Development of Prediction Model For System Performance

by

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15034

Dissertation submitted in partial fulfilment of
the requirements of

Bachelor of Engineering (Hons)

(Mechanical)

JANUARY 2014

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ABSTRACT

A system by definition is an assemblage or combination of things or parts forming a complex or unitary whole. When a system fails to operate its function, it interrupts the system's performance. The aim of this study is to develop a neural network based prediction model to predict a system's performance. A system in this scope of study is portrayed as equipments centrifugal pumps, centrifugal compressors and expanders. Failure modes of these equipments are listed down and the causes of failure will be monitored and used as inputs for the prediction. The prediction model is simulated using Neural Network tool from MATLAB software. Initial modelling of the model has been done using data from Jahirul et al research paper to test the functionality of the model. Actual data of centrifugal compressor and expander were then used in the model. The result for both compressor and expander models were very accurate with an average percentage errors of 0.13% and 0.176% respectively. These models are considered reliable and can be used to predict future target data of these equipment. The objective of this research is achieved as these models are able to predict the performance of a system in this case equipments centrifugal compressor and expander.

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CHAPTER 1

INTRODUCTION

1.1 Background

A system by definition is an assemblage or combination of things or parts forming a complex or unitary whole. In order for a system to operate or function, the parts or assemblage that contribute to the main system must play their part. An example of a system is an equipment, where it has numbers of parts that contribute in order to make the equipment functioning. When a system fails to operate its function, it will interrupt the system's performance.

Centrifugal pumps, expanders and compressors are example of a system. These equipments are widely used in the industries for various purposes. However, continuous condition monitoring of some crucial parts in these rotary equipments are essential for preventing early failure, production line break down, improving plant safety, efficiency and reliability. Centrifugal pumps often shut down unexpectedly (Nally). Most equipment shutdowns are related to critical failure : a failure which causes immediate and complete loss of a system's capability of providing its output; and degraded failure : a failure which is not critical, but which prevents the system from providing its output within specifications.

Critical failure modes of a these rotary equipments according to OREDA handbook are breakdown, external leakages at the process medium, fail to start on demand, spurious stop and vibrations. On the other hand, degraded failure modes are external leakage at the utility medium, internal leakages and parameters deviation (OREDA, 2009).

This study is to develop a prediction model to predict the performance of a system in this case expander, centrifugal pump and compressor. In this study, the common critical failures and degraded failures are focused. In order to predict the performance, certain essential variables that contributes to the equipments failure which in this case are the causes of the failure have to be recognized. Once these variables are recognized, monitoring of these variables will be done. These variables will be inputs to an Artificial Neural Network (ANN) based prediction model. These input variables will be taken from the historical data of the equipments. The historical data gathered will be divided 70% as the training sample for the model and the rest which is 30% will be the validation sample for the prediction.

These validation sample will evaluate and determine whether the prediction is going to be correct. This model will provide a prediction of the pump failure in the future.

1.2 Problem Statement

Unexpected failure of systems in this case equipments due to critical and degraded failure often occur in the industries. This can interrupt the performance of a system. The current or conventional method of predictive maintenance method such as, machine history, visual inspection and vibration analysis are not very applicable because these methods predict the failure based on the life span of a certain component of the equipment. These premature failures can cause interruption in production lines in plants which will lead to increase in maintenance costs. It also can cause safety hazards which will eventually lead to fatality.

1.3 Objectives & Scope of Study

The main objective of this study is to:

- Develop a neural network based prediction model to predict the performance of systems in this case centrifugal pump, expander and compressor.

In order to achieve the main objective, these sub-objectives must be completed which are:

- Identifying the critical and degraded failures and their causes that can lead premature failure of the equipments.
- Monitoring the performance and essential variable of the equipments that can contribute to its premature failure.

CHAPTER 2

LITERATURE REVIEW

Unscheduled failure of plant equipments can cause major economical loss due to the disruption of the production line. The crucial equipment failures that occur in petrochemical plants are related to piping, compressors and pumps (Lees, 1996). Pumps and compressor are equipments that their main function is to deliver fluid from a certain point to a certain point by adding energy to them.

2.1 Centrifugal Pump

Centrifugal pump is a type of dynamic pump that is most used in the world. They are widely used industries since they are varied in types, sizes designs and material of construction (Azadeh, Ebrahimipour, & Bavar, 2010).An increase in the fluid pressure from the pump inlet to its outlet is created when the pump is in operation. Centrifugal pump is usually driven by an engine or a electrical motor. Pressure difference is created by transferring mechanical energy from the motor to the fluid through a rotating impeller (GRUNDFOS). The fluid flows from the inlet to the impeller centre or eye and out along its blades. The centrifugal force hereby increases the fluid velocity and consequently also the kinetic energy is converted to hydrodynamic energy. There are three types of commonly used impellers in centrifugal pumps which are open, semi-open and closed impeller. The selection of these impellers varies according to their functions and purposes.

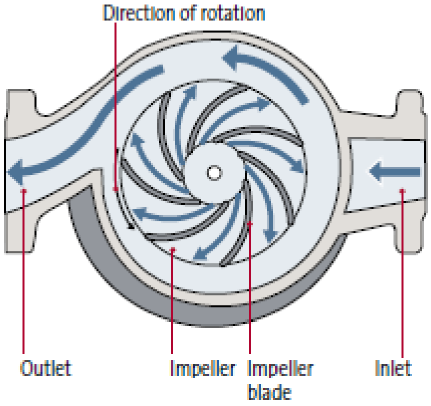


Figure 1: Fluid path through the centrifugal pump (GRUNDFOS)

Unscheduled or unexpected shutdown often occur to centrifugal pumps and these reliability problems according to Marscher are resulting in huge amount of maintenance budget and lost-opportunity cost in refineries, plants and many electric utilities (Marscher, 1999).

2.2 Expander

An expander is a rotary type equipment. It consist of two primary part which are the expansion turbine which acts as the driver and the centrifugal compressor which acts as the driven unit. Both the turbine and compressor are connected on a single shaft. The expander function is mainly to efficiently generate refrigeration in the process gas stream (Simms, 2009). The expansion turbine will extract heat energy from the gas stream and convert it to mechanical energy thus, turning the turbine and shaft. The shaft then transfer the mechanical energy to the centrifugal compressor thus running it. The compressor then, partially recompress the residue of gas from the expansion turbine.

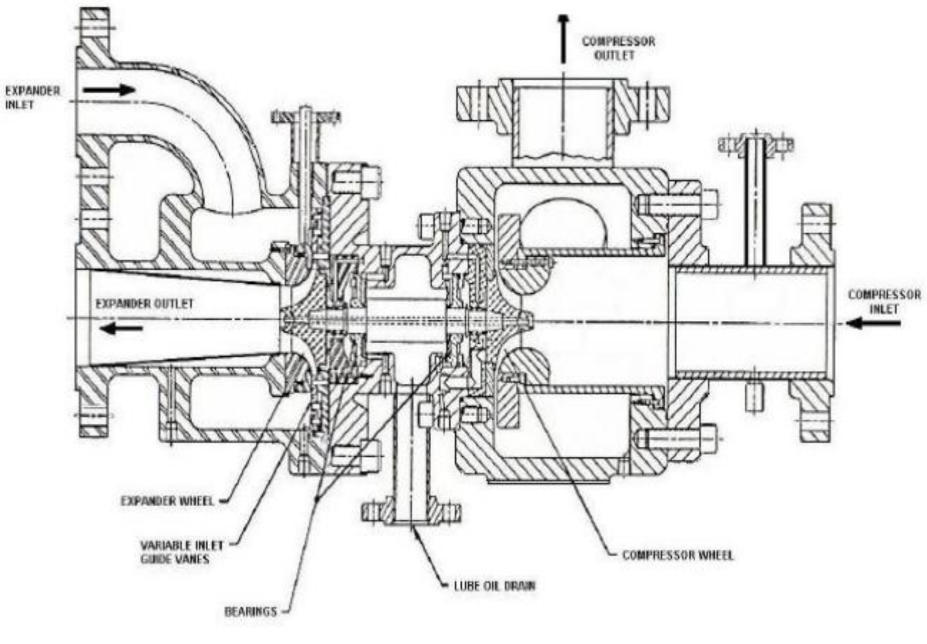


Figure 2: Cross-Section of a Expander (Simms, 2009)

2.3 Centrifugal Compressor

Centrifugal compressor is a dynamic type compressor which handles compressible fluid mainly gas. Compressor operates by transferring energy to the fluid medium thus delivering the fluid at an elevated pressure conditions (Boyce). Centrifugal compressor is normally driven by a motor or another rotary equipment such as an expander. Centrifugal compressors are quite similar to centrifugal pumps where the energy from the driver is transferred to the fluid through a series of rotating impellers. This energy is then converted to an increase static pressure by slowing the flow through a diffuser.

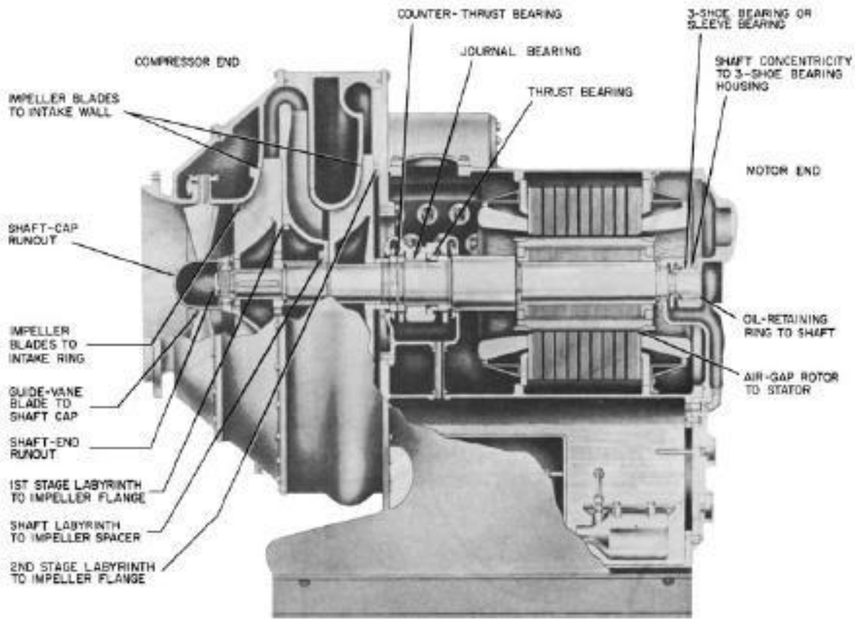


Figure 3: Cross-Section of a Centrifugal Compressor

2.2 Failure Modes

Failure that occurs inside a system can interrupt the system's performance. In the case of equipments critical and degraded failures are most likely to cause an equipment to shutdown unexpectedly. According to Offshore Reliability Data Handbook, critical failures are failures that results in abrupt and fully loss of the equipment's capability to function while the degraded failures are failures that prevents the equipment to produce output which meet its specifications (OREDA Participants, 2009). The most common critical failures faced by centrifugal pump and compressor according to OREDA data collection are leakages at both utility and process medium. On the other side, leakage at utility medium, low output and vibration are the most common degraded failures.

Table 1: Critical and degraded failures for centrifugal pump and compressor (OREDA Participants, 2009)

Critical Failure	Degraded Failure
External leakage in process medium	External leakage in utility medium
External leakage in utility medium	Vibration
Vibration	Low output

These failure modes can be broken down to their failure mechanism and the failed component. From these failed mechanism and component, the causes can be identified more specifically. (Bloch), in his studies, has listed down the causes of common centrifugal pump and compressor failures and can be matched with the failure modes obtained from OREDA Handbook.

Table 2: Failure mode of centrifugal pump and compressor and its causes (Bloch)

Failure mode	Failure mechanism / failed component	Causes
External leakage at process medium	Mechanical seals	• Misalignment • Bent shaft • Pump/Compressor running at or near critical speed

External leakage at utility medium	Seals	• Misalignment • Bent shaft • Pump/Compressor running at or near critical speed
Vibration	Suction troubles	• Pump suction pipe not completely filled with liquid
	Mechanical troubles	• Misalignment • Resonance between operating speed and natural frequency • Couplings lack of lubricant
	Bearings	• Excessive axial thrust • Lack of lubricant
Low output	Insufficient capacity	• Pump suction pipe not completely filled with liquid • Insufficient available NPSH • Air pocket/Liquid in suction line • Pump/Compressor operated at closed or partially closed suction valve • Speed of pump/compressor too low • Wrong direction of

		rotation
	Insufficient pressure	• Air leak/liquid into suction line • Inlet suction pipe insufficiently submerged • Pump/Compressor operated at closed or partially closed suction valve • Speed of pump/compressor too low • Wrong direction of rotation

The most common critical failure faced by the expander according to OREDA Handbook is breakdown. While the degraded failures are external leakage in utility medium and other failure which includes the incapability of the equipment to perform its function as per design.

Table 3: Critical and degraded failures for expander (OREDA Participants, 2009)

Critical Failure	Degraded Failure
Breakdown	External leakage in utility medium
	Others

The failure modes of the expander are also broken down to their failure mechanism or failed component. From these failure mechanism or failed component, their causes can be identified. In (Simms, 2009) paper of "Fundamental of Turboexpanders" stated the factors that affect the performance of the expander. These factors can be matched with the failure mechanism of high output temperature.

Table 4: Failure mode of expander and its causes (Bloch)

Failure mode	Failure mechanism / failed component	Causes
Breakdown	Breakage	• Misalignment • Bent shaft • Deformation
External leakage at utility medium	Seals	• Misalignment • Bent shaft • Expander running at or near critical speed
Others	High Output Temperature	• Low flow at inlet expander • Unstable pressure inside the expander • Speed of expander too low

The ability to predict the premature shutdown of an equipment is essential and can save refineries and plants their budget. Prediction of this event can be done by monitoring the performance and the causes of the equipment failures in example; misalignment and bent shaft can be measured and monitored by proximity sensors, lack of lubricant can be measured and monitored by the oil level, insufficient NPSH can be monitored by measuring suction pressure, inadequate coolant can be monitored by temperature, etc.

2.3 Artificial Neural Network: Prediction

Artificial neural networks (ANN) are computer system that comprises of many artificial neurons or in other words plain processing unit (Jahirul, Saidu, & Masjuki, 2010). Palme and Fast stated in their studies that ANN is a tool of statistical data modelling that learns from experience or in other words adaptive (Fast & Plame, 2010). ANN can do a variety types of task such as classification, regression or in this case prediction. This system basically consist of several layers which are input layers, hidden layers and output layers. The artificial neurons are interconnected to each other through a synaptic weights.

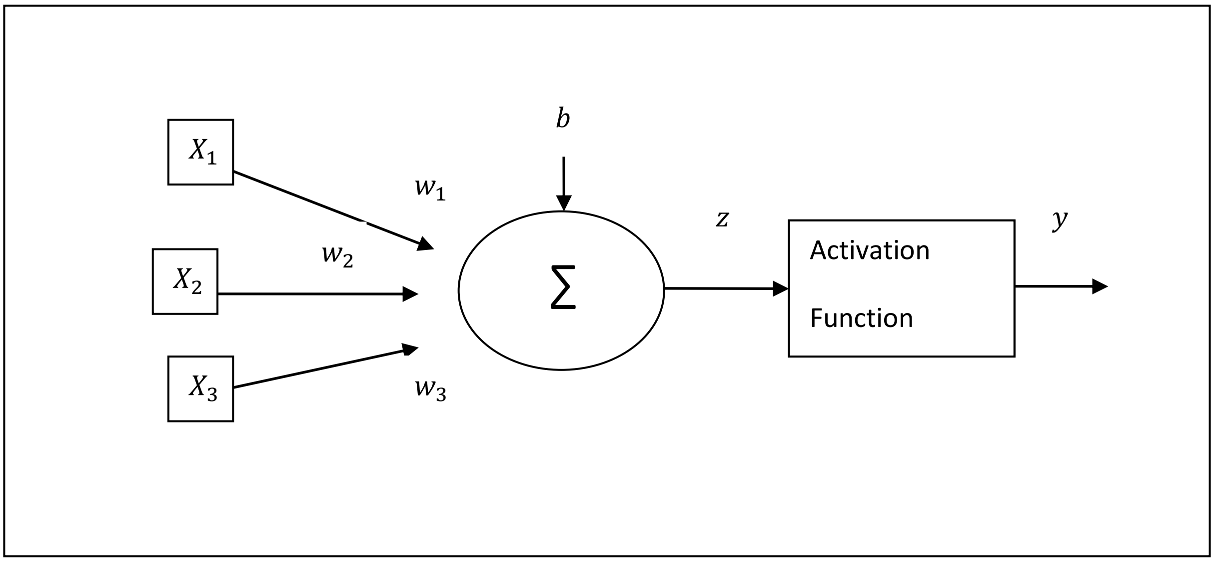


Figure 4: Simple artificial neural network

From figure 4, the modelling is represented by the equation:

$$z = \sum_{i=1}^{N}(w_i x_i + b) \quad \text{and} \quad y = f(z)$$

Where,

i : number of input

w_i : weight

x_i : input variable

f() : activation function

b : bias value

y : output

The input neuron receives weighted values. Then the sum of the neurons are processes by the activation function thus, producing the output.

ANN prediction model in this case will receive input data which is the monitored parameters from the failure causes. These data will be divided into a fraction of 70/30. 70% of the data will used for training of the ANN. Training is where calibration of the connection weights occurs (Mena, Rodriguez, Castilla, & Araha, 2014). In other words, the system is learning the trend of the data. The remaining 30% is used as the validation data where these data will validate the prediction of the system after the training. If there is minimum error, the prediction is valid. The benefit of applying ANN model in predicting the failure of a system is that it can process nonlinearities among the variables. The ability of ANN to develop a complex nonlinear relationship makes this model suitable to use in different application and produce accurate result. On the other hand, there are also several drawbacks of using ANN such as it has the characteristics of black box thinking. Liamond states in his studies of using ANN to predict future transport energy demand in Thailand, this approach disables the researcher to study the relationship between input parameters and output parameters (Liamond, Jomnonkwao, & Srikaew, 2011).

CHAPTER 3

METHODOLOGY

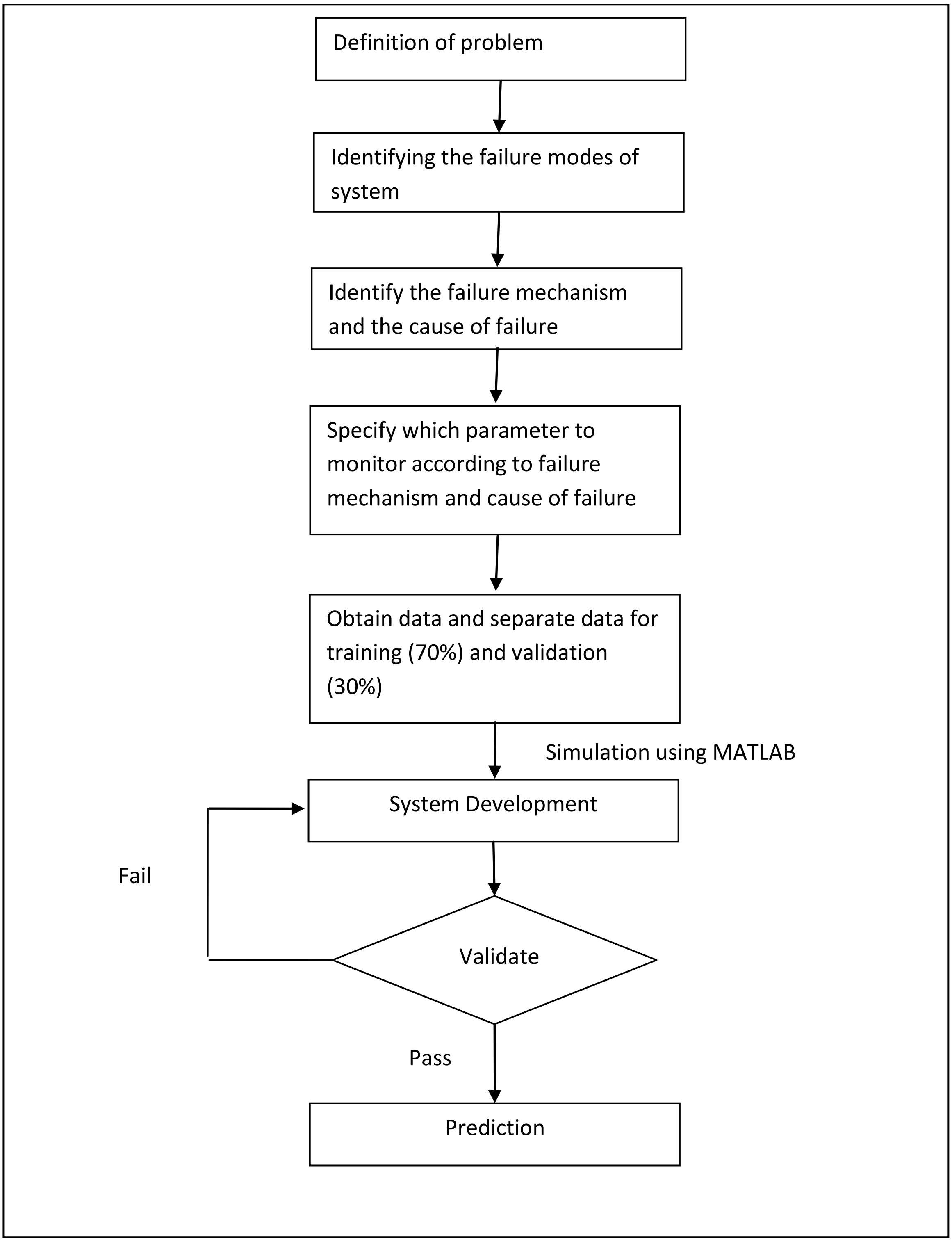


Figure 5: Flow of project methodology

The methodology flow of this project starts with the definition of problem in this case is the unexpected failures in equipments. Then, the failure modes and causes of the failure are identified. From the causes, monitoring the parameters that cause the failure can be done. These monitored data from a certain period is then obtained and separated for training and validation purposes. The data is the processed using MATLAB software tool. The software will receive these input data together with specified initial weight. Then, system is trained based on the input data and validated. If the output differs from the validation data, the system will return to training and calibrate the weight until there is no error. Finally predicting can be done after validation.

3.1 Gantt Chart

			FYP I														FYP II													
No.	Subject	Week	1	2	3	4	5	6	7	8	9	10	11	12	13	14	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	FYP topic selection																													
2	Project introduction																													
3	Preliminary research work on pump failure modes and ANN predictions > identify failure modes > identify how ANN works																													
4	Extended proposal writing																													
5	Extended proposal submission																													
6	Proposal defense																													
7	Initial modelling using MATLAB > Getting use to the software > Decide number of prediction models > Input using random raw data																													
8	Submission of interim draft report																													
9	Submission of interim report																													
10	Project work continues > Identify suitable model parameters (type,transferfunction etc) > Obtain data																													
11	Submission of progress report																													
12	Final modification of ANN prediction model > Final touch up > Test using different sets of data																													
13	Pre-SEDEX																													
14	Submission of draft final report																													
15	Submission of dissertation (soft bound)																													
16	Submission of technical paper																													
17	Viva																													
18	Submission of project dissertation (hard bound)																													

3.2 Key Milestones

Completion Target	Goal	Status
10 November 2014	Extended proposal submission	Completed
21 November 2014	Proposal Defense	Completed
13 December 2014	Initial Modeling Complete	Completed
19 December 2014	Submission draft report	Completed
26 December 2014	Submission interim report	Completed
Week 7 FYP II	Suitable parameters for model identified Submission progress report	Completed Completed
Week 10 FYP II	Final modification of model completed Pre-SEDEX	Completed Completed
Week 11 FYP II	Submission of final draft report	
Week 12 FYP II	Submission of dissertation softbound Submission of technical paper	
Week 13 FYP II	Viva	
Week 14 FYP II	Submission of dissertation hardbound	

Figure 6: Project key milestones

CHAPTER 4

RESULTS AND DISCUSSIONS

Initially this study is to focus on predicting mainly four types of failure modes for centrifugal pumps and compressor which are external leakage at process medium, external leakage at utility medium, vibrations and low output and three types of failure modes for expander which are breakage, external leak in utility medium and high output temperature. These failure modes have the highest rate of occurrence in industries according to (OREDA Participants, 2009). The causes of these failure modes are listed and these causes will be inputs to a neural network prediction model.

However, there are limitations to this study where the causes of the failure modes listed are mostly not monitored continuously in the industries. For example, misalignment, bent shaft and lack of lubricant at bearing area. These variables can be measured from time to time but there are no available continuous monitoring of them in the industries. Thus, these variables cannot be used as inputs for ANN prediction model. The causes of these failure modes are filtered to segregate `the non-continuous monitored variables and the continuously monitored variable.

Table 5: The availability of continuous monitoring for the causes of failure modes for centrifugal pump and compressor

Failure Mode	**Causes**	**Continuous Monitoring Availability**
External leakage at utility medium	Misalignment	Not available
	Bent shaft	Not available
	Pump running at critical speed	Available
External leakage at	Misalignment	Not Available

process medium	Bent shaft	Not Available
	Pump running at critical speed	Available
Vibration	Misalignment	Not Available
	Suction pipe liquid level	Not Available
	Lubricant level	Not Available
	Excess axial thrust	Not Available
Low output	Insufficient NPSH	Available
	Speed of pump too low	Available
	Suction valve closed	Available
	Wrong direction of rotation	Available

Table 6: The availability of continuous monitoring for the causes of failure modes for expander

Failure Mode	**Causes**	**Continuous Monitoring Availability**
External leakage at utility medium	Misalignment	Not available
	Bent shaft	Not available
	Expander running at critical speed	Available
Breakage	Misalignment	Not Available
	Bent shaft	Not Available

	Deformation	Not Available
High Output Temperature	Low flow at inlet expander	Available
	Unstable pressure in expander	Available
	Speed of expander too low	Available

Based on the tables above the only failure mode that is possible to predict for centrifugal pump and compressor is low output and for expander is high output temperature. This is because there are available continuous monitoring to each of its causes in the industries.

4.1 Initial Modelling

Initial modelling has been conducted using Neural Network tool from MATLAB software. The data used for this modelling is taken from (Jahirul, Saidu, & Masjuki, 2010) research where they used ANN to predict the performance of a CNG engine. The data taken are speed (rpm), time (t) and efficiency (%). Only 70 % of the data used.

Table 7: Sample data (Jahirul et al, 2010)

No	rpm	%	t
1	1600	45	2.5
2	5500	45	2.5
3	1600	80	2.5
4	5500	80	2.5
5	1600	45	5
6	5500	45	5
7	1600	80	5
8	5500	80	5
9	3000	60	3.5
10	3000	60	3.5
11	3000	60	3.5
12	3000	60	3.5
13	3500	45	2.5
14	2500	80	2.5
15	4500	80	3.5

16	2000	50	3.5
17	4500	50	5

The targeted data for this initial modelling is time (t) while the input data are the efficiency (%) and speed (rpm). The number of layer specified is two which consist of ten neurons on the first layer and one neuron on the second layer.

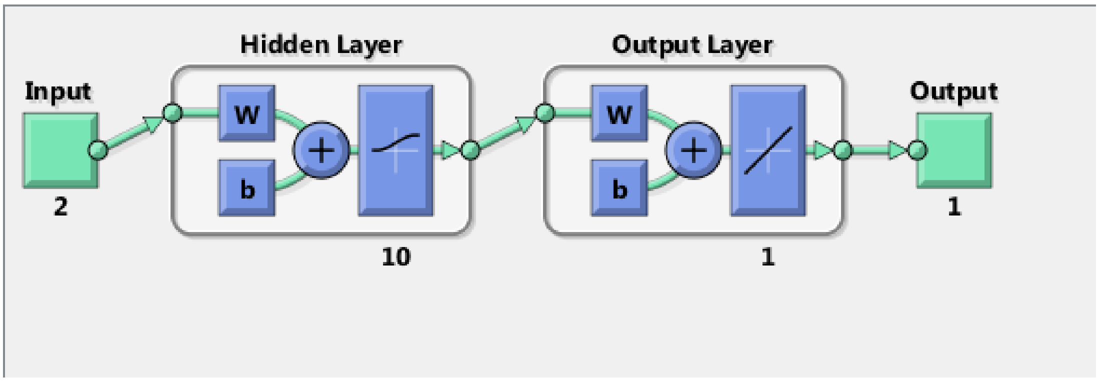


Figure 7: Initial modelling ANN using MATLAB software

Table 8: Results from initial modelling using MATLAB

Actual Data	Trial Data	Error	Error Percentage (%)
2.5	2.50364855	-0.00364855	-0.145941986
2.5	2.506916786	-0.00691679	-0.276671447
2.5	3.749129582	-1.24912958	-49.96518327
2.5	2.491403084	0.00859692	0.343876658
5	2.50364855	2.49635145	49.92702901
5	2.506916786	2.49308321	49.86166428
5	3.749129582	1.25087042	25.01740837
5	2.491403084	2.50859692	50.17193833
3.5	3.487847114	0.01215289	0.347225326
3.5	3.487847114	0.01215289	0.347225326
3.5	3.487847114	0.01215289	0.347225326
3.5	3.487847114	0.01215289	0.347225326
2.5	2.630207944	-0.13020794	-5.208317767
2.5	3.445534177	-0.94553418	-37.82136707
3.5	3.564634071	-0.06463407	-1.846687755
3.5	2.577243288	0.92275671	26.36447748
5	4.930212899	0.0697871	1.395742012

The results obtained from this modelling are not very accurate. A few of the trial data deviates more than 5% from the actual data. On the other hand, the rest of trial data only deviates 0 - 1 % from the actual data. The pattern of the accuracy of the data is also uneven. Although there are only a few of inaccurate data, this model is still not ready for predicting pump performance. The expected predicting model will have the capability to produce an even and accurate data which consist of minimal errors. The accuracy of this predicting model can be determined by adjusting several variables of the model such as number of hidden layer and number of neurons. The adjusting of these variables is done by trial and error.

4.2 Neural Network Modelling Parameters and Procedure

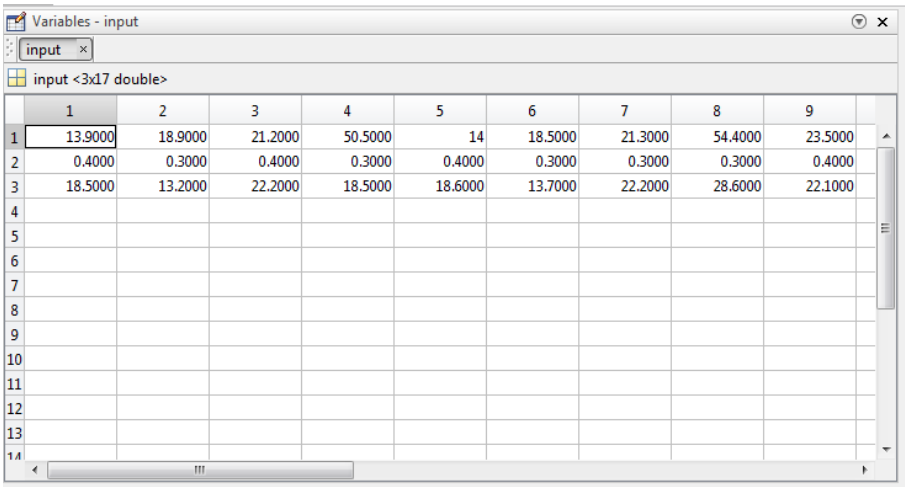
In order to develop an accurate neural network predicting model, the parameters used in the model must be adjusted by trial and error with reference from (Yaichi & Entchev, 2014) until an accurate output is obtained. Procedures on how to design a prediction model are also develop based on (MathWorks, 2014).

Procedure

1) Launch MATLAB software.

2) Select new variable 

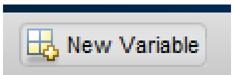
3) Insert input data. Each row represents one type of data. In this case there are 3 types of data at row 1,2 and 3 respectively.



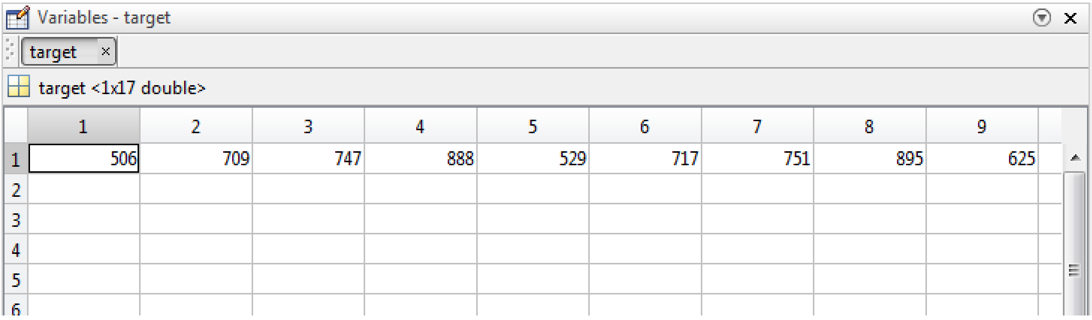
Variables - input

input <3x17 double>

	1	2	3	4	5	6	7	8	9
1	13.9000	18.9000	21.2000	50.5000	14	18.5000	21.3000	54.4000	23.5000
2	0.4000	0.3000	0.4000	0.3000	0.4000	0.3000	0.3000	0.3000	0.4000
3	18.5000	13.2000	22.2000	18.5000	18.6000	13.7000	22.2000	28.6000	22.1000

4) Select new variable. 

5) Insert target data and rename the variable as target.

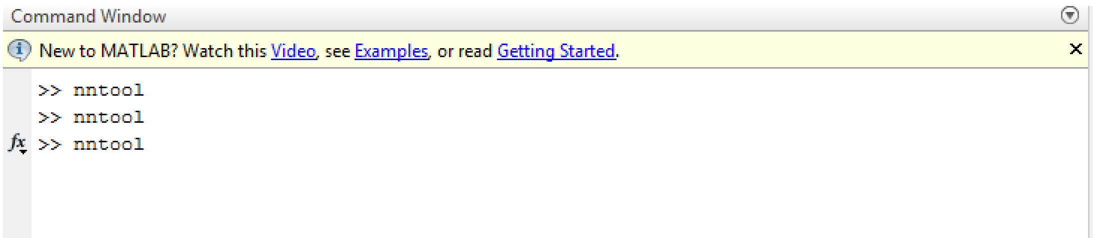


Variables - target

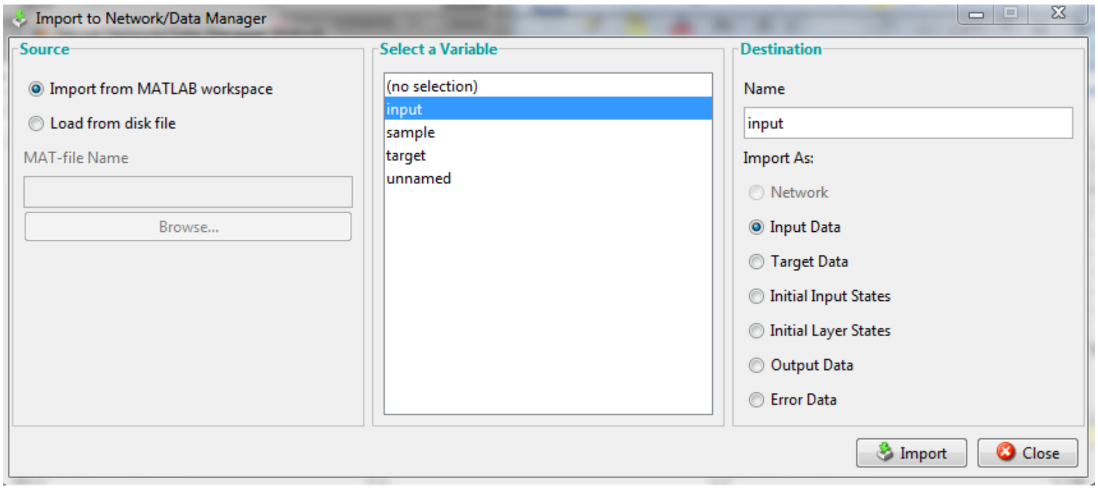
target <1x17 double>

	1	2	3	4	5	6	7	8	9
1	506	709	747	888	529	717	751	895	625

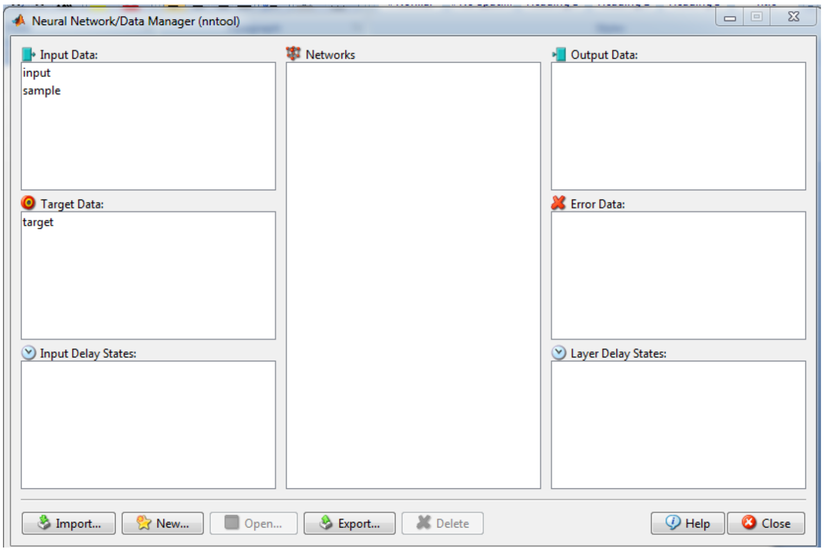
6) Enter "nntool" at the command windo and press "enter" to launch the Neural Network Tool of MATLAB.



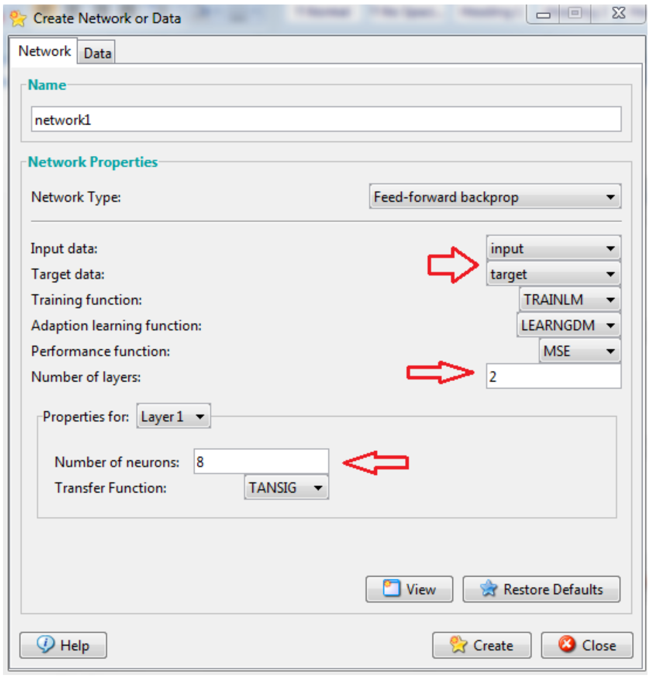
7) A Neural Network window will appear. Select "import" to import variables as input and target data which have been entered earlier. Close the import window.



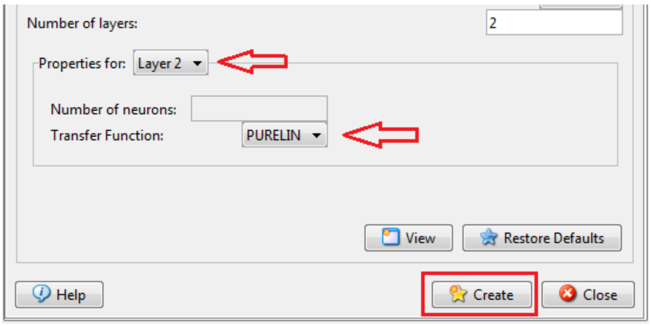
8) Select "new" to create a new network.



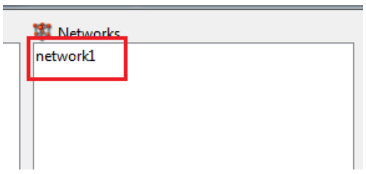
9) Specify input and target data. Use 2 number of layers with 8 neurons on Layer 1 (Yaichi & Entchev, 2014).



10) On Layer 2 use PURELIN as transfer function and create network.

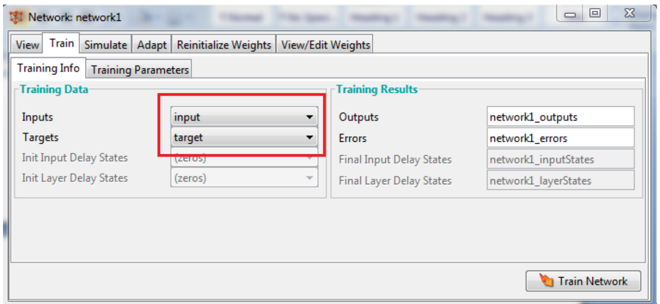


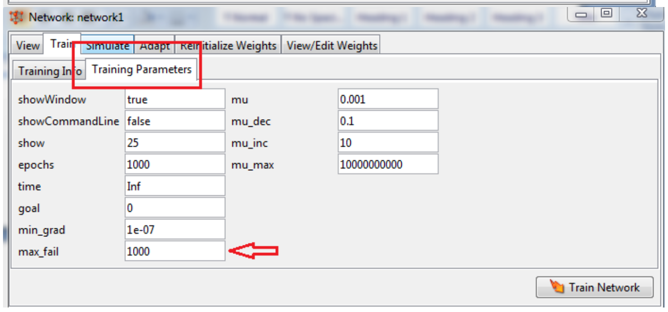
11) Select the new network created at the network manager window.



12) Select train specify training parameters such as number of iterations and train network.

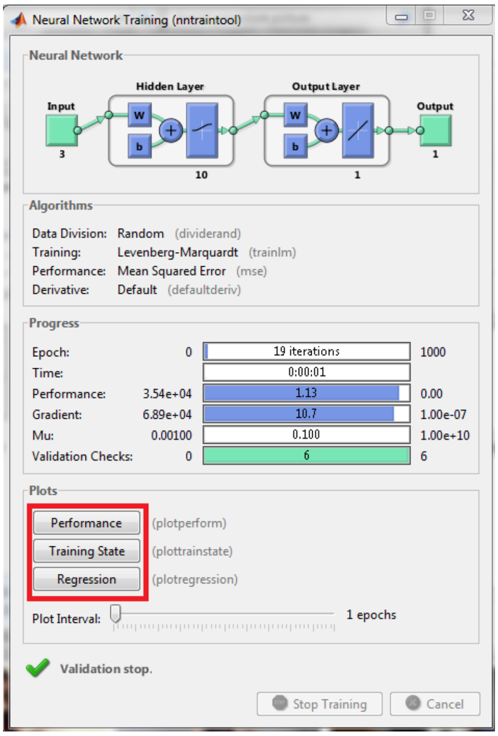
- This part is done by trial and error until the results are accurate.





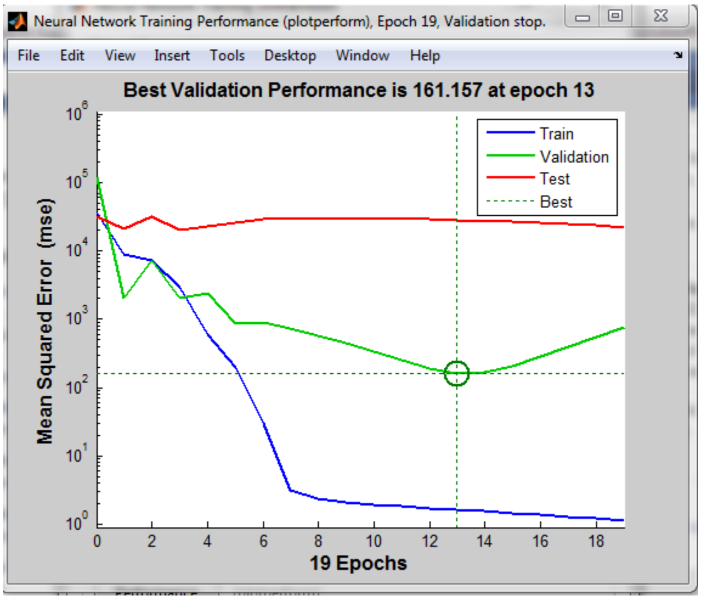
13) The summary of the performance of the training window will appear.

- From this window plots of performance, training state and regression can be access.
- Performance plot indicates the performance of the network.
- Regression plot shows the relationship between the output of the network and the target.



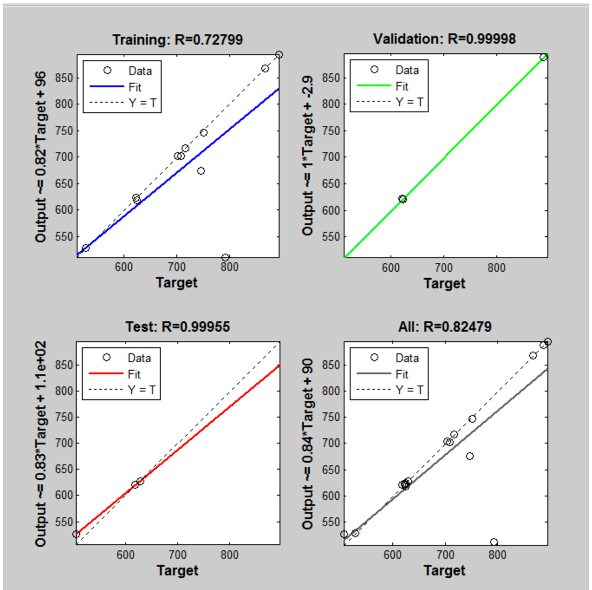
14) Performance plot

- The validation performance is best at its minimum.

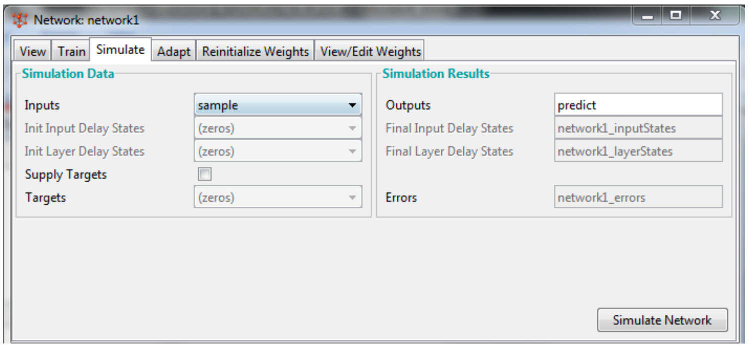


15) Regression plot

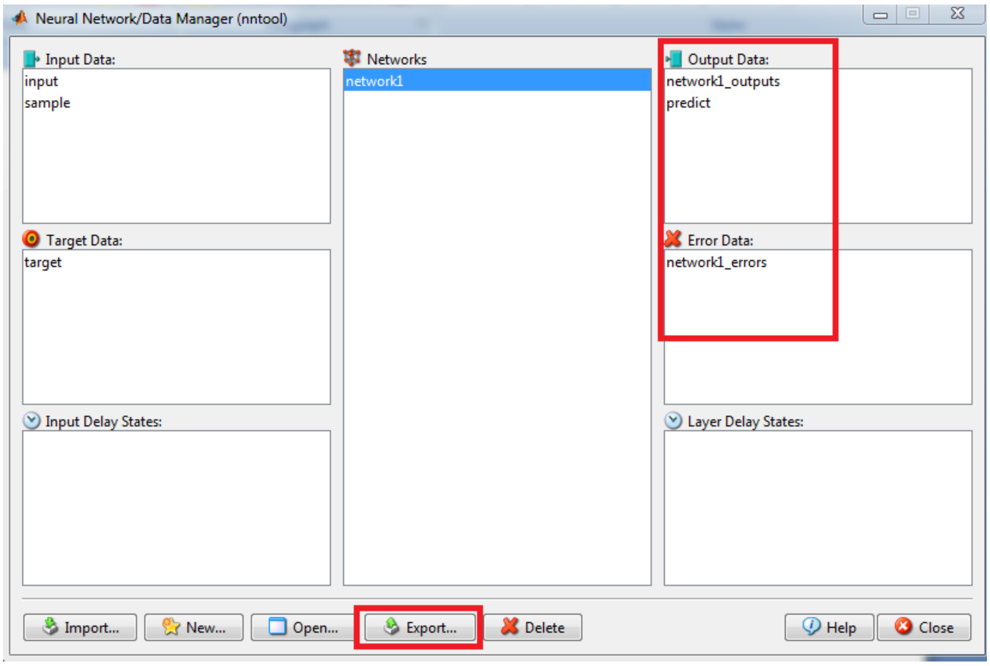
- The solid lines represents the best fit regression line between output and target.



16) Simulate the network based on the trained data to start prediction



17) The output of the network, training errors and the prediction output will be available at the network manager window. The data can be import and display on Microsoft Excel.



4.3 Prediction Modelling

Further modelling has been done using a different set of data from (Jahirul, Saidu, & Masjuki, 2010) research. The data consist of four variables which is similar to this research. The data is shown as in Table 9 below.

Table 9: Results from initial modelling using MATLAB

No.	bp (kW)	bsfc (kg/kW)	n (%)	T °C
1	13.9	0.4	18.5	506
2	18.9	0.3	13.2	709
3	21.2	0.4	22.2	747
4	50.5	0.3	18.5	888
5	14	0.4	18.6	529
6	18.5	0.3	13.7	717
7	21.3	0.3	22.2	751
8	54.4	0.3	28.6	895
9	23.5	0.4	22.1	625
10	23.2	0.4	22	629
11	23.4	0.4	22.1	618
12	23.4	0.4	22.2	623
13	18.6	0.4	17.4	624
14	26.3	0.3	25.5	793
15	46	0.3	28.5	868
16	15.8	0.4	20.8	622
17	19.9	0.4	17	703
18	21.6	0.5	17.2	748
19	20	0.3	23.7	718
20	27.7	0.3	24.3	774
21	38.7	0.4	25.3	832
22	20.7	0.4	22	690
23	28.3	0.4	21	741
24	30.1	0.4	20.6	810

Based on Table 9 above he input variables for this model are bp (kW), bsfc (kg/kW) and n (%) while T is the target variable. 70 % of this data (data 1 - data 17) are used for the training phase of this model while the rest (data 18 - data 24) are used for prediction. The neural network model is done based on the procedure above.

Based on table 10 below the results obtained from training phase had a good improvement compared to the initial modelling done before. The errors in the training data is ranged from 0% - 4%. Only one data point has error percentage of 35.5%.

Table 10: Results for training phase of prediction modelling

Actual Data	Trial Data	Error	Error Percentage (%)
506	526.235	-20.235	-3.999
709	701.5484	7.451562	1.051
747	675.1533	71.8467	9.618
888	888.0103	-0.01035	-0.001
529	529.0204	-0.02038	-0.004
717	716.9571	0.042853	0.006
751	746.7	4.299985	0.573
895	894.9908	0.009209	0.001
625	618.3847	6.615254	1.058
629	627.1462	1.853823	0.295
618	621.3662	-3.36617	-0.545
623	621.2012	1.798821	0.289
624	624.0223	-0.0223	-0.004
793	511.258	281.742	35.529
868	867.9642	0.035761	0.004
622	622.0939	-0.09389	-0.015
703	703.0358	-0.03582	-0.005

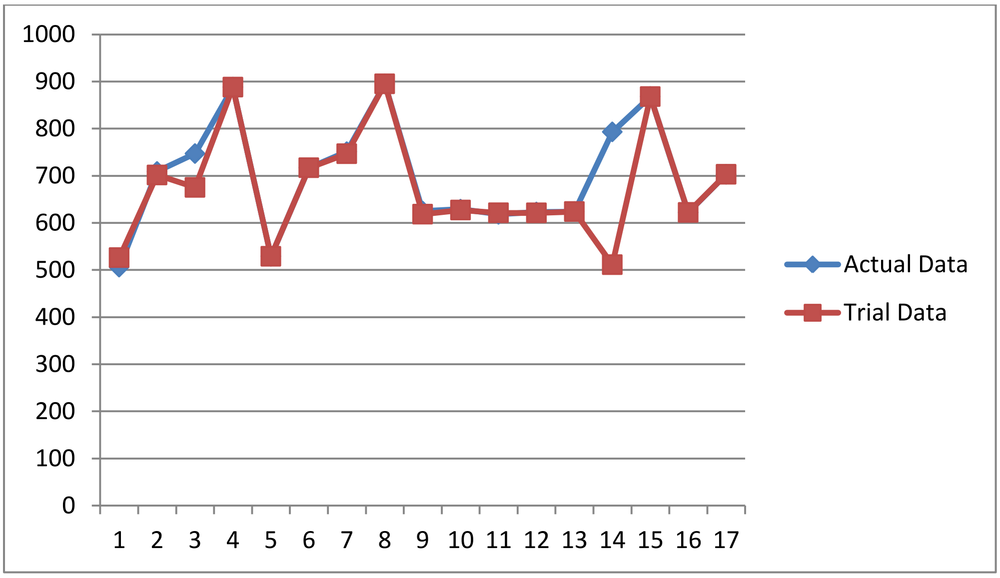


Figure 8: Comparison between Actual Data and Trial Data

After training phase, prediction is done for the rest of 30% of the data which is data 18 - data 24 from table 9. Prediction is also done based on the procedures stated earlier.

Table 11: Results for prediction phase

Actual Data	Prediction Data	Error	Error Percentage (%)
748	900.3939521	-152.394	-20.37352301
718	732.8819931	-14.882	-2.072700991
774	641.7370911	132.2629	17.08823113
832	725.6465728	106.3534	12.78286385
690	677.4730674	12.52693	1.815497477
741	612.8690755	128.1309	17.29162274
810	725.544193	84.45581	10.42664285

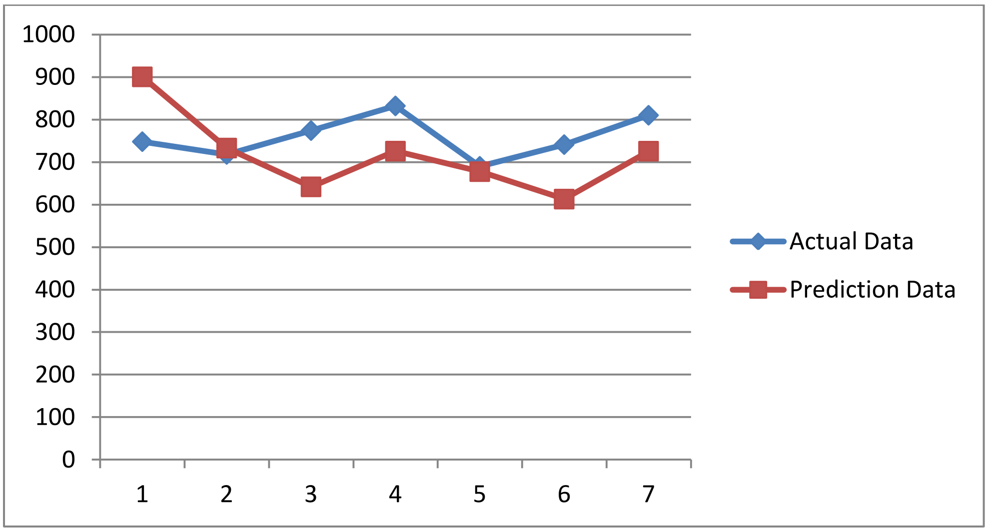


Figure 9: Comparison between actual data and

Table 11 shows the result of the prediction. There are high percentage of errors recorded for the prediction phase. The highest percentage of error is 20.37% while lowest is 1.8%. Most of the prediction data consist errors that are more than 10%. This prediction is considered not reliable due to its high error percentage. Although during the training phase, the errors are minimum but the is still one data point that has an error of 35.5%. this shows that the data is not consistent at one point. Consequently, it affects the trained model because the prediction of neural network is based on the training phase of the model where it studies the input data. This model can still be improved by adjusting the training parameters as shown in the procedure earlier.

4.4 Prediction Using Actual Data

After testing the model using sample data obtained from (Jahirul, Saidu, & Masjuki, 2010) research and proven accurate, the model is ready to be tested using actual data of the equipments. Only expander and centrifugal compressor data were able to be obtain from the industries. Centrifugal pump data was unavailable due to limited number monitored parameters. Data of expander and centrifugal compressor consist of continuous monitored data based on the failure mode and the failure causes listed earlier in this research.

Table 12: Causes of failure and monitored data of expander and compressor

Equipment	Failure Mode	Causes	Monitored Data
Expander	High Output Temperature (Target Data)	Low flow at inlet expander	Inlet Guide Vane Opening
		Unstable pressure in expander	Inlet Pressure (Barg)
		Speed of expander too low	Speed of Expander (RPM)
Centrifugal Compressor	Low Output (Target Data)	Speed of compressor too low	Speed of compressor (RPM)
		Suction valve closed	Inlet Guide Vane Opening
		Wrong direction of rotation	Direction of rotation

Table 12 shows the monitored data of the failure mode. For expander, the monitored data are inlet guide opening, inlet pressure and speed of expander. For centrifugal compressor, the monitored data are speed of compressor, inlet guide vane opening and direction of rotation. The monitored data acts as the input variable for the modelling and the failure mode acts as the target data.

4.4.1 Expander Prediction

Expander data consist of three input data are the inlet guide vane opening, inlet pressure and the expander speed. On the other hand, the target data is the output temperature of the expander. The data set consist of 166 data points taken from 1st January 2012 until 14th June 2012 daily. 70% of the data is used for training of the model and 30% of the data is used for prediction. Refer Appendix for data.

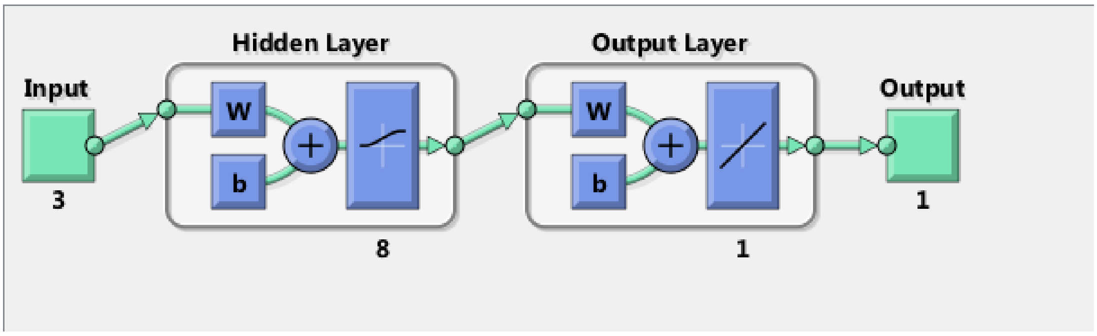


Figure 10: Summary of prediction model for expander

Figure 10 shows the summary of the model. The model has three inputs and 8 neurons in the first layer and 1 neuron for the second layer. The model uses LOGSIG as the first layer's transfer function and PURELIN for the second layer. Figure 11 below shows the results of the prediction.

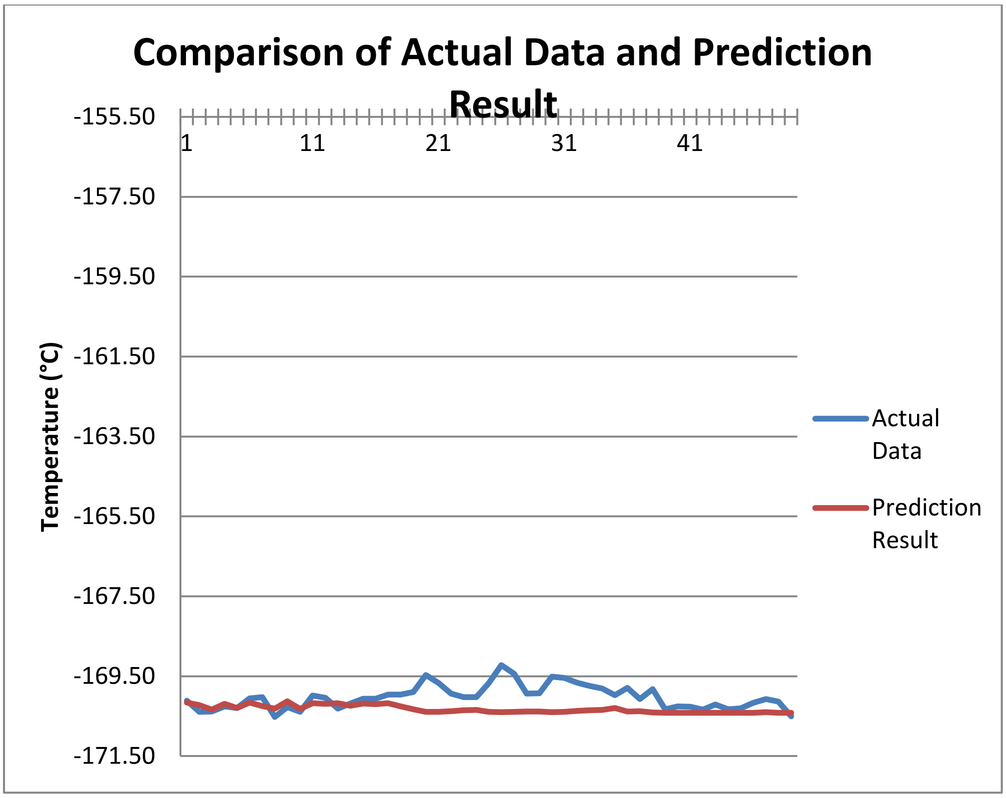


Figure 11: Comparison between actual data and prediction result for expander

The result obtained was quite successful. The model was able to predict the actual data accurately for 50 data points. Figure 12 below shows the percentage error between the actual data and the predicted data. Very low percentage of error was obtained. The average percentage of error is 0.176% which is very low. This proves that this model is reliable and can predict very accurately.

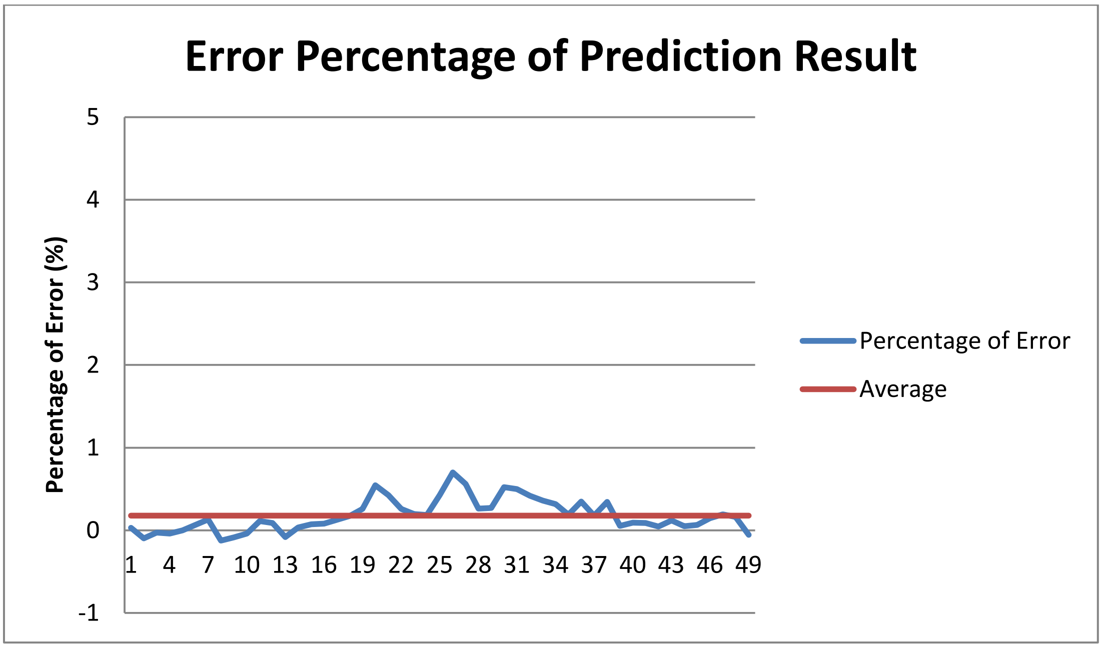


Figure 12: Percentage error of prediction result for expander

4.1.2 Centrifugal Compressor Prediction

Centrifugal compressor data consist of three input data are the inlet guide vane opening, compressor speed and direction of rotation. On the other hand, the target data is the discharge pressure of the compressor. The data set consist of 166 data points taken from 1st June 2008 until 13th November 2008 daily. 70% of the data is used for training of the model and 30% of the data is used for prediction. Refer Appendix for data.

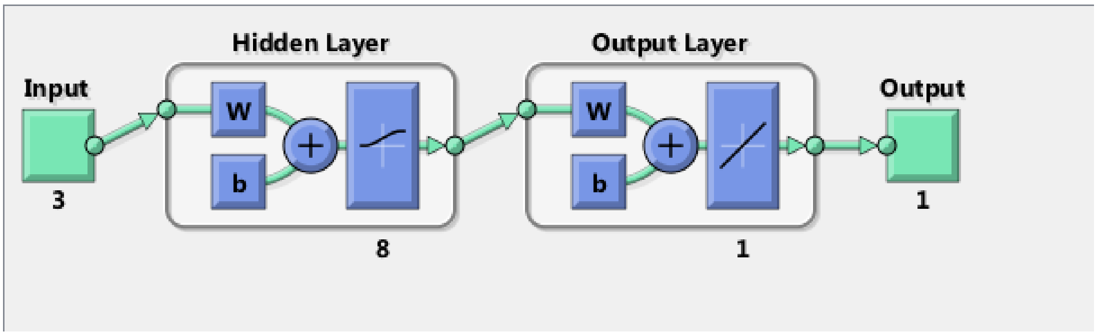


Figure 13: Summary of prediction model for centrifugal compressor

Figure 13 shows the summary of the model. The model has three inputs and 8 neurons in the first layer and 1 neuron for the second layer. The model uses LOGSIG as the first layer's transfer function and PURELIN for the second layer. Figure 14 below shows the results of the prediction.

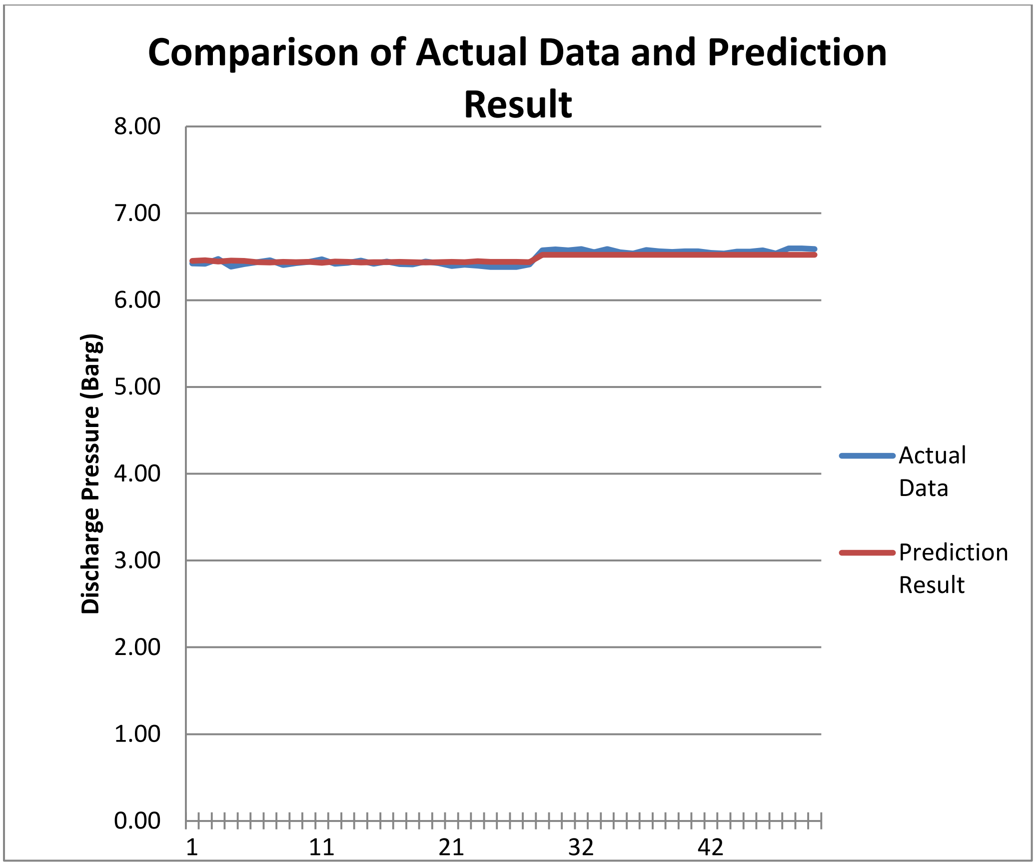


Figure 14: Comparison between actual data and prediction result for centrifugal compressor

The result obtained was also successful. The model was able to predict the actual data accurately for 50 data points. Figure 15 below shows the percentage error between the actual data and the predicted data. Very low percentage of error was recorded. The average percentage of error is 0.13% which is lower than the expander prediction model. This proves that this model is equally reliable with the expander prediction model and can predict very accurately.

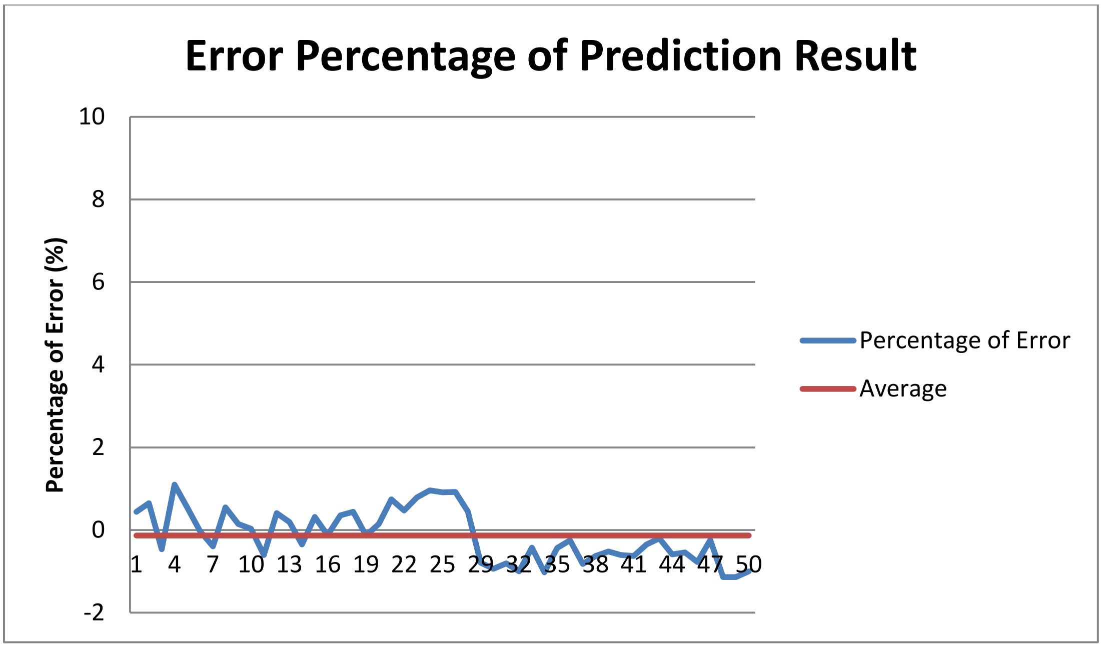


Figure 15: Percentage error of prediction result for centrifugal compressor

Both prediction model of expander and compressor showed good results. The percentage of error for the models are 0.176% and 0.13% respectively. Both models are reliable to predict future target data with the respective input data used in each model above. The target data of these models are failure indicators of these respective equipments. For example the expander is considered fail if the output temperature exceeds a certain pre-determined amount, thus interrupts its performance. The results of this prediction also indicate that neural network is a suitable tool for predicting performance of a system.

CHAPTER 5

CONCLUSIONS

This study will focus on predicting one failure mode of a centrifugal compressor and expander which is low output and high temperature output respectively. This is because the causes for the failure modes vibration, leakage at utility and process medium are not commonly monitored continuously in the industries. Therefore, they cannot be used as input variables for this model to predict their respective failure modes. Centrifugal pump data was unavailable due to limited number monitored parameters. Furthermore, initial modelling is done using data from Jahirul et al studies. The results are not sufficiently accurate for the initial modelling stage as the deviation of a few trial data from the actual data is very high. Although most of the data are accurate but the pattern is uneven.

Further studies have been made based on Wahiba et al research paper and MathWorks website which is the developer of MATLAB software. A procedure on how to design a neural network prediction model have been develop in this studies. Remodelling of the network using a different set of data taken from Jahirul et al research. The data set taken consist of the same number of variables intended for this studies which is four. Results of the training phase consist of minimum average percentage of error which is of 2.58%. Moreover the results of the prediction phase still consist of high percentage of error which is 5.28% suspected to be caused by the high error in the training phase.

Finally actual data of centrifugal compressor and expander is used. Two separate models with the same parameters are used. The prediction models showed good results. The prediction for expander obtained an average percentage of error of 0.176% while prediction for centrifugal compressor obtained 0.13%. This proves that these models are very accurate and reliable to use for performance prediction of a system. Therefore, the objective of this research have been achieved.

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APPENDIX I: EXPANDER DATA

Outlet Temperature	Inlet Pressure	IGV Opening	Expander Speed
-170.32	76.69	64.95	433.27
-170.30	76.67	66.15	439.71
-170.42	76.68	66.69	447.39
-170.46	76.93	67.89	441.62
-170.30	76.82	68.14	446.82
-170.30	76.84	68.24	456.59
-170.30	76.87	68.34	458.39
-170.44	76.86	68.44	460.70
-170.34	76.88	68.54	464.10
-170.22	76.85	68.64	455.75
-170.25	76.83	68.74	457.18
-170.34	76.84	68.85	453.71
-170.35	76.84	68.95	465.25
-170.28	76.82	70.02	449.69
-170.20	76.84	70.21	459.86
-170.05	76.83	70.35	462.74
-170.10	76.82	70.49	462.68
-170.24	76.83	70.64	448.74
-170.37	76.84	70.78	452.59
-170.18	76.81	70.92	460.92
-170.34	76.83	71.07	461.66
-170.34	76.82	71.21	461.52
-170.36	76.82	71.35	462.64
-170.42	76.82	71.50	465.95
-170.28	76.83	71.64	468.55
-170.28	76.82	71.78	467.96
-170.25	76.85	71.93	465.16
-170.22	76.83	72.02	469.39
-170.07	76.83	72.07	467.58
-170.05	76.83	72.12	465.52
-170.09	76.80	72.17	462.92
-170.05	76.82	72.21	465.72
-170.08	76.79	72.26	465.86
-170.26	76.81	72.31	474.04
-170.21	76.83	72.36	472.05
-170.18	76.81	72.40	470.53
-170.02	76.82	72.45	471.78
-169.80	76.82	72.50	460.26
-170.04	76.80	72.55	464.32
-170.01	76.80	72.59	469.19

-169.86	76.83	72.64	467.37
-169.84	76.82	72.69	462.97
-169.74	76.79	72.74	456.51
-169.89	76.80	72.78	463.63
-169.94	76.78	72.83	466.33
-169.94	76.79	72.88	464.25
-169.78	76.85	72.93	458.49
-169.79	76.88	72.98	461.81
-169.85	76.79	73.00	462.93
-169.67	76.79	73.00	457.39
-169.92	76.79	73.00	466.24
-169.84	76.80	73.00	438.82
-169.80	76.81	73.00	464.20
-169.92	76.80	73.00	468.06
-170.07	76.80	73.00	468.18
-170.17	76.80	73.00	471.12
-170.06	76.77	73.00	469.29
-170.14	76.80	73.00	472.19
-170.06	76.79	73.00	459.64
-170.30	76.79	73.00	463.34
-170.24	76.81	73.00	464.56
-170.21	76.82	73.00	465.65
-170.08	76.79	73.00	464.19
-169.91	76.78	73.00	458.34
-169.98	76.80	73.04	453.73
-169.98	76.82	73.09	461.08
-170.25	76.79	73.14	461.16
-170.31	76.82	73.19	467.76
-170.42	76.84	73.24	470.32
-170.43	76.82	73.29	466.33
-170.44	76.80	73.33	463.52
-170.45	76.83	73.38	468.02
-170.47	76.83	73.43	471.88
-170.45	76.80	73.48	473.30
-170.41	76.80	73.53	471.01
-170.31	76.79	73.58	471.48
-170.34	76.80	73.63	473.14
-170.45	76.81	73.68	469.34
-170.36	76.81	73.73	471.56
-170.32	76.81	73.78	475.57
-170.39	76.83	73.83	476.78
-170.33	76.82	73.88	472.34
-170.23	76.83	73.92	475.17
-170.32	76.79	73.97	476.41
-170.32	76.80	73.97	478.53

-170.29	76.77	73.90	473.49
-170.22	76.83	73.83	475.87
-170.36	76.82	73.77	487.44
-170.37	76.81	73.70	486.33
-170.23	76.84	73.63	478.96
-170.32	76.82	73.56	482.71
-170.21	76.83	73.50	479.42
-170.23	76.81	73.43	483.18
-170.16	76.82	73.36	478.27
-170.21	76.83	73.29	469.84
-170.05	76.83	73.23	467.56
-170.23	76.83	73.16	476.33
-170.27	76.85	73.09	477.35
-170.40	76.84	73.03	479.70
-170.36	76.83	72.97	479.86
-170.29	76.85	72.92	479.58
-170.34	76.82	72.87	481.61
-170.36	76.85	72.82	483.39
-170.29	76.83	72.77	478.06
-170.29	76.84	72.72	480.83
-170.30	76.79	72.67	476.75
-170.25	76.82	72.62	482.24
-170.33	76.80	72.57	487.27
-170.40	76.84	72.52	487.48
-170.43	76.81	72.47	488.63
-170.44	76.84	72.42	487.00
-170.31	76.84	72.37	482.40
-170.47	76.85	72.32	484.26
-170.26	76.84	72.27	466.04
-170.14	76.83	72.22	450.22
-169.93	76.85	72.18	454.53
-170.11	76.85	72.13	467.62
-170.39	76.84	72.08	473.30
-170.39	76.84	72.03	482.52
-170.26	76.82	71.93	473.74
-170.30	76.83	71.79	481.95
-170.05	76.89	71.64	469.33
-170.03	76.87	71.49	475.52
-170.52	76.89	71.35	482.98
-170.28	76.82	71.20	467.31
-170.39	76.87	71.06	486.22
-169.99	76.86	70.91	471.52
-170.04	76.87	70.77	472.02
-170.32	76.86	70.62	471.59
-170.18	76.89	70.47	477.89

-170.06	76.87	70.33	468.10
-170.07	76.88	70.18	475.34
-169.96	76.86	69.75	479.07
-169.96	76.86	67.72	487.97
-169.89	76.86	67.13	473.96
-169.47	76.87	65.03	475.37
-169.67	76.86	65.10	478.31
-169.93	76.86	65.17	484.74
-170.02	76.89	65.24	485.87
-170.03	76.88	65.31	492.86
-169.67	76.88	65.37	474.21
-169.22	76.86	65.44	468.82
-169.44	76.86	65.51	473.51
-169.93	76.82	65.58	483.64
-169.93	76.84	65.64	477.92
-169.51	76.81	65.71	475.50
-169.55	76.83	65.78	476.36
-169.66	76.83	65.85	483.44
-169.75	76.82	65.92	489.49
-169.81	76.80	66.25	493.16
-169.98	76.82	67.54	481.53
-169.80	76.79	66.54	474.02
-170.07	76.85	65.54	482.10
-169.82	76.82	64.49	474.94
-170.33	76.81	59.64	478.07
-170.26	76.81	53.35	489.45
-170.27	76.80	47.07	485.05
-170.34	76.85	40.78	488.24
-170.21	76.84	34.49	475.73
-170.33	76.86	28.20	479.27
-170.31	76.85	21.92	473.43
-170.17	76.83	15.63	480.09
-170.07	76.83	9.34	463.67
-170.14	76.85	3.34	477.06
-170.51	76.92	60.20	484.91
-165.37	75.30	52.58	485.02

APPENDIX II: CENTRIFUGAL COMPRESSOR DATA

Air Discharge Pressure	IGV Opening	Compressor Speed	Direction of Rotation (1/0)
6.4461	78.0262	8331.0642	1
6.4436	77.9855	8330.7201	1
6.4480	78.0146	8332.6580	1
6.4548	77.9879	8332.7618	1
6.4449	78.0433	8332.6435	1
6.4381	78.0049	8332.7919	1
6.4594	78.0102	8331.3018	1
6.4508	77.9765	8331.1553	1
6.4502	77.9748	8330.8933	1
6.4718	78.0123	8331.2513	1
6.4830	78.0188	8330.8776	1
6.4515	78.0091	8331.3295	1
6.4520	78.0527	8332.0103	1
6.4634	78.2169	8331.3639	1
6.4936	78.3724	8331.4806	1
6.5238	78.4359	8331.2925	1
6.5422	78.4413	8331.4395	1
6.4562	78.4554	8331.4601	1
6.4672	78.4685	8332.0461	1
6.5462	78.4429	8331.9594	1
6.4846	78.4985	8334.5211	1
6.5151	78.4862	8334.0501	1
6.4665	78.4476	8329.9160	1
6.5087	78.4257	8330.0804	1
6.4893	78.4500	8329.5657	1
6.4662	78.4481	8329.7262	1
6.4726	78.4556	8329.6353	1
6.4148	78.4144	8330.0284	1
6.4762	78.4211	8329.8785	1
6.4565	78.4438	8329.8742	1
6.4333	78.4483	8330.1881	1
6.4710	78.4902	8330.3572	1
6.4276	78.4782	8330.7365	1
6.5070	78.4776	8329.6350	1
6.4489	78.4687	8330.3948	1
6.4732	78.4235	8330.0553	1
6.4025	78.5065	8330.8802	1

6.4268	78.4868	8330.8307	1
6.4490	78.4770	8330.6631	1
6.4573	78.4608	8330.1914	1
6.4689	78.4633	8329.8596	1
6.4411	78.4566	8329.6321	1
6.4005	78.4453	8330.1342	1
6.4136	78.4465	8329.8939	1
6.4449	78.4593	8330.4345	1
6.4580	78.4674	8330.9769	1
6.4111	78.4709	8331.0009	1
6.4980	78.4511	8330.4701	1
6.5062	78.4500	8330.4640	1
6.5129	78.4619	8330.7284	1
6.5062	78.4842	8332.1076	1
6.5287	78.4844	8331.9411	1
6.5434	78.4859	8332.0671	1
6.5248	78.4954	8331.8115	1
6.5313	78.4844	8332.1811	1
6.4979	78.4683	8332.5016	1
6.5754	78.4309	8332.1435	1
6.5212	78.4702	8332.4491	1
6.4635	78.4596	8331.7423	1
6.4309	78.4687	8331.6228	1
6.4298	78.4742	8331.3450	1
6.4237	78.4830	8331.7143	1
6.4216	78.4692	8331.6953	1
6.4462	78.4790	8332.3087	1
6.5015	78.4863	8332.8413	1
6.4527	78.4720	8332.2862	1
6.5104	78.4574	8331.9711	1
6.4558	78.4814	8331.9621	1
6.5079	78.4462	8331.5221	1
6.4937	78.4298	8331.4634	1
6.4877	78.4404	8331.6276	1
6.5087	78.4930	8331.7413	1
6.5241	78.4337	8331.6132	1
6.5566	78.4643	8333.4156	1
6.5061	78.4905	8333.3140	1
6.5395	78.4526	8332.0273	1
6.5112	78.4543	8331.8749	1
6.5132	78.4863	8331.9298	1
6.4905	78.4688	8331.8274	1
6.5291	78.4772	8331.9496	1
6.5288	78.4547	8331.8886	1
6.4690	78.4487	8332.2040	1

6.4936	78.4569	8332.2987	1
6.5334	78.4684	8331.9755	1
6.5373	78.4577	8332.0353	1
6.5282	78.4605	8331.8552	1
6.5087	78.4569	8332.1607	1
6.5212	78.4545	8332.0150	1
6.4909	78.4492	8332.1649	1
6.5094	78.4465	8332.2541	1
6.5278	78.4697	8331.8331	1
6.4784	78.4546	8332.1421	1
6.4535	78.4540	8331.9730	1
6.4800	78.4250	8332.1257	1
6.4690	78.9945	8331.8146	1
6.4381	78.9672	8331.8194	1
6.4498	78.9614	8331.8366	1
6.4722	78.9611	8331.7640	1
6.4835	78.9593	8331.3676	1
6.4520	78.9515	8331.9304	1
6.4661	78.9604	8332.1265	1
6.4132	78.9456	8332.4614	1
6.4243	78.9536	8332.9678	1
6.3867	78.9325	8332.8233	1
6.4096	78.9469	8332.5239	1
6.4954	78.9589	8332.2615	1
6.4475	78.9282	8332.4540	1
6.4235	78.9043	8330.5641	1
6.4794	78.9240	8330.2078	1
6.4310	78.9225	8330.4993	1
6.4087	78.9154	8330.7544	1
6.4312	78.9464	8331.0400	1
6.4196	78.9604	8331.6805	1
6.5059	78.9807	8332.2482	1
6.4378	78.9490	8331.4362	1
6.4005	78.9354	8331.2296	1
6.4225	78.9382	8331.3180	1
6.4185	78.9440	8331.7699	1
6.4741	78.9494	8331.1167	1
6.3853	78.9292	8331.4862	1
6.4166	78.9939	8331.4861	1
6.4383	78.9867	8331.0864	1
6.4589	78.9868	8330.9829	1
6.4059	78.9977	8331.2796	1
6.4262	78.9955	8331.1156	1
6.4403	78.9934	8331.2670	1
6.4703	78.9853	8330.8626	1

6.4181	78.9688	8331.2573	1
6.4295	78.9788	8331.2202	1
6.4575	78.9734	8330.8663	1
6.4183	78.9628	8330.9691	1
6.4446	78.9622	8330.8186	1
6.4168	78.9504	8330.9103	1
6.4102	78.9582	8330.9616	1
6.4439	78.9621	8330.6523	1
6.4281	78.9578	8330.8878	1
6.3944	78.9533	8331.0535	1
6.4070	78.9579	8330.8673	1
6.3971	78.9592	8331.3106	1
6.3808	78.9506	8331.0460	1
6.3838	78.9364	8330.8901	1
6.3823	78.9394	8330.7855	1
6.4107	78.9516	8330.8834	1
5.7237	72.5202	8352.8476	1
6.5740	60.0440	8461.4394	1
6.5836	60.0622	8462.9361	1
6.5750	60.0716	8462.7322	1
6.5877	60.0395	8462.6686	1
6.5500	60.0556	8462.7045	1
6.5891	60.0598	8462.6470	1
6.5501	60.1399	8462.4072	1
6.5380	60.0436	8462.2969	1
6.5760	60.1029	8461.8655	1
6.5630	60.1376	8461.8411	1
6.5562	60.0481	8461.7162	1
6.5618	60.0410	8459.8165	1
6.5629	60.0266	8459.7183	1
6.5447	60.0395	8459.5717	1
6.5353	60.0334	8459.5796	1
6.5607	60.0314	8459.3092	1
6.5574	60.0201	8459.3299	1
6.5726	60.0242	8459.7147	1
6.5378	60.0320	8459.8681	1
6.5969	60.0436	8459.4789	1
6.5972	60.0340	8459.7135	1
6.5880	59.9980	8459.2712	1