

**MODEL DEVELOPMENT FOR TURBINE
ENERGY YIELD (TEY), CARBON MONOXIDE
(CO) AND NITROGEN OXIDE (NO_x) FROM GAS
TURBINE POWER PLANT**

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UNIVERSITI SAINS MALAYSIA

2021

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(CO) AND NITROGEN OXIDE (NO_x) FROM GAS
TURBINE POWER PLANT**

by

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**Thesis submitted in fulfilment of the requirements
for the degree of
Bachelor's Degree of Chemical Engineering**

June 2021

ACKNOWLEDGEMENT

I wish to express my sincere thanks to Kementerian Pendidikan Malaysia (KPM) through Fundamental Research Grant Scheme (FRGS) grant number PJKIMIA/6071414, Universiti Sains Malaysia, for providing me with all the necessary facilities for the research. I place on record, my sincere thank you to Prof. Ir. Dr. Zainal Ahmad, Dean of the School of Chemical Engineering USM, as well as my supervisor for the continuous encouragement and support. I am extremely thankful and indebted to him for sharing expertise, and sincere and valuable guidance and encouragement extended to me. I also thank my parents for the unceasing encouragement, support and attention. I am also grateful to my partner, Farhanah and Thaaranni who supported me throughout this journey. I also place on record, my sense of gratitude to one and all, who directly or indirectly, have lent their hand in this venture.

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LIST OF SYMBOLS

AT	Ambient temperature	°C
AFDP	Air filter difference pressure	mbar
AH	Ambient humidity	(%)
AP	Ambient pressure	mbar
CO	Carbon monoxide	mg/m ³
CDP	Compressor discharge pressure	mbar
GTEP	Gas turbine exhaust pressure	mbar
NO _x	Nitrogen oxide	mg/m ³
TAT	Turbine after temperature	°C
TEY	Turbine energy yield	MWH
TIT	Turbine inlet temperature	°C
ϕ [.]	Activation function	-
$B_{i,k}$	Bias value applied to neuron i in layer k	-
r	Correlation coefficient	-
x_i	Each value from the population	-
L	Likelihood under the fitted model	-
\bar{x}	Mean of the values of x-variables	-
\bar{y}	Mean of the values of y-variables	-
M (k)	Number of neurons in layer k	-
n	Number of process input	-
$y_{i,k}$	Output of neuron i in layer k	-
p	Parameter numbers in the model	-
d	Past values	-
μ	Population mean	-
σ	Population of standard deviation	-

N	Population size	-
$u(t)$	Process input at time t ,	-
$y(t)$	Process output at time t	-
x_i	Values of x -variables in a sample	-
y_i	Values of y -variables in a sample	-
$\omega_{i,j,k}$	Weight between neuron j in layer $k-1$ and neuron i in layer k ,	-

LIST OF ABBREVIATIONS

AFDP	Air filter difference pressure
AH	Ambient humidity
AI	Artificial intelligence
AIC	Akaike information criteria
ANN	Artificial neural network
AP	Ambient pressure
AT	Ambient temperature
CDP	Compressor discharge pressure
CEMS	Continuous emission monitoring system
CO	Carbon monoxide
CO ₂	Carbon dioxide
ELM	Extreme learning machine
GA	Genetic algorithm
GTEP	Gas turbine exhaust pressure
IR 4.0	Industrial revolution 4.0
MIMO	Multiple input multiple output
MISO	Multiple input single output
MSE	Mean squared error
N ₂ O	Nitrous oxide
NARX	Nonlinear autoregressive with external input
NN	Neural network
NO _x	Nitrogen oxide
OFA	Overfire air
PEMS	Predictive emission monitoring system
SSE	Sum squared error
SVM	Support vector machine
TAT	Turbine after temperature
TEY	Turbine energy yield
TIT	Turbine inlet temperature
UNFCCC	United Nations Framework Convention on Climate Change

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**PEMBANGUNAN MODEL UNTUK HASIL TENAGA TURBIN (TEY),
KARBON MONOKSIDA (CO) DAN NITROGEN OKSIDA DARIPADA
TURBIN GAS JANAKUASA**

ABSTRAK

Dalam menangani isu alam sekitar yang semakin meruncing pada zaman kini, pelbagai kaedah telah digunakan serta diaplikasikan di serata dunia. Antara cara-cara bagi menyelesaikan masalah alam sekitar terutama masalah pencemaran udara dari pelepasan gas rumah hijau, kaedah sistem pantauan pelepasan secara jangkaan (PEMS) telah diperkenalkan. Dibantu oleh rangkaian neuron buatan (ANN) ia menggunakan data yang dikumpul daripada Kaya et al. (2019) dari gas turbin janakuasa seperti suhu ambien (AT), tekanan ambien (AP), kelembapan ambien dan lain-lain bagi tujuan ramalan pelepasan gas rumah hijau. Beberapa model akan dibangunkan dan akan diklasifikasikan mengikut keluaran pemboleh ubah masing-masing. Masukan pelbagai keluaran tunggal (MISO), di mana CO, NO_x dan TEY akan menjadi keluaran bagi model masing-masing dan masukan pelbagai keluaran pelbagai (MIMO) di mana CO, NO_x dan TEY akan menjadi keluaran serentak. Bagi setiap model tersebut, akan dipecahkan pula kepada dua kategori, iaitu model tanpa pemilihan masukan dan model dengan pemilihan masukan. Prestasi model tersebut akan dinilai berdasarkan nilai min ralat kuasa dua (MSE), R dan R². Nilai R² bagi setiap model latihan dengan pemilihan masukan ialah 0.5094, 0.8260, 0.7573 dan 0.6922 bagi CO, NO_x, TEY sebagai keluaran dan model MIMO masing-masing dibandingkan dengan nilai R² bagi setiap model latihan tanpa pemilihan masukan ialah 0.5382, 0.8278, 0.7627 dan 0.6950 bagi model CO, NO_x, TEY sebagai keluaran dan model MIMO masing-masing. Model dengan pemilihan masukan dilihat mampu

bersaing dengan model tanpa pemilihan masukan dari segi prestasi jika dilihat berdasarkan nilai MSE, R dan R^2 mereka, walaupun mempunyai masukan yang lebih sedikit berbanding model tanpa pemilihan masukan. Model MIMO dilihat sebagai model lebih baik dibandingkan dengan model MISO, walaupun ia menggabungkan 3 keluaran serentak, tetapi ANN masih mampu berjaya membuat ramalan dengan tepat.

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ABSTRACT

In order to combat the environmental issues that have been constantly rising since the start of the first Industrial Revolution in the 18th century, many solutions have been introduced and been applied around the world. One of the approaches for overcome air pollution issues from greenhouse gas emissions is by monitoring their release from its most abundant sources, for example, gas turbine power plants. Predictive emission monitoring system (PEMS) is one of the methods for monitoring these greenhouse gas emissions. It is powered by an artificial neural network (ANN) by taking into account the collected data from Kaya et al. (2019) such as ambient temperature, ambient pressure, ambient humidity and many more from selected gas turbine power plants for the emission prediction purpose. Several models will be developed and will be classified according to their responding outputs. Multi input single output (MISO), where carbon monoxide (CO), nitrogen oxide (NO_x) and turbine energy yield (TEY) will be operated as separate output and multiple inputs multiple outputs where CO, NO_x and TEY will be its output simultaneously. For each model's type, it will be further classified into the model with input selection and the model without input selection. The performance of the model will be demonstrated by the value of its respective mean squared error (MSE), R and R². The model with input selection is having almost the same performance as the model without input selection although having fewer input variables compared to the latter. R² values for each training model with input selection are 0.5094, 0.8260, 0.7573 and 0.6922 for the

model with CO, NO_x, TEY as output and MIMO model respectively compare to the R² values for each training model without input selection are 0.5382, 0.8278, 0.7627 and 0.6950 for model with CO, NO_x, TEY as output and MIMO model respectively. MIMO model is the better model compared to MISO, even though it combines 3 outputs and could be more complex, but ANN still able to predict accurately. Therefore, developing MIMO model could be better than developing MISO model as it will reduce model times (one model for 3 outputs rather than a separate model for each output).

CHAPTER 1

INTRODUCTION

1.1 Introduction

This research study will focus on the development of the model of CO and NO_x gases emission and turbine energy yield (TEY) from a gas turbine power plants based on the operating condition of the gas turbine itself. An artificial neural network (ANN)-based predictive emission monitoring system (PEMS) will be simulated in MATLAB software to determine and analyse the behaviour of CO and NO_x gases emission and TEY towards the changing of the operating condition of the turbine.

1.2 Background of study

Power plant is an essential industrial facility to generate electricity and light up the country. It converts mechanical energy to electrical energy via generators that are being powered up by primary energy such as natural gas, coal and also fossil fuels (Afeework et al., 2020). Electrical energy then being supplied to society through an electrical grid, or in Malaysia, it is called Grid Nasional, for everyday uses and needs. Manjung Power Plant, also known as the Sultan Azlan Shah Power Station is a coal fired power facility located at Perak, Malaysia that can supply 4.1 Gigawatt (GW) of electricity throughout the nation (Manjung Power Plant, Perak - One of the Biggest Power Plants in Malaysia, n.d.).

At the heart of a power plant, is where the gas turbine located. Just like how a human's heart pumped blood across the whole body, a gas turbine's function is to produce electric current to the society such as residential areas. It uses natural gas or other liquid fuels to convert into mechanical energy that drives the generator to produce electrical energy via combustion of those fuels (What Is a Gas Turbine | Knowledge Base | GE Power Generation, n.d.). In general, a gas turbine has three major components

which are an air compressor, a combustor and the turbine and it uses the principle of the Brayton cycle to operate while adding a regenerator as a variation from the basic cycle. As shown in Figure 1.1 below, the presence of a regenerator, or basically a heat exchanger, is to recapture some of the energy in the exhaust gas for preheating the air that entering the combustor (Zohuri et al., 2018).

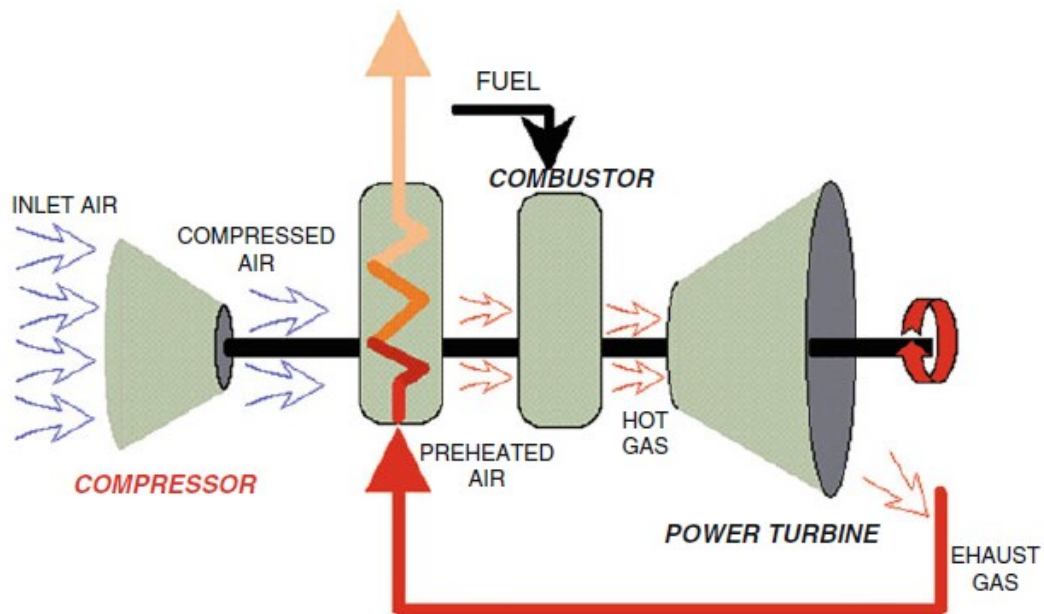


Figure 1.1 Schematic diagram of the gas turbine with regeneration (Zohuri et al., 2018)

Generation of electricity energy via combustion of fuel in the gas turbine can contribute to global warming as such process will release gases that could pollute the environment, for instance Carbon Monoxide (CO) and Nitrogen Dioxide (NO_x) gases (Shahsavari Alavijeh et al., 2013). Emission of those gases could pose a potentially huge risk to human health and also the environment (López et al., 2005). CO and NO_x are one of the greenhouse gases that could be trapped in the atmosphere, thus will affecting the whole world temperature and caused global warming. In conjunction to that problem, Paris Agreement was adopted by 196 participating nations. Paris Agreement or Paris Convention on Climate Change is an agreement within the United

Nations Framework Convention on Climate Change (UNFCCC), aim to deal with the emission of greenhouse gases on a global scale (*The Paris Agreement* | UNFCCC, n.d.).

Being the core subject of the convention, shows that greenhouse gas emissions of CO and NO_x can pose a threat to humanity and the environment if not being treated carefully. A study on greenhouse gas emissions by a various power plants in Malaysia from 1990-2017 has been conducted and it shows an upward trend from the year 1990 and reach its peak in the year 2011 and start to decrease gradually until the year 2017. Emission of greenhouse gases from natural gas power plants specifically shows a great increase from 3,199,815.26 tons per year in 1990 before reaching its peak at 32,094,546.75 tons per year in 2008 before starts to drop to only 27,955,130.78 tons per year in 2017 (Wan Mansor et al., 2020). However, prevention is better than cure. Hence, a proactive method must be taken into action before it worsens. The proposed method is to do data analysis for CO, NO_x and TEY prediction from the gas turbine power plants.

It is important to monitor the emission of those flue gas (CO and NO_x) to ensure the concentration of the gases doesn't exceed the requirement of the Industrial Emissions Directive (IED) for the power plant that has a total capacity of 100 MW and above (Korpela et al., 2015). According to Kaya et al. (2019), three solutions are developed to monitor the emission of flue gas from the combustion unit, especially gas turbine, which are (Kaya et al., 2019):

- i. Periodic measurement
- ii. Continuous emission monitoring system (CEMS)
- iii. Predictive emission monitoring system (PEMS)

First method, periodic measurement, was performed in the lab using typical calibrated equipment by emission testing laboratories at a moderate cost. Meanwhile,

CEMS use monitoring equipment such as a sensor set that being installed on-site, for instance, a gas turbine. It can provide a better reading and real-time information on CO and NO_x gas emission collected directly from the sensor on the gas turbine. The reliability of the information gathered on the gas emission depends on proper maintenance and calibrations of the sensor. The last method is a predictive emission monitoring system or PEMS. It uses past data on greenhouse gas emissions to create a predictive model for estimating the emission of CO and NO_x gases. PEMS also takes input variables of some processes to allow it to be operated as an expert system (Kaya et al., 2019).

Table 1.1 Example of input variables use in PEMS (Kaya et al., 2019)

Variable	Unit	Min	Max	Mean
Ambient temperature	°C	-6.23	37.10	17.71
Ambient pressure	mbar	985.85	1036.56	1013.07
Ambient humidity	(%)	24.08	100.20	77.87
Air filter difference pressure	mbar	2.09	7.61	3.93
Gas turbine exhaust pressure	mbar	17.70	40.72	25.56
Turbine inlet temperature	°C	1000.85	1100.89	1081.43
Turbine after temperature	°C	511.04	550.61	546.16
Compressor discharge pressure	mbar	9.85	15.16	12.06

The main focus of this project is to be able to do data analysis on CO and NO_x gases emission and also the turbine energy yield (TEY) from the gas turbine power plant. First and foremost, study and research on the input features of the gas turbine on CO and NO_x gases emission and TEY correlation must be conducted. This is to see how those outputs behave towards the input features of the gas turbine. Then, a model on CO and NO_x emission and TEY will be constructed based on the operating conditions of the gas turbine. Finally, by using MATLAB software, a model of CO and NO_x

emission and TEY as multiple inputs and multiple outputs (MIMO) will be modelled to achieve a minimum amount of the release of the flue gases to the environment and achieve maximum energy output from the turbine.

1.3 Problem Statement

According to the United States of America's National Centers for Environmental Information (NOAA) 2019 Global Climate Summary Report, the year 2019 was the second warmest year in 140 years, since the record was started. The global land and ocean surface temperature experience an anomaly of temperature rise at the average of +0.95 °C, which only behind 0.04 °C from the record high value recorded in 2016 (Menne et al., 2018). One of the reasons, if not the main reason, is the emission of greenhouse gas effects such as CO and NO_x. CO and NO_x gases usually being released from automobile vehicles, trucks and also from an industrial source such as gas turbine power plants that use natural gas/ fossil fuel/ coal as the source of combustion. Global greenhouse gas emissions can be broken down into several economic activities. Electricity and heat production leads the chart as the main source of global greenhouse gas emissions with 25% of gas emissions globally coming from these activities, followed by agriculture and industry activities with 24% and 21% respectively (Eickemeier et al., 2014).

In order to address this problem seriously, an approach to predict and analyse the CO and NO_x emission while optimizing the gas turbine to reach maximum turbine energy yield (TEY) from the gas turbine power plant is being proposed. In the early 1970s, CEMS had been a popular mechanism to monitor the emission of flue gas (CO and NO_x gas) from gas turbine power plants. However, due to its high capital investment and high operation and maintenance cost of hardware, an alternative had been

introduced in the late 1970s to early 1980s, which is PEMS. By applying thermodynamic or statistical methods, a mathematical model can be constructed to predict the emissions using a computer program based on the operating condition of the gas turbine (Chien et al., 2012). Low installation, operating and maintenance costs, faster to configure and maintain and also can provide some feasible information for industrial process optimization are the proof why PEMS is superior compared to CEMS (Chien et al., 2012). This project intends to develop an ANN-based PEMS for monitoring the emission of CO and NO_x gas from the gas turbine power plant while optimizing the operating condition of the gas turbine for maximum turbine energy yield (TEY).

1.4 Objectives

- i. To study the features input correlation towards CO, NO_x gases emission and turbine energy yield (TEY)
- ii. To predict/model the emission of CO, NO_x and TEY based on the operating condition of the turbine in multiple input single output (MISO) and multiple input multiple output (MIMO)

1.5 Sustainability

With the emerging of Industrial Revolution 4.0 (IR 4.0), artificial intelligence (AI) and big data analytics are expected to play an important role in the development of environmental sustainability. Globally, energy consumption is rising, and greenhouse gas emissions are rising as well. As a result of this change, global temperatures rise, triggering further climatic shifts (e.g. rise in sea levels, desertification, and El Nino). The usages of AI in combating environmental issues are in line with the United Nation's Sustainability Development Goals number 13, Climate Action, where it urges to take

urgent action to combat climate change and its impacts. Conventionally, the release of the flue gases from the power plant will be released after its get treated, while using current technology, we can predict the amount of greenhouse gas released from the plant thus, can minimize its impacts on the environment. There are many examples of AI usage in combating environmental issues especially in controlling emissions of greenhouse gases.

The emission of nitrous oxides (NO_x) gases from power generation plants is surging globally. However, it can be controlled by implementing a hybrid genetic algorithm and linear regression for prediction purposes in those said plants. Linear regression can estimate unknown model parameters from input data by modelling the relationship between an output dependent, y with explanatory variable, x . A genetic algorithm is used to search for the optimal solution until specific criteria are met causing termination. By providing good solutions as compared to one optimal solution for complex problems. By combining those two methods, this innovative method may identify the most significant input features while also providing more accurate predictions by reducing prediction mistakes. The results are very encouraging (Bunyamin et al., 2013).

According to Hong et al (2012), carbon dioxide (CO_2) gases emission by existing residential buildings occupies 9% of total CO_2 emission in South Korea. However, very minimal research has been done to ensure those existing buildings emit a minimal amount of CO_2 from their consumption of energy. In order to develop a decision support model for multi-family housing complex, 362 cases of multi-family housing were selected with the potential to be effective in saving energy. The following were carried out: (i) using the Decision Tree, a group of multi-family housings was established based on gas energy consumption; (ii) using case-based reasoning, a number

of similar multi-family housings were retrieved from the same group of multi-family housings; and (iii) using a combination of genetic algorithms, artificial neural network, and multiple regression analysis, prediction accuracy was improved. The results of this research can be useful in the following: (i) preliminary research for continuously managing the gas energy consumption of multi-family housings; (ii) basic research for predicting gas energy consumption based on the characteristics of multi-family housings; and (iii) practical research for selecting an optimum multi-family housing complex (with the potential to be effective in saving gas energy), which can make the application of an energy-saving program more effective as a decision support model (Hong et al., 2012).

1.6 Scope of thesis

Global warming is very serious issue that need to be addressed correctly with proper planning. One of the reasons for this issue is the excessive emission of greenhouse gases such as CO and NO_x. Thus, one of the methods to overcome this problem is by predicting the emission of those gases from the power plant, one of the big sources of greenhouse gas emission, by studying the input correlation between the gas turbine and the CO and NO_x emission. Besides, the turbine energy yield (TEY) output of the gas turbine can also be predicted to ensure the electricity generation from the power plant can be maximized. By predicting the greenhouse gas emission, we can optimize the operating condition of the gas turbine to minimize the release of those gases to the atmosphere. The modelling is carried out by utilizing MATLAB software with Gas Turbine CO and NO_x Emission dataset provided by Kaya et al. (2019).