CHAPTER 4
RESULTS AND DISCUSSION

The objective of data gathering and collection which explained previously is to construct ANN model which can finally forecast the trip before the real trip. The unit selected for this project is boiler unit 1 (sub-critical pressure unit) whereby the unit is shutdown due to the leakage of the boiler tubes. Based on the real data collected from the selected thermal power plant, the unit has been shutdown from 25th April 2008 until 30th April 2008 and it is approximately about 5.17 days according to the plant annual outages.

After undergo the data processing procedure, the data are shortlisted into 32 important variables based on plant operator experience as listed in table 4.1. The variables are shortlisted based on the critical sensors that contributed to the trip of that particular unit of boiler. Among all those 32 variables, there are several variables that had been identified contributed to the trip before the real shutdown. However, this study is focused on the trips which arise before the real shutdown. All those contributions to the trip from each variable are evaluated and classified as "the influenced" (TI) and "the most influenced" (TMI) if the trip occurs slightly a few minutes before the real shutdown.

Based on the fault introduced table below, variable 20 (V20) is classified as TMI because the trip occurs after 2612 minutes of operation whereby the real shutdown occurs after 2615 minutes. The difference between V20 and the real shutdown is less than three (3) minutes. Hence, this variable is very important because it caused immediate trip to the boiler once the sensors detect the fault. This situation is surmountable when implementing ANN model because the model can forecast the trip earlier and the operators of the plant will have sufficient period to overcome the real shutdown.

Table 4.1 Fault Introduced in Trip 1

Var.	Description of the Sensors	Unit	Fault Introduced (Minute Intervals)
V1	Total Combined Steam Flow	T/H	705
V2	Feed Water Flow	T/H	704
V3	Boiler Drum Pressure	Barg	704
V4	Superheater Steam Pressure	Barg	704
V5	Superheater Steam Temperature	Deg C	2471
V6	High Temp. Re-Heater Outlet Temp.	°C	963
V7	High Temp Superheater Exchange Metal Temp.	°C	-
V8	Inlet Temp Superheater Exchange Metal Temp.	°C	2472
V9	High Temp. Superheater Intermediate Header Metal Temp.	°C	2471
V10	Final Superheater Outlet Temp.	°C	-
V11	Superheater Steam Pressure Transmitter	Bar	2471
V12	Feedwater Valve Station	T/H	704
V13	Feedwater Control Valve Positon	%	704
V14	Drum Level Corrected (Ctrl)	Mm	2214
V15	Drum Level Compensated (From Protection)	Mm	704
V16	Feedwater Flow Transmitter	%	-
V17	Boiler Circ Pmp1 Pressure	Bar	2031
V18	Boiler Circ Pump2 Pressure	Bar	1959
V19	Low Temp SuperHeater Left Wall Outlet Before superheater dryer	°C	704
V20	Low Temp SuperHeater Right Wall Outlet Before superheater dryer	°C	2612
V21	Low Temp SuperHeater Left wall After superheater dryer	°C	958
V22	Low Temp SuperHeater Right Wall Exchange Metal Temp	°C	2474
V23	Intermediate SuperHeater Exchange Metal Temp	°C	1948
V24	Intermediate SuperHeater Outlet Before superheater dryer	°C	1944
V25	Intermediate SuperHeater Outlet Header Metal Temp	°C	2007
V26	High Temp SuperHeater Outlet Header Metal Temp	°C	2480
V27	High Temperature ReHeater Outlet Steam Press	Bar	2477
V28	Superheated Steam From Intermediate Outlet Pressure	Bar	-
V29	Superheater Water Injection Compensated Flow	Ton/Hr	-
V30	Economiser Inlet Pressure	Bar	961
V31	Economiser Inlet Temp	°C	-
V32	Economiser Outlet Temp	°C	-
TI	V5, V8, V9, V11, V14, V17, V20, V22, V26, V27		
TMI	V20		

After identifying and assuming the very important variable which is "*Low Temp Superheater Right Wall Outlet Before Superheater Dryer*", the data will be fed into the real ANN model for further rationalization to obtain the acceptable and justified results. Based on the figure 4.1 below, the behavior of the data for the first 200 minutes of operation is very steady eventhough there are sensors that had detected faults. However, after the sensors at "*Low Temp Superheater Right Wall Outlet Before Superheater Dryer*" (V20) detect faults after 2612 minutes of operations, the unit shutdown 3 minutes later.

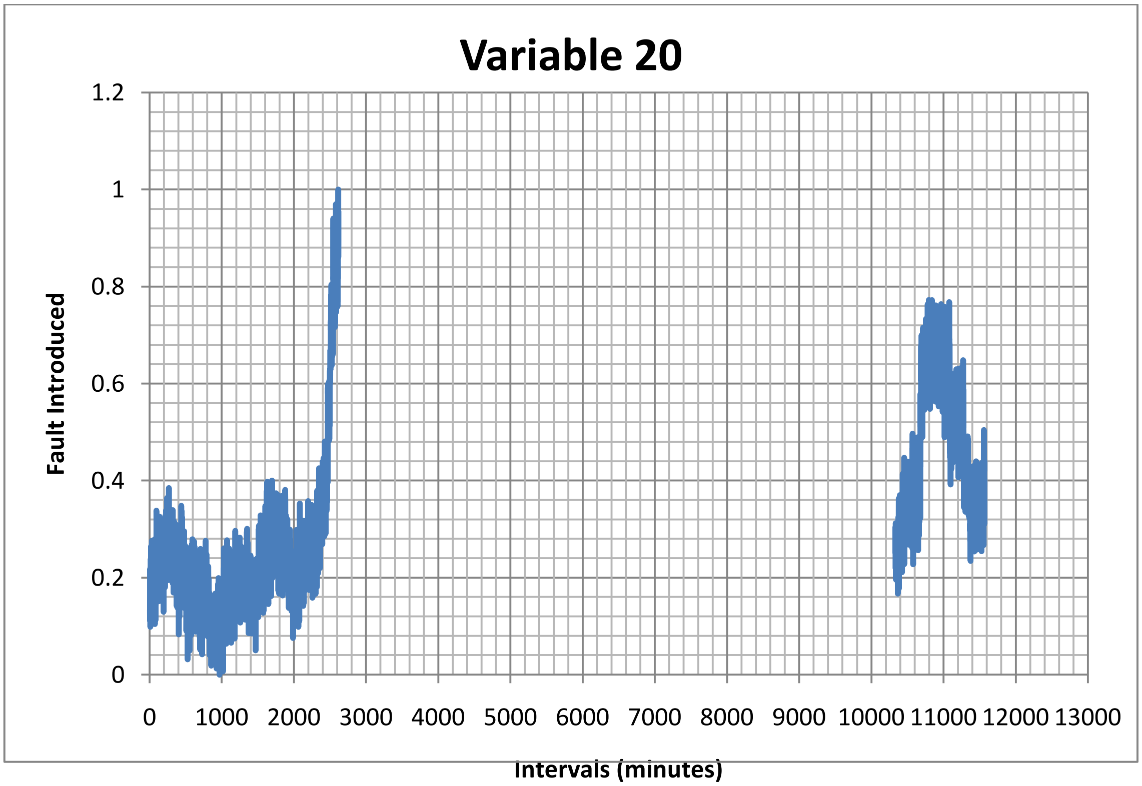

Figure 4.1 Variable of Low Temp Superheater Right Wall Outlet Before Superheater Dryer

Next step of this study is to model the NN network to produce a NN model that finally can forecast the trip earlier before the real shutdown for the ease of operator to take appropriate actions to avoid the shutdown. The data selected based on the 32 variables and fed into the NN model whereby the data is the normalized data which consists of all data before the real shutdown. This step is crucial since the primary objective is to forecast the trip before the real shutdown. The data undergone training and validation and there are 2 types hidden layers are used. First model is constructed by using only one (1) hidden layer with 10 neurons and the other model is constructed by using 2 hidden layers with 10 neurons. The neurons used in the model are only up to 10 neurons because the RMSE will be much higher than 0.5 and even up to 1.0 if using more than 10 neurons. The reason of using only 1 and 2 hidden layers is because the RMSE for 3 or more hidden layers will be constant. Hence, the ANN model is simulated with only up to 2 hidden layers.

For model with 1 hidden layer, there are two types of activation functions that had been combined together and used. The combinations are *purelin* and *logsig* (P+L), *tansig* and *logsig* (T+L), *purelin* and *tansig* (P+T) and so on. There are about 9 combinations of activation functions that had been simulated in this 1 HL model. Each combination will produced different root mean square errors (RMSE) under 1 neuron up to 10 neurons. Hence, the smallest RMSE produced under certain combination of activation function and certain neurons will be taken as the best combination for respective training algorithms.

For 2 HL model, there are 27 combinations of activation functions that had been simulated and each combination produced different values of RMSE. However, the ANN model is constructed with only 1 and 2 hidden layers because the 3 hidden layers model are constantly producing the value of RMSE which similar to the model with 2 hidden layers.

Each combination of the activation functions are simulated under different training algorithms because each training algorithms producing different functions as mentioned in the introduction part previously. Below are the data that has been tabulated and also has been compared by using comparison graph for the ease of analysis.

NHL1	1	2	3	4	5	6	7	8	9	10	1	2	3	4	5	6	7	8	9	10
	Trainlm										Trainrp									
L+L	0.513	0.510	0.535	0.490	0.486	0.510	0.537	0.565	0.474	0.456	0.513	0.537	0.537	0.518	0.537	0.537	0.536	0.536	0.536	0.536
L+T	0.463	0.468	0.457	0.499	0.691	0.467	0.468	0.472	0.443	0.622	0.583	0.560	0.554	0.533	0.585	0.495	0.624	0.679	0.508	0.483
L+P	0.522	1.614	0.522	0.561	0.534	0.487	2.905	0.524	11.154	0.505	0.541	0.842	0.582	0.530	0.539	0.538	0.585	0.524	0.623	0.582
T+T	0.501	0.539	0.479	0.582	0.533	0.506	0.619	0.463	0.586	0.871	0.526	0.637	0.532	0.543	0.522	0.523	0.545	0.581	0.505	0.509
T+L	0.504	0.504	0.470	0.460	0.536	0.512	0.547	0.463	0.478	0.456	0.536	0.507	0.525	0.536	0.536	0.535	0.536	0.500	0.525	0.522
T+P	0.511	0.518	0.525	0.551	0.540	0.537	0.589	5.558	4.272	1.396	0.669	0.546	0.514	0.522	0.746	0.508	0.605	0.522	0.516	0.542
P+P	0.763	0.785	0.764	0.763	0.763	0.763	0.763	0.725	0.763	0.763	0.580	0.558	0.529	0.539	0.594	0.570	0.468	0.536	0.534	0.559
P+L	0.463	0.517	0.569	0.527	0.521	0.787	0.493	0.486	0.491	0.503	0.534	0.535	0.535	0.536	0.536	0.536	0.524	0.534	0.536	0.537
P+T	0.588	0.594	0.586	0.589	0.596	0.878	0.593	0.844	0.844	0.596	0.585	0.511	0.570	0.638	0.568	0.563	0.606	0.601	0.612	0.509
	Trainbfg										Trainscg									
L+L	0.530	0.486	0.524	0.524	0.472	0.465	0.537	0.504	0.501	0.536	0.449	0.462	0.536	0.524	0.499	0.433	0.535	0.481	0.537	0.474
L+T	0.497	0.513	0.511	0.534	0.568	0.487	0.650	0.499	0.504	0.606	0.513	0.507	0.536	0.607	0.603	0.559	0.539	0.497	0.511	0.596
L+P	0.522	0.534	2.427	0.486	0.481	0.757	0.520	0.553	2.888	0.501	0.542	0.538	0.576	0.521	0.529	0.593	0.525	0.539	0.500	0.589
T+T	0.498	0.521	0.527	0.492	0.441	0.480	0.459	0.490	0.471	0.447	0.500	0.613	0.632	0.724	0.586	0.584	0.734	0.585	0.549	0.579
T+L	0.513	0.500	0.506	0.457	0.465	0.460	0.467	0.514	0.537	0.507	0.517	0.518	0.464	0.520	0.464	0.460	0.526	0.521	0.511	0.529
T+P	0.530	0.512	0.459	0.508	0.711	0.474	0.465	3.342	0.488	0.489	0.515	0.528	0.661	0.520	0.645	0.619	0.501	0.525	0.604	0.518
P+P	0.569	0.638	0.625	0.522	0.733	0.923	0.730	0.815	0.782	0.671	0.562	0.579	0.564	0.587	0.509	0.550	0.520	0.535	0.503	0.537
P+L	0.537	0.478	0.486	0.507	0.536	0.498	0.535	0.466	0.467	0.537	0.450	0.472	0.536	0.498	0.470	0.482	0.536	0.537	0.531	0.473
P+T	0.699	0.688	0.555	0.724	0.698	0.666	0.738	0.675	0.616	0.657	0.562	0.523	0.561	0.590	0.569	0.578	0.544	0.545	0.592	0.606

Table 4.2 RMSE for training functions of 1 hidden layer

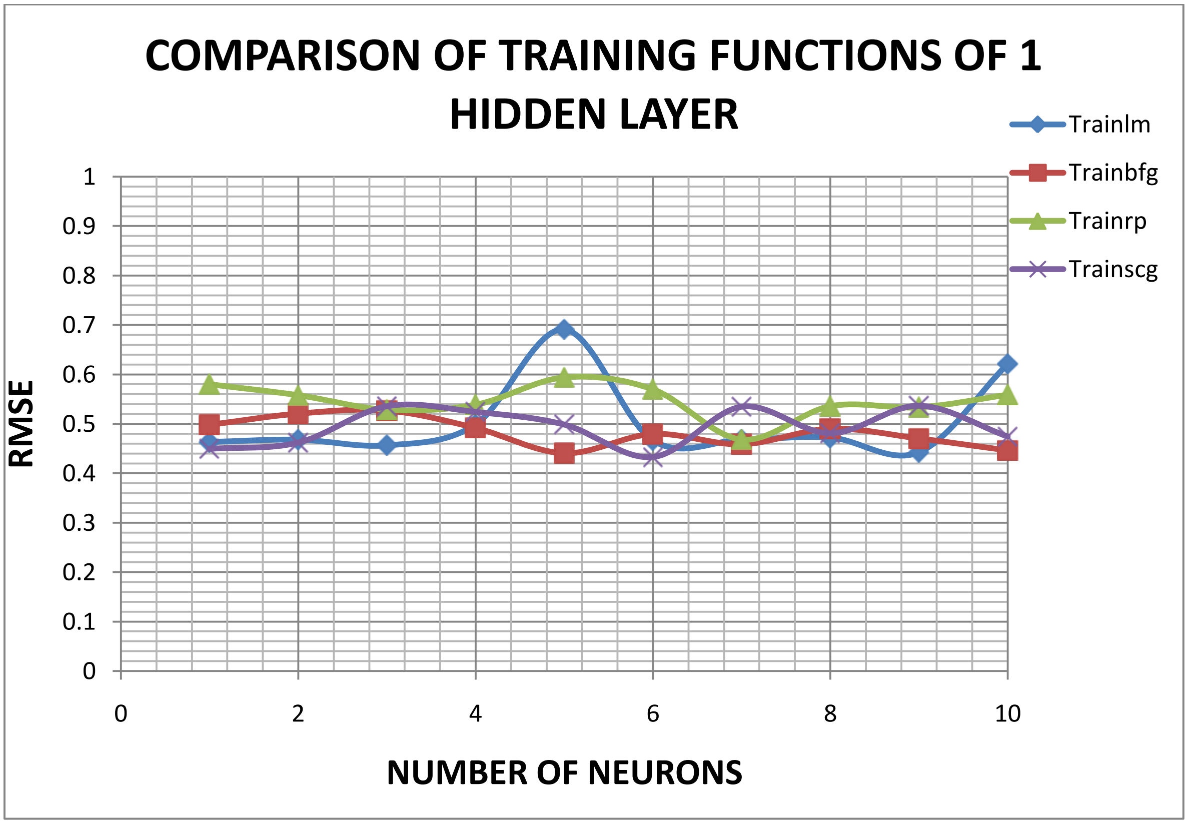

Figure 4.2 Comparison of training functions of 1 hidden layer

Above is the graph of the comparison of training functions of 1 hidden layer which produced different RMSE under the combination of 2 activation functions from 1 neuron up to 10 neurons. This graph is for the ease of selection of the best training algorithm and combination of activation functions which produced the smallest RMSE.

Based on the data of root mean square error (RMSE) tabulated for each training algorithms, the best training algorithm for 1 hidden layer is ***trainscg*** with the combination of ***logsig*** and ***logsig*** (L+L) activation functions. Under the combination of "L+L" activation functions with up to 6 neurons, the ***trainscg*** had produced the smallest RMSE of 0.4335005 among all of the small RMSE produced.

Next is to select the best combination of activation function and training algorithm of 2 hidden layers model which produced the smallest RMSE.

NNHL2	1	2	3	4	5	6	7	8	9	10	1	2	3	4	5	6	7	8	9	10
NNHL1	**T+T+T**					**Trainlm**					**P+T+L**					**Trainscg**				
1	0.501	0.511	0.494	0.516	0.491	0.477	0.516	0.516	0.509	0.515	0.513	0.544	0.507	0.505	0.525	0.519	0.530	0.514	0.527	0.465
2	0.535	0.537	0.537	0.491	0.516	0.524	0.566	0.537	0.716	0.502	0.529	0.535	0.513	0.528	0.507	0.532	0.546	0.439	0.459	0.518
3	0.495	0.641	0.513	0.536	0.555	0.474	0.687	0.557	0.484	0.478	0.513	0.513	0.474	0.525	0.579	0.526	0.460	0.497	0.527	0.508
4	0.741	0.505	0.650	0.464	0.565	0.496	0.481	0.486	0.482	0.522	0.452	0.533	0.537	0.523	0.508	0.528	0.513	0.534	0.515	0.522
5	0.459	0.531	0.480	0.530	0.578	0.523	0.511	0.440	0.495	0.468	0.513	0.504	0.515	0.513	0.513	0.537	0.534	0.524	0.503	0.506
6	0.466	0.494	0.475	0.595	0.773	0.503	0.721	0.651	0.886	0.472	0.527	0.513	0.463	0.467	0.525	0.525	0.475	0.515	0.454	0.496
7	0.544	0.480	0.514	0.650	0.622	0.616	0.520	0.707	0.637	0.487	0.513	0.535	0.515	0.536	0.529	0.529	0.503	0.510	0.435	0.448
8	0.756	0.765	0.719	0.844	0.429	0.615	0.844	0.492	0.522	0.526	0.513	0.517	0.471	0.491	0.528	0.472	0.502	0.455	0.531	0.498
9	0.498	0.640	0.694	0.624	0.596	0.476	0.493	1.005	0.447	0.575	0.513	0.522	0.534	0.514	0.528	0.531	0.531	0.531	0.535	0.517
10	0.495	0.902	0.458	0.470	0.524	0.562	0.684	0.653	0.527	0.510	0.513	0.460	0.535	0.531	0.475	0.533	0.510	0.507	0.531	0.515
NNHL1	**T+T+L**					**Trainrp**					**L+P+L**					**Trainbfg**				
1	0.524	0.533	0.535	0.531	0.529	0.513	0.506	0.529	0.537	0.534	0.527	0.475	0.537	0.513	0.537	0.513	0.537	0.513	0.459	0.525
2	0.512	0.527	0.533	0.513	0.536	0.532	0.536	0.536	0.531	0.534	0.537	0.537	0.537	0.513	0.489	0.462	0.520	0.537	0.536	0.533
3	0.513	0.512	0.535	0.536	0.535	0.532	0.522	0.537	0.529	0.539	0.536	0.491	0.513	0.467	0.536	0.452	0.480	0.537	0.460	0.496
4	0.513	0.533	0.531	0.536	0.519	0.536	0.536	0.536	0.537	0.537	0.461	0.471	0.537	0.534	0.468	0.460	0.537	0.518	0.537	0.508
5	0.536	0.535	0.524	0.533	0.533	0.536	0.536	0.536	0.528	0.514	0.487	0.494	0.537	0.529	0.536	0.502	0.496	0.537	0.535	0.485
6	0.537	0.512	0.522	0.530	0.535	0.537	0.506	0.448	0.536	0.528	0.526	0.537	0.497	0.516	0.474	0.537	0.532	0.537	0.529	0.508
7	0.536	0.536	0.535	0.537	0.536	0.529	0.534	0.496	0.483	0.537	0.495	0.514	0.529	0.537	0.537	0.523	0.506	0.524	0.505	0.530
8	0.537	0.533	0.510	0.537	0.536	0.487	0.519	0.532	0.473	0.535	0.536	0.487	0.463	0.529	0.534	0.535	0.537	0.537	0.537	0.504
9	0.531	0.537	0.534	0.535	0.446	0.528	0.537	0.534	0.536	0.537	0.452	0.536	0.453	0.449	0.536	0.534	0.536	0.537	0.536	0.537
10	0.537	0.533	0.533	0.536	0.535	0.532	0.531	0.537	0.537	0.508	0.491	0.474	0.456	0.537	0.537	0.537	0.537	0.523	0.537	0.490

Table 4.3 RMSE for training functions of 2 hidden layers

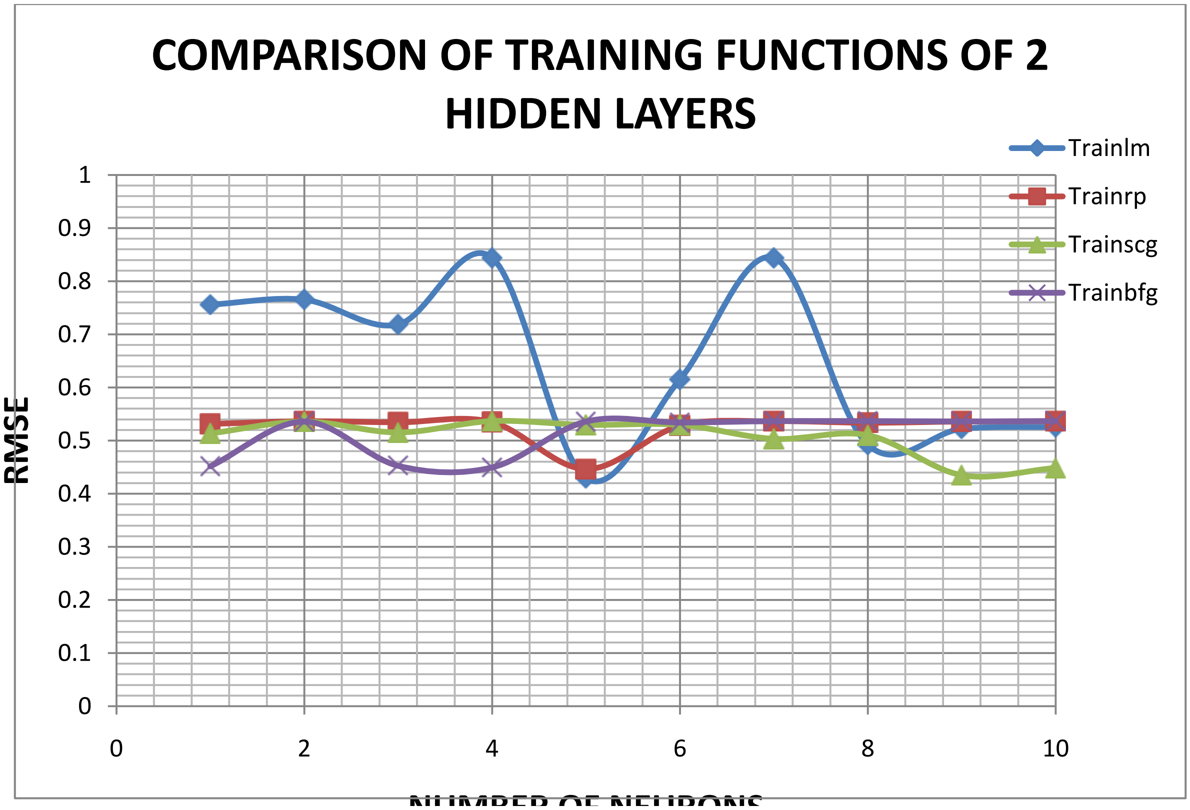

Figure 4.3 Comparison of training functions of 2 hidden layers

Training Algorithm	Trainrp	Trainlm	Trainscg	Trainbfg
RMSE	0.446	**0.429**	0.434	0.449
Architecture	9HL1-5HL2	**8HL1-5HL2**	7HL1-9HL2	9HL1-4HL2

Table 4.4 The Best Combination For FDDNN Models.

The graphs tabulated above is the graph of the comparison of training functions of 2 hidden layers which had produced root mean square errors under the combination of 3 activation functions (*purelin*, *logsig* and *tansig*). There are 27 combinations of activation functions that been simulated for each training algorithms. Based on the data of root mean square error (RMSE) tabulated for each training algorithms, the best training algorithm for 2 hidden layer2 is ***trainlm*** with the combination of *tansig*, *purelin* and *tansig* (T+P+T) activation functions. Under the combination of "T+P+T" activation functions with 8 neurons in 1 hidden layer and 5 neurons in 2 hidden layers, the ***trainlm*** had produced the RMSE value of 0.429.

After the comparison of the best training algoritms in 1 hidden layer model and 2 hidden layers model, the ***trainlm*** in 2 hidden layers model which produced the smallest is chosen to undergo the next step which is the validation step whereby in this step, the model will simulated by using different coding to finally produced the final forecasted graph which is important to prove that the trips are able to be forecasted earlier before the real shutdown. The graph below represents the forecasted graph whereby the forecast trip is known as the "Actual RMSE" and the real trip is known as "Predicted RMSE".

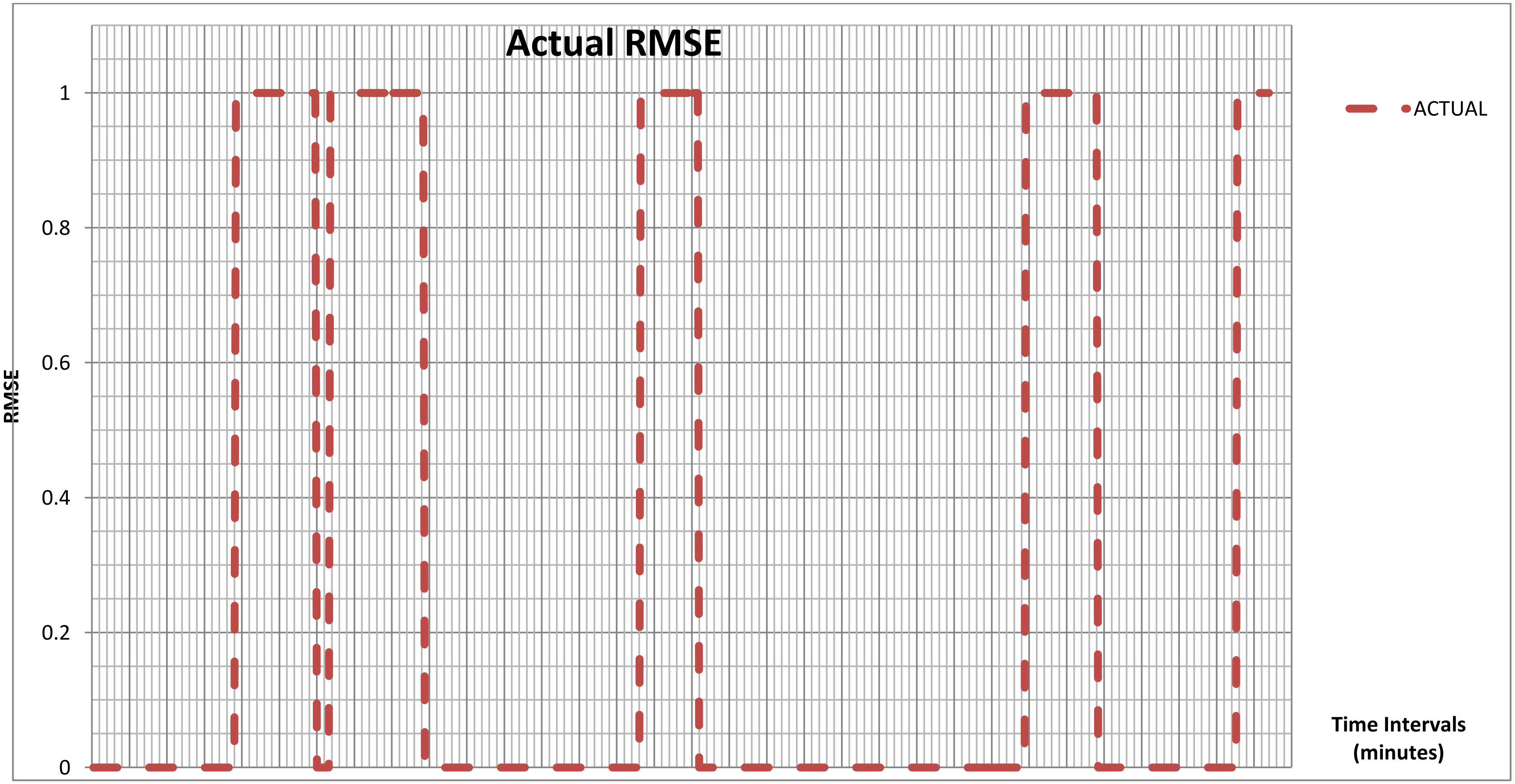

Figure 4.4 Actual RMSE

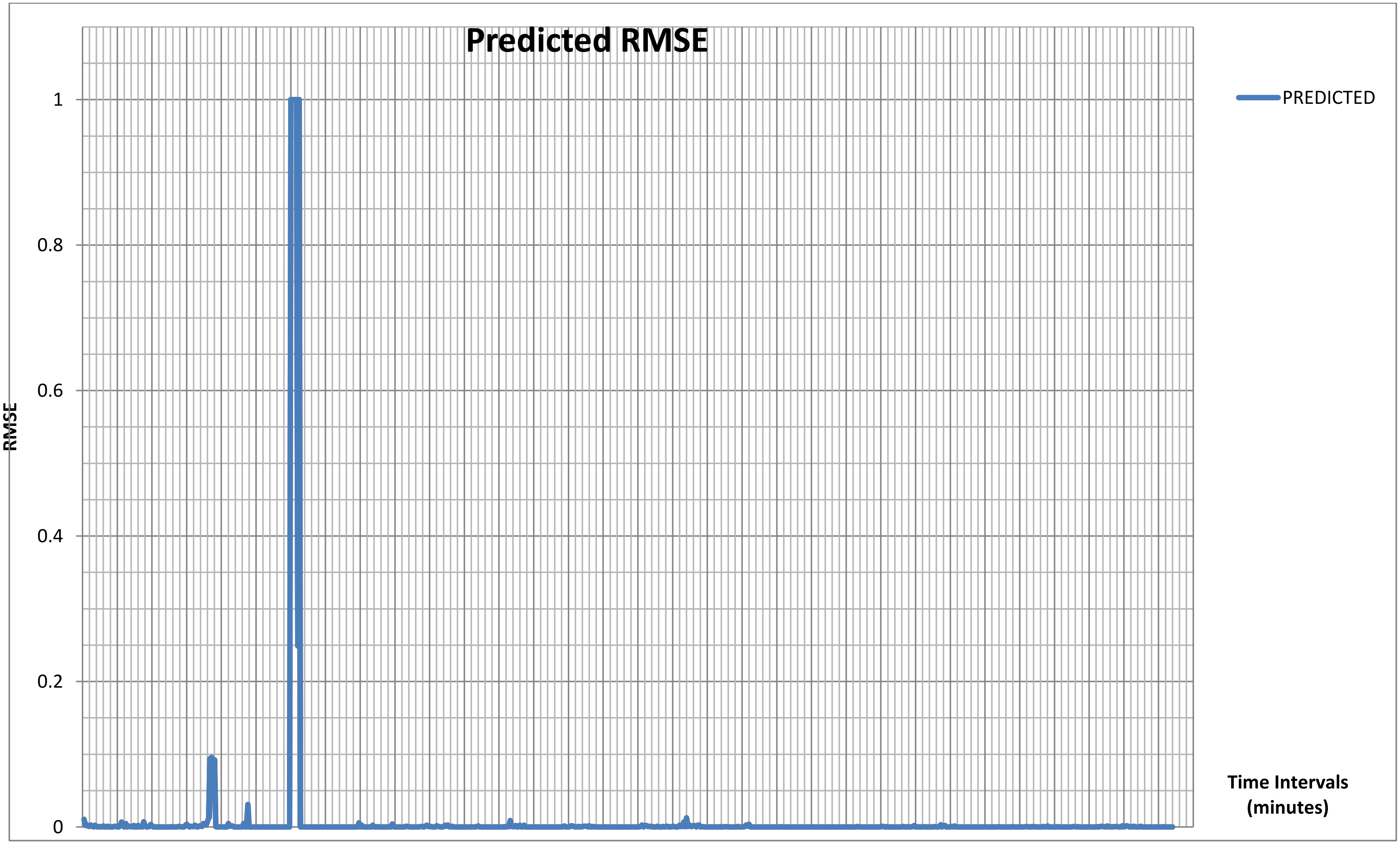

Figure 4.5 Predicted RMSE

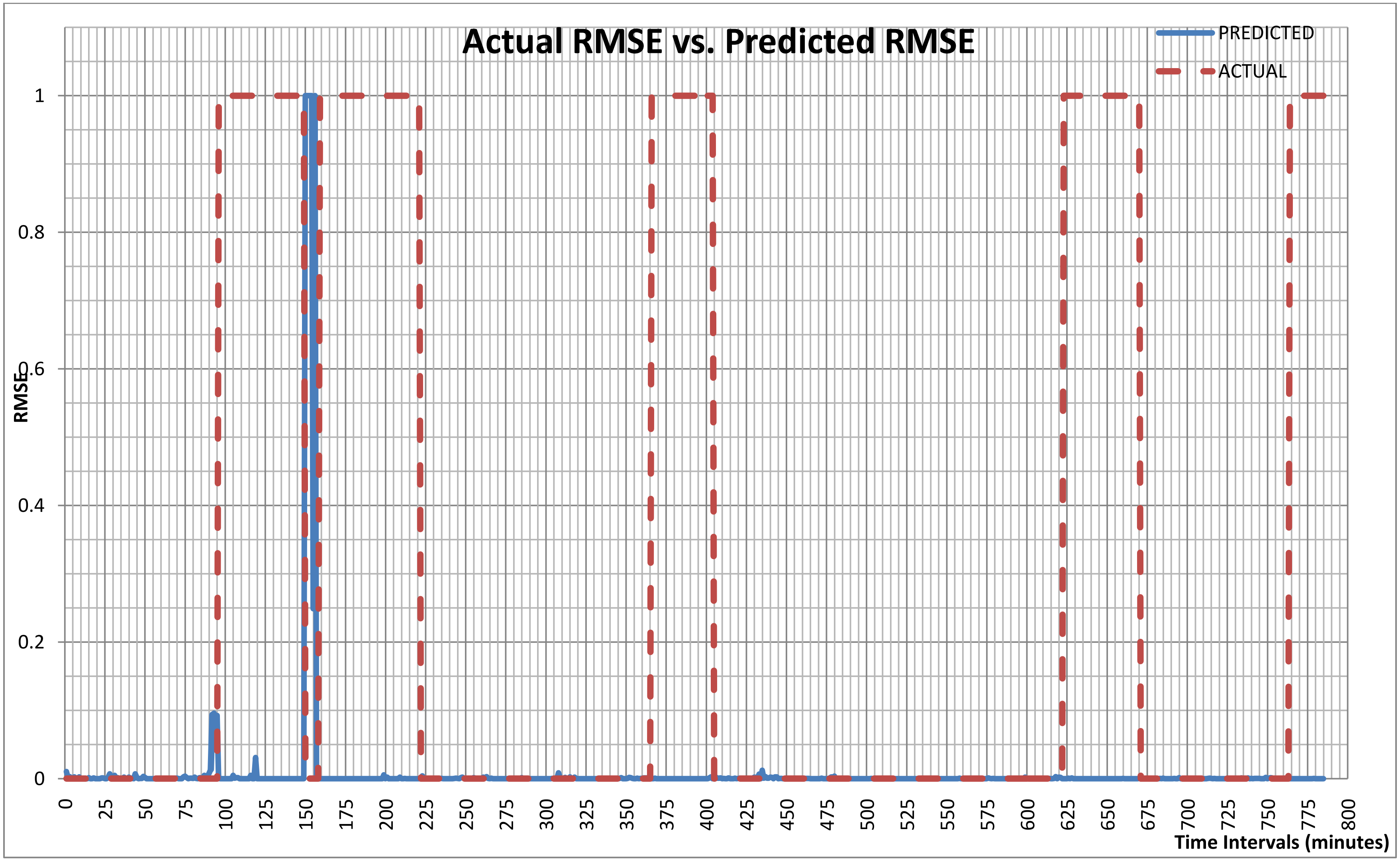

Figure 4.3 Actual RMSE vs. Predicted RMSE

As discussed above, the two models are quite similar though they have slightly different RMSE. Regarding accuracy, model with 2 hidden layers produced better RMSE whereby model with 1 hidden layer is slightly better. Since NN model with 2 hidden layers produced the smallest RMSE, hence it is chosen to undergo the validation process whereby the process is to validate the steps before and finally came up with the forecasting graph which consists of the predicted output and actual output. The predicted output is the forecast model which is essential to occur before the actual output whereby the output is the real trip which occurs.

Without implementing this ANN system, the trip will continuously occur as shown in figure 4.4. In the graph, the trip will eventually occur for every 200 minutes of operation and this will affect the plant operations. The graph shown in figure 4.5 is the predicted (forecast) trip that will ultimately occur before the real trip. This forecast trip will actually help the plant operator to take premature or prevention actions to prevent the real trip that will occur after a few minutes.

Based on the graph above, the predicted (forecast) trip in blue lines occurs after 150 minutes of operation whereby it can forecast the trip about 10 minutes earlier before the real trip (red lines) which occur after 160 minutes of operation. The data is classified as trip once it reaches the trip value (‘1’). The difference between the actual and predicted RMSE is essential and has been prove in this study that with the gap of 10 minutes, the real trip is possible to be eliminated or avoided which will ensure the boiler unit running continuously. Since this ANN system is a continuous-learning system, the future trip that will occur in the future can be forecasted again since the ANN system will detect it earlier.