "time". Time series analysis enables forecasts using correlated historical data. It is a sequence of observations and aligned according to the order of time. Time series forecasting collects historical observations and predicts the future by developing a quantitative model [14]. Data that are collected irregularly are not considered as time series data. There are different conventional time series modeling. In linear time series, the data points can be viewed as a linear combination. Nonlinear time series are generated by nonlinear dynamic equations. Time series analysis enables to dragonize the trends, cycles, and seasonal variance. Some predecessors are Error, Auto-Regressive Integrated Moving Average(ARIMA), Holt-Winters, and so on.

"Auto-regressive" and "moving average" means lags of the differenced series and lags of the forecasted errors and data that requires to be stationary by differencing [16]. ARIMA model is accurate compared to any other models in time series [15]. This model is based on the idea of using data with precise values and without any measurement errors having the benefit of versatility and better seasonal patterns [16]. Time series modeling has the least forecasting errors [15] but the data requires historical data continuity [16].

2) Linear Regression: Simple linear regression enables to study of the relationship between two quantitative variables. It's a statistical method that has one dependent variable and one independent variable. A regression line shows the positive relationship, negative relationship, and no relationship. A Linear relationship between forecast variable y and single predictor variable x is:

$$y_t = \beta_0 + \beta_1 x_t + \varepsilon_t \quad (1)$$

3) Livestock Exercise in Malaysia: The Malaysian government has strategized agricultural production as the third economic growth [16]. To succeed in this, different kinds of measurements are being taken. Investments are now being provided by financial institutions to interested inventors [16]. According to the National Meat Policy in Malaysia, they have increased the number of cows and buffaloes from 1.0 to 1.6 million and the number of goats from 9 to 35 percent. It's reported that Federal Land Development Authority Unit has invested RM688 million on livestock projects [16]. Two million hectare of palm has been planted for cattle to increase breeding stock [16].

B. Previous Empirical Research

1) *Common Approaches for Forecasting CO2(eq) Emissions:* A research team from Johor used the ARIMA model to predict methane emissions from livestock in Malaysia [16]. They have used two specific approaches, computing methane emissions from 1980 to 2008 according to the IPCC guideline and forecasting methane emission. CO2 emissions, energy consumption, economic and population growth has been identified as having an impact on GDP growth in Malaysia [4]. CO2 emissions based in Iran have been forecasted using time series and regression analysis [9]. Multiple Linear Regression(MLR) and Multiple

Polynomial Regression(MPR) have been used to forecast CO2 emissions. Another study has adopted Bees Algorithm and Artificial Neural Network (ANN) to forecast world CO2 emissions [24]. Trend analysis is also a part of time series analysis which has been used in forecasting CO2 emissions from fuel [8]. By using Grey System and ARIMA, researchers from Iran have used these two models by RMSE, MAE, and MAPE metrics [15]. Sweden has implemented time series forecasting and regression analysis to analyze the energy systems [12]. Research from China used the LSTM-STRIPAT model to forecast china's 2030 emissions peak [3].

2) *Regenerative Agriculture:* Reducing agricultural emissions can change the way of farming, the amount of waste, and natural carbon sinks. Global agriculture is producing food for 10 billion people but 30% of these produced foods are being wasted [16]. The goal for regenerative agriculture is to implement the concept of producing more from less. Regenerative agriculture is based on the idea of managing soil fertility, improving soil structure, controlling water and wind erosion, managing soil acidification [17]. The manure from livestock emits methane. Nitrous oxide is also released during soil application by manure. Applying sensors to measure soil health can be effective. Drones are used to monitor crops and the heath of plants [10]. Smaller farms tend to collect and spread solid manure daily or weekly while larger farms typically have sizable lagoons for long-term liquefied manure storage pending application to fields or off-site transport [10]. Emissions tend to be higher from liquid treatment systems. Enteric fermentation happens when plant material is digested and emits methane in the process. The solution for this is to provide a healthy diet food to cows and other poultry animals. Compiling different types of farm-level data input adds complexity. This overwhelming data can be confusing to the farmers in that case Artificial Intelligence can take place. The Paris target implies decarbonization by 2060 is not easy to achieve with the growing population and demand for food [13].

Research on forecasting emissions is going on for decades, but research on agricultural emissions has started. The researches conclude to have immense aftermath on weather from agricultural emissions. The research from Johor[16] used the ARIMA model for predicting methane emissions and had a quite successful prediction. Time series modeling (ARIMA and LSTM) has been used for years for forecasting purposes. ARIMA and LSTM modeling was chosen for having successful emissions forecasting results according to the researches from China[3], Johor[16], Iran[9], and Sweden[12]. The proposed methodology has been implemented to illustrate the forecasts for methane emissions, temperature increment, and as well as total emissions from agriculture which was missing from the previous works.

III. Methodology

The models have been developed in five stages.

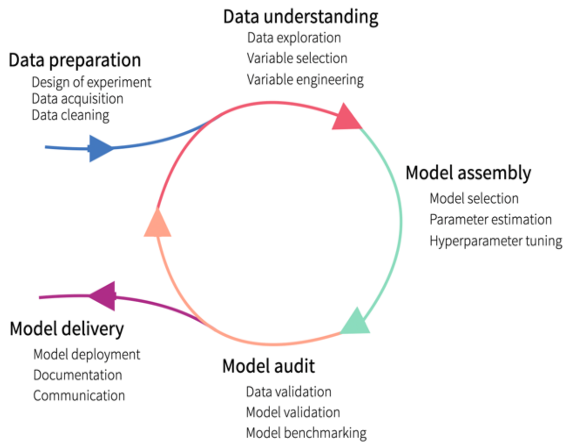

Fig. 1 Steps in Developing the Model [24]

For developing a good model, five stages need to be followed. After data acquisition, the first step is to clean or pre-process the data. Pre-processing includes checking for null values, checking for outliers.

After the pre-processing, comes exploratory data analysis (EDA). For variable selection, EDA acts as a primary role. EDA allows to visualization of the dataset closely and assists in selecting variables. The models should be selected based on the requirements of the project and the dataset. It's mandatory to check if the dataset can fit in the model and to check the model's validity. If the performance of the model is acceptable, then it's ready for deployment. Firstly, R was used for the pre-processing stage. In the second stage, Tableau and Microsoft Azure were used for data visualization and lastly, Python Jupyter Notebook was used for model development.

A. Dataset

The datasets [7], retrieved for this research paper are from FAOSTAT [7] standing for Food and Agriculture Organization of the United Nations, a famous website for sources of data related to agriculture. FAO is working with other countries to solve hunger and poverty and to mitigate climate change. The datasets consist of values from 2000 until 2017 in Malaysia. Each dataset describes the values from 2000 until 2017. From several datasets, fermentation, temperature, total emissions, and manure management datasets were chosen for Malaysia for having a higher impact on the environment. All the datasets consist of a variable of both categorical and numerical. The temperature dataset contains the values for temperature for every year and month. This dataset contains 1700 rows and 7 variables or columns having the values for every month. The "value" feature consists of both floating points and integer points for manure, fermentation, temperature, and total emissions dataset and is used against the "year" variable to create forecasting.

1) Pre-processing: Data preparation is the first step for any experimental research design. Performing data pre-processing, exploratory data analysis and visualization are the parts of data preparation. R has been used for checking for the need for data preparation. As the data were retrieved from FAOSTAT, it was already normalized.

B. Auto-Regressive Moving Average (ARIMA)

The ARIMA model has three parameters, d=number of differences for stationarity, p=order of the AR component, and q=order of the MA component. The value of d is typically 0 and occasionally 2 [22]. Choosing the value for p and q has difficult stages. It consists of three stages. The first one is the AR process in high order. The regression with the smallest value is selected in step two by taking residuals [15]. The last step is using ARMA models fitted using estimated residuals [19]. The ARIMA model is considered more accurate than any other model. Before finding the values for p, d, and q it's compulsory to check for the stationary [15]. If the data is not stationary it's compulsory to make the data stationary. The equation for regression is:

$$y_t = m + \alpha_1 y_{t-1} + \alpha_2 y_{t-2} + e_t + \beta_1 e_{t-1} + error \quad (2)$$

The equation for first-order difference:

$$y_t = \emptyset y_{t-1} + w_t \quad (3)$$

For p-th order difference:

$$y_t = \emptyset y_{t-1} + \emptyset_2 y_{t-1} + \cdots + \emptyset_y y_{t-p} + \varepsilon_t \quad (4)$$

For the p-th difference equation, the properties for ε_t are:

$$E[\mathcal{E}_t] = 0, \quad (5)$$

$$E[\mathcal{E}^2{}_t] = \sigma^2, \quad (6)$$

$$E[\varepsilon_t\, \varepsilon_s] = 0, for\ all\ t \neq s. \quad (7)$$

In order to calculate the accuracy of the forecast, three different statistical methods are being used. Root Mean Square Error(RMSE), Mean Absolute Error(MAE), and Mean Absolute Percentage(MAPE).

$$RMSE = \sqrt{\sum_{i=1}^{n} (P_i - A_i)^2 / n} \quad (8)$$

C. Long Short-Term Memory

LSTM is a recurrent neural network(RNN) that remembers the earlier values and capable of using that for forecasting.

1) *Recurrent Neural Network (RNN)*: The concept behind the recurrent neural networks is that, to observe sequentially and learn from the previous stages and use those learning data to forecast. This summarizes that the earlier stages need to be remembered to forecast [18]. The hidden layer in RNN allows the model to play an internal storage role for storing information. By the word "recurrent" in RNN means playing the same role or task for every element in the sequence [18]. The only problem with RNN is that it can remember fewer earlier stages which means it can be only used in fewer amounts of data.

2) Long Short-Term Memory: LSTM adds a special feature to the RNN to memorize the sequence of the data [18]. Each LSTM has cells to capture and store the data stream [18]. The cells have a transport line that connects one module to another. The gates in each cell are used to dispose of, filter, and add for the next cells [18]. The sigmoid layer yields number of zeros ranging from zero to one. Estimation of zero value implies not letting anything pass [18]. And estimation of one indicates to let everything pass. RNN is powerful in handling the dependency among the variables [18]. It can hold the values and learn from the long sequence observation.For implementing the algorithm, the Keras library was installed.

IV. Results and Discussions

A. Results from the ARIMA Model

For the fermentation dataset, the best Akaike information criterion (AIC) value was found in order of 1,1,0 and seasonal order 1,1,0,12 with the value of 342.56. From fig.2, the AIC value determines the best-fitted model for the dataset used. The lowest AIC value yields the best-fitted model. The p-value from fig.2 shows it's close to "0" which means the features can be included in the model for the forecasting purpose.

```
                                 SARIMAX Results
==========================================================================
=================
Dep. Variable:          Emissions (CO2eq) (Enteric)   No. Observations:
58
Model:               SARIMAX(1, 1, 0)x(1, 1, 0, 12)   Log Likelihood
-168.273
Date:                              Tue, 22 Dec 2020   AIC
342.546
Time:                                      15:31:02   BIC
346.943
Sample:                                  01-01-1961   HQIC
344.003
                                       - 01-01-2018
Covariance Type:                                opg
==========================================================================
=====
                 coef    std err          z      P>|z|      [0.025      0
.975]
--------------------------------------------------------------------------
-----
ar.L1         -0.1976      0.230     -0.860      0.390      -0.648
0.253
ar.S.L12      -0.6100      0.155     -3.930      0.000      -0.914      -
0.306
sigma2      2162.8240    568.930      3.802      0.000    1047.742     327
7.906
```

Fig. 1 Finding the best order for fermentation dataset

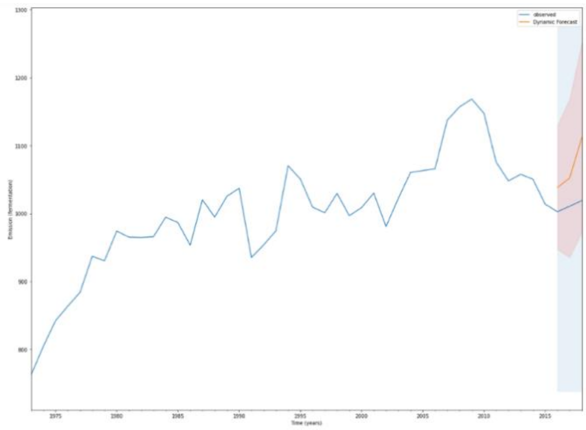

Fig. 2 Actual value vs Predicted value for fermentation dataset

From fig.3, it illustrates that the KDE line on the top right corner is closed to the N(0,1) line. N(0,1) means, a mean value with "0" and a standard deviation of "1", which concludes the residuals are normally distributed. The Q-Q plot on the left bottom corner illustrates the distribution of residuals which are the blue dots following the Linear trend which concludes to have a normal distribution of the residuals.

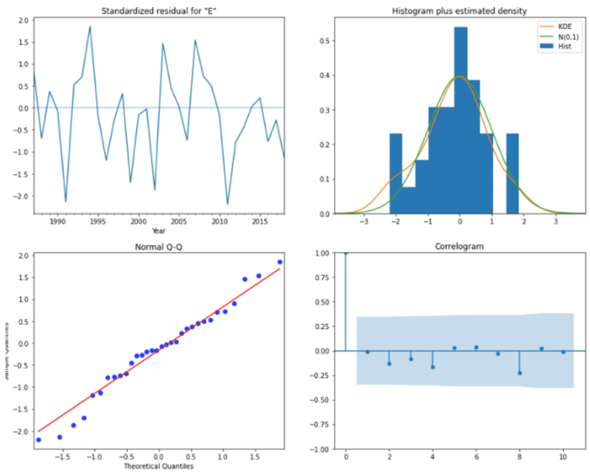

Fig. 3 Plots for fermentation dataset

The RMSE value for the forecasted model was found to be 62.1624. Fig.4 shows that the actual curved line and the predicted curved line follow almost the same line which concludes to have close values with the actual values. The result can be concluded with the RMSE value that, the forecasting is moderately good and can be used and appropriate for the dataset for using further forecasting purposes.

Fig.5 illustrates the forecasting values generated by the ARIMA model until 2040 in Malaysia.

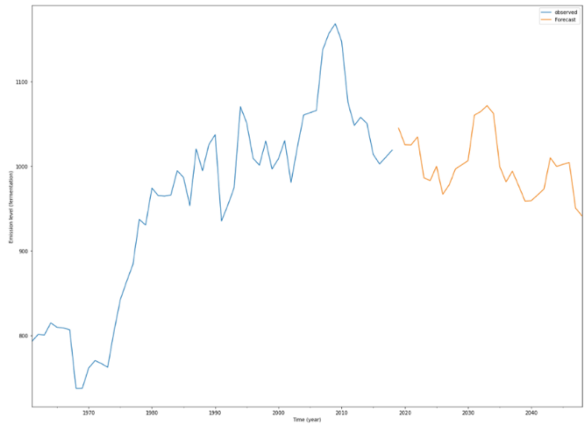

Fig. 3 Forecasting emissions from fermentation

The MSE value for the manure dataset for the ARIMA model is 11259.67. The best AIC was found at 1,1,0 with the value of 358 from Fig.6. The p-value from fig.6 shows it's close to "0", and that concludes that the features can be included.

```
                                 SARIMAX Results
==========================================================================================
====
Dep. Variable:     Emissions (CO2eq) (Manure management)   No. Observations:
58
Model:                    SARIMAX(1, 1, 0)x(1, 1, 0, 12)   Log Likelihood                  -176
.459
Date:                                   Sun, 13 Dec 2020   AIC                              358
.917
Time:                                           01:57:09   BIC                              363
.314
Sample:                                       01-31-1961   HQIC                             360
.375
                                            - 01-31-2018
Covariance Type:                                     opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1         -0.0282      0.272     -0.104      0.917      -0.561       0.505
ar.S.L12      -0.6425      0.261     -2.460      0.014      -1.154      -0.131
sigma2      3607.5371    783.294      4.606      0.000    2072.309    5142.766
------------------------------------------------------------------------------------
```

Fig. 4 Finding the best ARIMA order for manure management dataset

From fig. 7, it illustrates that the KDE line on the top right corner is closed to the N(0,1) line. N(0,1) means, a mean value with "0" and a standard deviation of "1", which concludes that the residuals are normally distributed. The Q-Q plot, on the left bottom corner, illustrates the distribution of residuals, which are the blue dots. The blue dots depict somewhat following the Linear trend which concludes to have a normal distribution of the residuals.

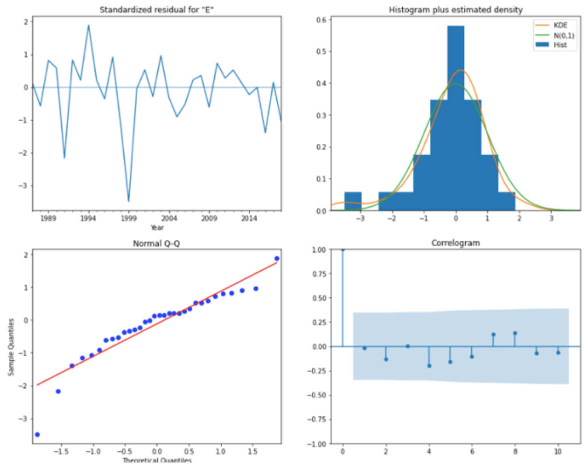

Fig. 5 Plots for Manure management dataset

From fig.8, it depicts the predicted values for the manure management dataset that follow the actual values. It concludes this to be a valid model for forecasting for the manure dataset.

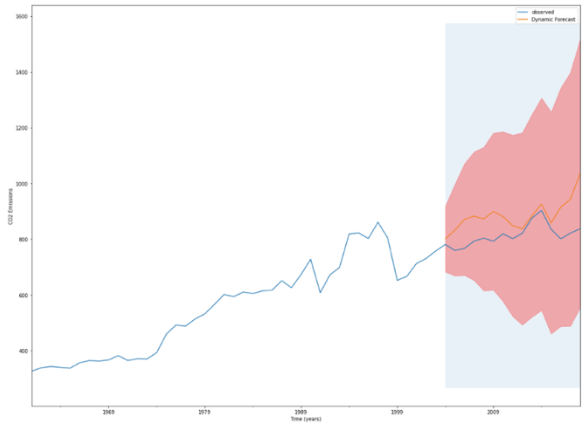

Fig. 6 Predicted vs Actual plot for manure dataset

From fig.9, the forecasting values proclaim to be following an upward trend until 2040 in Malaysia. This summarizes, based on the previous data for manure emissions, Malaysia is likely to have an ascending trend up to 2040 if a plausible approach is not being taken.

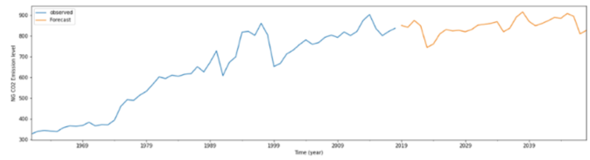

Fig. 7 Forecasting manure emission using ARIMA

B. *Results from the LSTM*

The results from the LSTM model in fig.10 provide a decreasing trend for value_loss after each epoch. Which concludes the LSTM to be a favorable model quality.

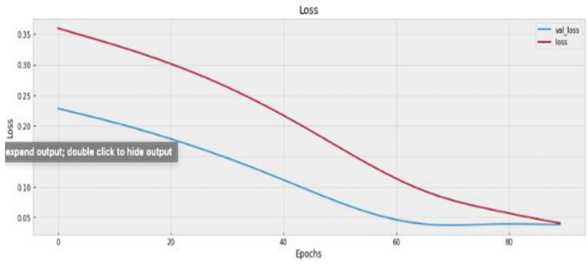

Fig. 10 val_loss graph for fermentation dataset using LSTM

The results from the LSTM model provide close predicted values to the actual values which validate the model's forecasted values. From fig.11, it depicts a similar trend for both the LSTM (fig.11) and ARIMA model (fig. 5) for the fermentation dataset.

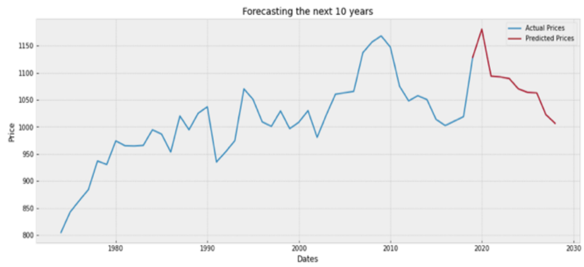

Fig. 11 Forecasting fermentation emission using LSTM

The results from the LSTM model in fig.12 provide a decreasing trend for value_loss after each epoch. This concludes the designed model to be an acceptable model for forecasting values for the manure management dataset.

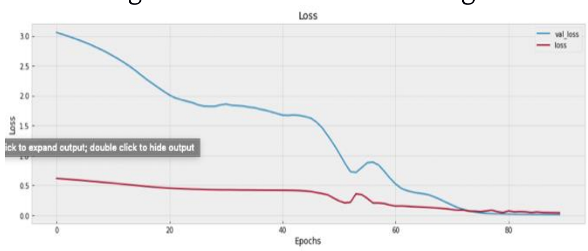

Fig. 12 val_loss for manure dataset for manure management

The results from the LSTM model provide close predicted values to the actual values which validate the model's forecasted values. From fig.13, it depicts a similar ascending trend for both the LSTM (fig.13) and ARIMA model (fig.9) for the manure management dataset.

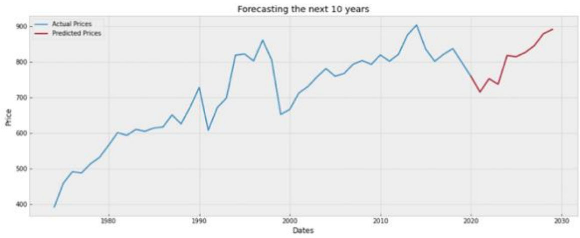

Fig. 13 Forecasting manure emission using LSTM

V. Conclusion

All the forecasting values show a soaring trend which is an adverse weather condition for Malaysia. Fig.14 provides a simulation forecasting using time series to provide an illustration of how the temperature in Malaysia can increase over time due to agricultural emissions. The fermentation and manure emissions forecasting models also illustrate the increasing amount of emissions in Malaysia by the year 2040.

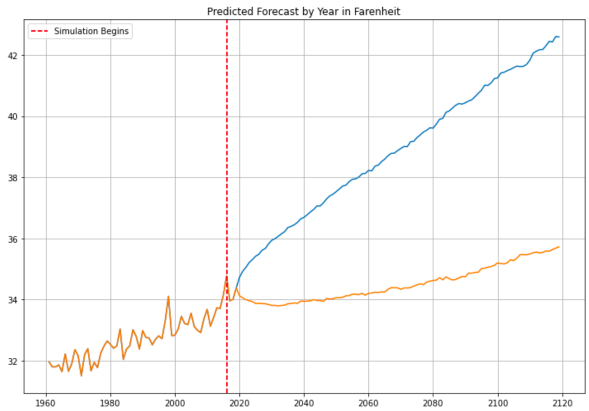

Fig. 14 Temperature forecast simulation

For the total emissions from agriculture, from fig.16, the total emissions values are presenting an upward trend up to 2040. The total agricultural emission is increasing since 1960 at an alarming rate over time in Malaysia due to the lack of proper knowledge in agricultural emissions and their implausible effect. Fig.15 was generated using Linear Regression Model, having a model accuracy of 85%. Therefore, this can be considered as a favorable model for the total emissions dataset for forecasting.

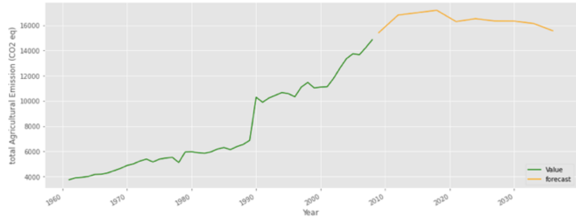

Fig. 15 Forecasting total agricultural emissions using linear regression

The temperature in Malaysia is increasing at an alarming rate because of Agricultural emissions, which have been forecasted through machine learning techniques. It has become extremely essential for the Malaysian government to take necessary measures to implement regenerative agriculture procedures in all farming sectors. Regenerative agriculture can solve these uprising emissions and also can produce more food without using a lot of farming lands.

VI. Future Works

The developed models hold the most accuracy of 85% for forecasting. Due to the Covid-19 pandemic, the forecasting values might vary. Including data after the covid-19 hit and checking how that affects the forecasting results would have provided better results. The developed models' accuracy can be improved. The plan for future work is to forecast agricultural emissions in Malaysia after using the regenerative agriculture method and identifying what are the changes that are helping to reduce emissions to gain a better understanding of how regenerative agriculture can reshape Malaysia's climate change.

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