DISCRETE-TIME NEURAL NETWORK MODELLING OF INDUSTRIAL AIR COMPRESSION SYSTEM

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**This report is submitted
in fulfillment of the requirement for the degree of
Bachelor of Mechanical Engineering with Honours**

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DECLARATION

I declare that this project report entitled "Discrete-Time Neural Network Modelling of Industrial Air Compression System" is the result of my own work except as cited in the references

Signature	:	....
Name	:	....
Date	:	....

APPROVAL

I hereby declare that I have read this project report and in my opinion this report is sufficient in terms of scope and quality for the award of the degree of Bachelor of Mechanical Engineering with Honours.

Signature : ....

Supervisor's Name : ....

Date : ....

DEDICATION

Dedicated to Associate Professor Ir. Dr. Md Fahmi for his advice, his faith, and his patience in me on my road toward project completion.

ABSTRACT

System identification is an approach of constructing the mathematical model of a dynamical system using the instrumentation signal of input and output of the system. This approach could be integrated into industrial processes such as air compression system by using the NARX model as a base model with the functions of the neural network. Basically, in any industrial process, the non-linearity behaviour of the system makes the predictive control to be complicated because the existence of random variable is unavoidable. Furthermore, the random behavior must not be ignored as it may indicate any unknown event occurring during the process. This project aims to perform system identification using neural network techniques for industrial air compression system. Besides, the validation of model's predictive performance is also included in this report. The proposed methodology of this project involves the data acquisition stage until the end of simulation and validation stages. The outcome of the simulation would undergo a series of analysis to determine the most suitable NARX-NN model architecture configuration. Finally, the predicted data is compared to the industrial data to verify its accuracy and difference, which shows that this model had successfully ruled out the suspicious random event data.

ABSTRAK

Identifikasi sistem merupakan suatu cara untuk membina model matematik dari sistem dinamik dengan menggunakan isyarat instrumentasi input dan output sistem tersebut. Pendekatan ini dapat diintegrasikan dalam pelbagai jenis proses industri seperti sistem pemampatan udara, dengan menggunakan model NARX sebagai model asas dengan fungsi rangkaian neural. Secara asasnya, dalam mana-mana proses industri, kelakuan tidak lelurus yang sukar dielakkan telah merumitkan kerja kawalan ramalan. Selanjutnya, kelakuan rawak ini tidak patut diabaikan kerana ia mungkin merupakan sesuatu kejadian yang tidak diketahui. Projek ini bertujuan untuk melaksanakan pendekatan identifikasi sistem dengan bantuan teknik rangkaian neural pada sistem pemampatan udara industri. Selain itu, validasi prestasi ramalan model juga dijalankan. Metodologi yang dicadangkan untuk projek ini termasuk peringkat pemerolehan data sehingga peringkat simulasi dan validasi. Hasil simulasi akan menjalani suatu siri analisis untuk menentukan kongifurasi seni bina model NARX-NN yang paling sesuai. Akhirnya, data ramalan dibandingkan dengan data industri untuk mengesahkan ketepatan dan perbezaannya. Perbandingan ini telah menunjukkan bahawa model ini telah berjaya mengesampingkan data rawak.

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF APPENDICES

LIST OF ABBEREVATIONS

ANN	Artificial Neural Network
AR	Autoregressive
ARMAX	Autoregressive - Moving Average with Exogenous input
ARX	Autoregressive with Exogenous input
FRL	Filter-Regulator-Lubricator
GUI	Graphical User Interface
MITI	Ministry of International Trade and Industry
ML	Machine Learning
MSE	Mean Square Error
NARX	Nonlinear Autoregressive with Exogenous input
NN	Neural Network
PSM	*Projek Sarjana Muda*
SI	System Identification
U.S.	United States of America

CHAPTER 1

INTRODUCTION

1.1 Background

System Identification (SI) is a statistical method of building mathematical models for dynamical systems (Söderström and Stoica, 1989). In the 21st century, the use of system identification involved wind speed prediction (Cadenas et. al., 2016), chiller compressor motor overheating predictor (Tulpule, 1997), residential HVAC fault detection (Turner et. al., 2017) and modelling of AE index for geomagnetic substorms (Gu et. al., 2019). System identification approach is generally using every possible time-domain variable in a dynamic system to develop a model. The time-domain variable is usually a series of data and could be identified as input, output or disturbance. The function of the model is to quantify the uncertainty parameters, estimation and prediction. The advantages of using system identification are it could either use both input and output data or only use one. Generally, it is known that utilizing both input-output data would be more accurate, and input data are not always present. The aim of using system identification in this study is to obtain a close-loop performance mathematical model from the past experimental data for predictive and preventive control.

A deep learning network is a branch of machine learning methods based on artificial neural networks (ANN) but with a more complex network (LeCun et. al., 2015). The main elements in neural networks are neurons and it has information-processing units and distributed communication nodes. The concept of ANN is inspired by the dendrites and axons in the biological nervous system, while it consists of many neural units connected via the axon (Chen et. al., 2019). Specifically, the difference between them is the neural networks is static while the biological neural system is dynamic and analogue. It has multiple hidden layers (filters) between input and output, where they could either be a linear or non-linear relationship. The probability of each output is calculated when the input signal passes through the filters. These artificial networks are being useful in many industrial problems. It could be used in predictive modelling, adaptive control and applications because it is well-known with its learning potential via given data sets. When deep learning network is exposed to enough series of data, it can initiate and form correlations between present events and future events. It could run regression between past and future. Deep learning may read and predict future event when given time-domain data. The difference between general neural network and deep learning is deep learning could be explained as stacked neural networks where the networks comprised of several layers of nodes. A node is a unit where computation occurs. When a node receiving an input signal from data with a set of coefficients that would amplify or dampen the input, those signals are summed and pass through an activation function to determine the further output.

The air compression system is widely used in industry and it is known as the fourth utility after electricity, natural gas and water. However, this system is the most expensive among the 4 basic industry utility. This is because the energy consumption per unit is undoubtedly high. A compressed air system is much more complicated than the air compressor. An essential compressed air system is made up of 5 main components: Air Intake Filter, Air Compressor, Cooler, Storage and Air Dryer (Quincy Compressor, 2020). Air intake filter could stop atmospheric airborne particles from reaching the compressor. Air compressor is a machine used to convert electrical power into kinetic energy by compressing and pressurizing air. The cooler is used to cools the system lubricant and preventing it from overheating thus destroying the engine. Storage is made up of thick-walled and high-capacity tank to meet peak demand. Air dryer removes condensation in the storage and prevents system failure. All 5 components are to be maintained regularly and placed in a special chamber for monitoring using the SCADA system.

1.2 Problem Statement

System Identification is a widely used method for solving problems in predictive and preventive control of a dynamical system. To perform prediction of the potential outputs, an appropriate mathematical model that could describe the characteristic of the system is needed. However, in a traditional mathematical model, it has a limitation in performing prediction for non-linear relationship data. Furthermore, for an industrial system, the relationship between inputs and outputs data are mostly classified as non-linear. This situation indicates that the traditional mathematical model hardly performs forecasting as it has a restriction in regression. Therefore, the ability to simulate a non-linear mathematical model is essential for the industrial system.

1.3 OBJECTIVE

The objectives of this project are as follows:

i. To perform system identification using deep learning network (neural network).
ii. To apply the method of neural networking in model identification of industrial air compression system.
iii. To analyze and validate the quality and performance of the mathematical model derived from system identification.

1.4 SCOPE OF PROJECT

The scopes of this project are:

i. This project will focus on the method of applying neural network for system identification.
ii. The project requires utilization of MATLAB software as a simulation tool.
iii. This project aims to solve a single input – single output (SISO) system.
iv. Analysis of the behaviour of the dynamical system and mathematical model will be carried out based on common performance indicators.

1.5 GENERAL METHODOLOGY

The procedure that needs to be put into action to obtain the objectives in this project are as below:

1. Literature review

   Journals, articles, and any other related informative materials regarding this project are reviewed to gain adequate understanding and knowledge.
2. Trial run with MATLAB's toolbox

   A neural network mathematical model is built from a sample data set. The performance of the neural network mathematical model will be analyzed.
3. Data acquisition

   SI requires industrial real-time data to create a robust mathematical model. Data is obtained via supervisory control and data acquisition (SCADA) system of an industrial air compression system.

4. Simulation of SI using Neural Network

   By using the mathematical modelling technique learned from the past trial run and replacing the data set with real-time industrial air compression system data, a neural network model is simulated.

5. Analysis and discussion

   Analysis are presented by analyzing and validating the quality and performance of the neural network model from simulation.

6. End reporting

   A project report is written after the analysis of project is completed.

The methodology of this study is summarized in the flow chart as shown in Figure 1.1.

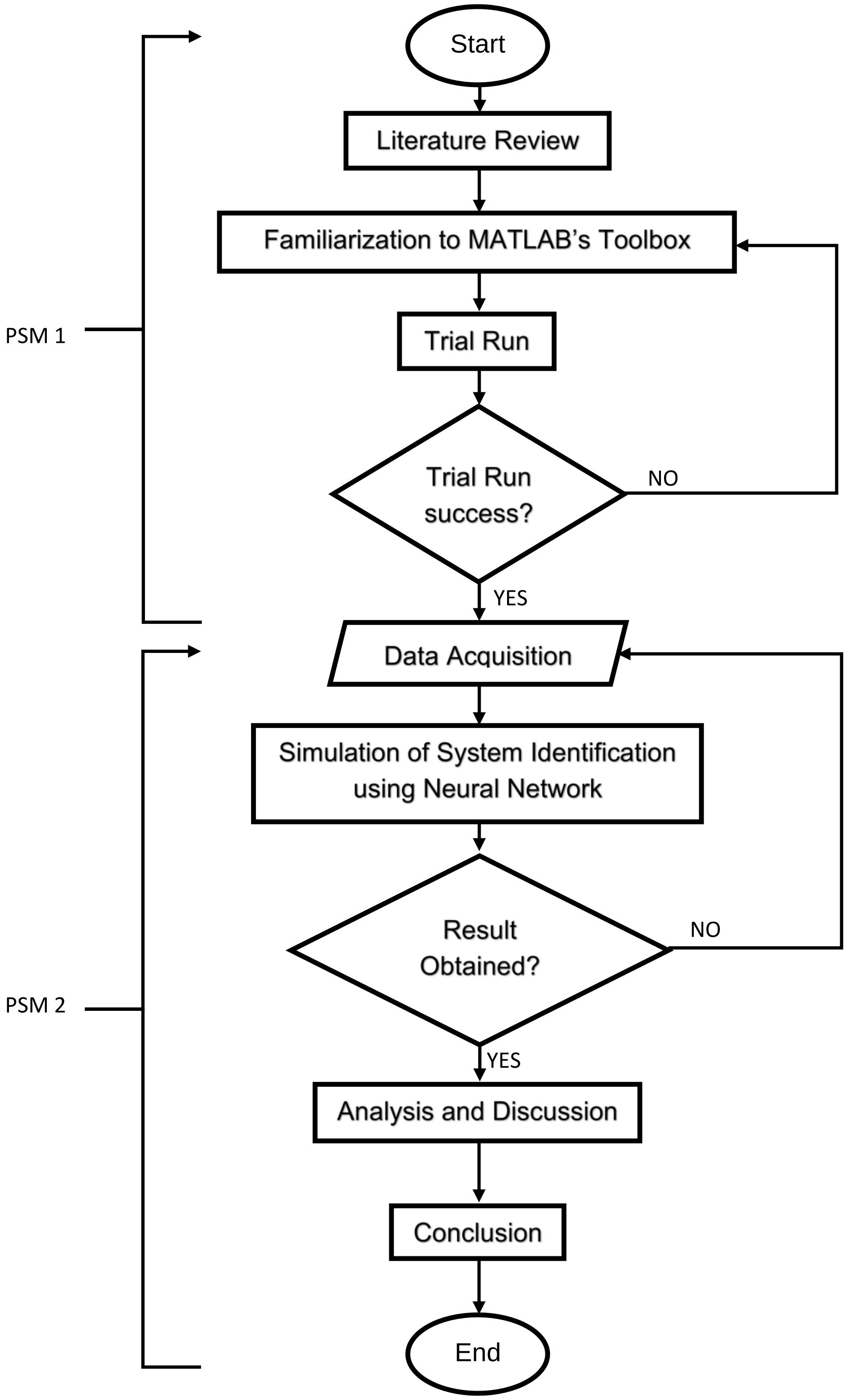

Figure 1.1: Flow chart of general methodology.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

This literature review aims to discuss three keywords regarding the research title: system identification, artificial neural network, and industrial air compression system. This section is written to function as a foundation of knowledge for the following chapters, including methodology and analysis of the project report. It is a critical and focusing summary of the references that are related to the research topic and field.

2.2 System Identification

2.2.1 Dynamical system

Ljung (1987) states that a system is an object with different types of variables interacting and produce output signals. Variables that could control are inputs, while others are disturbances. Disturbances can divide into two groups, measured disturbance (can be directly measured) and unmeasured disturbance (can only be observed through influence towards output). A dynamical system is a system with time-domain variables and output. Thus, the dynamical system does not always rely on variables but previous output values.

2.2.2 Mathematical model

Mathematical models are used to describe the relationships between the system variables in terms of mathematical descriptions like difference or differential equations. It could be further characterized by signifying the type of difference or differential equation used (linear or non-linear, time-continuous or time discrete). (Ljung, 1987)

2.2.3 Method of building mathematical model

Mathematical models may be developed along with two methods. The first route does not involve any experimentation on the actual system, and it typically involves the structuring of the process into block diagrams with blocks using first principles.

The second route, as well as graphical models, is directly based on experimentation. Fundamentally, this type of model is built from observed data. The input and output signals are recorded and subjected to data analysis in order to form a model. This method is known as system identification. (Ljung, 1987)

2.2.4 Foundation of system identification

Bittanti (2019) claim that a proven method, which develops from experimental data and variables, is observed under a certain period in a system to set up a model. By using this method, the data will provide a suitable character and mathematical model to describe the input-output of the system. According to observation, this type of mathematical model only provides a logical definition of the existing relationship between the input and output variables. In this situation, the mathematical model is clarified as a black box model while a white-box model is referring to a classical model which uses physics and mathematical law. Commonly, a model contains uncertain and unknown parameters and variables. In such a condition, the parameter can be estimated by analyzing through experimentation on the way the system works under specific condition. In other cases, the signal identification problems could be regarded as estimating unmeasurable variables from data relating to observable variables. The ideas for designation of a model on the foundation of experimentation are regarded as the science of identification.

2.2.5 System identification process

Ljung (1987) states that there are four steps for the System Identification process.

- Data record - Input & output signals are identified and recorded for a certain period from the regular operation of the system to make the data informative and controllable.
- Modelling - Engineering knowledge and understanding are applied to obtain a set of candidate models. Model is constructed from fundamental physical laws and other correlation. The most suitable model is selected bases on the performance of each model, where they attempt to reproduce the measured data.
- Validation - Validation of the model is made by testing their performance. Weak and limited model behaviour is rejected, while a model with excellent performance will be developed continuously. No model can be accepted as an accurate description of the system, as it only can be regarded as a suitable description.
- Revision - The system identification procedure consists of collecting data, choose and select the best from a model set, and model validation. If the model does not pass the model validation test, then the procedure loop must be revised. There are reasons for a weak model: numerical procedure failed to find the best model according to criterion, the criterion was not well chosen, the model set was not appropriate, and recorded data is not informative enough.