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Gas turbine combustion profile modelling for predictive maintenance using am artificial neural network

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Abstract. Dry Low Emission (DLE) gas turbine has been developed as a solution to encounter the harmful high NOx emission from conventional gas turbine. However, it is prone to create a Lean Blowout (LBO) error that causes frequent shutdown due to its stringent condition that needs to be operate inside its desired operating condition that can be monitored through the temperature, NOx and CO emission concentration. This paper develops an Artificial Neural Network – Multilayer Perceptron (ANN-MLP) predictive maintenance model using actual DLE gas turbine data that predict trips from the gas exhaust emission and classification of warning stages on the LBO error. 94.12% of R^2 for the regression model and 100% accuracy of the classification model using Python is obtained using four months period data. This proposed ANN-MLP model manage to predict the suitable maintenance time of DLE gas turbine using real time data which can help reduce cost lost from unscheduled shutdown.

Introduction

Gas turbines are internal combustion engine that converts mechanical to electrical energy from the air-fuel combustion that spins the turbine. However, this process emits high Nitrogen Oxide (NOx) emissions due to the high temperature at stoichiometric conditions, which is a poisonous and dangerous pollutant to humans and the environment. To encounter this problem, Dry Low Emission (DLE) gas turbines is introduced to lower the NOx emission by applying lean premixed combustion that lowers its flame temperature [1-4].

This lean premixed condition, however, causes the DLE gas turbine to frequently trip due to its flame and combustion instability, which leads to frequent unscheduled shutdown of gas turbine affecting the maintenance cost and energy production [5]. This instability is observed to occur when the flame fuel/air ratio (equivalence ratio) is too low outside of the desired operating range that causes Lean Blowout (LBO) condition, as shown in Fig. 1. The desired operating range and LBO area can be monitored through the CO and NOx emission as well as the fuel/air ratio or temperature.

This paper proposes that DLE gas turbine [1,2] trips can be prevented using Predictive Maintenance (PdM) approach by early prediction of the LBO error from the gas emission concentration (CO and NOx). Predictive Maintenance is a method that determines the necessary time for maintenance by early failure prediction through continuous monitoring of the system [6]. Based on the literature reviewed, data-driven methods using artificial intelligence (AI) such as

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Artificial Neural Network (ANN) and Multilayer Perceptron (MLP) are some of the preferable methods for PdM due to a large amount of data of the system that can be obtained easily.

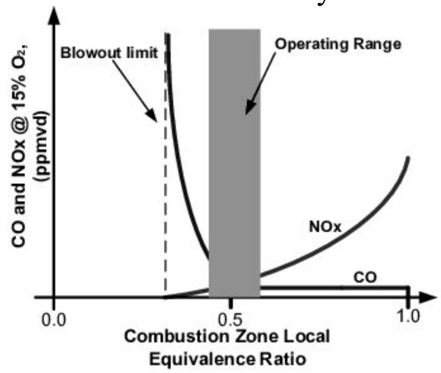

Fig. 1. Effect of Emission Concentration to Lean Blow-Out Condition

Literature review has been done on DLE Gas Turbine based on seven journals where the model used, predicted value and mode of study is observed and compared. From the literature, [7] uses NARX model using actual gas turbine data as an artificial intelligent simulation method to predict the gas turbine pressure, temperature, power and fuel flow rate. [8] uses Computational Fluid Dynamic Method using experimental data from a combustor to predict the LBO error of a DLE Gas Turbine through its temperature and emission concentration respectively. [9] perform emission identification study through predicting emission concentration on experimental data using CFD and ANN model respectively. [10] and [11] perform fault identification of the gas turbine system where uses ANN model to predict the gas exhaust temperature, gas turbine speed and angle while uses numerical ROWEN model [12,13,14] to predict the gas turbine efficiency.

Various work on PdM for conventional gas turbine were also compared. Among those that use ANN architecture, [15,16] were simulated using actual gas turbine data. uses ANN to predict the emission concentration, fuel flow, pressure and temperature, while [15,16] uses MLP to predict emission concentration, mass flowrate, temperature, power, pressure ratio, efficiency and flow capacity. [4] performed ANN or MLP modelling on an experimental mode that predicts the temperature, power, pressure ratio, temperature, flowrate, instability frequency and amplitude. [17] develop modelling in experimental mode to predict the LBO error using numerical modelling. Numerical modelling however takes much time to be developed compared to data-driven methods of modelling such as ANN and MLP due to the abundance of data collected from the plant.

Based on the literature review done, ANN is a favourable model to use for PdM of gas turbine systems. ANN is an artificial intelligence method that requires many data to get accurate result for regression and classification analysis. ANN is suitable for modelling complex and uncertain data, and is applicable for real and live operating data. There are many types of ANN model, and the most basic model is MLP [18,19]. MLP is a feedforward neural network that consists of an input layer, one or more hidden layers and an output layer. The nodes in the hidden and output layer contain their respective transfer function that allows the model to predict and develop a trendline for complex and non-linear system. MLP as a universal approximator that can predict most of the system with a few lines of codes without developing any specific mathematical model makes it a time and cost-efficient method [20] to be used for this project.

It is summarized that less study on prediction model of LBO error and gas emission concentration is observed where mostly were done on experimental mode for DLE gas turbine. PdM on actual gas turbine has been studied for conventional gas turbine where mostly utilizes ANN model. Therefore, this project will study further on developing a PdM model through the prediction of the LBO error and emission concentration using actual DLE gas turbine data from the plant while implementing similar approach that have been done on conventional gas turbine studies.

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Methodology

In this chapter, the methodology of the project is elaborated starting from data pre-processing, regression model, classification model and lastly on the model performance.

A. Data Pre-processing and Analysis

39,324 clean data from three months of DLE gas turbine operation from a plant that consists of fuel gas flow, fuel gas pressure interstage, stop ratio valve (SRV), opening, gas turbine control valve (GCV) opening, splitter opening, compressor discharge, ambient air temperature, speed, exhaust press, inlet guide vanes (IGV) opening, temperature, load, nitrogen oxide (NOx) concentration and carbon monoxide (CO) concentration is used to develop the machine learning model. The data are visualized and screened to remove outliers consisting of its transients during any start-up and shut-down operation, as well as corrupted data that gives error signals. Other outliers are further identified through boxplot and regression-based method [21]. Next, the tripping period of the DLE gas turbine is identified based on its load and speed, and the dataset is labelled to be either in 90, 75, 60, 45, 30 or 15 minutes before tripping as the unhealthy condition dataset. The remaining is labelled as normal condition. The datasets are randomly separated into three types which are training, testing and validation datasets with a ratio of 60:15:25, respectively [22].

B. Regression Models Development

Regression model using machine learning models from python *sklearn* library such as artificial neural network (ANN), multilayer perceptron (MLP), k-nearest neighbors (kNN), random forest (RF), decision tree (DT) and logistic regression (LR) is developed to predict NOx, CO and temperature from the remaining parameter. The models' accuracy is evaluated and compared in terms of their root mean square error (RMSE), mean absolute error (MAE) and regression coefficient (R^2) to clarify if ANN-MLP is a suitable model. The ANN-MLP regression model is further optimized through a trial-and-error method by changing its hyperparameters in order of activation function, the number of neurons followed by the number of hidden layers [3,17]. The hyperparameters tuned are as in Table 1. The model's R^2 is tabulated and compared to identify the highest result as the best model.

Table 1. ANN-MLP Regression Model Hyperparameters

Hyperparameter	Value
Activation Function	Identity, relu, logistic, tanh
Number of Hidden Layers	1 to 5
Number of Neurons	10 to 1000
Number of iterations	10000

b. Classification Model Development

The predicted value from the regression model is then plotted to be NOx and CO concentration against temperature. The trend of emission concentration during the DLE Gas Turbine tripping and the normal condition is analysed and classified into two healthy and unhealthy state regions based on the gas emission concentration and temperature range as in Fig. 2. The yellow region is classified as a healthy condition represented as '0', while the rest is identified as unhealthy defined by '1'. After determining the classification type, a classification model is developed using temperature, CO and NOx emission concentration as the input data and DLE gas turbine performance of healthy and unhealthy as the predicted output data. The model will be tuned by adjusting the hyperparameters of the ANN-MLP model, such as activation function, number of hidden layers, and number of nodes until the highest accuracy model is identified. The classification model is evaluated by its accuracy percentage and confusion matrix.

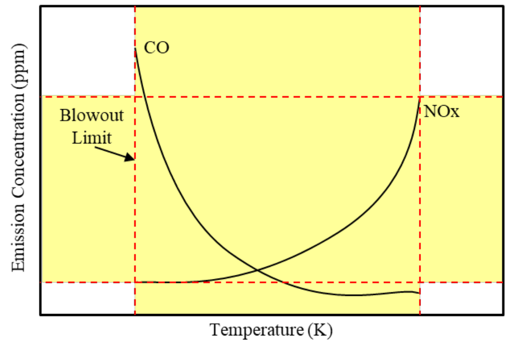

Fig. 2. Healthy and Unhealthy Data Classification from Regression Result

D. Model Performance and Evaluation

To validate the model's performance, the validation dataset set aside is run through both ANN-MLP regression and classification model simultaneously. The R^2, MAE and RMSE values of the training and validation data are compared for the regression model, while the accuracy and confusion matrix are compared for the classification model. Using validation dataset can validate that the ANN-MLP can predict NOx, CO, temperature and DLE gas turbine healthiness of different datasets that the model has never trained. Next, the significance of NOx and CO in predicting the healthiness of DLE gas is further investigated by developing another classification model using ANN-MLP with three different sets of inputs namely MLP-1, MLP-2 and MLP-3. MLP-1 is set to have only NOx, CO and temperature as the input. MLP-2 uses all inputs except NOx and CO, while MLP-3 uses all the inputs including NOx and CO. The accuracy and confusion matrix of the models are compared and studied to investigate if having NOx and CO as the input parameters give significant results in predicting the healthiness of the DLE Gas Turbine.

Result And Discussion

In this chapter, results from the regression model development, classification model development and model performance are discussed.

A. Regression Models Development

The accuracy of five machine learning models developed to predict DLE gas turbine temperature, NOx and CO concentration is compared and tabulated in Table 2. All models have higher accuracy than Linear Regression model for NOx and CO emission prediction, indicating that NOx and CO have a non-linear behaviour. The average correlation coefficient, R^2, of NOx, CO and temperature (T) prediction is calculated to ease the comparison between models. The highest average R^2 of 94.12% from the ANN-MLP model indicates its suitability for this system. Based on the comparison, MLP has the highest accuracy in predicting the overall model with an average R^2 of 94%, followed by RF. However, RF is slightly more accurate than MLP when predicting temperature. Since both models can predict temperature up to 99% accuracy, MLP is considered an excellent model to predict NOx, CO and temperature compared to the other ML models.

Through tuning of the hyperparameters of the ANN-MLP regression model, 94.12% accuracy is obtained using ANN-MLP using logistic activation function with 200 neurons in 4 hidden layers. The first hyperparameter tuned is the activation function where logistic gives the highest accuracy. Using logistic as the activation function, the number of neurons is varied from 1 until 500 and its R^2 is plotted. R^2 increases significantly as the number of neurons increase from 1 to 50 until it reaches 87% R^2 and starts to become constant from 200 to 500 neuron. Using the range of 50 to 300 neurons, the number of hidden layers is varied from 1 to 4, and its R^2 is presented as in Fig. 3. Four hidden layers provide the highest R^2, where five layers drop the model's performance.

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Therefore, the optimized ANN-MLP model is selected to use a logistic activation function with two hundred neurons in four hidden layers.

Table 2. Machine Learning Regression Model Comparison

		MLP	RF	kNN	DT	LR
NOx	R^2	89.04	88.52	80.34	75.88	62.74
	MAE	1.836	1.859	2.471	2.587	3.501
	RMSE	2.470	2.529	3.309	3.665	4.556
CO	R^2	93.98	92.91	82.77	84.97	57.07
	MAE	5.114	5.734	8.979	7.486	16.29
	RMSE	8.981	9.747	15.19	14.18	23.99
T	R^2	99.32	99.61	97.91	98.9	98.64
	MAE	1.006	0.765	1.918	1.306	1.71
	RMSE	1.512	1.144	2.651	1.92	2.139
Average R^2		94.12	93.63	87.00	86.58	72.82

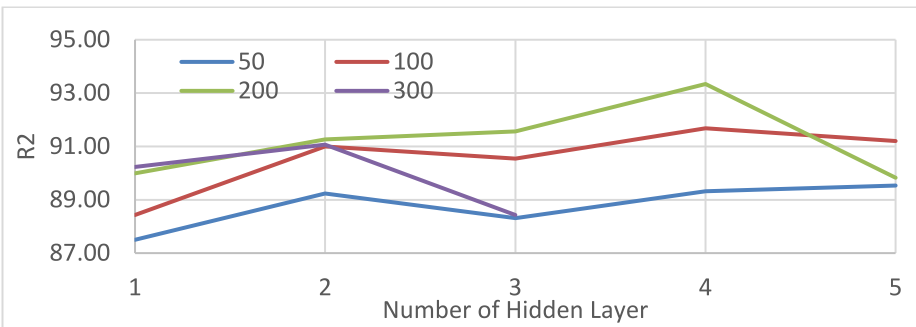

Fig. 3. R^2 of MLP-ANN by Number of Neuron and Hidden Layer

B. Classification Model Development

The predicted NOx, CO and Temperature from the ANN-MLP regression model is then plotted as in Fig. 4 to identify the baseline for the desired operating condition of the DLE gas turbine. The desired operating condition is identified to be between temperature 775 K to 915 K and NOx concentration between 74 ppm to 140 ppm. Too low temperature causes the flames to become unstable leading to LBO condition and tripping [1,2]. From the data plot, the results show similar trends of temperature, NOx and CO concentration according to literature where NOx increases while CO decreases with temperature [23]. The healthiness of the gas turbine can be reflected on the NOx and CO emission, where higher NOx emission indicates that the DLE gas turbine operates at higher temperature similar to conventional gas turbines, that will emit higher amount of the harmful NOx. Lower NOx concentration indicates that the combustion occurs at very low temperature near the lean extinction point, resulting to the possibility of flame extinction and tripping [1]. This result is similar to the analysis on actual data, where datapoints out of this range occur when approaching tripping, indicating that temperature and emission concentration can predicts the healthiness of gas turbine before tripping.

The predicted output of the ANN-MLP regression model [24,25] is used as the input to train the ANN-MLP Classification model based on the operating range, resulting in an accuracy of 100%. The model can accurately predict all healthy conditions that are represented as 0 and unhealthy conditions that are represented as 1.

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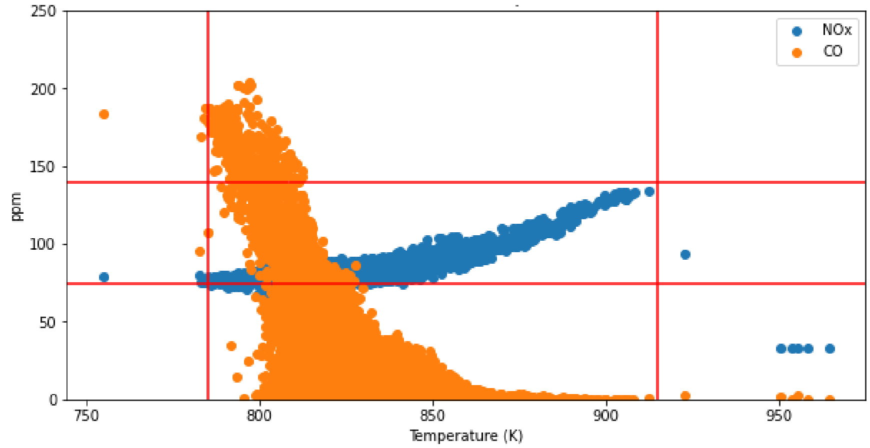

Fig. 4. Desired Operating Range of DLE Gas Turbine between 775K to 915K and 74ppm to 140ppm

C. Model Performance and Evaluation

The regression model performance of the validation dataset presents similar R^2, RMSE and MAE as the training and testing value tabulated in Table 3. Similar results in R^2, RMSE and MAE indicates that the ANN-MLP regression model is not overfitting and manage to predict a new set of data that it has never trained before and can predict future set of data from the plant. The predicted NOx, CO and temperature validation data is then input into the ANN-MLP classification model, where 99.996% accuracy is achieved. The performance of the validation data is described in the confusion matrix where all 22,2261 healthy datasets are accurately predicted. 12 out of 13 unhealthy datasets manage to be accurately predicted for the unhealthy dataset, indicating that this model can predict another untrained dataset with great precision.

Table 3. Regression Performance of ANN-MLP Validation Data

	NOX	CO	TEMPERATURE
R^2	88.92	94.39	99.49
RMSE	2.469	8.577	1.302
MAE	1.818	4.899	0.988

To further investigate if NOx and CO contribute to the prediction of DLE gas turbine healthiness, another classification model is developed using ANN-MLP with three different sets of inputs. MLP-1 is set to have the same input as the classification model developed. MLP-2 uses all inputs apart from NOx and CO, while MLP-3 uses all the inputs available from the dataset. The comparison is made to observe the impact of NOx and CO on predicting the healthiness of gas turbines. Comparing the accuracy, MLP-1 (99.71%) and MLP-2 (99.72%) have very little difference in their accuracy in predicting the healthiness of DLE gas turbines. However, when both inputs from MLP-1 and MLP-2 are combined, creating MLP-3, the model's accuracy increases to 99.77%. The increment in accuracy indicates that adding NOx and CO as the input and other parameters helps increase the model's prediction accuracy.

Conclusion

In conclusion, this project manages to develop a regression and classification MLP-ANN model to predict the healthiness of DLE gas turbines by predicting temperature, NOx and CO emission. ANN-MLP is the best model for this study by achieving the best prediction performance of 94.12% R^2 accuracy of prediction from the regression model and 100% accuracy from the classification model compared to RF, DT, kNN and LR. The optimized ANN-MLP model identified uses a logistic activation function with 4 hidden layers with 200 neurons for the regression model and a *relu* activation function with 1 hidden layer of 100 neurons for the classification model. The desired operating condition of the DLE gas turbine that is used to classify the healthiness of the model is identified to be in the range of between temperature 775K to 915K and NOx concentration between 74 ppm to 140 ppm. The classification model developed shows that incorporating CO and NOx as input could better predict the healthiness of the DLE gas turbine.

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